Some Capital Gains are Consumed More Equally than Others*

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Abstract

This paper studies whether investors consume more out capital gains from funds that are more highly ranked in their online portfolio interface. Using linked account-level data on mutual fund holdings and consumption records from 180,000 active investors on the world's largest mobile payment platform, we document substantially larger consumption responses to capital gains from funds that are ranked more highly. Exploiting quasi-exogenous variation due to the platform's group-based ranking rule, we find that capital gains from a mechanically elevated fund generates an additional 2.15% in consumption. We also show that the extra consumption is financed by larger redemptions of mechanically elevated funds. Consistent with limited and selective attention, the effects are strongest at the top of the platform's ranking, concentrated in capital gains rather than losses, and larger among investors holding more funds. Finally, we show that fund-level attention effects aggregate to persistent portfolio-level consumption differences across investors with varying exposure to salient holdings.

JEL codes: G5, D90, G41, D14
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1 Introduction

People are inundated with information, and advances in financial technology have further amplified both its volume and immediacy. In such an environment, the ranking of information helps determine what investors notice and what remains in the background. Recent theory and evidence show that salience, top-of-the-list placement, and interface design affect portfolio choice (Manzini and Mariotti, 2014; Bordalo et al., 2012, 2013; Koszegi and Szeidl, 2013; Hartzmark, 2015; Frydman and Wang, 2020; Kaniel and Parham, 2017; Barber et al., 2022). Yet much less is known about whether the same variation in ranking and attention changes how households consume out of stock market wealth.[1]

This paper studies whether display ranking breaks within-portfolio fungibility of capital gains. Standard portfolio-choice models imply that gains of different funds within the same portfolio should have the same marginal propensity to consume (MPC). But if attention is scarce, then gains that appear at the top of the screen may be more likely to be noticed and spent than economically similar gains displayed farther down. Ranking-induced attention can therefore change how fluctuations in stock market wealth pass through to household consumption.

We examine this question using linked account-level data on mutual fund holdings and monthly expenditures for 180,000 active investors on Alipay, the world's largest digital payment provider and China's largest mutual fund distribution platform, from January 2019 to December 2020. During our sample period, the platform's default interface orders holdings by purchase recency, so the most recently purchased fund appears at the top of the display. A second display rule groups funds from the same fund company in a single block, which can move some older holdings closer to the top.

[1] Loos et al. (2020) and Agarwal et al. (2020) show that behavioral biases in investing affect consumption, but do not exploit direct variation in the salience of investments within the same portfolio.

Together, these features generate a default recency ranking and, within that ranking, a mechanical source of variation in the prominence of older holdings.

We first show that a 100 RMB gain from recently purchased funds is associated with a 1.60 RMB increase in next-month consumption, compared with 1.00 RMB for gains from older holdings in the same portfolio. Under the default recency ordering, the differential consumption effect is concentrated at the very top of the ranking: the coefficient on gains from month $t-1$ purchases is 0.0131, whereas the corresponding coefficients for month $t-2$ and $t-3$ purchases are smaller and not statistically significant. This pattern is consistent with the top-ranked holding receiving the greatest visual prominence on the interface. By itself, however, it does not yet show that rank, rather than some other difference between recent and older holdings, is what matters.

The paper's principal identification design exploits the platform's group-based display rule. Because funds from the same fund company are displayed in a single block, some older holdings are mechanically moved closer to the top when they belong to the same family as the most recent purchase. Using this design-based variation, we show that a 100 RMB gain from a mechanically elevated older fund generates an additional 2.15 RMB of next-month consumption relative to a lower-ranked older fund. The benchmark response for an older fund is only 0.26 RMB per 100 RMB of gains.

Redemption behavior is consistent with this spending response. A 100 RMB gain from a highly-ranked older fund is associated with an additional 56 RMB of redemption relative to a less visible older fund, and gains from recently purchased funds generate an additional 67 RMB of redemption per 100 RMB of gains. Beyond looking at portfolio-level redemption, we can also look at fund-level redemption. We show significant effects of the mechanical elevation in this specification as well including not only account times month-by-year fixed effects but also funds times month-by-year fixed effects. Salient gains are therefore not only noticed more; they are also more likely to be turned into spendable cash.

The Chinese mutual fund industry is concentrated and dominated by a handful of well-capitalized large fund families. To address the concern that the mechanically elevated older fund elicits a greater consumption response because of its family association with the recently purchased fund rather than its ranking, we conduct a robustness check in which we restrict our analysis to the largest fund families by assets under management. Additionally, we show that the elevated response appears for relatively recent same-company older funds, not for much older same-company holdings, which is what a ranking mechanism predicts and what is not consistent with a confounding family-level correlation mechanism.

In terms of heterogeneity, we show that the differential response is stronger for gains than for losses: the interaction between high-attention gains and the positive-gain indicator is 0.0181, with a similar estimate of 0.0144 when dividends are included. It is also concentrated among investors holding more funds, where even allocation of attention is hardest: the interaction coefficient is 0.0084 to 0.0085 for the more constrained group, compared with 0.0032 to 0.0045 for the less constrained group.

The differential responses do not wash out in aggregation. The aggregate MPC of investors with greater exposure to salient capital gains exhibit systematically larger portfolio-level consumption responses: the monthly MPC rises from 0.0068 in the bottom exposure tercile to 0.0182 in the top tercile, and the same monotonic pattern remains in quarterly specifications, where the corresponding estimates are 0.0114 and 0.0299. These results suggest that platform ranking may affect not only which gains an investor notices inside a portfolio, but also how fluctuations in stock market wealth propagate into aggregate household demand.

Finally, in a corroberating test, we exploit the fact that, in July 2020, the platform began allowing investors to sort their holdings by performance rather than only by recency. After that change, gains on the top-performing fund matter much more for spending: a 100 RMB gain on the top-performing fund translates into 4.62 RMB of next-month consumption, compared with 0.75 RMB for non-top-performing funds. Because we do not observe actual sorting take-up, we use this setting as corroborating reduced-form evidence rather than as a design equal to the main co-grouping test. Its value is that once the interface makes performance ranking easier to activate, unequal pass-through appears along a new ranking dimension as well.

The paper contributes to the literature on salience and attention in financial markets by showing that ranking-induced attention affects not only what investors trade or search for, but also how they spend out of portfolio gains (e.g., Kaniel and Parham, 2017; Hartzmark, 2015; Frydman and Wang, 2020; Barber et al., 2022; Liao et al., 2021; Hong et al., 2025). Existing work mainly studies trading, search, and fund-flow responses to salient information. Our setting adds a direct consumption margin, using quasi-exogenous variation in within-portfolio prominence to link display rank to household spending rather than only to portfolio choice.

The paper also contributes to the literature on consumption out of stock market wealth (Campbell, 2006; Poterba, 2000; Baker et al., 2007; Di Maggio et al., 2020; Chodorow-Reich et al., 2021; Imas et al., 2022). That literature typically asks how overall wealth shocks pass through to spending. Our evidence shows that the pass-through is not uniform even within the same investor's balance sheet: equal unrealized gains from different holdings can generate different MPCs because they occupy different positions on the interface. Our contribution is therefore to highlight a source of considerable heterogeneity in the consumption-wealth literature.

More broadly, the paper contributes to work on attention, information frictions, and macroeconomic transmission (Coibion and Gorodnichenko, 2015; Link et al., 2023; Parker, 1999, 2015; Agarwal et al., 2007; Jappelli and Pistaferri, 2010; Olafsson and

Pagel, 2018; Johnson et al., 2006; Agarwal and Qian, 2014; Jappelli and Pistaferri, 2014, 2000). Our results show that platform ranking rules shift the distribution of MPCs out of financial wealth and that these fund-level attention effects persist when aggregated to the portfolio level. In that sense, the paper provides suggestive evidence on one channel through which interface design may affect how stock market wealth shocks propagate into household demand.

The remainder of this paper is organized as follows. Section 2 describes the institutional setting, the default display rule, and the data. Section 3 presents the baseline evidence under the default ranking. Section 4 develops the main identification design and the corroborating post-July 2020 interface experiment. Section 5 traces the results from display rank to mechanism. Section 6 discusses the magnitudes of the estimates and their theoretical interpretation, and Section 7 concludes.

2 Institutional Background and Data

We use data from Alipay, a third-party mobile and online payment platform launched by the Alibaba Group in 2004. By 2013, Alipay had overtaken PayPal to become the world's largest digital payment provider. As of June 2020, the platform served over 1.3 billion users and 80 million merchants globally (Hong Kong Exchange News, October 20, 2020), and held approximately 55% of the third-party payment market in mainland China as of Q4 2018. Given this dominant market position, Alipay captures a significant share of users' day-to-day consumption activities. Beyond payments, Alipay has evolved into a comprehensive financial "super-app," offering a wide array of services including ride-hailing, healthcare appointments, travel bookings, and, importantly for our study, mutual fund investments.

In addition to its role in digital payments, Alipay is also a central player in China's asset management sector. Through its investment platform, Ant Fortune, Alipay has become the country's largest mutual fund distribution platform by assets under management (AUM) as of the end of 2024. The platform provides access to a broad range of fund types, including money market funds, bond funds, mixed-asset funds, equity funds, index funds, Qualified Domestic Institutional Investor (QDII) products, and gold funds. These offerings cater to a wide spectrum of retail investors, enhancing the platform's representativeness in capturing investment behavior.

Taken together, Alipay's dual function as both a dominant payment provider and the leading distributor of mutual funds uniquely positions it to reflect users' broader financial behaviors. We therefore regard the consumption and investment data from Alipay users as reasonably representative of household-level financial activity in China.[2]

To focus on users with meaningful investment activities, we restrict our sample to Alipay users whose mutual fund holdings exceeded 10,000 RMB at the beginning of 2019. Results are qualitatively unchanged using thresholds of 5,000 RMB or 20,000 RMB. From this group, we randomly selected 200,000 investors and tracked their behavior from January 2019 to December 2020. For each user, we collected detailed information on monthly mutual fund investments, monthly consumption, and individual characteristics.

To address the concern that hyperactive investors may exhibit distinct behavioral patterns—particularly, the tendency to be sensitive to high-frequency price movements and consequently underreact to monthly capital gains—we exclude from our main analysis those investors whose trading frequency ranks in the top 10% of the sample. This leaves a sample of 180,000 active investors, which forms the basis of our main results.[3] Results using the full investor sample are qualitatively similar and are reported

[2]All data was sampled, desensitized, and analyzed remotely on the Ant Open Research Laboratory. The laboratory operates as a secure sandbox environment where researchers can only use the packages provided by the lab and only a limited number of observations are visible to researchers.

[3]Panel A of Appendix Figure A1 shows that this top decile of active investors trade, on average,

in Internet Appendix Tables A1 and A2. All variables are winsorized at the 0.5 and 99.5 percentiles to reduce the influence of outliers.

Our dataset includes demographic and socioeconomic characteristics such as gender, age, residential location, and whether the investor works in their city of residence. We also observe investors' self-reported risk tolerance, which is collected through mandatory surveys in accordance with China Securities Regulatory Commission (CSRC) guidelines. According to Panel A in Table 1, we have 61% male investors, with an average age of 38 and self-reported risk tolerance level of 3 out of a 0 to 5 range.[4]

[Insert Table 1]

For consumption data, we utilize each user's monthly spending recorded through Alipay, which is also categorized into Taobao and non-Taobao spending. Taobao consumption refers to purchases on Alibaba's flagship e-commerce platform, while non-Taobao spending captures other transactions such as in-person purchases at restaurants, supermarkets, or local merchants. Given Alipay's substantial market share, especially in mobile payments, we consider monthly consumption through Alipay to be reasonably representative of these users' overall consumption behavior. According to Panel B in Table 1, the average monthly spending per user is approximately 6,525 RMB, including 1,559 RMB on Taobao and 4,833 RMB on non-Taobao purchases.[5]

Regarding mutual fund investment activities, we obtain detailed product-level records of purchase and redemption values and holdings for each investor at the monthly frequency on the Ant Fortune investment platform. Because we observe each investor's

about 120 times per month—four times more than the top 20% decile and roughly eight times more than the top 30% decile. Importantly, this high trading frequency is not driven by wealth differences, as shown in Panel B.

[4]Based on a series of questions regarding investment choices and attitudes, the system will assess each investor's risk level scaled from 0 to 5, with 0 indicating the highest level of risk aversion and 5 indicating the lowest.

