The Fixed Disposition Effect*

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June 2025

Abstract

We propose that the disposition effect is best understood as a stable, investor-specific behavioral trait rather than a universal bias. Using matched experimental and real-world trading data from a large sample of retail investors, we find that individual disposition tendencies are persistent over time and across contexts. Extrapolative beliefs and realization preferences jointly explain this stability: contrarian investors exhibit stronger disposition effects, and all investors display a sharp increase in selling at the zero-return threshold. Our findings highlight the value of combining experimental and field data to identify psychologically grounded, cross-context-stable components of investor behavior, with implications for personalized financial education and product design.

Keywords: Disposition effect, Extrapolative belief, Realization preference, Investment style, Retail investor

JEL Classification: G11, G41, D81, D84

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1 Introduction

Since the seminal work by Shefrin and Statman (1985), the tendency of investors to "sell winners too early and ride losers too long"—known as the disposition effect—has emerged as one of the most robust and widely documented behavioral patterns in financial markets. A vast body of evidence, from brokerage data to laboratory experiments, consistently shows that investors are more inclined to realize gains than losses.[1] This tendency persists even after accounting for rational considerations such as transaction costs, portfolio rebalancing, or tax optimization. Accordingly, the disposition effect is often treated as a universal bias — a systematic behavioral tendency assumed to apply broadly across investors. Much of the literature focuses on aggregate-level prevalence, largely abstracting away from individual-level heterogeneity. We challenge this conventional view. Rather than a universal bias, we show that the disposition effect is better understood as a stable, investor-specific behavioral trait — one that varies meaningfully across individuals, yet remains consistent across contexts and over time. That is, it behaves like a fixed effect.

We test this fixed-effect view of the disposition effect by leveraging recently compiled, individual-level data from Alipay, one of the world's leading financial services platforms. Our analysis integrates two distinct yet linked datasets for the same set of investors. We begin by constructing a dataset from a large-scale virtual investment experiment hosted on the Alipay platform, designed as an interactive trading game. This setup, conceptually similar to Weber and Camerer (1998), enables us to elicit participant-specific disposition tendencies in a controlled and stylized environment. Then, we match these investors to their actual fund trading records over a four-year period (2017–2021) on mutual funds, allowing us to track their real-world selling decisions. This integrated design allows us to examine whether disposition tendencies are

[1] Evidence of the widely existing disposition effect has been documented among retail investors (Odean, 1998; Kaustia, 2010; Ben-David and Hirshleifer, 2012; An et al., 2024), institutional investors (Grinblatt and Keloharju, 2001), professional commodity traders (Locke and Mann, 2005), and under experimental setups (e.g., Weber and Camerer, 1998; Talpsepp et al., 2014). In real estate markets, Genesove and Mayer (2001) showed that homeowners are far more loss-averse in selling decisions than investors in the housing market, leading owner-occupants to hang on to houses longer and set higher asking prices when facing a potential loss.

stable across decision-making contexts and over time. We find that they indeed are: investors who exhibit a stronger disposition effect in the experiment tend to do so in the field as well, and individual disposition measures are highly persistent across time periods within the real-world data.

Our two-setting framework offers several advantages. First, it enables a clean test of within-investor consistency in disposition behavior across two similar but distinct environments: one is low-stake simple game, while the other is high-stake complex financial market. Second, the experimental context isolates disposition effects and other trading features from real-world confounding factors such as transaction costs, liquidity shocks, or tax considerations. Third, the real-world dataset captures investor behavior in a modern mobile trading environment with low frictions and frequent return visibility, reducing the concern that measured behavior reflects inattention or delayed account checking.[2] [3] Moreover, modern trading platforms provide real-time or alike return tracking, minimizing ambiguity about the reference point which is considered vital for identification of the disposition effect (e.g., Meng and Weng, 2018; Pitkäjärvi et al., 2025; Quispe-Torreblanca et al., 2024).

Our empirical setup also allows us to investigate the underlying mechanisms driving the disposition effect. Traditionally, the literature has identified two broad explanations: beliefs and preferences.

Belief-based accounts attribute the disposition effect to biased expectations about future returns. For instance, optimistic beliefs can lead investors to hold onto losing positions in anticipation of a rebound, while realizing modest gains early to "lock in" profits — a behavior consistent with the theoretical predictions of Barberis and Xiong (2009) and observed empirically in Andersen et al. (2021). A particularly intuitive variant of this logic is the belief in mean reversion: investors expect winners to decline

[2]A large body of literature relies on brokerage data from the early 1990s, ensuring comparability but reflecting notably higher trading frictions (e.g., Odean, 1998; Ben-David and Hirshleifer, 2012; Chang et al., 2016). Similarly, administrative data in Finland from the late 1990s has been extensively studied (Grinblatt and Keloharju, 2001; Kaustia, 2010). There are only a few exceptions which leverage data after the widespread adoption of mobile internet platforms (e.g., Andersen et al., 2021, 2024; Andries et al., 2024).

[3]As Ben-David and Hirshleifer (2012) suggest, increased investor attention can influence beliefs by more extensive revisions, potentially leading to heightened trading activity when returns become salient.

and losers to recover, and thus tend to sell the former and retain the latter. Experimental evidence supports the prevalence of such expectations (Weber and Camerer, 1998): participants are on average more likely to buy after experiencing downward price change during the last period. However, empirical studies have raised doubts about whether mean-reversion beliefs alone can fully explain the disposition effect. For example, Odean (1998) finds that unsold stocks tend to underperform those that were sold, suggesting that such beliefs are not reliably predictive. Similarly, Kaustia (2010) documents that the disposition effect appears consistently regardless of whether held stocks outperform or underperform the market. These inconsistencies call for a closer examination of how mean-reversion beliefs contribute to the disposition effect — and, crucially, a more concrete and operational definition of what such beliefs entail.

Using a regression-based approach on experimental data, we isolate each investor's responses to prior asset price changes, separately from their reaction to unrealized gains or losses. This yields an investor-level measure of extrapolative belief, which we term the Degree of Extrapolation (DOX). Based on this measure, we classify investors into two types: momentum and contrarian. Momentum investors tend to trade in the direction of recent price movements — buying more after prices rise and selling after prices fall — while contrarian investors do the opposite. Notably, the investor type is also found to be stable across contexts.

We find that momentum traders exhibit minimal disposition bias, whereas contrarian investors display a substantially stronger disposition effect. This pattern holds not only in the experimental setting but also in the real-world trading data, even after controlling for conventional demographic characteristics. Our finding aligns with Giglio et al. (2021) who document that investor beliefs and behaviors exhibit persistent individual heterogeneity not explained by simple demographic factors. Taken together, these results suggest that the well-documented aggregate-level disposition effect may largely reflect the behavior of contrarian investors, who account for approximately 80% of our sample across both contexts. This further suggests that some investors may psychologically conflate return status (gain vs. loss) with prior price movements (up vs.

down), interpreting both as signals about future returns. For instance, both holding a winning position and observing an upward price change may reinforce momentum traders' belief that the asset will continue to rise. To this end, our paper is closely related to Andersen et al. (2024) who connect experiment-elicited forecast bias to Danish individual investor's trading decisions, highlighting the role of belief, although they do no explicitly test how the individual bias affects their disposition effect. We complement their research by leveraging a larger-scale experiment, and scrutinizing whether individual forecast bias is persistent in different investment contexts. [4]

The other major explanation for the disposition effect centers on preferences — specifically, the psychological value investors derive from the act of realizing gains or losses. The original account by Shefrin and Statman (1985), grounded in prospect theory (Kahneman and Tversky, 1979), attributes the disposition effect to mental accounting and loss aversion: investors prefer to realize gains early while deferring the realization of losses. However, this framework alone struggles to explain the heterogeneity of the disposition effect across individuals and settings (e.g., Dhar and Zhu, 2006; Kaustia, 2010).

In response, two strands of refinement have emerged. One focuses on defining the appropriate reference point from which gains and losses are evaluated, which plays a central role in determining whether realization is perceived as pleasurable or painful (e.g., Meng and Weng, 2018; Quispe-Torreblanca et al., 2024). The other focuses on when this utility is experienced — whether from the mere holding of a gain/loss position, or specifically upon the act of realizing it (Barberis and Xiong, 2009). The latter line of work leads to the realization utility model proposed by Barberis and Xiong (2012), in which investors feel direct psychological reward from realizing gains and discomfort from realizing losses. While experimental and neuro-scientific studies lend support to this theory (Frydman et al., 2014; Imas, 2016), direct empirical evidence in field settings remains limited. Using a regression-discontinuity design, Ben-David and

[4] In Andersen et al. (2024), forecast bias is estimated based on a general-context prediction task, instead of a clearly investment-related one. The authors then link the forecast bias to purchase of past winning stocks and sell of past losing stocks, suggesting a strong generalizability of general forecast bias.

Hirshleifer (2012) argue that realization utility plays only a modest role in explaining the disposition effect.

We revisit the realization-utility explanation using recent, granular transaction-level data from retail investors on the Alipay platform. Compared to other widely-investigated traditional brokerage datasets starting from Odean (1998), our setting offers several advantages: investors can monitor asset prices and portfolio values in real time, trade at minimal cost, and are not subject to capital gains taxation — as capital gains are untaxed for Chinese retail investors. These features significantly reduce common frictions and confounds such as delayed account attention, transaction costs, and tax-driven behavior.

Applying a regression-discontinuity design as in Ben-David and Hirshleifer (2012), we detect a sharp and statistically significant increase in the probability of selling at the zero-return threshold. Specifically, holding a slightly winning position raises the likelihood of sell by approximately 35%, and this discontinuity persists for at least six weeks after the asset's initial purchase. Importantly, this pattern is evident for both contrarian and momentum investors, indicating a broadly shared realization preference.

This paper contributes to the literature in several veins. First and foremost, it pushes forward our understanding of the disposition effect by showing that it is best understood as a stable, investor-specific behavioral trait — not a universal bias. This within-individual perspective complements prior work on cross-sectional heterogeneity in the disposition effect (e.g., Calvet et al., 2009; Dhar and Zhu, 2006), and fills an important gap in the literature: while previous studies have documented that disposition bias varies across individuals with different levels of experience, little is known about how it evolves within the same individual over time.

For instance, Feng and Seasholes (2005) show that trading experience tends to reduce the bias, but a substantial portion remains even among sophisticated investors. Similarly, Locke and Mann (2005) find that professional floor traders continue to exhibit disposition effects, albeit at attenuated levels compared to retail investors. More recently, Andries et al. (2024) find that financial advisors may inadvertently amplify disposition effects in client portfolios when provided with performance information.

Second, we contribute to a broader literature on investor beliefs and their role in shaping trading behavior and biases (e.g., Da et al., 2021; Greenwood and Shleifer, 2014; Beutel and Weber, 2022; Liu et al., 2022). In particular, we link extrapolative beliefs — expectations that recent price trends will continue — to the disposition effect at the individual level.

A closely related study by Andersen et al. (2021) elicits investor expectations about average market returns using surveys and incentivized experiments, and finds that optimism predicts a stronger disposition effect. We differ from their approach in several important ways. First, rather than measuring beliefs about market-level returns, we focus on extrapolative beliefs about asset-level price dynamics — that is, beliefs about whether an asset's recent performance is likely to continue. Second, we classify investors based on their revealed trading behavior in both a controlled experimental environment and a real-world trading context. Finally, we use the belief types identified in the experiment to predict variation in disposition effect in the field, providing a novel cross-context validation of belief-driven heterogeneity in investor behavior.

Third, we contribute to understanding the composition of retail investors in terms of trading styles, particularly their tendency to extrapolate or mean-revert. This is especially important in emerging markets, where retail investors play a larger role in shaping asset prices (An et al., 2024; Liao et al., 2022). We find that the majority of retail investors in our sample exhibit contrarian (i.e., mean-reverting) behavior, a pattern that aligns with previous findings on institutional investors in both U.S. and international markets (Badrinath and Wahal, 2002; De Haan and Kakes, 2011), as well as experimentally observed patterns (Weber and Camerer, 1998). This suggests that mean-reversion-based trading may be a broadly shared style across investor types, geographies, and contexts.

Notably, our findings stand in contrast to those of Liao et al. (2022), who report that most Chinese retail investors behave like extrapolators. This discrepancy likely stems from differences in measurement: their extrapolative belief measure is based only on initial stock purchases, whereas ours incorporates the full sequence of trades. By capturing a more complete picture of trading behavior, our approach offers a more robust assessment of investors' belief orientation.

Finally, we contribute to a growing methodological paradigm in behavioral finance that integrates experimental and field data to study investor behavior (e.g., An et al., 2024; Andersen et al., 2024). A common critique of laboratory experiments is that they lack external validity and may fail to generalize to real-world financial decisions. Our findings suggest that such concerns may be overstated. We show that individual-specific behavior patterns elicited in a stylized investment game — notably, the disposition effect and extrapolative belief type — are remarkably stable over time and across contexts, and can predict real-life portfolio choices. This approach echoes similar efforts in other domains, such as risk preference elicitation, where individual-level measures derived from experimental tasks have been shown to generalize across settings (e.g., Falk et al., 2018). Together, these findings support the use of experimentally grounded measures to uncover persistent behavioral traits relevant for real-world financial behavior.

The rest of the paper is structured as follows. Section 2 introduces the experimental setting and describes the data. Section 3 examines whether the disposition effect reflects a stable individual trait, using cross-context validation. Sections 4 and 5 explore the belief-based and preference-based mechanisms underlying the disposition effect, respectively. Finally, Section 6 concludes.

2 Experiment and Data

2.1 Platform Background

The experiment is designed and implemented as a virtual trading game by Alipay, one of the leading mobile payment platforms in China as well as around the globe. Before we elaborate the details about the virtual game, it is useful to provide a brief introduction of the platform. As of mid-2020, Alipay serves over 1 billion annual active users and over 80 million monthly active merchants. In addition to payment service, this platform also features various personal financial management tools, enabling across-bank account management, credit card repayment, mortgage loan repayment, mutual fund investment and etc. Note that direct investment in common stocks is, however, impossible via the platform. With various kinds of mutual funds provided, Alipay documents a total asset under management (AUM) over 4.1 trillion CNY ($\sim$ 560 billion USD using current exchange rate) as of June 2020.

The experiment is made available to all Alipay users, regardless of whether they invest in mutual funds on the platform, since July 2019. The game, branded as an investment-related personality test, is cost-free to participate. The participant will be provided an assessment report after finishing the game, covering various behavioral aspects, such as overconfidence, loss aversion, overoptimism and risk seeking. By the end of 2021, around 20 million Alipay users had participated in the investment game at least once.

2.2 Experiment Description

2.2.1 Design

The experiment setup, following the spirit of Weber and Camerer (1998), is identical to the one used by Han et al. (2019), and we summarize it as follows from the perspective of participant. Once in the experiment, the participant receives an endowment of imaginary 10,000 CNY as starting capital, and they will decide the initial allocation between a risky asset and a risk-free asset (cash). After the first decision, the participant will be directed to an interactive interface where they are presented a series of the risky asset's prices in a line chart. Along with the visualized price movement information, the participant will receive an extra inflow of 1,000 CNY cash in their game account to finance their next decision. One could choose to sell, hold or buy extra of the risky asset, but not short-sell. After the choice, the same procedure will repeat. In total, the participant has the opportunity to make 11 active decisions including one initial allocation without any price information and 10 consecutive decisions with historical price information. The idea of design is to mimic real-life trading processes with respect to a single risky asset. For every decision-period except for the first, the participant has the information on how the price evolves since the beginning, the total value of their portfolio (risky asset plus cash), the sum of capital inflows (10,000 + 1,000 $\times$ period number), the accumulated return rate, the accumulated profits/losses, the asset return rate during the past period, the risk-free balance, and the market value of risky asset holding. Figure B.1 shows an illustrative screenshot before a decision is to be made. After the final (11th) active decision, the price will evolve for another period, then the experiment will conclude in accordance with the final asset price and present the eventual investment return rate of the player.

As a key component of the experiment design, the underlying risky asset reflects the real-world market index. More specifically, each and every price path that is randomly assigned to the participant is extracted from the historical prices of the China Shanghai Composite Stock Market Index (SSE Composite) spanning from 2011 to 2018. Each period in a game session is roughly equivalent to a month in real life, thus making a full game session approximately correspond to one year's market fluctuations. There are in total 160 alternative price paths in the experiment, facilitating substantial variations of market conditions among participants.

2.2.2 Experimental data

Designed and branded as a personality test, the game allows investors to participate as many times as they would like. Unlike most of the experiments that feature one trail per person, the unique advantage of our investment game enables us to leverage data generated from several sessions by the same participant, thus helping capture individual-specific and, to some extent, time-invariant characteristics.

To exploit the possibility of multi-participation, we randomly select a sample of 50,000 participants with one constraint that requires the participant to have played at least five sessions before the sample collection time, i.e., July 2021. We argue that this sample is representative for investors with strong interest in financial markets and high propensity to trade at both extensive and intensive margins. [5] After removing clearly abnormal experiment entries, we construct a baseline sample consisting of 4,527,250 decision-level observations. Note that we drop the very first decision in each game session, as those decisions are made without any price or return information generated within the experiment.

Panel A of Table 1 summarizes the decision-level data. On average, it takes around six seconds between the two adjacent decisions, suggesting that the participants tend to digest the new information before making the investment decision. The participants seem to trade fairly frequently, and when they trade, they are more likely to buy instead of to sell: 41% of the time they increase the risky position, 13% of the time they do the opposite, while the remaining 46% belongs to not making active trading decisions. Furthermore, they usually do not trade substantially: the average turnover is about 7%, which is defined by the value of trade over current position in the risky asset (i.e., the market index) and is bounded on $[-1, 1]$. The participants in general exhibit meaningful exposure to risk, leading to an average of 55% risky share that is computed by current risky holding over total holdings. In addition, the market performance is overall weakly positive: 0.33% return rate since the previous decision and 1.55% since the start of the experiment. Finally, we measure the participant's performance, before each decision, by their paper profits over accumulated cash inflow. Consistent with the generally positive market conditions, the average participant's return is positive at 0.38%.

Our Alipay dataset also allows us to connect most of the experiment participants to their demographic information as it is mandatory to upload a valid identification document before an user could enable payment- and investment-related services. The document contains several key features including age, gender and place of birth. Additionally, users can self-report other information, including but not limited to occu-

[5] We do, however, acknowledge that this sample might not be a perfect representation of general retail investors. To alleviate the concern, we collect another sample by randomly selecting 50,000 participants who have ever played the game regardless the total number of game sessions. We document similar patterns of disposition effect with the sample.

pation and educational level in exchange for better customized Alipay services and functions. Panel B of Table 1 summarizes those important demographic characteristics in the cross-section of July 2021. The sample size varies across variables due to the nature of self-reporting. *Bachelor* is a binary dummy that equals one if the user holds at least a bachelor's degree. *Occupation* is a categorical dummy that covers three types: students, blue-collar workers and white-collar workers. *Total Alipay asset* refers to the average of end-of-month total market value of all financial products, primarily various kinds of mutual funds, that users hold directly on Alipay. We consider this as a proxy for wealth.

[Insert Table 1 around here.]

Our investor sample is somewhat younger—averaging 31 years old—than those in prior studies using traditional stock brokerage datasets across various countries (e.g., An et al., 2024; Andersen et al., 2021; Odean, 1998). This is not particularly surprising, as digital financial platforms tend to be more accessible and popular among younger individuals. The gender distribution is slightly unbalanced: approximately 67% of participants are male, which may reflect both lower average risk aversion and a greater inclination toward competitive engagement with the investment game.

Participants also hold meaningful financial assets through Alipay. While the distribution of portfolio values is positively skewed, the median market value is around 30,000 CNY ($\sim$ 4,200 USD). Finally, self-reported demographic information indicates that the typical participant in our sample is well educated and highly likely to be employed in a white-collar occupation.

2.3 Real-life Data

To serve the goal of investigating real-life disposition effect and within-investor consistency, we link the experiment participants to their actual financial holdings. For each investor-month, we have access to their end-of-month asset allocation snapshots which describe all the positions held on the Alipay platform. As described earlier, although

Alipay users could invest in various financial assets including mutual funds, insurance and deposit certificate, they cannot invest directly in common stocks. We therefore focus solely on investors' equity mutual fund holdings, given the pivotal role of stocks and funds in households' balance sheet (Calvet et al., 2007) and the prevalence in the literature on households' stock market participation (e.g., Andersen et al., 2019).

The data is organized at investor-fund-month level, spanning over the period of January 2017 - October 2021. Each observation documents end-of-month details including but not limited to fund code, fund name, fund management company, the number of shares, market value (holding position), holding profit and holding return rate. [6] As such, the data enables us to construct a panel with which we could calculate the active change in number of shares. The key outcome variable, a *Sell* dummy, equals to one for an investor-fund-month if the number of shares is reduced when compared with that of previous month. This indicator by construction includes both partial and complete redemption. To ensure that the variable is meaningfully defined, we drop all positions that are opened during the given month, that is, we keep the ones with a positive market value as of previous month. With the *Sell* dummy, we follow Odean (1998) and exclude investor-month-fund observations if there is no selling record within the investor-month. Then, we keep investors with no less than 100 valid fund-month observations to ensure active participation. Furthermore, we compute the holding length for each investor-fund pair based on its first appearance.

As a result, we obtain a sample consisting of 6,680,923 observations, of which the summary statistics are presented in Panel C of Table 1. Notably, an average investor has a probability of 29% to sell a given fund within their portfolio on a monthly basis. In contrast, Chang et al. (2016) documents a 5% probability of selling equity funds with a sample from the early 90's in the United States. The significant upward shift

[6] There is no standard way of computing holding profit as the cost basis could be calculated in several manners in case of multiple purchases and redemptions. Alipay implements a common way that updates cost basis according to the weighted average cost *only* when extra purchase is made. Put differently, when an investor sells partially its fund shares, the cost basis does not change. The cost basis resets after a full liquidation. The holding profit as well as the return rate are based on the cost basis and current net asset value of the fund. We argue that the way of calculating returns has minor effects on our findings, as retail investors usually take what they are provided and do not re-calculate their return rates.

could be plausibly attributed to lower trading costs, simpler trading executions as well as enhanced attention. It also relates to the fact that our sample consists of investors who participate the trading games multiple times, and they are expected to trade more actively. The average market value of fund holding is 4,240 CNY ($\sim$ 580 USD) with an average holding-period return rate of 6%, and the majority of the observations carry a positive return.