[5]We omit the starting month of the sample (i.e., January 2019) when reporting the summary statistics as it is not used in the regression analysis due to the lagged construction of regressors.

product-level cumulative capital gains, our analysis focuses on total capital gains, as well as the sum of total capital gains and dividends. In China, dividends from actively managed mutual funds are subject to the discretionary decisions of fund managers within the scope of the fund's prospectus. In contrast, index funds generally aim to pass through dividends received from the constituent stocks of the benchmark index, often on a scheduled basis, though the exact distribution frequency and method may vary by fund. Finally, under current tax policy, individual investors in China are not subject to capital gains taxes on mutual fund investments. Internet Appendix Table A9 summarizes the main variable definitions used throughout the paper.

As shown in Panel C of Table 1, the average mutual fund holding per user is 82,804 RMB, with a median of 36,499 RMB. On average, users hold approximately 8 funds per month, with a median of 6. Panel C shows that recent investments (purchased within the past month) generate an average monthly capital gain of 522 RMB (or 558 RMB including dividends), whereas earlier investments yield a gain of 1,038 RMB (or 1,096 RMB with dividends). We also classify funds into top-performing and other funds based on their cumulative gains and losses. Top-performing funds deliver an average monthly capital gain of 673 RMB (or 708 RMB with dividends), compared with 951 RMB (or 1,013 RMB including dividends) for other funds. Across all categories, capital gains exhibit sizable dispersion, with standard deviations ranging from 2,389 RMB to 8,132 RMB.

The share variables—*Recent fund share* and *Top Performer share*—can take values outside the unit interval because the denominator (total capital gains) may be negative or close to zero in months when overall portfolio gains are negative or when gains and losses largely offset each other. In such months, the ratio of one component's gain to total gains is not bounded between zero and one; values below zero or above one reflect these near-zero or sign-changing denominators. All share variables are winsorized at the 0.5th and 99.5th percentiles to limit the influence of extreme observations arising from this construction.

3 Unequal Consumption Under the Default Display

3.1 Recency-Based Salience in the Default Ranking

During our sample period, the default setting on the Ant Fortune platform places recently purchased funds at the top of the holdings page. If display rank affects how investors translate gains into spending, gains from those recent holdings should generate a larger consumption response than gains from older holdings in the same portfolio. To test that prediction, we estimate the following baseline specification:

$$\begin{aligned} Consumption_{i,t} = \alpha + \beta_1\ CG_{i,t-1} \times Recent_{i,t-1} + \beta_2\ CG_{i,t-1} + \beta_3 Recent_{i,t-1} \\ + \Sigma_j Control^j_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

Here, $Consumption_{i,t}$ is total consumption in month t, $CG_{i,t-1}$ denotes capital gains or losses in month $t-1$, and $Recent_{i,t-1}$ is the share of gains generated by funds purchased in month $t-1$. When an investor purchases the same fund multiple times, we use the most recent purchase date so that the measure matches the interface logic. In an additional specification, we simply replace $CG_{i,t-1}$ with $(CG+Div)_{i,t-1}$, which denotes capital gains plus dividends. All regressions include account fixed effects and year-month fixed effects. Additional controls include total fund holdings and the number of funds held.

We use an interaction specification in which the variable $Recent_{i,t-1}$ captures the share of gains generated by recently purchased funds, so that the coefficient on $CG_{i,t-1}$ captures the consumption response to gains from older holdings and the interaction term $CG_{i,t-1} \times Recent_{i,t-1}$ directly identifies the incremental response attributable to the higher display rank. This formulation has two advantages. First, it naturally nests the null hypothesis of fungibility: under standard portfolio theory, the interaction coefficient should be zero, since gains from recently purchased and older funds should generate the same consumption response. Second, because $Recent_{i,t-1}$ is a continuous share rather than a binary split, the specification exploits the full cross-sectional variation in how concentrated an investor's gains are in recently purchased funds in a given month, rather than discretizing portfolios into two types. We include the constituent main effects $CG_{i,t-1}$ and $Recent_{i,t-1}$ following standard practice (Wooldridge, 2010; Angrist and Pischke, 2009; Greene, 2012); excluding them leaves the interaction coefficient unchanged, confirming that the results are not sensitive to this choice.

[Insert Table 2]

Table 2 shows a clear effect of salience under the default display. In Column (2), a 100 RMB gain from older holdings is associated with a 1.00 RMB increase in next-month consumption, whereas a 100 RMB gain from recently purchased funds is associated with a 1.60 RMB increase. Column (4) yields the same qualitative pattern when dividends are included: the implied response is 0.95 RMB for older holdings and 1.62 RMB for recent holdings. Across specifications, the top of the display carries a meaningfully larger pass-through from portfolio gains to consumption.

This baseline evidence is consistent with salience, but it does not yet establish that display rank is the driver. Recently purchased funds may differ from older holdings for reasons unrelated to prominence, including rebalancing motives, private information, or time-varying demand for risky assets. The next section therefore turns to design-based variation in prominence within the default ranking itself.

4 Identification

The baseline recency result is consistent with a salience mechanism, but alternative explanations remain possible. The most direct concern is that prominent funds simply proxy for different return opportunities or different investor intentions. This section addresses that concern using the paper's main identification design, which exploits a mechanical grouping rule embedded in the default interface.

4.1 Same-Company Grouping in the Default Display

During our sample period, the default interface groups together funds from the same fund company as the most recent purchase. This feature creates plausibly exogenous variation in the display rank of older holdings. As an illustrative example, consider an investor who holds three funds: A, B, and C. Fund A is the most recent purchase, while B and C were acquired earlier. If A and C belong to the same fund company, C is displayed immediately below A, while B appears farther down the page. In that case, C receives a higher display rank and becomes more salient than B even though both are older holdings. Panel A of Figure 1 illustrates this display rule schematically, and Panel B (right column) shows a representative screenshot of the actual Ant Fortune holdings interface, where fund-family blocks (e.g., Bosera Funds, CSOP Fund Family) make the co-grouping rule visible in practice. Crucially, the co-grouping assignment depends only on fund company membership at the time of the most recent purchase — it is determined before and independently of contemporaneous fund returns or any current investor intention — so cross-sectional variation in which older funds fall into the co-grouped block is orthogonal to the gains realized in that period. Furthermore, co-grouping is assigned mechanically by the platform's display algorithm rather than by investor choice, and the account fixed effects in our specifications absorb any time-invariant preferences investors may have for particular fund families, ensuring that the estimated effect reflects display salience rather than a selection preference.

We exploit this grouping rule to ask whether two older funds with the same level of gains generate different consumption responses because one of them is placed higher in the default display. To do so, we interact the baseline recency specifications with $Same\,Company_{i,t-1}$, defined as the share of gains from earlier holdings that comes from funds belonging to the same fund company as the investor's most recent purchase. We thus run the following specification:

$$\begin{aligned} Consumption_{i,t} = \alpha &+ \beta_1\ CG_{i,t-1} \times (1 - Recent_{i,t-1}) \times Same\,Company_{i,t-1} \\ &+ \beta_2\ CG_{i,t-1} \times Recent_{i,t-1} + \beta_3\ CG_{i,t-1} + \beta_4 (1 - Recent_{i,t-1}) \times Same\,Company_{i,t-1} \\ &+ \beta_5 Recent_{i,t-1} + \Sigma_j Control^j_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

Where all variables are specified analogous to Specification 1. Table 3 provides the paper's main design-based evidence. In Column (2), the coefficient on $CG_{i,t-1} \times (1 - Recent_{i,t-1}) \times Same\,Company_{i,t-1}$ implies that a 100 RMB gain from a co-grouped older fund generates an additional 2.15 RMB of next-month consumption relative to a non-co-grouped older fund. The benchmark response to a non-co-grouped older fund is 0.26 RMB per 100 RMB of gains, as captured by the coefficient on CG, implying a total MPC of 2.41 RMB for co-grouped older funds. Column (4) delivers nearly the same conclusion when dividends are included: the incremental effect for co-grouped older funds is 2.11 RMB per 100 RMB of gains, relative to a baseline response of 0.26 RMB for non-co-grouped older funds, implying a total MPC of 2.37 RMB for co-grouped older funds.[6]

[Insert Table 3]

The Chinese mutual fund industry during our sample period provides a setting that is broadly favorable to the co-grouping identification design. By 2019–2020, all of China's approximately 116 licensed mutual fund management companies had joined the Ant Fortune platform, collectively offering over 4,000 products. The industry is characterized by moderate concentration at the top — with a handful of large, well-capitalized, and broadly diversified asset managers (E Fund Management, China AMC, Bosera, Harvest, ICBC Credit Suisse, and GF Fund, among others) dominating AUM rankings — alongside a fragmented tail of smaller and more specialized firms.[7] These large fund companies offer broad product menus across asset classes and investment styles. For the investors in our sample who hold multiple funds from one of these large, diversified houses, the co-grouping assignment is unlikely to carry information about the relative return prospects of the co-grouped fund: these firms offer many broadly substitutable products across asset classes, and same-company membership at the time of the most recent purchase reflects the breadth of a large fund family's product shelf rather than a deliberate investor signal about quality or expected returns. This feature of the market structure supports the identifying assumption that co-grouping variation is orthogonal to contemporaneous fund-level gains.

[6]One potential concern is that funds from the same company may have correlated returns, which could mechanically generate significant and positive MPCs for high-attention, earlier invested funds as recently purchased funds from the same fund company. To address this issue, we explore variations in salience across high-attention, older holdings. Specifically, we further split older holdings that share the same fund company as the recent investment into two groups: (i) relatively recent holdings purchased between $t-2$ and $t-4$, and (ii) relatively older funds purchased in $t-5$ or before. In unreported tests, we find that an elevated MPC appears only among the relatively recent funds purchased in $t-2$ to $t-4$, whereas the coefficient for the relatively older holding is close to zero and statistically insignificant.

[7]See Hong et al. (2025) and `https://www.amac.org.cn/hyyj/hjtj/`.

To nevertheless address the concern that same-company membership captures correlated fund returns or beliefs about returns rather than display salience, we conduct the same test but restrict to the largest fund families. For investors holding multiple funds from these diversified companies, same-company membership is less likely to proxy for a narrow style shock or common return component. Internet Appendix Table A4 therefore defines same-company older funds using only fund companies in the top half of the sample distribution by number of funds. The estimates are similar to those in Table 3: in Column (2), a 100 RMB gain from a co-grouped older fund raises next-month consumption by an additional 2.32 RMB relative to a non-co-grouped older fund; in Column (4), the dividend-inclusive estimate is 2.27 RMB. These results support the interpretation that the same-company estimates reflect display prominence rather than mechanically correlated returns within fund families.

Taken together, these results show that moving an older fund higher in the default display increases how strongly its gains pass through to consumption.

5 From Display Rank to Mechanism

This section first traces the wedge more directly to display rank, then turns to the interface change that made performance-based ranking easier to use, and finally examines the behavioral channels behind the spending response.

5.1 Equal Gains, Unequal Consumption Across Display Ranks

Table 4 links the unequal consumption response more directly to display rank itself. Panel A replaces the simple recent-versus-older split with separate gain shares for funds purchased in months $t-1$, $t-2$, and $t-3$, which under the default interface correspond to progressively lower positions on the holdings page. The incremental response is concentrated at the very top of the display: in the capital-gains-plus-dividends specification, Column (2), the coefficient on $(CG+Div)\times Purchase\,in\,month\,t-1$ is 0.0130 and significant at the 1% level. The baseline coefficient on $CG+Div$ in Column (2) is 0.0061, so the total implied response for the top-ranked group is 1.91 RMB (= 0.61 + 1.30) per 100 RMB of gains. By contrast, the corresponding coefficients for $t-2$ and $t-3$ purchases are not statistically distinguishable from zero. The same qualitative pattern and nearly identical magnitudes appear in the capital-gains-only specification. This is the pattern one would expect if unequal pass-through operates through display rank: the wedge is strongest at the top and fades quickly farther down the page.