3 Is Disposition Effect Fixed?

3.1 Disposition effect at aggregate level

Before examining the within-individual persistency, we evaluate whether disposition effect is prevalent at aggregate level in a modern experimental setup. To this end, we follow the canonical measure proposed by Odean (1998). Specifically, we count the number of sell and non-sell decisions under different return scenarios, thus calculating the proportions of gains realized (PGR) and losses realized (PLR):

$$PGR = \frac{\#Realized\ Gains}{\#Realized\ Gains + \#Paper\ Gains}, \tag{1}$$

$$PLR = \frac{\#Realized\ Losses}{\#Realized\ Losses + \#Paper\ Losses}. \tag{2}$$

Note that this calculation can be easily extended to various settings, e.g., applied at individual level (Andries et al., 2024). The difference in propensity to sell between two return regimes, *PGR* - *PLR*, reflects the so-called disposition effect. Figure 1 suggests that the effect wildly exists across all periods of game sessions: when a player is facing a negative accumulated return, the chance they lower risky holding is below 5%, whereas the chance rockets to about 20% in case of positive accumulated returns. This finding, once again, confirms the prevalence of disposition effect in experiment settings (Talpsepp et al., 2014; Weber and Camerer, 1998), and implies that our virtual investment game seems capable of capturing investors behavioral biases although it is not implemented in a laboratory-like environment. We will provide more in-field evidence on the prevalence of disposition effect in the later sections.

[Insert Figure 1 around here.]

3.2 The fixed disposition effect

3.2.1 Over-time persistence

In this section, we test whether the disposition effect is a persistent individual trait. This hypothesis has two testable implications: (i) an individual's disposition effect should be stable over time, and (ii) it should also be consistent across different decision-making contexts.

We begin by examining real-life mutual fund trading behavior. Specifically, we split each investor's transaction history into two periods: before and after January 2020. This cutoff serves two purposes. First, it provides a roughly even split within the overall sample period (2017–2021). Second, it coincides with the outbreak of COVID-19, which plausibly induced substantial shifts in investor behavior and market sentiment. If individual-level disposition tendencies remain stable across this break, it would suggest that the bias is rather fixed than merely a function of prevailing macroeconomic or psychological conditions.

To ensure meaningful identification of within-individual stability, we restrict the sample to investors who have at least 50 monthly observations in both subperiods. We then compute the individual-level *PGR* and *PLR*, as well as the corresponding disposition effect. Figure 2 plots the measures from the two subperiods against each other. The linear fit (in orange) reveals a strong positive association between the pre- and post-2020 disposition measures. A simple OLS regression yields an R^2 of approximately 0.20, indicating substantial predictive power of past disposition behavior on future behavior at the individual level.

[Insert Figure 2 around here.]

To validate these findings in a controlled environment, we turn to the experimental data. Leveraging repeated participation in our investment game, we construct individual-level disposition measures for each experimental session. We then estimate the following panel regression model with several sets of fixed effects:

$$DE_{i,j} = \beta \cdot DE_{i,j-1} + FE_n + FE_y + FE_m + \varepsilon_{i,j} \tag{3}$$

where $DE_{i,j}$ denotes the disposition effect of investor i in their j^{th} experimental session. A set of fixed effects are introduced. FE_n represents session order fixed effects, capturing systematic differences across the second, third, ..., and sixth-or-later sessions. FE_y denotes assigned market year fixed effects, which account for variation in the underlying price paths participants were exposed to. FE_m controls for calendar month fixed effects, capturing any time-varying macroeconomic conditions or platform-wide behavioral shocks. Standard errors are clustered at the investor level.

The results, presented in Table 2, closely mirror those from the real-life setting. Participants who exhibit stronger disposition bias in one session tend to do so again in the next. The R^2 of 4.9% in the baseline specification (Column 1) reflects a strong degree of persistence. Moreover, the sizable intercept of 0.211 confirms that the disposition bias is prevalent at the aggregate level. Columns (2) through (4) present increasingly saturated specifications, all of which continue to show a robust relationship between past and current disposition effects.

To further explore the possibility of learning over repeated trading experiences, we examine session order fixed effects more closely. This analysis is motivated by prior studies suggesting that investor experience and sophistication may attenuate the disposition effect (e.g., Calvet et al., 2009; Costa et al., 2013; Feng and Seasholes, 2005). While the existing literature focuses primarily on cross-sectional differences across individuals, we depart from this approach by investigating the within-individual evolution of disposition behavior across experimental sessions. As shown in Column (1) of Table A.1, we find no economically meaningful evidence that later sessions are associated with systematically higher or lower levels of the disposition effect. Furthermore, when we augment the specification with individual fixed effects to isolate within-person variation, the results remain stable. See Column (2). These findings reinforce the interpretation that the disposition effect is a persistent individual trait rather than a behavior shaped by short-term adaptation or repeated exposure.

[Insert Table 2 around here.]

3.2.2 Cross-context persistence

We now examine whether the experimentally elicited disposition effect can predict its real-life counterpart. While both settings capture investor realization behavior, they differ substantially in context and structure: the experiment involves a single risky asset with low stakes, whereas the real-world portfolio consists of multiple risky assets under high-stakes, real-money conditions. If the disposition effect were not a persistent individual trait, one would expect little cross-predictive power between these two domains.

To test this hypothesis, we link the two datasets and focus on a subsample of investors for whom both experimental and real-life disposition measures are well defined. We estimate a simple univariate OLS regression of real-life DE on experimental DE. The result is presented in Figure 3.[7] The linear fit (in orange) reveals a positive relationship, qualitatively similar to Figure 2. The regression yields an R^2 of 3.3% and a pairwise correlation of 0.181 which is statistically significant at the 1% level.

Despite the presence of potential measurement noise—arising from the monthly frequency and multi-asset aggregation of real-life data—we still document a statistically significant cross-context correlation of 0.181 (at the 1% level) and an R^2 of 3.3%. These results offer compelling evidence that the experimentally elicited disposition effect captures a meaningful component of real-world investor behavior. Notably, the magnitude of the correlation is well in line with benchmarks from the broader experimental-versus-field literature (e.g., Falk et al., 2018).

[7] The full estimation includes slightly over 20,000 investors. For visual clarity, we plot a random subsample of 2,000 investors in the figure.

[Insert Figure 3 around here.]

4 The Belief Channel of the Disposition Effect

Having established that the disposition effect exhibits strong within-individual stability across both experimental and real-world settings, a natural next question arises: what drives this persistent behavioral pattern? To explore the underlying mechanisms, we draw on prior literature, which typically attributes the disposition effect to two broad sources—beliefs and preferences. Preference-based explanations, such as realization utility and loss aversion, have received substantial empirical support (e.g., Barberis and Xiong, 2012; Kaustia, 2010; Meng and Weng, 2018), and we will return to these motivations in the next section. In contrast, belief-based explanations have received less attention and are often dismissed as incomplete (e.g., Grinblatt and Keloharju, 2001; Odean, 1998). In this section, we revisit the belief-based channel by constructing a measure of individual *investment style*—specifically, how investors respond to recent price movements. We classify individuals as either contrarian or momentum traders, based on whether they tend to trade against or in line with recent market returns. This classification serves as a proxy for investors' subjective beliefs about future price trajectories. We then examine how these belief-driven investment styles relate to the strength of the disposition effect.

4.1 Evidence from the experiment

We begin with data from a cleaner and better-controlled environment—the experimental trading game. To identify investment style, we estimate the following decision-level regression separately for each investor i. The idea is to isolate how investors respond to recent price movements, while controlling for return-related components that may reflect preference-based responses, especially around the break-even point:

$$\textit{Turnover}_{i,d} = \alpha_i + \beta_i \textit{Recent return}_{i,d} + \gamma_i \textit{Gain}_{i,d} + \lambda_i |\textit{Player return}_{i,d}| + \varepsilon_{i,d} \tag{4}$$

Here, $\textit{Turnover}_{i,d}$ is the trading activity of investor i at decision d, and $\textit{Recent return}_{i,d}$ is the return since the last decision period of the market index. The variable $\textit{Gain}_{i,d}$ indicates whether the investor has a positive accumulated return before the decision, and $|\textit{Player return}_{i,d}|$ is the absolute size of that return. Our coefficient of interest, β_i, captures the sensitivity of trading to recent market movements and is referred to as the *Degree of Extrapolation (DOX)*. A positive β_i suggests momentum-style behavior—trading in the direction of past returns—while a negative value indicates contrarian behavior. Figure B.2 shows the distribution of DOX, revealing that approximately 86% of participants fall into the contrarian category.[8]

To examine how investment style relates to the disposition effect, we first follow Odean (1998) and compute the difference in the propensity to realize gains versus losses. Figure 4 plots the distribution of this difference for both contrarian and momentum investors, with the vertical line indicating no bias. We observe a stark contrast: most contrarian investors display a sizable disposition effect, while momentum traders exhibit little to none.

We then take a more granular view, plotting the probability of selling as a function of current unrealized return, following Ben-David and Hirshleifer (2012); Kaustia (2010). We restrict the return interval to $[-7\%, 7\%]$, corresponding to the 5^{th} and 95^{th} percentiles of the sample. Figure 5 shows the resulting patterns. As expected, contrarian investors show a sharp difference in selling likelihood between gains and losses, while momentum investors show a flatter pattern. Interestingly, for both groups, we observe a discrete jump in selling probability around the zero-return threshold, consis-

[8]Despite the different classification method, our finding that most retail investors exhibit contrarian-style behavior aligns with earlier studies (e.g., Grinblatt and Keloharju, 2001; Jonsson et al., 2017). However, when the financial investment context is replaced by a more general forecasting task, Andersen et al. (2024) report a mildly higher prevalence of momentum-style behavior, an average DOX-equivalent of 0.14 among Danish retail investors.

tent with the prediction of realization utility theory (Barberis and Xiong, 2012).[9] We explore this preference-based explanation more closely in Section 5.

[Insert Figures 4 and 5 around here.]

To formally test the interaction between investment style and the disposition effect, we estimate the following regression similar to Andries et al. (2024) and Ben-David and Hirshleifer (2012):

$$\begin{aligned} 100 \times \mathit{Sell}_{i,y,p} = {} & \gamma \mathit{Gain}_{i,y,p} + \beta \mathit{Gain}_{i,y,p} \times \mathit{Momentum}_i \\ & + \mathit{FE}_i + \mathit{FE}_y + \mathit{FE}_p + \varepsilon_{i,y,p} \end{aligned} \tag{5}$$

The dependent variable $\mathit{Sell}_{i,y,p}$ is an indicator for whether investor i reduces their risky position during period p in a game session based on the market path from year y. We restrict the sample to observations with positive risky holdings to ensure the possibility of a sale—this filter reduces the sample by only about 4%. We include individual (FE_i), market-path-year (FE_y), and game-period (FE_p) fixed effects to control for unobserved heterogeneity.