[Insert Table 4]

Panel B shows that this conclusion does not depend on measuring *Recent* as the combined gain share of all last-month purchases. Instead, it redefines *Recent* as the share of gains generated by the single most recently purchased fund, which is the fund displayed at the very top of the holdings page. Under this alternative definition, the coefficient on $CG \times Recent$ remains positive and significant at the 1% level. In Column (2), the implied response to gains on that top-ranked fund is 1.75 RMB (= 0.66 + 1.09) per 100 RMB, compared with 0.66 RMB for other funds. The same qualitative pattern and similar magnitudes appear when dividends are included. Taken together, the two panels point to display rank as the mechanism: the excess response is concentrated at the top of the display and fades quickly farther down the page.

5.2 Corroborating Evidence from the Interface Change

The rank-gradient evidence above shows that display rank drives the unequal pass-through. We next ask whether the same salience logic emerges along a different ranking dimension when the platform changes the interface itself. Existing work shows that investors pay disproportionate attention to extreme performers in ranked settings (Hartzmark, 2015). Our setting is useful because it lets us distinguish top-performer salience per se from salience created by the interface ranking. Prior to July 2020, fund holdings on the platform were displayed strictly in order of purchase. In July 2020, however, Ant Fortune allowed investors to customize the order of their holdings using alternative criteria such as cumulative gains, cumulative returns, daily proceeds, daily returns, or the timing of NAV updates. Panel C of Figure 1 summarizes this interface change.

Although we do not observe which investors chose to sort by performance, the before-after contrast remains informative: if interface ranking is what draws investor attention, the top-performer effect should emerge mainly after performance-based sorting becomes easier to activate. A key concern is that July 2020 coincided with an equity market rally that mechanically increased the gains on top-performing funds. We address this in two ways. First, the year-month fixed effects in all specifications absorb any aggregate time-series shift in consumption or gains levels. Second, the triple interaction in Equation (3) tests whether the *incremental* consumption response to top-performing funds specifically—over and above the response to all funds—widened after July 2020; a market-wide rally would raise the level of gains on all funds but would not differentially amplify the top-performer coefficient unless the interface change itself altered how investors weighted top-performer gains.

To evaluate that prediction, we estimate the following specification:

$$\begin{aligned} Consumption_{i,t} = \alpha &+ \beta_1\, CG_{i,t-1} \times TopPerformer_{i,t-1} \times After_t \\ &+ \beta_2\, CG_{i,t-1} \times TopPerformer_{i,t-1} + \beta_3\, CG_{i,t-1} \times After_t \\ &+ \beta_4\, CG_{i,t-1} + \beta_5\, TopPerformer_{i,t-1} \times After_t \\ &+ \beta_6\, TopPerformer_{i,t-1} + \Sigma_j Control^j_{i,t} + \lambda_i + \gamma_t + \epsilon_{i,t}. \end{aligned} \tag{3}$$

Here, $TopPerformer_{i,t-1}$ is the share of gains in month $t-1$ generated by the fund with the highest cumulative gains in investor i's portfolio, and $After_t$ is an indicator for July 2020 and later months. We also estimate a parallel specification that replaces capital gains with the sum of capital gains and dividends.

Again, we use this interaction specification with the share of gains generated by top-performing funds after the platform change, so that the significance level of the triple interaction term directly represents our main coefficient of interest. Again, we include the constituent main effects following standard practice (Wooldridge, 2010; Angrist and Pischke, 2009; Greene, 2012); excluding them leaves the interaction coefficient unchanged.

[Insert Table 5]

Table 5 shows a sharp widening of the performance-salience wedge after the interface change. In Column (2), before July 2020 the response to gains on non-top-performing funds is 0.27 RMB per 100 RMB of gains, while the response to gains on the top-performing fund is 0.37 RMB (= 0.27 + 0.10), so the incremental top-performer effect is economically small and statistically insignificant. After July 2020, the response to gains on non-top-performing funds rises to 0.75 RMB (= 0.27 + 0.48), while the response to gains on the top-performing fund rises to 4.62 RMB (= 0.27 + 0.48 + 0.10 + 3.77) (Column 2). The implied post-change incremental top-performer effect is therefore 3.87 RMB (= 0.10 + 3.77) per 100 RMB of gains (Column 2). The additional 3.77 RMB post-change widening is statistically significant at the 1% level, indicating that the top-performer wedge increases sharply after the interface change rather than merely reflecting a common rise in the consumption response to all fund gains. The same pattern appears when dividends are included.[8] July 2020 also coincided with a period

[8] Internet Appendix Table A6, "Alternative Performance Ranking: Top Performer Defined by Cumulative Return," shows a similar result when the top-performing fund is defined by cumulative return rather than cumulative gains.

of elevated Chinese equity market returns and heightened retail investor attention. The year-month fixed effects in all specifications absorb these aggregate time-series shocks.

The key result is that the top-performer effect is economically small and statistically insignificant before the interface change. It becomes large only after the platform makes performance-based ranking easier to use. This pattern suggests that display ranking matters more than top-performer status per se for investor attention, and that unequal consumption arises when the interface makes a particular ranking dimension salient.

5.3 Redemption as the Financing Channel

To spend out of investment gains, investors may need to convert those gains into cash by redeeming shares. If display salience changes how strongly gains affect spending, it should therefore also change how strongly those gains are redeemed. Table 6 mirrors the same-company grouping specification with next-month redemption as the dependent variable. In Column (2), a 100 RMB gain from a co-grouped older fund is associated with an additional 56 RMB of redemption relative to a non-co-grouped older fund, closely paralleling the consumption result in Table 3. Gains from recently purchased funds also generate a larger redemption response: an additional 67 RMB per 100 RMB of gains in Column (2). The same qualitative pattern and similar magnitudes appear when dividends are included.

[Insert Table 6]

These findings make the consumption results more economically plausible. The fact that higher-ranked funds are also redeemed more aggressively provides indirect evidence that investors are in fact paying more attention to those funds. Salient gains are not only noticed more; they are also more likely to be converted into spendable cash.

Appendix Table A5 shows that the redemption result is also robust at the fund level. Instead of aggregating redemption to the account-month level, this specification uses fund-by-account-month observations and includes both account-by-year-month fixed effects and fund-by-year-month fixed effects. The estimates therefore compare, within the same investor-month, whether redemption is stronger for funds whose gains are more visually salient under the same-company grouping rule, while absorbing month-specific shocks to each fund. The results are consistent with the account-level evidence in Table 6: capital gains on same-company earlier holdings predict significantly higher subsequent redemption, and the pattern remains similar when dividends are included in the gain measure.

5.4 Selective Attention to Gains versus Losses

Given the extant evidence for selective, not only limited, attention (Galai and Sade, 2006; Karlsson et al., 2009; Olafsson and Pagel, 2025; Quispe-Torreblanca et al., 2025), we next distinguish between gains and losses to ask whether display salience amplifies consumption responses symmetrically. If investors are more likely to notice and act on favorable performance than on unfavorable performance, then the recency wedge should be stronger for positive gains than for losses.

[Insert Table 7]

To test that prediction, Table 7 augments the baseline recency specification with an indicator for whether the relevant gain is positive and allows the recent-holding effect to differ between gains and losses. Under a selective-attention mechanism, the gain-loss asymmetry should be larger for recent holdings than for earlier holdings, since recent holdings are the funds that receive the highest display salience under the default interface.

The results match that prediction. In Column (1), the coefficient on $CG \times Recent \times Positive$ is 0.0181 and significant at the 5% level, implying that the gain-loss asymmetry is 1.81 RMB per 100 RMB larger for recent holdings than for earlier holdings. By contrast, the coefficient on $CG \times Positive$ is only 0.0056 and statistically insignificant, indicating little corresponding asymmetry for earlier holdings. The same qualitative pattern appears when dividends are included. This asymmetry stands in contrast to the traditional marginal propensity to consume literature, where liquidity constraints and precautionary motives typically imply larger responses to negative income shocks (Bunn et al., 2018). Instead, it is more consistent with attention-based frameworks such as the ostrich effect, in which investors selectively attend to gains while cognitively discounting or avoiding negative portfolio information.

5.5 Attention Constraints

If salience matters because investors cannot allocate equal attention across all holdings, the wedge should be larger among investors facing tighter attention constraints. Table 8 tests that prediction by splitting the sample according to the number of funds held at the start of the sample.

The logic is straightforward: the more funds an investor holds, the harder it is to monitor all of them evenly, so default display rank should matter more when the portfolio itself is more attentionally crowded. To test that implication, we split the sample by the number of funds held in the first month of the sample. Investors holding at least six funds are classified as more attention constrained, while those holding five or fewer are classified as less constrained.

[Insert Table 8]

The results match that prediction. In Column (3), the coefficient on $(CG + Div) \times$

Recent is 0.0085 for the more constrained group and significant at the 10% level, compared with 0.0045 and statistically insignificant for the less constrained group in Column (4). The same qualitative pattern appears in the capital-gains specification. What grows with attention constraints is the within-portfolio wedge between recent and earlier holdings, which is exactly what one would expect if display rank matters because investors have limited capacity to spread attention evenly across many funds.[9]

5.6 Robustness

The remaining robustness checks are reported in the Internet Appendix. First, we verify that the baseline recency effect and the same-company identification result are not sensitive to allowing for correlated shocks at both the account and year-month levels. Internet Appendix Table A3 repeats the two main default-display specifications with standard errors two-way clustered by account and year-month. Both results remain statistically significant, consistent with Tables 2 and 3. We note that in Panel A, Column (1)—the specification without controls—the interaction coefficient becomes insignificant under two-way clustering; this is expected given that the no-controls specification absorbs less variation. The preferred specification with controls, Column (2), remains significant, and the same pattern holds for the identification design in Panel B.

Second, the same-company estimates are robust to using a stricter definition of same-company funds. Internet Appendix Table A4 restricts same-company classification to fund companies in the top half of the sample distribution by number of funds. In Column (2), a 100 RMB gain from a co-grouped older fund raises next-month con-

[9] In unreported results, available upon request, we replicate the analysis by classifying investors based on their average number of funds held during the first three months of the sample period, and the conclusions are unchanged. Investor classifications based on the number of funds held are also highly stable from month to month.

sumption by an additional 2.32 RMB, and the dividend-inclusive estimate in Column (4) is 2.27 RMB—both close to the main estimates in Table 3.

Third, including the top 10% most active investors leaves the main patterns intact. In Internet Appendix Table A1, Column (2), a 100 RMB gain from a co-grouped older fund generates an additional 1.71 RMB of next-month consumption relative to a non-co-grouped older fund, with a baseline response of 0.29 RMB for non-co-grouped older funds.

Internet Appendix Table A2 shows a similar conclusion for the corroborating post-July 2020 setting: in Column (2), the additional post-change widening for the top-performing fund is 3.55 RMB per 100 RMB of gains and is significant at the 1% level. The corroborating performance result is not sensitive to ranking funds by cumulative return instead of cumulative gains. In Internet Appendix Table A6, Column (2), the post-change triple interaction remains positive at 3.04 RMB per 100 RMB and significant at the 5% level, with a similar estimate when dividends are included.

We can also break down consumption into in-person versus online retail purchases. Internet Appendix Table A7 separates consumption on Taobao, Alibaba's major online retail marketplace, from non-Taobao spending, which includes offline and other non-marketplace purchases. The differential response is concentrated in the latter category: in Column (3), a 1 RMB gain from recent funds is associated with 1.41 cents of non-Taobao consumption (= 0.83 + 0.58), compared with 0.83 cents for earlier holdings, while the corresponding response for Taobao purchases is only 0.18 cents and is statistically indistinguishable from the response to earlier funds.

Using cumulative rather than monthly gains also leaves the recency pattern intact. In Internet Appendix Table A8, the coefficient on cumulative gains interacted with *Recent* remains positive and significant at the 1% level, and the implied response to gains on recent funds is roughly twice as large as the response to gains on earlier holdings. Because cumulative gains are stock variables rather than monthly flows, we interpret those coefficients as robustness evidence rather than as literal monthly MPCs.

6 Discussion

6.1 Standard Portfolio Theory

We start our discussion by reviewing what a standard portfolio choice model would predict in terms of the consumption response to capital gains. In a standard portfolio choice model with constant relative risk aversion (CRRA) utility and multiple risky assets (see, e.g., Merton, 1969; Campbell and Viceira, 2002, and outlined in Internet Appendix B), an additional unit of wealth brings a proportional response in additional consumption. This proportional response equals the consumption-wealth ratio, which we denote as ρ, and is independent of attention. For the log utility case, the consumption-wealth ratio boils down to $\rho = 1 - \beta$ with β denoting the agent's discount factor. Using the discount-factor calibration in Gourinchas and Parker (2001) and expressing it at the monthly frequency of our data, we obtain $\beta = 0.9569^{1/12} = 0.9963$. The corresponding proportional consumption response is therefore $\rho \approx 0.0036$, or about 0.36% per month. This benchmark is low primarily because it is calibrated to a monthly decision interval with an infinite investment horizon. Nonetheless, it provides a conservative monthly benchmark against which the effects of display salience can be measured.

We observe that the estimated consumption response is not only larger than the benchmark model prediction, but also highly sensitive to display salience. In the recency baseline, Column (2) of Table 2 implies an MPC of about 1% out of overall portfolio gains, compared with the model benchmark of 0.36%. The incremental effect of display salience under the default ranking is 0.6% (Column 2). Under the paper's main identification design, the total MPC for co-grouped older funds rises to 2.41% in Table 3 (Column 2), of which 2.15% reflect the incremental same-company prominence effect relative to non-co-grouped older funds. In the corroborating post-July 2020 interface setting, the incremental top-performer effect reaches 4.62% in Table 5 (Column 2). Display salience therefore raises the pass-through of capital gains to roughly three to eleven times the monthly benchmark.

Our estimates are also comparable to the broader literature on consumption out of stock market wealth (Chodorow-Reich et al., 2021; Di Maggio et al., 2020), but the comparison should be interpreted cautiously because those papers study different wealth shocks and different horizons. The distinctive result here is that they vary sharply within the same portfolio depending on which gains become salient on the interface.

Next, we extend the within-portfolio analysis to a cross-sectional setting to examine whether limited attention affects consumption at the portfolio level across individuals who differ in their exposure to recently invested funds. Specifically, as shown in Table 9, we construct a measure of recency exposure for each investor as the time-series average of the monthly fraction of recently invested fund holdings relative to total portfolio holdings over the full sample period. We then partition investors into terciles based on this measure, where the bottom (top) tercile corresponds to the lowest (highest) recency exposure. Columns (1) to (3) aggregate consumption and capital gains at the monthly frequency, whereas columns (4) to (6) use quarterly aggregates.

[Insert Table 9]

The results in Table 9 show that the MPC increases monotonically with recency exposure across all specifications. This pattern suggests that within-portfolio heterogeneity in MPCs aggregates into economically and statistically significant portfolio-level effects on total consumption. Importantly, these cross-sectional differences remain evident in the quarterly regressions, indicating that the effects are unlikely to be short-lived or washed out in the aggregate.

This cross-sectional gradient has a direct bearing on aggregate demand. If platform design increases the fraction of investors holding high-recency-exposure portfolios — for example, by making recent-purchase funds even more prominently displayed —the aggregate MPC out of equity wealth would mechanically rise. Our results suggest that MPC heterogeneity of the type documented here, where display conventions rather than fundamental economic differences drive the dispersion, can shape the aggregate consumption response to equity wealth shocks in ways that standard representative-agent benchmarks do not capture, consistent with evidence that the distribution of MPCs matters for the macro response to wealth and income shocks (Mian et al., 2013; Parker et al., 2013; Auclert, 2015).

6.2 Behavioral Theories of Salience and Limited Attention

In the previous analysis, the main empirical proxy for salience was recency under the default ranking, and the performance result served as corroborating evidence after the interface change. We now review the literature that motivates these two channels.

It is widely acknowledged in the psychology literature that extreme ranks are inherently salient and captivating and play a pivotal role in decision-making (see Diecidue and Wakker (2001) and Wakker (2010) for a comprehensive review). In economics, rank-dependent models such as cumulative prospect theory (Tversky and Kahneman, 1992) also emphasize the importance of ordering. More directly, Manzini and Mariotti (2014) model salience as the result of what is prominently displayed. This logic fits our evidence closely: gains attached to higher-ranked holdings, especially those at the top of the default display, generate larger consumption responses.

Recency is also grounded in the psychology of memory. Individuals give disproportionate weight to recent experiences (Kahana, 2012), and investors recall recent outcomes more readily in financial settings (Jiang et al., 2023). In economics, Bordalo et al. (2020) likewise emphasize the interplay between memory and attention. Our main result fits naturally into this framework: more recent holdings are more top of mind and therefore have a larger spending impact when they generate gains. The post-July performance result complements this interpretation by showing that performance also becomes behaviorally important once the interface makes that ranking dimension easier to activate.

6.3 Extending Portfolio Theory to Display-Rank-Dependent Consideration Probabilities

The standard portfolio-choice model of Subsection 6.1 and Appendix B predicts a uniform MPC out of capital gains equal to the consumption-wealth ratio ρ, independent of which fund generates the gain. Appendix B.3 extends that framework by introducing consideration probabilities depending on display rank as in Manzini and Mariotti (2014): each fund j enters the investor's consideration set with probability $\pi_j \in [0, 1]$, strictly decreasing in display rank. The guess-and-verify argument of Appendix B.2 carries through with perceived wealth $\widetilde{W}_t = \sum_j \mathbf{1}_j W_{j,t}$ replacing total wealth, and because the fixed-point condition for ρ depends only on preferences and the return process, the frictionless consumption-wealth ratio is unchanged. The fund-level MPC therefore becomes $\text{MPC}_j = \rho \cdot \pi_j$, nesting the standard Merton benchmark as the special case $\pi_j = 1$ for all j.

This expression maps directly onto our empirical interaction specification. Partitioning the portfolio into recently purchased funds with consideration probability

π^R and older holdings with $\pi^O < \pi^R$, and rewriting in terms of total gains and the recent share $\text{Recent}_{i,t-1}$, the model delivers $\beta_2 = \rho\pi^O$ and $\beta_1 = \rho(\pi^R - \pi^O)$ in Equation (1). The null hypothesis of the standard model—that display rank does not affect consumption—corresponds to $\pi^R = \pi^O$ and hence $\beta_1 = 0$, while the estimated $\hat{\beta}_1 > 0$ in Table 2 directly identifies the attention gap $\pi^R - \pi^O$ scaled by ρ. The co-grouping identification design of Section 4 provides a sharper test of this expression: within the set of older holdings, the platform's same-company grouping rule shifts π^O upward for a subset of funds, so the coefficient on $CG_{i,t-1} \times (1 - \text{Recent}_{i,t-1}) \times \text{SameCompany}_{i,t-1}$ in Equation (2) identifies $\rho(\pi^{\text{SC}} - \pi^O)$, where $\pi^{\text{SC}} > \pi^O$ is the elevated consideration probability for co-grouped older funds. The model further generates the subsidiary predictions we test: allowing π_j to increase in the sign of the fund's gain produces the gain-loss asymmetry of Table 7, and imposing a fixed total attention budget $\Pi = \sum_j \pi_j$ implies that the gap $\pi^R - \pi^O$ widens with portfolio size, consistent with the attention-constraint gradient in Table 8.

7 Conclusion

This paper shows that capital gains inside the same portfolio are not consumed at the same rate. Under the platform's default interface, gains from recently purchased funds generate a larger consumption response than gains from older holdings. The paper's main identification design then shows that mechanically increasing the prominence of older holdings through the group-based display rule raises their pass-through to consumption.

We further show that the rank-gradient, redemption, gain-loss asymmetry, and attention-constraint results all point in the same direction: interface salience shapes how investors map financial gains into spending.

More broadly, the findings imply that platform design can affect how wealth shocks propagate into household demand. From a policy perspective, this has at least two implications. First, default display rules in retail investment apps are not neutral: they influence the distribution of MPCs across investors and may shift aggregate household spending in response to equity market movements. Platform designers and regulators who set guidelines for default interface conventions should consider these second-order consumption effects. Second, because the unequal pass-through operates through attention rather than through fundamentals, it is potentially reversible: interface changes that equalize the visibility of holdings—for example, requiring platforms to rotate the top-displayed fund or to present holdings in a randomized order—could reduce within-portfolio MPC heterogeneity. Our results therefore open a new margin through which consumer financial protection policy could operate.

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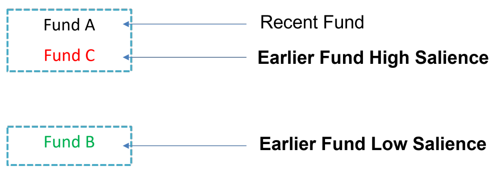
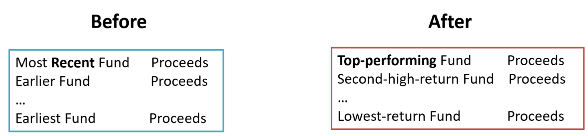
Figure 1: **Illustration of the Identification Settings**



A. **Same-Company Grouping in the Default Display: Schematic**



B. **Display Rule After Customization Feature Introduced**

C. **Same-Company Grouping in the Default Display: Screenshot**

Notes: Panel A illustrates the same-company grouping rule schematically. The most recently acquired fund is displayed at the top of the holdings page. Funds from the same fund company are grouped together within a single block, so that an older fund from the same company as the most recent purchase (Fund C in the example) is displayed closer to the top than an older fund from a different company (Fund B). Panel B shows a representative screenshot of the Ant Fortune holdings page under the default display, illustrating the co-grouping rule in practice. Holdings are organised into fund-family blocks (Bosera Funds, CSOP Fund Family, Zhong Ou Fund Family, GF Fund Family), so that multiple funds from the same company appear together regardless of purchase date. Panel C shows the display rule after July 2020, when Alipay allowed investors to customise the order of their holdings. Investors could keep the original setting or choose to sort funds by cumulative returns over the holding period.

Table 1: Summary Statistics

This table presents descriptive statistics for the sample of 180,000 Alipay users in our main analysis. Panel A summarizes users' personal characteristics, where risk aversion is measured on a scale from 0 (most risk-averse) to 5 (least risk-averse). Panel B reports total and category-specific monthly consumption. Panel C presents investment-related variables, including monthly mutual fund holdings amount, the number of funds held, capital gains, and capital gains plus dividends, all measured at the month end. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. The mean, median, and standard deviation, as well as the 1st, 25th, 75th, and 99th percentiles of each variable are provided.

	N	Mean	Std	1%	25%	Median	75%	99%
Panel A. Personal Characteristics								
Age	180,000	37.80	8.82	24	31	36	43	65
Gender 1=Male, 2=Female	180,000	1.39	0.49	1	1	1	2	2
Risk Attitude (risk level 0-5)	179,992	3.07	2.05	1	2	3	4	5
Panel B. Consumption								
Total Consumption	4,136,968	6,525	12,429	0	991	2,678	6,567	70,336
Taobao	4,136,968	1,559	3,442	0	52	396	1,463	19,211
Non-Taobao	4,136,968	4,833	10,719	0	472	1,597	4,408	60,989
Panel C. Investment								
Holding by each user	4,136,968	82,804	138,810	0	13,508	36,499	90,603	772,902
# of funds by each user	4,136,968	8.08	8.04	0	3	6	10	42
CG from recent investment	4,136,968	522	3,010	-7,418	0	0	283	15,043
CG from earlier investment	4,136,968	1,038	4,253	-8,193	0	72	878	22,186
CG+Div from recent investment	4,136,968	558	3,065	-7,285	0	0	307	15,442
CG+Div from earlier investment	4,136,968	1,096	4,332	-8,040	0	88	934	22,750
CG from top-performing funds	4,136,968	673	2,389	-3,881	0	72	610	12,670
CG from other funds	4,136,968	951	8,077	-11,378	-0.1	74	972	21,744
CG+Div from top-performing funds	4,136,968	708	2,456	-3,819	0	80	638	13,116
CG+Div from other funds	4,136,968	1,013	8,132	-11,187	0	92	1,027	22,184
Recent fund share of capital gains (CG)	4,136,968	0.41	78.62	-1.24	0.00	0.02	0.86	2.25
Recent fund share of total gains (CG+Div)	4,136,968	0.40	77.44	-1.23	0.00	0.02	0.86	2.22
Top Performer share of capital gains (CG)	4,136,968	0.45	89.12	-2.62	0.02	0.30	0.74	3.48
Top Performer share of total gains (CG+Div)	4,136,968	0.45	88.44	-2.56	0.03	0.29	0.74	3.41
Redemption	4,136,968	10,545	35,707	0	0	0	2,209	204,213