Table 3 reports the results. Columns (1)–(3) confirm a strong and significant disposition effect: participants are about 16 percentage points more likely to sell when holding unrealized gains. Column (4) shows that this effect is strongly moderated by investment style. The gain–loss asymmetry in selling probability is 18 percentage points for contrarian investors but decreases by 14.6 percentage points for momentum investors. In other words, belief-driven trading styles are key predictors of the strength of the disposition effect.

[Insert Table 3 around here.]

These findings contrast with prior studies that argue belief-based mechanisms—especially mean-reversion expectations—cannot explain the disposition effect. We believe the in-

[9] Both features observed from contrarian-style investors are highly similar to that in Kaustia (2010), but not for the momentum-style ones.

consistency stems from differences in how beliefs are measured. Prior studies often rely on performance relative to a benchmark index (e.g., Grinblatt and Keloharju, 2001; Kaustia, 2010; Talpsepp et al., 2014), whereas we use absolute recent price movements. Our approach mirrors Andersen et al. (2024) and is justified for several reasons. First, our experimental setup does not feature any market benchmark, so relative performance is undefined. Second, as we show later, our real-life mutual fund dataset also renders relative performance problematic—funds vary in investment goals and cash holdings (Chernenko and Sunderam, 2016), and investors cannot observe precise real-time relative returns. Finally, from a behavioral standpoint, absolute performance is cognitively more salient for most retail investors. We do not argue that investors disregard outperformance entirely, but that tracking relative returns across all fund positions is impractical on a daily basis.

As a wrap-up to this line of analysis, we address a natural question: is investment style merely a repackaging of standard demographic characteristics?

To test this, we estimate the following cross-sectional OLS regression:

$$DE_i = \alpha + \beta \, \textit{Momentum}_i + \zeta Z_i + \varepsilon_i, \tag{6}$$

where DE_i denotes the investor-level disposition effect, and Z_i is a vector of demographic controls including gender, age, education, occupation, and total assets. Table A.2 reports the results. Columns (1) and (2) show the separate associations of investment style and demographics with the disposition effect. Momentum-style investors, as well as male, older, and working (non-student) individuals, are all significantly less prone to the disposition effect.

In Column (3), we include both sets of variables simultaneously. The coefficient on the momentum dummy remains large and highly significant, suggesting that investment style explains variation in disposition behavior beyond what is captured by demographic characteristics.

While not the primary focus of this section, it is noteworthy that the education and wealth proxies are both positively and significantly associated with the disposition effect. That is, investors with higher educational attainment or more financial assets tend to display a slightly stronger bias. This finding contrasts with earlier studies suggesting that financial sophistication mitigates the disposition effect (e.g., Calvet et al., 2009; Dhar and Zhu, 2006), but is broadly consistent with more recent evidence from Andersen et al. (2021). These results highlight the need for further research on the nuanced and possibly context-dependent relationship between sophistication and behavioral biases.

4.2 Evidence from the field

The experimental findings highlight the important role of investment style in shaping the strength of the disposition effect. In this section, we assess the external validity of this relationship using real-life trading data. As in the experimental analysis, we classify investors based on their investment style, inferred using the same regression-based approach. While the core methodology remains the same, we adjust the specification to reflect the real-life context: we use the previous month's fund return as a proxy for recent price movement, and additionally control for the logarithms of holding position and holding duration. The dependent variable is the percentage change in the number of fund shares held, bounded on $[-1, 1]$. To ensure sufficient variation for identification, we retain only investors with more than 100 valid fund-month observations.

Using this approach, we identify approximately 76% of investors as contrarian, consistent with our experimental findings that suggest the majority of retail investors tend to trade against recent price trends. Figure B.3 visualizes the distribution of the Degree of Extrapolation (DOX).

To examine whether investment style predicts the real-life disposition effect, we estimate the following regression:

$$\begin{aligned}100 \times \mathit{Sell}_{i,f,t} = \delta\, \mathit{Gain}_{i,f,t-1} + \beta\, (\mathit{Gain}_{i,f,t-1} \times \mathit{Momentum}_i) + \omega \log(\mathit{Holding\ months}_{i,f,t}) \\ + \gamma \log(\mathit{Position}_{i,f,t-1}) + \mathit{FE}_{i\times t} + \mathit{FE}_{f\times t} + \varepsilon_{i,f,t}, \qquad (7)\end{aligned}$$

where i, f, and t denote investor, fund, and month, respectively. The dependent variable $Sell_{i,f,t}$ equals one if investor i reduces their position in fund f during month t, and zero otherwise. The dummy variable $Gain_{i,f,t-1}$ indicates whether the holding shows a positive unrealized return at the end of month $t-1$. *Holding months*$_{i,f,t}$ captures the duration since the investor last opened a position in fund f, and resets to zero after full liquidation. $Position_{i,f,t-1}$ is the lagged market value of the holding. We include investor-month and fund-month fixed effects ($FE_{i\times t}$ and $FE_{f\times t}$) to control for unobserved heterogeneity across time and across funds. Standard errors are two-way clustered at the investor and month levels.

Table 4 presents the results. Columns (1) through (3), despite the inclusion of saturated fixed effects, reinforce our experimental findings: momentum-style investors exhibit a significantly weaker, and in some cases reversed, disposition effect. Column (4) shows a simple univariate regression where the investor-level disposition effect is regressed on the momentum dummy. The significant negative coefficient confirms that investment style accounts for a substantial share of the cross-sectional variation in disposition effect among retail investors, and that momentum investors exhibit only minimal level of such bias.

[Insert Table 4 around here.]

Our findings stand in contrast to those of Chang et al. (2016), who report a reversed disposition effect for delegated assets such as mutual funds. They argue that investors shift blame for poor performance onto fund managers, which reduces the psychological cost of realizing losses. We believe the discrepancy can be explained by differences in perceived delegation. In our context, investors are able to closely monitor fund performance on a daily basis and submit orders conveniently at any time.[10] As a result, investors in our sample likely feel more responsible for their trading decisions and their portfolio outcomes, which may limit the psychological distancing that underpins the reverse-disposition pattern observed in other studies.

[10]During our sample period, Alipay users had access to estimated real-time returns for domestic mutual funds, based on quarterly portfolio disclosures. While not perfectly accurate, these estimates offered timely performance feedback. This feature was discontinued in July 2023.

4.3 Connecting experimental beliefs to real-Life behavior

So far, we have shown that momentum-style investors consistently exhibit a weaker disposition effect, both in the experimental environment and in real-world trading. However, one potential concern remains: our classification of investment style and the estimation of the disposition effect rely on the same dataset in each context. This raises the possibility that the observed relationship is partially mechanical, driven by correlated measurement error or overfitting. In other words, even though we control for two return-related variables in the classification regression, we cannot fully rule out that investor style merely captures a response to gain/loss status.

To address this issue, we perform an out-of-sample validation by bringing together the experimental and real-world data. Specifically, we revisit the regression specification in Eq. 7, but replace the real-life–based momentum dummy with the one inferred from the investment game. This design ensures that the classification of investment style and the measurement of the disposition effect are derived from entirely different contexts. The results are presented in Table 5. Consistent with our earlier findings, we observe that momentum-style investors—defined purely based on their experimental behavior—exhibit significantly weaker disposition effects in their real-life trading. This pattern holds both at the investor-fund-month level (Column 1) and at the investor level (Column 2).

[Insert Table 5 around here.]

Beyond reinforcing the belief–bias connection, these results speak to the within-individual stability of both investment style and the disposition effect. That is, individuals tend to react to price movements and gain/loss signals in a consistent manner across time and contexts. To further support this view, we implement a simple cross-context correlation test on the DOX measure. Figure B.4 plots the relationship between experimental and real-life DOX. [11] We document a statistically significant correlation of 0.23 at 1% level, with an R^2 of 5.1%. This confirms that the tendency to extrapolate

[11]Similar to Figure 3, the plot uses a random subsample of 2,000 investors (drawn from around 30,000) for visual clarity.

or revert based on recent returns—our proxy for belief-driven trading—is not context-dependent noise, but a meaningful and persistent individual trait.

To summarize, our findings demonstrate that retail investors tend to react to both price trends and gain/loss frames in a specific and consistent way. The belief-driven component of the disposition effect—captured through investment style—proves to be not only cross-sectionally explanatory but also stable across experimental and real-life domains.

5 The Preference Channel of the Disposition Effect

In addition to the belief-based explanations, preference-based theories also play a pivotal role in understanding the disposition effect. This section aims to leverage our comprehensive and granular data to empirically examine the role of realization preference (Barberis and Xiong, 2012; Ingersoll and Jin, 2013). The idea is that investors gain a utility from realizing gains instead of keeping paper gains, making them refrain from realizing losses unless facing a liquidity shock. Following this, we would expect a discontinuity around zero return; investors with returns incrementally grater than zero should be significantly more inclined to sell their holdings than the ones with returns slightly lower than zero.

As a preliminary attempt, we exploit the data from the investment game as it provides a setup that is largely free from various confounding factors. The jump around the zero-return line in earlier Figure 5 has provided some suggestive evidence. To further explore this explanation, we compile all decisions except for the ones made in the first period, and keep only those with player's accumulated return rate within a tiny range of [-1%, 1%]. The intuition is similar to a regression discontinuity design, namely, the discrepancy in the following trading decision could be solely attributed to whether the player is currently in the gain or loss regime. Since investor type plays an important role, the latest price movement before the decision is equally crucial. We, therefore, use up-versus-down to indicate the price dynamics. Combined with the gain-versus-loss status, we obtain four scenarios including up-loss, up-gain, down-loss, and down-gain. For contrarian and momentum investors, we plot the average probability of selling under each scenario respectively in Figure 7. There exists a consistent, although of varying magnitudes, gap of propensity to sell for both investor types, regardless of the direction of recent price movement. This finding motivates our further investigation using a real-life dataset that could support external validity.

[Insert Figure 7 around here.]

The investor-fund-month dataset used in previous sections, despite the relatively large sample size, does not fit our needs. This much nuanced test calls for more granular data, for which we introduce an additional transaction-level dataset and evaluate the regression discontinuity model as used in Ben-David and Hirshleifer (2012). The randomly selected sample covers a different and smaller group of Alipay investors, and it records all the transactions including, but not limited to, purchases and redemptions. We then construct a sample consisting of investor-fund-day observations that share the same idea as the baseline sample.[12]

With the more frequent data, we first present in Figure 8 the relation between holding return rate and unconditional probability of sell for both types of investors.[13] We limit the pooled observations to the ones with a holding length shorter than 10 weeks for the sake of a sufficient level of attention. The figure shares a largely similar pattern with the in-game counterpart (Figure 5). In general, both plots suggest that momentum investors have a higher propensity to sell than contrarian ones in the loss regime, while this pattern reverses in the gain regime; it persistently exhibits a distorted X-shape. More intriguingly, we notice a similar discontinuity of probability around the zero-return cutoff.