Table 2: Unequal Consumption Under the Default Display

This table reports the baseline evidence under the platform's default ranking. The dependent variable is total consumption. The key independent variables are capital gains (or capital gains plus dividends) from the previous month, the variable *Recent*, and their interaction. *Recent* is defined as the proportion of gains generated by funds purchased in the previous month. Columns (1) and (2) use capital gains, while columns (3) and (4) use capital gains plus dividends. Columns (2) and (4) additionally include controls for total fund holdings and the number of funds held. All specifications include account fixed effects and year-month fixed effects. Robust standard errors are clustered at the account level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × Recent	0.0046	0.0060*		
	(0.0031)	(0.0031)		
CG	0.0165***	0.0100***		
	(0.0018)	(0.0018)		
Recent	-15.814	-15.962		
	(11.088)	(11.507)		
(CG+Div) × Recent			0.0054*	0.0067**
			(0.0030)	(0.0030)
CG+Div			0.0161***	0.0095***
			(0.0017)	(0.0017)
Recent			-17.675	-17.872
			(11.761)	(12.204)
Holdings		0.0017***		0.0017***
		(0.0002)		(0.0002)
# Funds		1533.5***		1532.5***
		(200.74)		(200.74)
Account FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
R-squared	8.06E-05	0.0003	8.46E-05	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

Table 3: Identification: Same-Company Grouping in the Default Display

This table reports the paper's main identification design based on the platform's same-company grouping rule. The dependent variable is total consumption. The independent variables of interest in columns (1) and (2) (columns (3) and (4)) are capital gains (or capital gains plus dividends) from the previous month, *Recent*, and *Same Company*. *Same Company* is defined as the share of gains from earlier holdings that comes from funds belonging to the same fund company as the investor's most recent purchase. Columns (2) and (4) include controls for total fund holdings and the number of funds held. All specifications include account fixed effects and year-month fixed effects. Robust standard errors are clustered at the account level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × (1-Recent) × Same Company	0.0504***	0.0215**		
	(0.0108)	(0.0108)		
CG × Recent	0.0149***	0.0119***		
	(0.0028)	(0.0028)		
CG	0.0035***	0.0026**		
	(0.0011)	(0.0010)		
(1- Recent)× Same Company	-34.570***	-36.163***		
	(12.934)	(13.231)		
Recent	-21.085***	-21.496***		
	(6.1631)	(6.3135)		
(CG+Div) × (1-Recent) × Same Company			0.0497***	0.0211**
			(0.0106)	(0.0106)
(CG+Div) × Recent			0.0154***	0.0121***
			(0.0027)	(0.0027)
(CG+Div)			0.0036***	0.0026**
			(0.0010)	(0.0010)
(1-Recent) × Same Company			-36.416***	-38.170***
			(10.992)	(11.155)
Recent			-23.815***	-24.316***
			(5.1472)	(5.2168)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
YearMonth FE	Y	Y	Y	Y
R squared	6.976E-05	0.0003	7.308E-05	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

Table 4: Display Rank and Unequal Consumption Responses

This table links unequal consumption responses to display rank under the default interface. The dependent variable is total consumption in month t. Panel A estimates a rank-gradient specification using the shares of month $t-1$ gains from funds purchased in months $t-1$, $t-2$, and $t-3$, which correspond to progressively lower display positions. Columns (1) and (2) use capital gains and capital gains plus dividends. Panel B re-estimates the baseline recency specification using an alternative definition of *Recent*: the share of gains from the single most recently purchased fund, i.e., the fund displayed at the top of the holdings page. Columns (1) and (2) use capital gains, columns (3) and (4) use capital gains plus dividends, and columns (2) and (4) add controls. All specifications include account and year-month fixed effects; controls are total fund holdings and the number of funds held. Robust standard errors are clustered at the account level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Rank Gradient under the Default Display

Dep. Var.: Total Consumption	(1) Capital gain	(2) Capital gain + dividend
CG (or CG+Div) × Purchase in month $t-1$	0.0131***	0.0130***
	(0.0030)	(0.0029)
CG (or CG+Div) × Purchase in month $t-2$	0.0008	0.0024
	(0.0069)	(0.0068)
CG (or CG+Div) × Purchase in month $t-3$	0.0124	0.0122
	(0.0087)	(0.0084)
CG (or CG+Div)	0.0063***	0.0061***
	(0.0018)	(0.0018)
Purchase in month $t-1$	−4.2308***	−5.0146***
	(1.8898)	(2.2021)
Purchase in month $t-2$	4.5936	3.8729
	(4.3084)	(4.5358)
Purchase in month $t-3$	48.934*	50.923**
	(24.479)	(25.148)
Controls, Account FE, YearMonth FE	Y	Y
R squared	0.0001	0.0001
N	3,776,435	3,776,435

Panel B: Alternative Top-Rank Definition

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × Recent	0.0100***	0.0109***		
	(0.0031)	(0.0031)		
CG	0.0130***	0.0066***		
	(0.0021)	(0.0021)		
Recent	9.0242	9.5064		
	(12.664)	(12.861)		
(CG+Div) × Recent			0.0102***	0.0111***
			(0.0030)	(0.0030)
(CG+Div)			0.0129***	0.0064***
			(0.0021)	(0.0020)
Recent			7.4260	7.8851
			(12.480)	(12.678)
Holdings		0.0017***		0.0017***
		(0.0002)		(0.0002)
# Funds		1546.5***		1546.3***
		(200.73)		(200.72)
Account FE	Y	Y	Y	Y
YearMonth FE	Y	Y	Y	Y
R squared	8.46e-05	0.0003	8.73e-05	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

Table 5: Corroborating Interface Experiment: Performance Salience After July 2020

This table reports reduced-form evidence from the July 2020 interface change that allowed investors to customize the order of their holdings. The dependent variable is total consumption. The independent variables of interest in columns (1) and (2) (columns (3) and (4)) are capital gains (or capital gains plus dividends) from the previous month, *Top Performer*, defined as the share of gains generated by the top-performing fund, and *After*, an indicator for July 2020 and later. Because actual sorting take-up is unobserved, the estimates should be interpreted as reduced-form evidence from an interface regime change rather than as the effect of observed adoption. Columns (2) and (4) include controls for total fund holdings and the number of funds held. All specifications include account fixed effects and year-month fixed effects. Robust standard errors are clustered at the account level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × Top Performer × After	0.0394***	0.0377***		
	(0.0090)	(0.0090)		
CG × Top Performer	0.0043	0.0010		
	(0.0056)	(0.0056)		
CG × After	0.0084**	0.0048		
	(0.0035)	(0.0036)		
CG	0.0047**	0.0027		
	(0.0022)	(0.0022)		
Top Performer × After	-20.086**	-21.157**		
	(8.4329)	(8.6045)		
Top Performer	-11.016***	-10.694***		
	(3.8916)	(3.8972)		
(CG+Div) × Top Performer × After			0.0349***	0.0339***
			(0.0088)	(0.0087)
(CG+Div) × Top Performer			0.0060	0.0029
			(0.0055)	(0.0055)
(CG+Div) × After			0.0095***	0.0059*
			(0.0035)	(0.0035)
(CG+Div)			0.0042*	0.0019
			(0.0022)	(0.0021)
Top Performer × After			-23.775***	-24.778***
			(7.4832)	(7.6801)
Top Performer			-8.9608***	-8.6959***
			(3.2432)	(3.2850)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
R squared	0.0001	0.0003	0.0001	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

Table 6: Redemption Response to Capital Gains under Same-Company Grouping

This table presents regression results examining how same-company grouping affects redemption behavior. The dependent variable is the redemption amount (in RMB) for individual i in month $t+1$. The specification mirrors Table 3: the key independent variables are capital gains (or capital gains plus dividends), *Recent*, and *Same Company*, defined as the share of gains from earlier-invested funds belonging to the same fund company as the investor's most recent purchase. Columns (1) and (2) focus on capital gains, while columns (3) and (4) use capital gains plus dividends. Columns (2) and (4) include controls for total fund holdings and the number of funds held. All regressions include account fixed effects and year-month fixed effects. Within-group R-squared values are reported. Robust standard errors are clustered at the account level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: Redemption	(1)	(2)	(3)	(4)
CG × (1-Recent) × Same Company	2.2224***	0.5614***		
	(0.0789)	(0.0671)		
CG × Recent	0.9047***	0.6746***		
	(0.0279)	(0.0199)		
CG	0.1748***	0.0972***		
	(0.0168)	(0.0096)		
(1-Recent) × Same Company	−15.607	−134.51***		
	(17.480)	(31.032)		
Recent	−19.443*	−50.946***		
	(9.284)	(15.852)		
(CG+Div) × (1-Recent) × Same Company			2.2417***	0.5964***
			(0.0774)	(0.0657)
(CG+Div) × Recent			0.9050***	0.6618***
			(0.0276)	(0.0195)
(CG+Div)			0.1774***	0.0966***
			(0.0167)	(0.0093)
(1-Recent) × Same Company			−4.1372	−138.96***
			(24.700)	(31.897)
Recent			−11.814	−50.965***
			(11.911)	(15.008)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
YearMonth FE	Y	Y	Y	Y
R squared	0.0174	0.1183	0.0181	0.1183
N	4,136,968	4,136,968	4,136,968	4,136,968

Table 7: Selective Attention to Gains versus Losses

This table tests whether the salience effect is stronger for gains than for losses. The dependent variable is total consumption. *Recent* funds are funds purchased in the previous month; earlier holdings are all other funds in the portfolio. The key independent variables are CG (CG+Div) from recent and earlier funds, each interacted with a positive indicator for whether the gain is positive. All regressions control for total fund holdings and the number of funds held. Account fixed effects and year-month fixed effects are included in all specifications. Within-group R-squared values are reported. Robust standard errors are clustered at both the account level and year-month level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)
CG × Recent × Positive	0.0181**	
	(0.0090)	
CG × Recent	−0.0074	
	(0.0072)	
CG × Positive	0.0056	
	(0.0054)	
CG	0.0053	
	(0.0042)	
Recent	−15.779	
	(11.477)	
(CG+Div) × Recent × Positive		0.0144*
		(0.0077)
(CG+Div) × Recent		−0.0033
		(0.0059)
(CG+Div) × Positive		0.0093***
		(0.0026)
CG+Div		0.0011
		(0.0012)
Recent		−17.765
		(12.215)
Controls	Y	Y
Account FE	Y	Y
Year-Month FE	Y	Y
R squared	0.0003	0.0003
N	4,136,968	4,136,968

Table 8: Attention Constraints and the Salience Effect

This table tests whether the salience wedge is larger among investors who are more attention constrained. The sample is split by the number of funds held in the first month of the sample: investors holding at least 6 funds (above the median of 6) are shown in columns (1) and (3), while those holding 5 or fewer funds appear in columns (2) and (4). The independent variables are capital gains (plus dividends) and *Recent*, defined as the proportion of gains from funds invested in the previous month, and their interaction. All regressions control for total fund holdings and the number of funds held. Account fixed effects and year-month fixed effects are included in all specifications. Within-group R-squared values are reported. Robust standard errors are clustered at the account level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
	Most constrained	Least constrained	Most constrained	Least constrained
CG × Recent	0.0084*	0.0032		
	(0.0045)	(0.0042)		
CG	0.0062**	0.0147***		
	(0.0024)	(0.0026)		
Recent	-15.87	-18.48		
	(11.974)	(24.788)		
(CG+Div) × Recent			0.0085*	0.0045
			(0.0044)	(0.0041)
CG+Div			0.0062**	0.0136***
			(0.0024)	(0.0025)
Recent			-18.455	-10.006
			(13.218)	(12.229)
R squared	0.0003	0.0003	0.0003	0.0003
N	1,744,859	2,391,673	1,744,859	2,391,673
Controls	Y	Y	Y	Y
Account FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y

Table 9: Salience Exposure and Aggregate Consumption Responses

This table examines whether the within-portfolio salience wedge aggregates into portfolio-level consumption differences across investors with different exposure to salient (recently invested) fund holdings. For each investor, we compute the time-series average share of recent holdings over total portfolio holdings and sort investors into terciles. Columns (1) to (3) aggregate variables to the monthly level, whereas columns (4) to (6) use quarterly aggregates. Control variables include total fund holdings and the number of funds in the portfolio, where indicated. All regressions include account fixed effects and year-month fixed effects. Within-group R-squared values are reported. Robust standard errors are clustered at the account level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Monthly			Quarterly		
Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)	(5)	(6)
	Bottom	Middle	Top	Bottom	Middle	Top
CG+Div	0.0068***	0.0108***	0.0182***	0.0114**	0.0137***	0.0299***
	(0.0023)	(0.0022)	(0.0025)	(0.0050)	(0.0050)	(0.0055)
Holdings	0.0011***	0.0018***	0.0017***	0.0053***	0.0066***	0.0074***
	(0.0004)	(0.0002)	(0.0002)	(0.0016)	(0.0010)	(0.0009)
# Funds	1376.9***	1071.9***	1661.5***	5143.4***	4364.9***	5808.9***
	(467.84)	(349.78)	(291.89)	(1763.6)	(1336.5)	(1123.2)
Account FE	Y	Y	Y	Y	Y	Y
YearMonth FE	Y	Y	Y	Y	Y	Y
R squared	9.36E-05	0.0003	0.0004	0.0003	0.0008	0.0013
N	1,378,720	1,379,398	1,378,850	420,005	420,014	420,009

Internet Appendix

A Appendix Figures and Tables

A.1 Identification Test of the Recency Effect with Full Sample

This subsection repeats the main same-company grouping identification of Table 3 for the full investor sample, including the top 10% most active investors. Including these hyperactive traders leaves the main patterns intact.

A.2 Identification Test of the Top-Performing Effect with Full Sample

This subsection repeats the post-July 2020 performance-salience specification of Table 5 for the full investor sample, including the top 10% most active investors.

Table A1: Identification Test of the Recency Effect with Full Sample

This table presents the recency-effect identification results under the platform's same-company grouping rule for the full investor sample, including the top 10% most active investors. The dependent variable is total consumption. The independent variables of interest in Columns (1) and (2) (Columns (3) and (4)) are *Capital gains* (+*dividends*) in the previous month, *Recent*, defined as the proportion of these capital gains (plus dividends) attributable to funds invested in the previous month, and *Same Company*, defined as the share of those capital gains (plus dividends) from invested funds that are in the same fund company as the funds invested in the previous month. Control variables include total fund holdings and number of funds held in the portfolio. Robust standard errors are clustered at the account level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × (1-Recent) × Same Company	0.0475***	0.0171*		
	(0.0094)	(0.0094)		
CG × Recent	0.0133***	0.0101***		
	(0.0024)	(0.0024)		
CG	0.0037***	0.0029***		
	(0.0010)	(0.0010)		
(1- Recent) × Same Company	-8.3408	-9.0161		
	(13.636)	(14.116)		
Recent	-13.707*	-13.867		
	(8.2053)	(8.4756)		
(CG+Div) × (1-Recent) × Same Company			0.0473***	0.0170*
			(0.0093)	(0.0092)
(CG+Div) × Recent			0.0135***	0.0101***
			(0.0024)	(0.0024)
(CG+Div)			0.0037***	0.0029***
			(0.0009)	(0.0009)
(1-Recent) × Same Company			-34.458***	-36.197***
			(9.8645)	(10.005)
Recent			-23.442***	-23.976***
			(4.8255)	(4.8875)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
R squared	7.64E-05	0.0004	8.099E-05	0.0004
N	4,596,797	4,596,797	4,596,797	4,596,797

Table A2: Identification Test of the Top-Performing Effect with Full Sample

This table presents the results about the top-performer effect after the change in display setting. The dependent variable is total consumption. It includes the top 10% most active investors. The independent variables of interest in Columns (1) and (2) (Columns (3) and (4)) are *Capital gains* (+*dividends*) in the previous month, *Top performer*, defined as the share of those from the top-performing fund, and *After*, which is a dummy variable that equals one after the change in the display setting. Control variables include total fund holdings and number of funds held in the portfolio in the previous month. Robust standard errors are clustered at the account level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × Top performer × After	0.0351***	0.0355***		
	(0.0085)	(0.0085)		
CG × Top performer	0.0058	0.0021		
	(0.0053)	(0.0053)		
CG × After	0.0111***	0.0065**		
	(0.0032)	(0.0032)		
CG	0.0040**	0.0022		
	(0.0020)	(0.0020)		
Top performer ×After	-26.309***	-27.234***		
	(8.5893)	(8.7814)		
Top performer	-5.3131*	-5.1616*		
	(3.0577)	(2.9799)		
(CG+Div) × Top performer × After			0.0302***	0.0312***
			(0.0083)	(0.0083)
(CG+Div) × Top performer			0.0074	0.0039
			(0.0052)	(0.0052)
(CG+Div) × After			0.0122***	0.0075**
			(0.0031)	(0.0031)
(CG+Div)			0.0036*	0.0016
			(0.0019)	(0.0019)
Top performer × After			-24.295***	-25.312***
			(7.9477)	(8.1825)
Top performer			-9.0234***	-8.7750***
			(3.2661)	(3.3102)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
R squared	0.0001	0.0004	0.0001	0.0004
N	4,596,797	4,596,797	4,596,797	4,596,797

A.3 Baseline and Identification Results with Two-Way Clustering

This subsection verifies that the baseline recency effect and the same-company identification result are not sensitive to allowing for correlated shocks at both the account and year-month levels. Panel A repeats the baseline recency specification (Table 2) and Panel B repeats the same-company grouping identification (Table 3), both with standard errors two-way clustered by account and year-month. Both results remain statistically significant. In Panel A, the interaction coefficient in Column (1)—without controls—becomes insignificant under two-way clustering, which is expected because that specification absorbs less variation; the preferred Column (2) with controls remains significant throughout.

A.4 Same-Company Grouping among Top Fund Companies

This subsection addresses the concern that same-company membership proxies for correlated returns within fund families by restricting the same-company classification to fund companies in the top half of the sample distribution by number of funds offered. The estimates remain close to those in Table 3, supporting the interpretation that the same-company effect reflects display prominence rather than mechanically correlated returns.

Table A3: Baseline and Identification Results with Two-Way Clustering

This table reports robustness results using standard errors two-way clustered by account and year-month. Panel A repeats the baseline recency specification. Panel B repeats the same-company grouping identification specification. The dependent variable is total consumption. Columns (1) and (2) use capital gains, while columns (3) and (4) use capital gains plus dividends. Columns (2) and (4) include controls for total fund holdings and the number of funds held. All specifications include account fixed effects and year-month fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline Recency Effect				
Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × Recent	0.0046***	0.0060***		
	(0.0056)	(0.0031)		
CG	0.0165***	0.0100***		
	(0.0045)	(0.0033)		
Recent	−15.814	−15.962		
	(11.4050)	(11.8180)		
(CG+Div) × Recent			0.0054***	0.0067***
			(0.0053)	(0.0044)
CG+Div			0.0161***	0.0095***
			(0.0045)	(0.0033)
Recent			−17.675	−17.872
			(12.3210)	(12.7650)
Controls	N	Y	N	Y
Account& Year-Month FE	Y	Y	Y	Y
R-squared	8.23E-05	0.0003	8.46E-05	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

Panel B. Same-Company Grouping Identification				
Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × (1-Recent) × Same Company	0.0504***	0.0215**		
	(0.0128)	(0.0091)		
CG × Recent	0.0150***	0.0119***		
	(0.0077)	(0.0062)		
CG	0.0035***	0.0026**		
	(0.0013)	(0.0012)		
(1-Recent) × Same Company	−34.552***	−36.145***		
	(10.3060)	(10.5550)		
Recent	−21.048***	−21.460***		
	(5.1303)	(5.2647)		
(CG+Div) × (1-Recent) × Same Company			0.0497***	0.0211**
			(0.0124)	(0.0085)
(CG+Div) × Recent			0.0154***	0.0121***
			(0.0073)	(0.0059)
(CG+Div)			0.0036***	0.0026**
			(0.0013)	(0.0012)
(1-Recent) × Same Company			−36.416***	−38.171***
			(8.3520)	(8.4354)
Recent			−23.815***	−24.316***
			(5.3411)	(5.4042)
Controls	N	Y	N	Y
Account& Year-Month FE	Y	Y	Y	Y
R squared	6.96E-05	0.0003	7.31E-05	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

Table A4: Same-Company Grouping among Top Fund Companies

This table repeats the same-company grouping specification using an alternative definition of same-company funds. An earlier fund is classified as a same-company fund only if its fund company is in the top half of fund companies by the number of funds in our sample. The dependent variable is total consumption. Columns (1) and (2) use capital gains, while columns (3) and (4) use capital gains plus dividends. Columns (2) and (4) include controls for total fund holdings and the number of funds held. All specifications include account fixed effects and year-month fixed effects. Standard errors are two-way clustered by account and year-month. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
CG × (1-Recent) × Same Company	0.0528***	0.0232**		
	(0.0113)	(0.0112)		
CG × Recent	0.0150***	0.0119***		
	(0.0028)	(0.0028)		
CG	0.0035***	0.0026**		
	(0.0011)	(0.0010)		
(1-Recent) × Same Company	−34.390***	−36.015***		
	(13.6200)	(13.9260)		
Recent	−21.140***	−21.562***		
	(6.4512)	(6.6044)		
(CG+Div) × (1-Recent) × Same Company			0.0520***	0.0227**
			(0.0111)	(0.0110)
(CG+Div) × Recent			0.0154***	0.0121***
			(0.0027)	(0.0027)
(CG+Div)			0.0036***	0.0026**
			(0.0010)	(0.0010)
(1-Recent) × Same Company			−36.347***	−38.144***
			(11.6760)	(11.8410)
Recent			−23.917***	−24.430***
			(5.4224)	(5.4926)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
YearMonth FE	Y	Y	Y	Y
R squared	6.97E-05	0.0003	7.30E-05	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

A.5 Fund-Level Redemption Response to Capital Gains under Same-Company Grouping

This subsection verifies that the account-level redemption result in Table 6 holds at the fund level. The specification uses fund-by-account-month observations with account-by-year-month and fund-by-year-month fixed effects, comparing within the same investor-month whether redemption is stronger for funds whose gains are more salient under the same-company grouping rule.

Table A5: Fund-Level Redemption Response to Capital Gains under Same-Company Grouping

This table presents fund-level regression results examining how same-company grouping affects redemption behavior, using a random sample of 100,000 investors due to the large size of the full sample. The dependent variable is the redemption amount (in RMB) for fund j held by individual i in month $t+1$. The key independent variables are capital gains (or capital gains plus dividends), *Recent*, and *Same Company*, where *Same Company* captures whether an earlier-held fund belongs to the same fund company as the investor's most recent purchase. Columns (1) and (2) focus on capital gains, while columns (3) and (4) use capital gains plus dividends. Columns (2) and (4) include controls for total fund holdings and the number of funds held. All regressions include account-by-year-month fixed effects and fund-by-year-month fixed effects. Within-group R-squared values are reported. Standard errors, clustered at the account level, are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.: Redemption	(1)	(2)	(3)	(4)
CG × (1-Recent) × Same Company	0.9702***	0.5206***		
	(0.0351)	(0.0359)		
CG × Recent	0.1552***	0.2371***		
	(0.0121)	(0.0124)		
CG	0.8074***	0.1924***		
	(0.0082)	(0.0079)		
(1-Recent) × Same Company	−2624.6***	1755.6***		
	(541.45)	(523.53)		
Recent	78130***	43730***		
	(814.46)	(653.34)		
(CG+Div) × (1-Recent) × Same Company			0.9918***	0.5546***
			(0.0346)	(0.0353)
(CG+Div) × Recent			0.1591***	0.2348***
			(0.0118)	(0.0122)
(CG+Div)			0.8036***	0.1869***
			(0.0080)	(0.0077)
(1-Recent) × Same Company			−3082.7***	1360.6***
			(541.93)	(523.24)
Recent			77830***	43680***
			(811.97)	(651.21)
Controls	N	Y	N	Y
Account × Year-Month FE	Y	Y	Y	Y
Fund × Year-Month FE	Y	Y	Y	Y
R squared	0.3544	0.3975	0.3550	0.3975
N	18,340,436	18,340,436	18,340,436	18,340,436

A.6 Alternative Performance Ranking: Top Performer Defined by Cumulative Return

This subsection shows that the corroborating post-July 2020 performance-salience result is not sensitive to how the top-performing fund is defined. The top performer is here identified by cumulative return rather than cumulative gains, and the triple interaction coefficient remains positive and significant after the interface change.