[Insert Figure 8 around here.]

[12]We do not link this extra sample to the experiment because the sample was extracted from the Alipay investor population, and only a tiny fraction of the sample has an experiment participation record.

[13]The classification method is largely the same as the one described at monthly level, except that we replace return from the previous month with that from the previous week to accommodate the more frequent data. We implement the classification on investors with at least 200 fund-day observations.

The evidence implies that the realization preference and belief-driven investment style seem to work separately in affecting retail investor's selling decision. We implement a more rigorous regression discontinuity design to examine the hypothesis, following Ben-David and Hirshleifer (2012). The specification is largely close to Eq. 7 except for the inclusion of third-degree polynomials and their interaction with holding length as well as investor type.[14] We present the estimation results with varying holding-length windows in Table 6, to account for the possibility that attention decays over time. The coefficients on *Gain* dummy capture the discontinuity around zero return. In contrast to Ben-David and Hirshleifer (2012), we document a statistically significant and economically meaningful jump up to six weeks since the position opening for a given investor-fund pair. We conclude from the table that the realization preference could potentially account for up to 37% of disposition effect among the sample investors. The discontinuity lessens as holding length extends, which is not surprising and could potentially be justified by less attention and arrival of liquidity shocks.

In order to shed light on the relative independence of preference-based from belief-based attributes, we examine the significance of the estimate of interaction term *Gain* $\times$ *Momentum*. Our results suggest that belief-driven investment style is not significantly associated with the discontinuity around the zero-return threshold. Put differently, both contrarian and momentum investors exhibit a jump of selling probability when the holding return rate crosses the return border from the loss to the gain regime, which we interpret as a piece of evidence in favor of the realization utility theory (Barberis and Xiong, 2012).

[Insert Table 6 around here.]

6 Concluding Remarks

This paper reconsiders the disposition effect not as a universal behavioral bias, but as a stable, investor-specific trait. Leveraging a uniquely integrated dataset that com-

[14] We alter the degree of polynomials to fourth and fifth, the results, available upon request, remain highly stable.

bines experimental trading behavior with real-world fund transactions from a major digital platform, we document strong within-individual consistency in disposition tendencies over time and across decision-making contexts. These findings challenge the conventional view of the disposition effect as a uniform tendency, and instead point to meaningful and persistent heterogeneity across investors.

Our analysis further identifies two key drivers of this heterogeneity: subjective beliefs and realization preferences. By classifying investors based on their trading responses to past returns, we show that contrarian investors consistently exhibit stronger disposition effects than momentum investors. Importantly, this belief-based heterogeneity persists across both experimental and real-life settings. Complementing this, we document a robust discontinuity in selling behavior around the zero-return threshold, consistent with realization utility theory. The fact that both belief-driven and preference-based mechanisms operate independently reinforces a multifaceted understanding of the disposition effect.

Together, these insights underscore the value of combining experimental and field data to uncover stable, psychologically grounded features of investor behavior. By disentangling belief and preference channels, our study not only clarifies the sources of the disposition effect, but also highlights the limitations of one-size-fits-all behavioral interventions. Going forward, incorporating investor heterogeneity—particularly in beliefs and motivations—may be crucial for designing more effective financial education programs and personalized investment tools.

References

An, L., Engelberg, J., Henriksson, M., Wang, B., Williams, J., 2024. The Portfolio-driven Disposition Effect. The Journal of Finance 79, 3459–3495.

Andersen, S., Dimmock, S.G., Nielsen, K.M., Peijnenburg, K., 2024. Extrapolators and Contrarians: Forecast Bias and Individual Investor Stock Trading. Working paper.

Andersen, S., Hanspal, T., Martinez-Correa, J., Nielsen, K.M., 2021. Beliefs and the Disposition Effect. Working paper.

Andersen, S., Hanspal, T., Nielsen, K.M., 2019. Once bitten, twice shy: The power of personal experiences in risk taking. Journal of Financial Economics 132, 97–117.

Andries, M., Bonelli, M., Sraer, D., 2024. Financial Advisors and Investors' Bias. Working paper.

Badrinath, S.G., Wahal, S., 2002. Momentum trading by institutions. The Journal of Finance 57, 2449–2478.

Barberis, N., Xiong, W., 2009. What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation. The Journal of Finance 64, 751–784.

Barberis, N., Xiong, W., 2012. Realization utility. Journal of Financial Economics 104, 251–271.

Ben-David, I., Hirshleifer, D., 2012. Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. The Review of Financial Studies 25, 2485–2532.

Beutel, J., Weber, M., 2022. Beliefs and Portfolios: Causal Evidence. SSRN Electronic Journal .

Calvet, L.E., Campbell, J.Y., Sodini, P., 2007. Down or out: Assessing the welfare costs of household investment mistakes. Journal of political economy 115, 707–747.

Calvet, L.E., Campbell, J.Y., Sodini, P., 2009. Measuring the financial sophistication of households, in: American Economic Review, pp. 393–398. doi:10.1257/aer.99.2.393.

Chang, T.Y., Solomon, D.H., Westerfield, M.M., 2016. Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect. The Journal of Finance 71, 267–302.

Chernenko, S., Sunderam, A., 2016. Liquidity Transformation in Asset Management: Evidence from the Cash Holdings of Mutual Funds. Technical Report. National Bureau of Economic Research. URL: http://www.nber.org/papers/w22391.pdf, doi:10.3386/w22391.

Costa, N.D., Goulart, M., Cupertino, C., Macedo, J., Silva, S.D., 2013. The disposition effect and investor experience. Journal of Banking and Finance 37, 1669–1675.

Da, Z., Huang, X., Jin, L.J., 2021. Extrapolative beliefs in the cross-section: What can we learn from the crowds? Journal of Financial Economics 140, 175–196.

De Haan, L., Kakes, J., 2011. Momentum or contrarian investment strategies: evidence from dutch institutional investors. Journal of Banking & Finance 35, 2245–2251.

Dhar, R., Zhu, N., 2006. Up Close and Personal: Investor Sophistication and the Disposition Effect. Management Science 52, 726–740.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., Sunde, U., 2018. Global evidence on economic preferences. Quarterly Journal of Economics 133, 1645–1692.

Feng, L., Seasholes, M.S., 2005. Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Financial Markets? Review of Finance 9, 305–351.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P., Rangel, A., 2014. Using Neural Data to Test a Theory of Investor Behavior: An Application to Realization Utility. The Journal of Finance 69, 907–946.

Genesove, D., Mayer, C., 2001. Loss Aversion and Seller Behavior: Evidence from the Housing Market. The Quarterly Journal of Economics 116, 1233–1260.

Giglio, S., Maggiori, M., Stroebel, J., Utkus, S., 2021. Five Facts about Beliefs and Portfolios. American Economic Review 111, 1481–1522.

Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. Review of Financial Studies 27, 714–746.

Grinblatt, M., Keloharju, M., 2001. What Makes Investors Trade? The Journal of Finance 56, 589–616.

Han, L., Luo, X., Ouyang, S., 2019. Investor's Responses to Market Fluctuations. Working paper.

Imas, A., 2016. The Realization Effect: Risk-Taking after Realized versus Paper Losses. American Economic Review 106, 2086–2109.

Ingersoll, J.E., Jin, L.J., 2013. Realization Utility with Reference-Dependent Preferences. The Review of Financial Studies 26, 723–767.

Jonsson, S., Söderberg, I.L., Wilhelmsson, M., 2017. Households and mutual fund investments: Individual characteristics of investors behaving like contrarians. Journal of Behavioral and Experimental Finance 15, 28–37.

Kahneman, D., Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica 47, 263–291.

Kaustia, M., 2010. Prospect theory and the disposition effect. Journal of Financial and Quantitative Analysis 45, 791–812.

Liao, J., Peng, C., Zhu, N., 2022. Extrapolative Bubbles and Trading Volume. Review of Financial Studies 35, 1682–1722.

Liu, H., Peng, C., Xiong, W.A., Xiong, W., 2022. Taming the bias zoo. Journal of Financial Economics 143, 716–741.

Locke, P.R., Mann, S.C., 2005. Professional Trader Discipline and Trade Disposition. Journal of Financial Economics 76, 401–444.

Meng, J., Weng, X., 2018. Can prospect theory explain the disposition effect? a new perspective on reference points. Management Science 64, 3331–3351.

Odean, T., 1998. Are investors reluctant to realize their losses? The Journal of Finance 53, 1775–1798.

Pitkäjärvi, A., Vacca, M., Vokata, P., 2025. Beliefs, reference points, and the disposition effect: Evidence from option traders. URL: https://www.fidelity.com/viewpoints/active-investor/hitting-the-right-strike-price. working paper.

Quispe-Torreblanca, E., Gathergood, J., Loewenstein, G., Stewart, N., 2024. Investor logins and the disposition effect. Management Science .

Shefrin, H., Statman, M., 1985. The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. The Journal of Finance 40, 777–790.

Talpsepp, T., Vlcek, M., Wang, M., 2014. Speculating in Gains, Waiting in Losses: A Closer Look at the Disposition Effect. Journal of Behavioral and Experimental Finance 2, 31–43.

Weber, M., Camerer, C.F., 1998. The Disposition Effect in Securities Trading: An Experimental Analysis. Journal of Economic Behavior & Organization 33, 167–184.

Table 1: **Summary Statistics**

This table provides descriptive statistics on key variables. **Panel A** presents decision-level characteristics after excluding first-periods of each game session. *Duration* is the time spent before making investment decision, measured in seconds. *Buy* and *Sell* dummies indicate the trade decision during the period. *Risky share* is the pre-decision ratio of risky value over total value. *Turnover* is calculated by trade amount over pre-trade risky position, bounded on [-1, 1]. *Market return* refers the performance of risky asset, either during the recent period or since the beginning (namely, [t-1, t] or [0, t]). *Current player return* documents the return rate achieved by the player before making the investment decision. **Panel B** relates to individual demographic and socioeconomic features. *Bachelor* is a dummy capturing the highest completed education. *Total assets* (in CNY) is the average monthly value of all types of assets held via Alipay. Finally, **Panel C** focuses on real-life investor-fund-month observations. *Holding length* documents the number of months since the initial purchase. *Holding position, profit,* and *return rate* refers to the end-of-month holding amount, the displayed profits or losses, and the displayed rate of return for a fund-month, respectively. These three variables are lagged for one month.

	Panel A: Decision level in experiment					
	N	Mean	SD	p25	Median	p75
Duration	4,527,250	6.26	6.81	2.54	4.37	7.60
Buy dummy	4,527,250	0.41	0.49			
Sell dummy	4,527,250	0.13	0.33			
Risky share (%)	4,527,250	55.09	35.57	25.50	59.06	88.94
Turnover (%)	4,527,250	6.94	40.91	0	0	13.88
Market return [t-1, t]	4,527,250	0.33	6.19	-3.05	0.72	3.78
Market return [0, t]	4,527,250	1.55	11.89	-5.54	0.73	7.79
Current player return (%)	4,527,250	0.38	4.94	-1.67	0.13	2.35

	Panel B: Individual level					
	N	Mean	SD	p25	Median	p75
Age	48,266	31.25	8.99	25	29	35
Gender	48,266	0.67	0.47			
Total Alipay assets	48,266	72500	154947	10009	29993	78316
Bachelor	34,680	0.31	0.46			
Occupation	30,785					
Student	30,785	0.17	0.38			
White collar	30,785	0.65	0.48			
Blue collar	30,785	0.18	0.38			

	Panel C: Individual-fund-month level in real life					
	N	Mean	SD	p25	Median	p75
Sell dummy	6,680,923	0.29	0.45			
Holding length	6,680,923	7.84	7.58	2	5	11
Holding position	6,680,923	4240.31	15579.05	137.32	907.55	3298.14
Holding profit	6,680,923	167.80	3022.58	-9.60	2.96	72.85
Holding return rate (%)	6,680,923	5.81	20.19	-2.55	2.00	9.80

Table 2: **In-Experiment Disposition Effect over Sessions**

This table examines how the experimentally measured disposition effect evolves over repeated sessions. *Lagged Disposition Effect* refers to the disposition measure obtained from the participant's most recent prior game session. *Session month* indicates the calendar month when the experiment was conducted, while *Market year* corresponds to the historical market index path shown in the session. *Session order* denotes the sequence of the session for a given investor. Standard errors are clustered at the individual level and reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: *Disposition Effect*			
	(1)	(2)	(3)	(4)
Lagged Disposition Effect	0.219***	0.215***	0.215***	0.215***
	(0.004)	(0.004)	(0.004)	(0.003)
Constant	0.211***			
	(0.001)			
Session month FE	No	Yes	Yes	Yes
Market year FE	No	No	Yes	Yes
Session order FE	No	No	No	Yes
Observations	148,198	148,198	148,198	148,198
Adj. R^2	0.049	0.070	0.070	0.071

Table 3: **In-Experiment Disposition Effect and Investment Style**

This table reports regression estimates based on Equation 5. The data are at the decision level, covering all game periods in which the participant held a positive risky position prior to the decision. *Sell* is a dummy equal to one if the participant reduced their risky asset holdings, and zero otherwise. *Gain* equals one if the participant's accumulated return before the decision is positive. *Momentum* is a dummy indicating investor type. *Period* is the sequence of the decision period within a given session. *Market year* corresponds to the historical market index path shown in the session. Standard errors are two-way clustered at the individual and game-period levels and reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: 100 × *Sell*			
	(1)	(2)	(3)	(4)
Gain	16.745***	16.161***	15.912***	17.945***
	(1.073)	(1.217)	(1.193)	(1.314)
Gain × Momentum				-14.587***
				(1.230)
Constant	4.429***			
	(0.271)			
Period FE	No	Yes	Yes	Yes
Market year FE	No	No	Yes	Yes
Individual FE	No	No	Yes	Yes
Observations	4,347,645	4,347,645	4,347,645	4,347,645
Adj. R2	0.059	0.067	0.120	0.125

Table 4: **Real-Life Disposition Effect and Investment Style**

This table reports regression results examining the disposition effect using real-life investor–fund–month observations, based on Equation 7. *Momentum* is a dummy variable indicating investment style. Columns 1–3 use fund-month-level data, where the dependent variable *sell* equals one if the investor reduced their fund holdings during the month, and zero otherwise. *Gain* equals one if the fund's return by the end of the previous month was positive. *Holding length* is the number of months since the most recent purchase. *Holding position*, *profit*, and *return rate* refer to the end-of-month market value, displayed profit or loss, and return rate, respectively. These three variables are lagged by one month. Standard errors are two-way clustered at the investor and calendar-month levels. Column 4 reports a univariate regression at the individual level, where the dependent variable is the disposition effect measure following Odean (1998). *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable:			
	(1)	(2)	(3)	(4)
		$100 \times$ *Sell*		*DE*
Gain	0.625	4.274***	6.148***	
	(0.828)	(0.479)	(1.193)	
Momentum				-0.102***
				(0.002)
Gain $\times$ Momentum			-10.272***	
			(0.903)	
Log(Holding length)	-2.834***	0.549***	0.583***	
	(0.190)	(0.151)	(0.152)	
Log(Holding position)	2.551***	3.301***	3.345***	
	(0.130)	(0.196)	(0.195)	
Constant				0.110***
				(0.001)
Investor-month FE	No	Yes	Yes	NA
Fund-month FE	Yes	Yes	Yes	NA
Observations	6,680,923	6,680,923	6,680,923	21,717
Adj. R^2	0.114	0.313	0.314	0.115

Table 5: **Real-Life Disposition Effect and Experiment-Elicited Investment Style**

This table reports regression results linking experimentally elicited investment style to real-life trading behavior. In both specifications, *Momentum* is a dummy variable indicating investment style based on the virtual investment game. Column 1 uses fund-month-level data, where the dependent variable *Sell* equals one if the investor reduced their fund holdings during the month. *Gain* equals one if the fund's return by the end of the previous month was positive. Standard errors are two-way clustered at the investor and calendar-month levels. Column 2 reports a univariate regression at the individual level, where the dependent variable is the disposition effect measure following Odean (1998). *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable:	
	(1)	(2)
	$100 \times$ *Sell*	*DE*
Gain	4.623***	
	(0.487)	
Momentum		-0.037***
		(0.003)
Gain $\times$ Momentum	-3.618***	
	(0.430)	
Log(Holding length)	0.540***	
	(0.154)	
Log(Holding position)	3.288***	
	(0.197)	
Constant		0.092***
		(0.001)
Investor-month FE	Yes	NA
Fund-month FE	Yes	NA
Observations	6,423,543	20,933
Adj. R^2	0.312	0.007

Table 6: **Real-Life Regression Discontinuity Design**

This table presents regression discontinuity results based on an investor–fund–day panel. The specification extends Equation 7 by introducing polynomial controls for holding return rates around the zero-return threshold. **Panel A** summarizes the sample used in the analysis. *Holding return rate* is the accumulated return since the most recent purchase, measured as of the previous day. *Holding position* is the market value of the holding as of the previous day. **Panel B** reports regression estimates. The dependent variable, *sell*, equals one if the investor partially or fully redeems the mutual fund on a given day, and zero otherwise. *Gain* is a dummy equal to one if the holding return as of the previous day is positive. Control variables include lagged holding position and holding length (in days), both in logarithmic form. *Effect* is calculated as the ratio of the estimated coefficient on *Gain* to the unconditional probability of sell within each holding-length window. *p<0.1, **p<0.05, ***p<0.01.

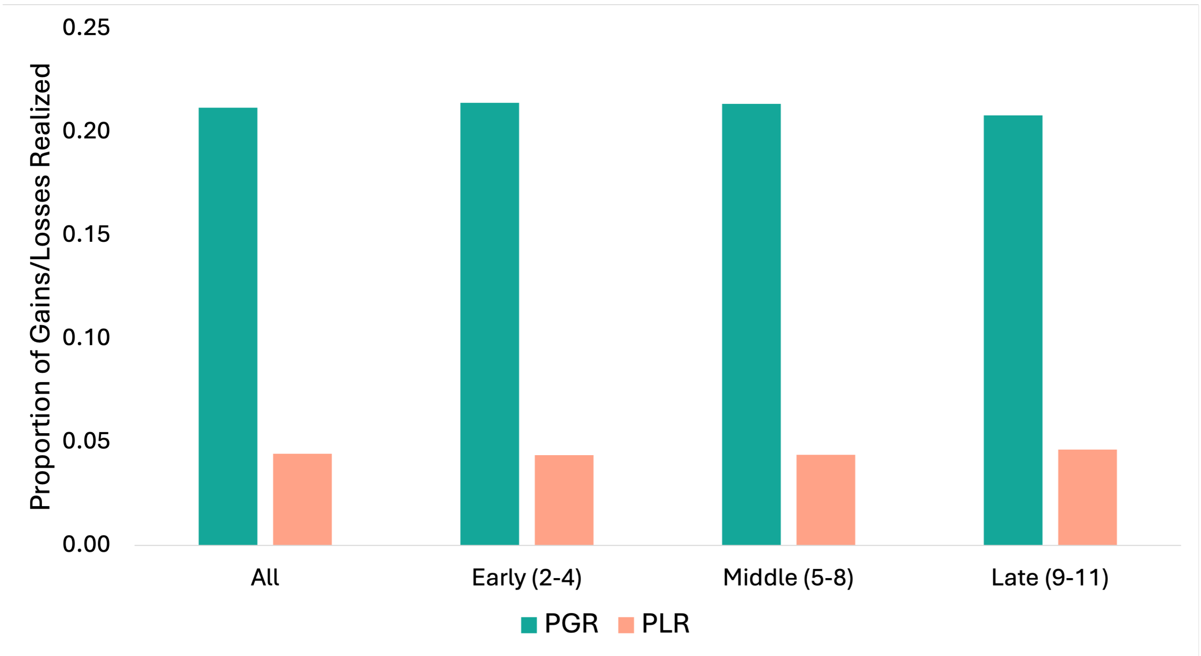
Panel A: Summary Statistics (N = 891,193)

	Mean	SD	Q1	Median	Q3
Sell dummy	0.01	0.10			
Gain dummy	0.54	0.50			
Holding return rate (%)	-0.07	0.41	-2.44	0.03	2.26
Holding length (days)	27.54	25.43	15	33	58
Holding position	4,689.64	17,304,72	102.09	855.37	3,077.40

Panel B: Regression Resuts

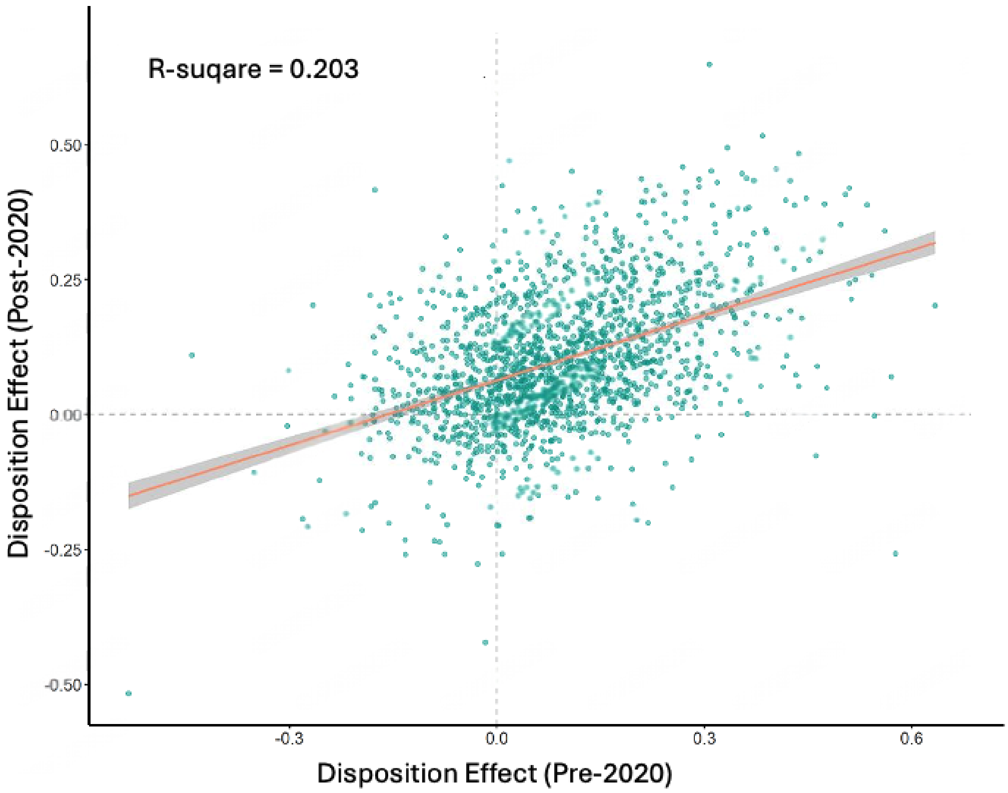
	Dependent Variable: *100*Sell*		
Holding days	1 to 21 (1)	22 to 42 (2)	43 to 70 (3)
Gain	0.432*** (0.083)	0.429*** (0.100)	0.125 (0.094)
Momentum	-0.120 (0.086)	-0.161 (0.103)	-0.323*** (0.098)
Gain × Momentum	-0.013 (0.132)	-0.110 (0.157)	0.113 (0.147)
Controls	Yes	Yes	Yes
3rd Polynomials of holding return rate	Yes	Yes	Yes
Polynomials × Investor types	Yes	Yes	Yes
Polynomials × Log(holding days)	Yes	Yes	Yes
Observations	361,154	269,153	260,886
Adj R^2	0.001	0.002	0.002
Unconditional probability of sell (%)	1.31	1.15	0.89
Effect (%)	32.98	37.30	14.04