Table A6: Alternative Performance Ranking: Top Performer Defined by Cumulative Return

This table reports the corroborating post-July 2020 performance-salience specification when the top-performing fund is defined by cumulative return rather than cumulative gains or losses. The sample excludes the top 10% most active investors. The dependent variable is total consumption. The independent variables of interest in columns (1) and (2) (columns (3) and (4)) are capital gains (+*dividends*) in the previous month, *Top Performer*, defined by cumulative return, *After*, and the corresponding interaction terms. Columns (2) and (4) include controls for total fund holdings and the number of funds held in the portfolio. Robust standard errors are clustered at the account level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.: Total Consumption	Capital gain		Capital gain + dividend	
CG (or CG+Div) × Top performer × After	0.0316**	0.0304**	0.0276**	0.0270**
	(0.01)	(0.01)	(0.0097)	(0.0097)
CG (or CG+Div) × Top performer	0.0031	0.0013	0.0043	0.0028
	(0.0062)	(0.0062)	(0.0061)	(0.0061)
CG (or CG+Div)× After	0.0152***	0.0109***	0.0157***	0.0115***
	(0.003)	(0.003)	(0.003)	(0.003)
CG (or CG+Div)	0.0046*	0.0018	0.0043*	0.0012
	(0.002)	(0.002)	(0.002)	(0.002)
Top performer	-0.9156	-0.4571	-10.102	-9.6074
	(7.9071)	(7.9467)	(7.5311)	(7.5169)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
YearMonth FE	Y	Y	Y	Y
R squared	0.0001	0.0003	0.0001	0.0003
N	4,135,923	4,135,923	4,135,923	4,135,923

A.7 Taobao Consumption versus Non-Taobao Consumption

Our data on each user's monthly consumption is categorized into Taobao consumption and non-Taobao consumption. Taobao consumption includes purchases on Alibaba's flagship online shopping platform, while non-Taobao consumption covers a wide range of activities outside Taobao, such as QR code payments at restaurants, supermarkets, or local merchants. This subsection analyses the recency effect separately across these two categories.

Table A7: Recency Effect on Taobao versus Non-Taobao Consumption

This table reports recency-effect estimates separately for Taobao and non-Taobao consumption. The dependent variable is Taobao consumption in columns (1) and (2), and non-Taobao consumption in columns (3) and (4). The independent variables are capital gains (or capital gains plus dividends) from the previous month, *Recent*, and their interaction. Columns (1) and (3) use capital gains, while columns (2) and (4) use capital gains plus dividends. All regressions control for total fund holdings and the number of funds held. Account fixed effects and year-month fixed effects are included in all specifications. Within-group R-squared values are reported. Robust standard errors are clustered at both the account level and year-month level. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Dep. Var.	(1)	(2)	(3)	(4)
	Taobao Consumption		Non-Taobao Consumption	
CG × Recent	0.0001		0.0058**	
	(0.0007)		(0.0028)	
CG	0.0017***		0.0083***	
	(0.0004)		(0.0016)	
Recent	-2.1406**		-13.366	
	(1.0096)		(11.769)	
(CG+Div) × Recent		0.0001		0.0061**
		(0.0007)		(0.0027)
CG+Div		0.0017***		0.0079***
		(0.0004)		(0.0015)
Recent		-2.6670***		-14.436
		(0.7738)		(12.332)
R squared	0.00003	0.00003	0.0003	0.0003
N	4,136,968	4,136,968	4,136,968	4,136,968

A.8 Consumption Response to Cumulative Capital Gains

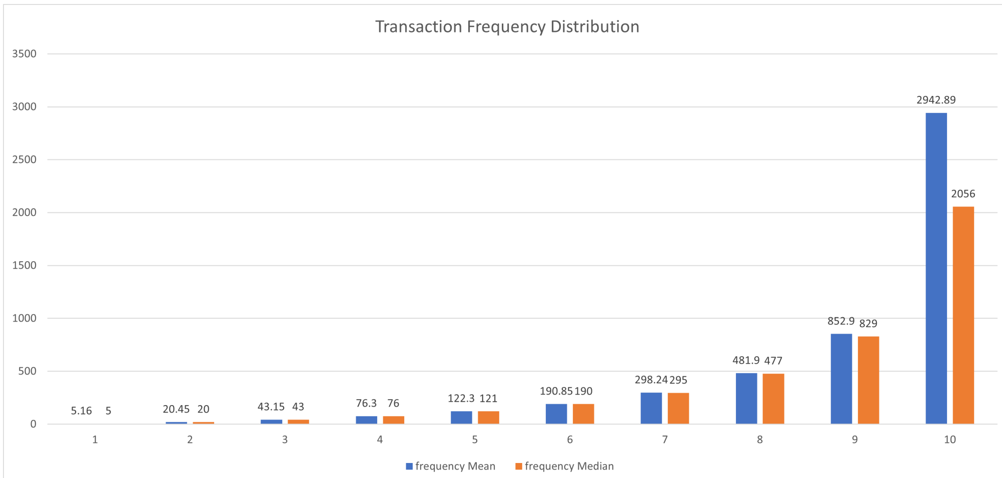
Trading apps like Alipay commonly display investment performance as cumulative proceeds rather than only focusing on returns from the last month. This subsection investigates the recency effect using cumulative performance.

Table A8: Recency Effect Using Cumulative Investment Gains

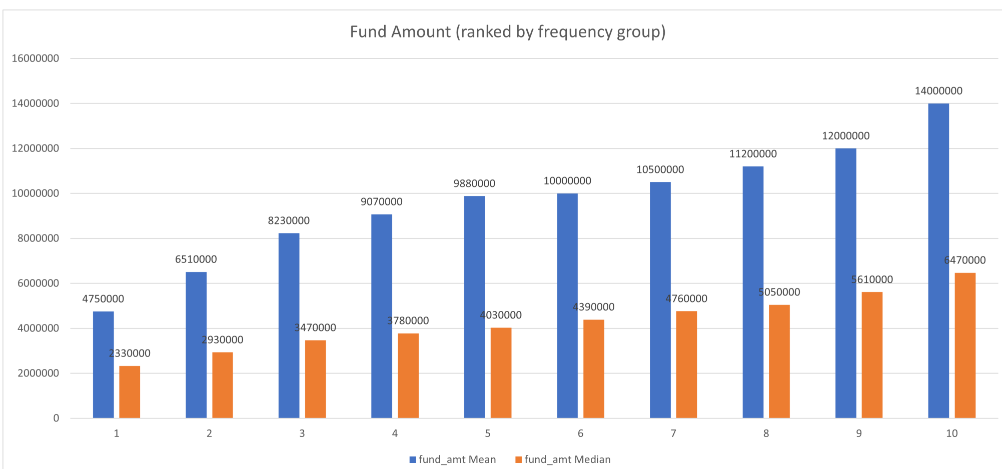
This table re-estimates the recency specification using cumulative gains instead of monthly gains. The dependent variable is total consumption. The independent variables are cumulative capital gains (or cumulative capital gains plus dividends), *Recent*, and their interaction. *Recent* is the share of cumulative gains generated by funds invested in the previous month. Columns (1) and (2) use cumulative capital gains, while columns (3) and (4) use cumulative capital gains plus dividends. Columns (2) and (4) include controls for total fund holdings and the number of funds held. Account fixed effects and year-month fixed effects are included in all specifications. Within-group R-squared values are reported. Robust standard errors, clustered at the account level, are reported. *, **, and *** denote significance at 10%, 5% and 1% levels, respectively.

Dep. Var.: Total Consumption	(1)	(2)	(3)	(4)
Cum. CG × Recent	0.0077***	0.0066***		
	(0.0012)	(0.0012)		
Cum. CG	0.0085***	0.0055***		
	(0.0007)	(0.0008)		
Recent	0.2815	0.3049		
	(0.2674)	(0.2645)		
(Cum. CG+Div) × Recent			0.0077***	0.0066***
			(0.0012)	(0.0012)
Cum. CG+Div			0.0085***	0.0055***
			(0.0007)	(0.0008)
Recent			0.1916	0.2152
			(0.2097)	(0.2077)
Controls	N	Y	N	Y
Account FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
R squared	3.00E-04	4.00E-04	2.00E-04	5.00E-04
N	4,136,968	4,136,968	4,136,968	4,136,968

Figure A1: **Transaction Frequency**



A. Transaction Frequency Distribution



B. Fund Amount (Ranked by Transaction Frequency Deciles)

Notes: Panel A shows the overall sample's transaction frequency distribution by deciles. Panel B shows the mutual fund holding amount ranked by transaction frequencies in deciles. The blue bars denote the mean values, whereas the orange bars denote the medians.

Table A9: Variable Definitions

This table defines the main variables used in the paper. The list includes only variables that remain in the current manuscript and appendix tables.

Variable	Definition
Investment and Gain Variables	
Capital Gains$_{i,t}$	Monthly capital gains or losses from fund investments.
Capital Gains+Dividend$_{i,t}$	Monthly capital gains plus dividends from fund investments.
Holdings$_{i,t}$	Total mutual fund holdings of investor i at the end of month t.
# Funds$_{i,t}$	Number of mutual funds held by investor i at the end of month t.
Redemption$_{i,t}$	Amount of mutual fund shares redeemed by investor i in month t.
Salience and Identification Variables	
Recent$_{i,t}$	Share of month-t gains generated by funds purchased in the previous month under the default display. In Table 4, Panel B, this variable is alternatively defined as the share of gains generated by the single most recently purchased fund.
Same Company$_{i,t}$	Share of gains from earlier holdings that comes from funds belonging to the same fund company as the investor's most recent purchase.
Top Performer$_{i,t}$	Share of month-t gains generated by the fund with the highest cumulative gains in investor i's portfolio. In Internet Appendix Table A6, the top-performing fund is alternatively defined using cumulative return.
After$_t$	Indicator equal to one for July 2020 and later months, when the platform allowed investors to sort holdings by performance.
Positive Gain$_{i,t}$	Indicator equal to one when the relevant gain measure is positive and zero otherwise.
Recency Exposure$_i$	Time-series average share of recent holdings over total portfolio holdings for investor i, used to sort investors into terciles in Table 9.
Consumption Variables	
Total Consumption$_{i,t}$	Total monthly spending by investor i recorded through the mobile payment platform.
Taobao$_{i,t}$	Monthly spending on Alibaba's Taobao platform.
Non-Taobao$_{i,t}$	Monthly spending outside Taobao, including in-person transactions such as restaurants and supermarkets.

B Standard Portfolio Choice Model

In the following, we first lay out the backward induction solution procedure starting in period T for the finite-horizon setting and then move on to the infinite horizon.

B.1 Finite horizon

Consider a model as in Merton (1969), assume that returns are iid log-normally distributed $R_t = e^{r_t} \sim log - N(\mu_r, \sigma_r^2)$. The agent lives for $t = \{1, 2, ..., T\}$ periods. The maximization problem in period $T - i$ is

$$max\{E_{T-i}[u(C_{T-i}) + \beta V_{T-i+1}(W_{T-i+1})]\} \text{ subject to } W_{T-i+1} = (W_{T-i} - C_{T-i})R_{T-i+1}$$

and characterized by the following first-order condition:

$$\Rightarrow C^*_{T-i} = \frac{W_{T-i}}{1 + (\beta E_{T-i}[R^{1-\theta}_{T-i+1} Q^0_{T-i+1}])^{-\frac{1}{\theta}}} = W_{T-i}\rho_{T-i}$$

$$\text{with } Q^\tau_{T-i} = R^{1-\theta}_{T-i+\tau}\rho^{1-\theta}_{T-i+\tau} \prod_{j=1}^{\tau-1} R^{1-\theta}_{T-i+j}(1 - \rho_{T-i+j})^{1-\theta}$$

The value function is given by:

$$V_{T-i}(W_{T-i}) = u(W_{T-i})Q^0_{T-i}$$

$$Q^0_{T-i} = \rho^{1-\theta}_{T-i} + (1 - \rho_{T-i})^{1-\theta}\beta E_{T-i}[R^{1-\theta}_{T-i+1} Q^0_{T-i+1}])$$

Now with iid returns $\rho_{T-i} = \frac{1}{1+(\beta E_t[R^{1-\theta}_{t+1}])^{\frac{1}{\theta}} + ... + (\beta E_t[R^{1-\theta}_{t+1}])^{\frac{i}{\theta}}}$. Therefore, each period the agent consumes a constant fraction out of his wealth.