Figure 1: **Aggregate Disposition Effect over Experiment Stages**



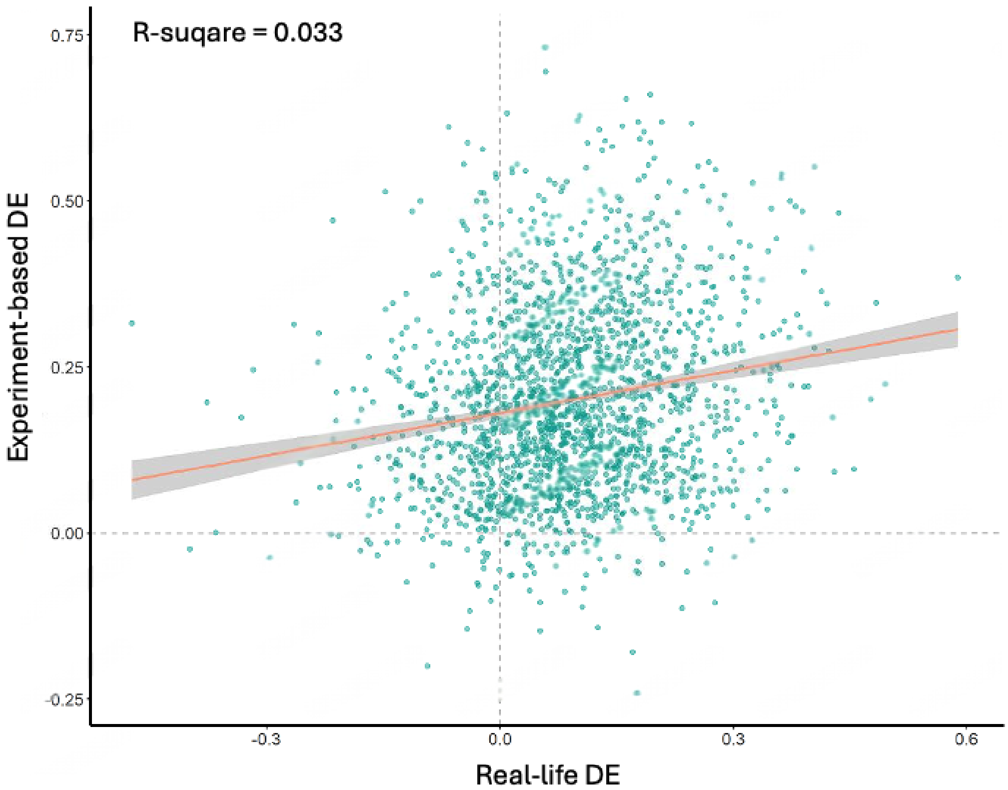
Notes: This figure shows aggregate disposition effect, and how the prevalence of disposition effect varies over different experiment stages. The sample further restricts the pre-decision risky position to be positive to guarantee the possibility of selling decision. *Early* stage pools all the investment choice documented during game periods 2-4, *Middle* for periods 5-8 and *Late* for periods 9-11. PGR and PLR are defined following Eq. 1 and 2.

Figure 2: **Real-Life Disposition Effect over Time**



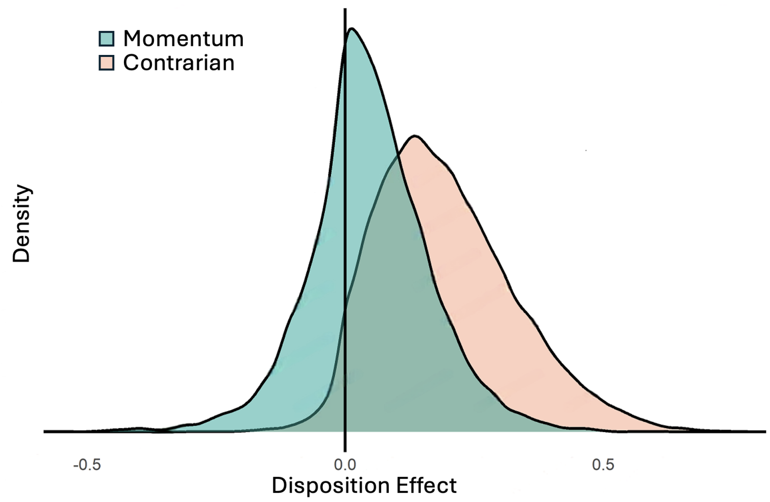
Notes: This figure plots the relation between investors' disposition effects before and after 2020, based on their real-life mutual fund holding changes via Alipay. Each point represents one investor. The sample includes investors with at least 50 monthly observations in both subperiods. The orange line is a linear fit.

Figure 3: **Cross-Context Consistency of Disposition Effect**



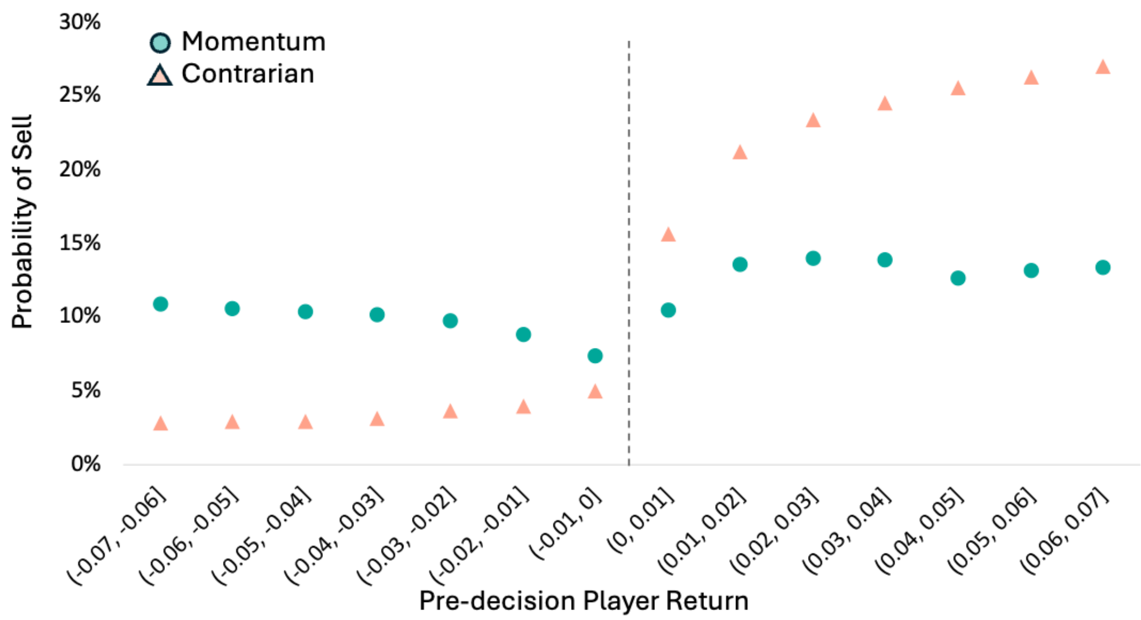
Notes: This figure plots the relation between disposition effects measured in the virtual investment game and in real-life mutual fund trading. Each point represents one investor. The orange line is a linear fit.

Figure 4: **Distribution of In-Experiment Disposition Effect by Investment Style**



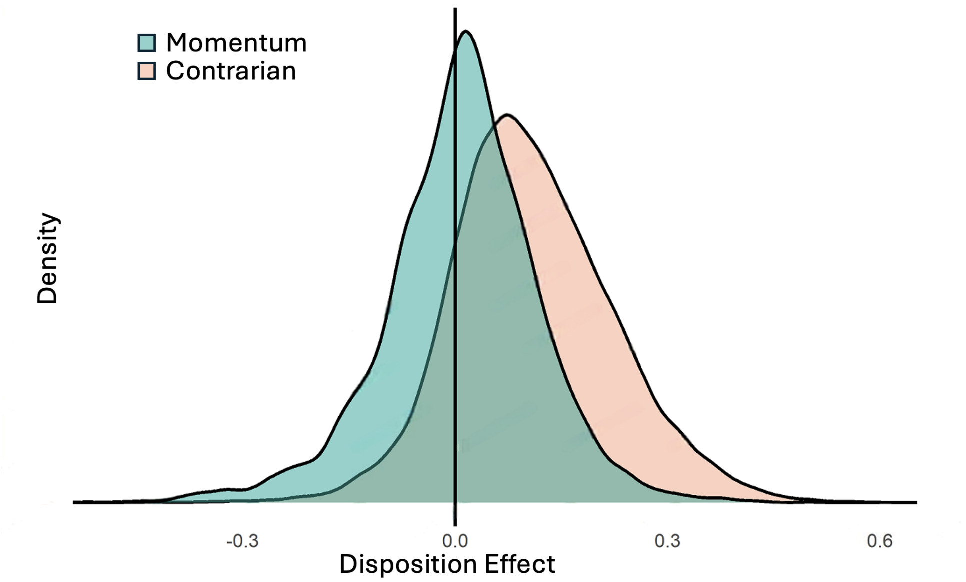
Notes: This figure compares the distribution of individual-level disposition effect between two types of investor. The classification method is described in Section 4.1. Disposition effect is measured by *PGR - PLR* following Odean (1998) with in-experiment decision-level observations.