B.2 Infinite horizon

Let's move on to the $T \to \infty$ case which can be derived by taking the $T - i$ case to the limit or alternatively directly via the Bellman equation

$$V_t(W_t, C_t^{t-1}, C_{t+1}^{t-1}, ...) = max\{u(C_t) + \beta E_t[V_{t+1}(W_{t+1}, C_{t+1}^{t}, C_{t+2}^{t}...)]\}$$

subject to the agent's budget constraint:

$$W_{t+1} = (W_t - C_t)R_t$$

Under CRRA utility, the first-order condition is then given by:

$$C_t^{-\theta} = (W_t - C_t)^{-\theta}\psi$$

The solution procedure follows a guess and verify approach. Guess that the solution has the following structure:

$$C_t^* = W_t\rho_t \text{ and } V_t(W_t) = u(W_t)Q_t^0$$

With ρ_t and Q_t^0 being iid, dependent on the realization of R_t only and independent of calender time or contemporaneous wealth W_t. The first-order condition can be derived under the guessed solution which then remains to be verified. Let's start with the left hand side, the derivative of the first part of the value function, consumption utility and gain-loss utility over contemporaneous consumption is given by:

$$\frac{\partial(u(C_t))}{\partial C_t} = C_t^{-\theta}$$

Under the guessed solution each future consumption level can be iterated to today's consumption-savings decision:

$$C_{t+\tau} = W_{t+\tau}\rho_{t+\tau} = (W_t - C_t)R_{t+\tau}\rho_{t+\tau}\prod_{j=1}^{\tau-1} R_{t+j}(1-\rho_{t+j})$$

Moreover, note that for iid returns $E_t[R_{t+1}^{1-\theta}\rho_{t+1}^{1-\theta}] = E_t[R_{t+\tau}^{1-\theta}\rho_{t+\tau}^{1-\theta}]$ for any $\tau \geq 1$ thus the infinite sum in the value function simplifies considerably:

$$= E_t[R_{t+1}^{1-\theta}\rho_{t+1}^{1-\theta}]\sum_{\tau=1}^{\infty}\beta^{\tau}(E_t[R_{t+1}^{1-\theta}(1-\rho_{t+1})^{1-\theta}])^{\tau-1} = \frac{\beta E_t[R_{t+1}^{1-\theta}\rho_{t+1}^{1-\theta}]}{1-\beta E_t[R_{t+1}^{1-\theta}(1-\rho_{t+1})^{1-\theta}]} = Q$$

The second part in the first-order condition refers to the first derivative of the continuation value with respect to C_t. The marginal value of savings is given by:

$$\frac{d\beta V_{t+1}(W_{t+1})}{dC_t} = \frac{\partial u((W_t - C_t)R_{t+1})Q_{t+1}^0}{dC_t} = -(W_t - C_t)^{-\theta}\beta E_t[R_{t+1}^{1-\theta}Q_{t+1}^0]$$

Note that again for iid returns $\beta E_t[R_{t+1}^{1-\theta}Q_{t+1}^0] = \beta E_{t+\tau-1}[R_{t+\tau}^{1-\theta}Q_{t+\tau}^0] = \psi$ thus:

$$\psi = \beta E_t[R_{t+1}^{1-\theta}Q_{t+1}^0] = \beta E_t[R_{t+1}^{1-\theta}\rho_{t+1}^{1-\theta} + R_{t+1}^{1-\theta}(1-\rho_{t+1})^{1-\theta}\psi]$$

The expression left over in the first-order condition is given by:

$$(W_t - C_t)^{-\theta}\beta E_t[R_{t+1}^{1-\theta}Q_{t+1}^0] = (W_t - C_t)^{-\theta}\psi$$

Accordingly, ρ_t varies solely with the realization of R_t and is thus iid which verifies the guess about ρ_t:

$$C_t^* = \frac{W_t}{1+\psi^{\frac{1}{\theta}}} = W_t\rho_t$$

And the value function can be easily used to verify the guess about Q_t^0 being iid and varying with the realization of R_t:

$$V_t(W_t) = u(W_t)Q_t^0 = u(W_t)(\rho_t^{1-\theta} + (1-\rho_t)^{1-\theta}\psi)$$

The three nonlinear equations for Q, ψ and ρ_t can be solved numerically: For any parameter combination the fixed point of Q, ψ and $\rho(Q,\psi)$, which gives out $\rho_t = \rho(R_t)$ for any R_t, can be found. The guess and verify procedure revealed a legal equilibrium.

Now, one may consider a return $R_t = R^f + (\tilde{R}_t - R^f)\alpha_{T-1}$ with $log(\tilde{R}_t) = r_t \sim N(r - \frac{\sigma_r^2}{2}, \sigma_r^2)$ and $R^f = e^{r^f}$, Campbell and Viceira (2002) show that a good approximation to the rate of return is

$$log(R_t) = r_t = r^f + \alpha_{T-1}\phi_t + \alpha_{t-1}\frac{\sigma_r^2}{2} - \alpha_{t-1}^2\frac{\sigma_r^2}{2} \text{ with } \phi_t \sim N(0,1).$$

As shown in Campbell and Viceira (2002), the optimal portfolio share for CRRA utility is then given by

$$\alpha_t = \frac{E_t[r_{t+1} - r^f]}{\theta\sigma_r^2}.$$

And in a model with many risky assets we have the vector

$$\boldsymbol{\alpha_t} = \frac{1}{\theta}\Sigma_t^{-1}E_t[r_{t+1} - r^f]$$

with the matrix Σ_t containing variances and covariances of excess returns.

B.3 Salience-Weighted Consumption: Formal Derivation

This section extends the infinite-horizon CRRA model of Section B.2 to incorporate limited and selective attention following Manzini and Mariotti (2014). We introduce heterogeneous consideration probabilities $\{\pi_j\}_{j=1}^J$ tied to display rank, derive the salience-weighted MPC expression, and show that the empirical interaction specification of Section 3 arises as a direct implication of the model.

Setup. The investor holds J funds with end-of-period values $W_{j,t}$, so total wealth is $W_t = \sum_{j=1}^{J} W_{j,t}$. Returns are iid log-normally distributed as in Section B.2. In each period, fund j enters the investor's consideration set with probability $\pi_j \in [0, 1]$, where $\mathbf{1}_j \sim \text{Bernoulli}(\pi_j)$ independently across funds and periods, and

$$\pi_j \;=\; \pi(\text{rank}_j)\,, \qquad \pi' < 0, \tag{B1}$$

so that π_j is strictly decreasing in display rank following the prominence ordering of Manzini and Mariotti (2014). The investor's perceived wealth is

$$\widetilde{W}_t \;=\; \sum_{j=1}^{J} \mathbf{1}_j\, W_{j,t}. \tag{B2}$$

The investor maximizes the standard infinite-horizon CRRA objective

$$\max_{\{C_t\}} \; \mathbb{E}\left[\sum_{\tau=0}^{\infty} \beta^{\tau} \frac{C_{t+\tau}^{1-\theta}}{1-\theta}\right] \tag{B3}$$

subject to the perceived budget constraint $\widetilde{W}_{t+1} = (\widetilde{W}_t - C_t)\bar{R}_{t+1}$, where $\bar{R}_{t+1}$ is the portfolio gross return. The realized budget constraint remains $W_{t+1} = (W_t - C_t)\bar{R}_{t+1}$.

Guess-and-verify. The Bellman equation conditional on $\widetilde{W}_t$ is

$$V(\widetilde{W}_t) \;=\; \max_{C_t} \left\{ \frac{C_t^{1-\theta}}{1-\theta} \;+\; \beta\, \mathbb{E}_t\Big[V\Big((\widetilde{W}_t - C_t)\bar{R}_{t+1}\Big)\Big] \right\}. \tag{B4}$$

Conjecture $V(\widetilde{W}_t) = \kappa\,\widetilde{W}_t^{1-\theta}/(1-\theta)$ and $C_t^* = \rho\,\widetilde{W}_t$ for constants $\kappa, \rho > 0$. The first-order condition yields

$$\rho^{-\theta} \;=\; \beta\,\mathbb{E}_t\Big[\bar{R}_{t+1}^{1-\theta}\Big] \cdot (1-\rho)^{-\theta}\kappa, \tag{B5}$$

which is identical to the fixed-point condition in Section B.2. Since this condition depends only on (β, θ) and the return process, the consumption-wealth ratio ρ is the same as in the frictionless case—consideration probabilities affect which wealth the investor acts on, but not the fraction she consumes out of perceived wealth. Substituting back into the Bellman equation verifies the guess: $\kappa = \rho^{1-\theta} + \beta\,\mathbb{E}[\bar{R}_{t+1}^{1-\theta}](1-\rho)^{1-\theta}\kappa$, which has a unique positive solution under the standard condition $\beta\,\mathbb{E}[\bar{R}^{1-\theta}] < 1$.

Expected consumption and fund-level MPC. Since $C_t^* = \rho\,\widetilde{W}_t$, taking expectations over the consideration set gives

$$\mathbb{E}[C_t^* \,|\, W_t] \;=\; \rho \sum_{j=1}^{J} \pi_j\, W_{j,t}. \tag{B6}$$

The fund-level MPC out of a gain $\Delta W_{j,t}$ on fund j is

$$\mathrm{MPC}_j \;\equiv\; \frac{\partial\,\mathbb{E}[C_t^* \mid W_t]}{\partial W_{j,t}} \;=\; \rho \cdot \pi_j. \tag{B7}$$

The frictionless Merton benchmark is the special case $\pi_j = 1$ for all j, giving $\mathrm{MPC}_j = \rho$ and $\mathbb{E}[C_t^*] = \rho W_t$. The multi-asset portfolio share under the Campbell-Viceira approximation, $\alpha_{j,t} = \theta^{-1}\Sigma_t^{-1}\mathbb{E}_t[r_{j,t+1} - r^f]$, is unaffected by $\{\pi_j\}$ since ρ is unchanged, so salience alters the consumption response to wealth shocks without distorting long-run portfolio weights.

Mapping to the interaction specification. Partition the portfolio into recently purchased funds $\mathcal{R}$ with consideration probability π^R and older holdings $\mathcal{O}$ with $\pi^O < \pi^R$. Let $\mathrm{CG}_{i,t-1} = \mathrm{CG}^R_{i,t-1} + \mathrm{CG}^O_{i,t-1}$ denote total gains and $\mathrm{Recent}_{i,t-1} = \mathrm{CG}^R_{i,t-1}/\mathrm{CG}_{i,t-1}$ the recent gain share. From equation (B6):

$$\mathbb{E}[C^*_{i,t}] = \underbrace{\rho\pi^O}_{\beta_2} \cdot \mathrm{CG}_{i,t-1} + \underbrace{\rho(\pi^R - \pi^O)}_{\beta_1} \cdot \mathrm{CG}_{i,t-1} \times \mathrm{Recent}_{i,t-1} + \text{other terms}, \quad \text{(B8)}$$

where "other terms" collects the contribution of total holdings to consumption, absorbed by controls in the empirical specification. This is precisely the structure of Equation (1). The standard-model null $\pi^R = \pi^O$ implies $\beta_1 = 0$; the estimated $\hat{\beta}_1 > 0$ in Table 2 identifies the attention gap $\hat{\pi}^R - \hat{\pi}^O = \hat{\beta}_1/\rho$.

Extensions. Two extensions of equation (B7) generate the subsidiary predictions of Sections 5.4 and 5.5. First, allowing π_j to depend on the sign of $\Delta W_{j,t}$ as in Karlsson et al. (2009) and Olafsson and Pagel (2025), with $\partial\pi/\partial\,\mathrm{sign} > 0$, implies MPC_j is larger for gains than for losses and that this asymmetry is amplified for high-ranked funds, delivering the prediction tested in Table 7. Second, imposing a fixed total attention budget $\Pi = \sum_{j=1}^{J} \pi_j$, a larger portfolio ($J$ higher) forces lower average π_j; because attention is allocated preferentially to higher-ranked funds, the gap $\pi^R - \pi^O$ widens with J, so $\beta_1 = \rho(\pi^R - \pi^O)$ is increasing in portfolio size. This delivers the prediction tested in Table 8.