Figure 5: **In-Experiment: Return, Probability of Sell, and Investment Style**



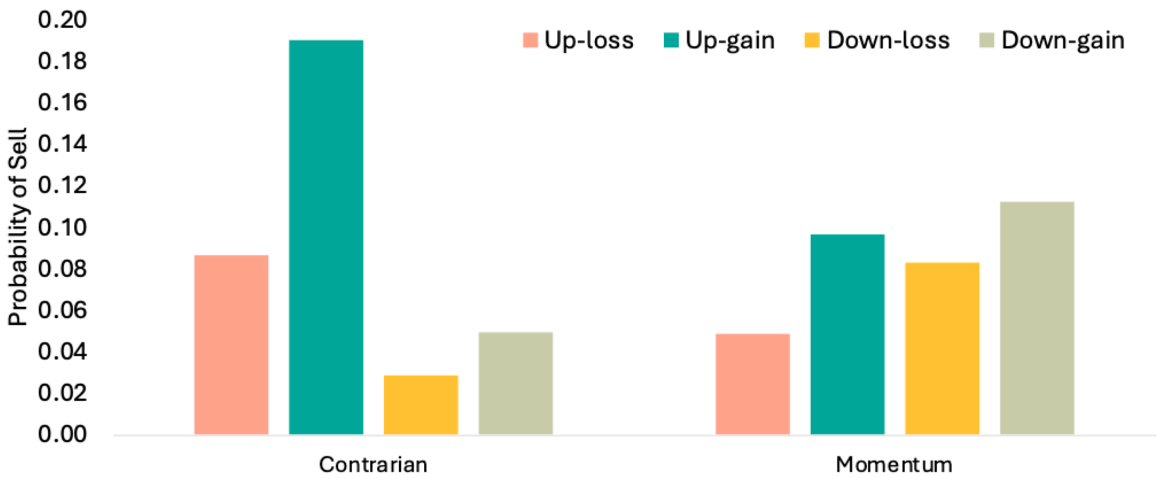
Notes: This figure depicts the relation between current in-game return and probability of selling, covering all decision-level investment decisions except for the first of each game session. The sample excludes observations with a zero pre-decision risky position. The classification method of investor type is described in Section 4.1. The dashed vertical line indicates zero return.

Figure 6: **Distribution of Real-Life Disposition Effect by Investment Style**



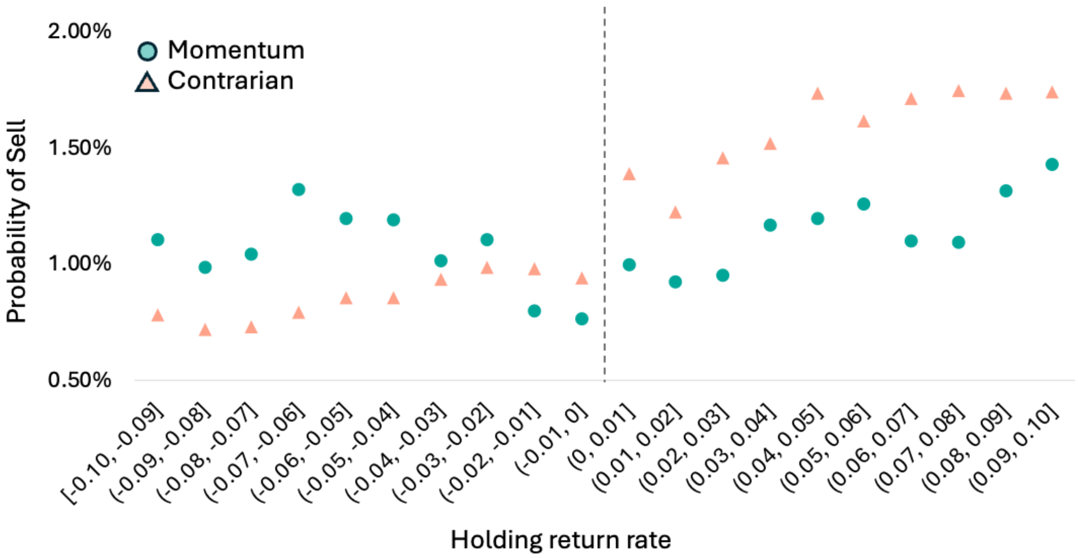
Notes: This figure compares the distribution of individual-level disposition effect between two types of investor. The classification method is similar to the in-game procedure described in Section 4.1. Disposition effect is computed by *PGR* - *PLR* following Odean (1998) with real-life investor-fund-month observations.

Figure 7: **In Experiment: Return Status, Recent Return, and Disposition Effect**



Notes: This figure uses a subsample of decision-level observations where the participant holds a positive risky position and the accumulated in-game return lies within the interval [–1%, 1%]. It compares the probability of selling across two investment styles under four scenarios, defined by the direction of the most recent price movement (up or down) and the sign of the player's current return (gain or loss).

Figure 8: **Holding return, Probability of Sell, and Investment Style**



Notes: This figure depicts the relation between holding return rate and probability of sell for pooled observations at investor-fund-day level. The sample excludes observations with a zero position in the previous day, to ensure the possibility of executing a sell order. The classification of investment style follows essentially the description in Section 4.1. The dashed vertical line indicates zero return.

A Supplementary Tables

Table A.1: **Session Order and Disposition Effect**

This table reports estimation results based on Equation 3. *Session order* is a categorical dummy which reflects the sequence of experiment within participant. *Lagged Disposition Effect* is obtained from the most recent session for the participant. *Session month* indicates the calendar month when the experiment was conducted, while *Market year* corresponds to the historical market index path shown in the session. Standard errors are clustered at individual level. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: *Disposition Effect*	
	(1)	(2)
Lagged Disposition Effect	0.215***	
	(0.004)	
Session order (benchmark: Session 2)		
Session 3	0.002	0.003
	(0.003)	(0.003)
Session 4	-0.000	0.001
	(0.003)	(0.003)
Session 5	0.006**	0.006*
	(0.003)	(0.003)
Session 6+	-0.007	0.003
	(0.003)	(0.003)
Session month FE	Yes	Yes
Market year FE	Yes	Yes
Individual FE	No	Yes
Observations	148,199	148,199
Adj. R2	0.071	0.215

Table A.2: **In-Experiment Disposition Effect and Demographics**

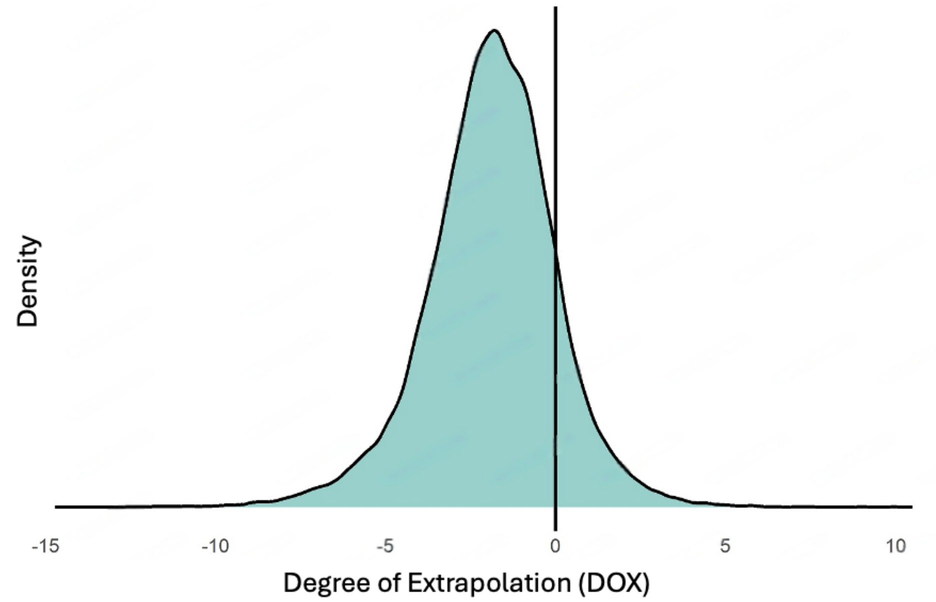
This table presents individual-level evidence of the relation between disposition effect and demographic characteristics. *Disposition effect* is measured according to Odean (1998). *Momentum* dummy is defined based on *Degree of Extrapolation* which is described in Section 4.1. *Bachelor* indicates highest completed education level. *Total assets* (in CNY) is the average monthly value of all types of assets held via Alipay. *p<0.1, **p<0,05, ***p<0.01.

	Dependent Variable: *Disposition Effect*		
	(1)	(2)	(3)
Momentum	-0.147***		-0.155***
	(0.002)		(0.003)
Male		-0.029***	-0.023***
		(0.002)	(0.002)
Log(Age)		-0.050***	-0.043***
		(0.011)	(0.011)
Bachelor		0.017***	0.013***
		(0.005)	(0.005)
Occupation (Benchmark: Student)			
Blue-collar		-0.020***	-0.020***
		(0.006)	(0.006)
White-collar		-0.020**	-0.029***
		(0.009)	(0.009)
Log(Total asset)		0.006***	0.003*
		(0.001)	(0.001)
Constant	0.194***	0.315***	0.342***
	(0.001)	(0.034)	(0.032)
Observations	48,266	17,197	17,197
Adj. R^2	0.127	0.012	0.126

B Supplementary Figures

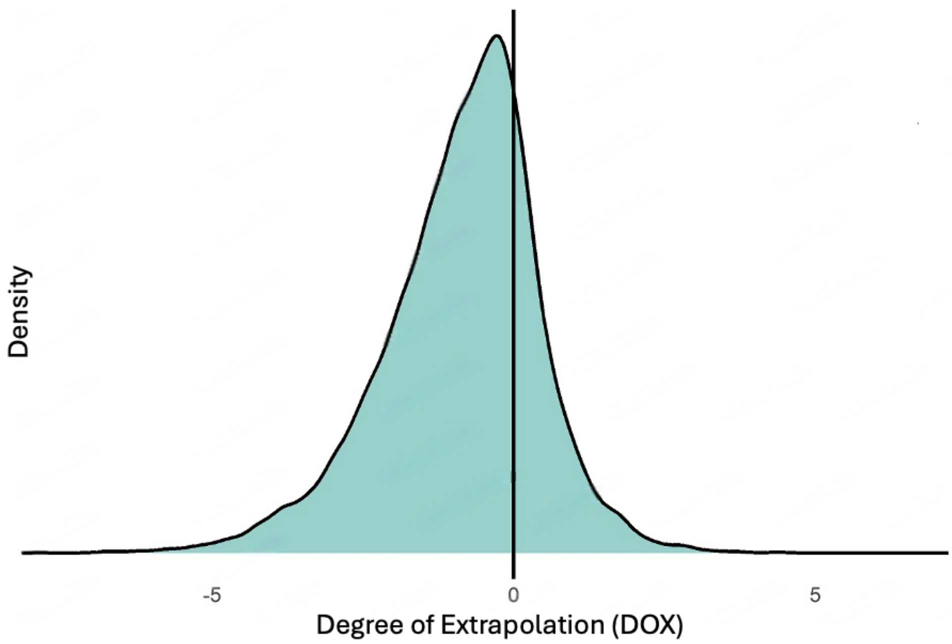
Figure B.1: **Illustration for Virtual Trading Game**

Figure B.2: Distribution of In-Experiment Degree of Extrapolation



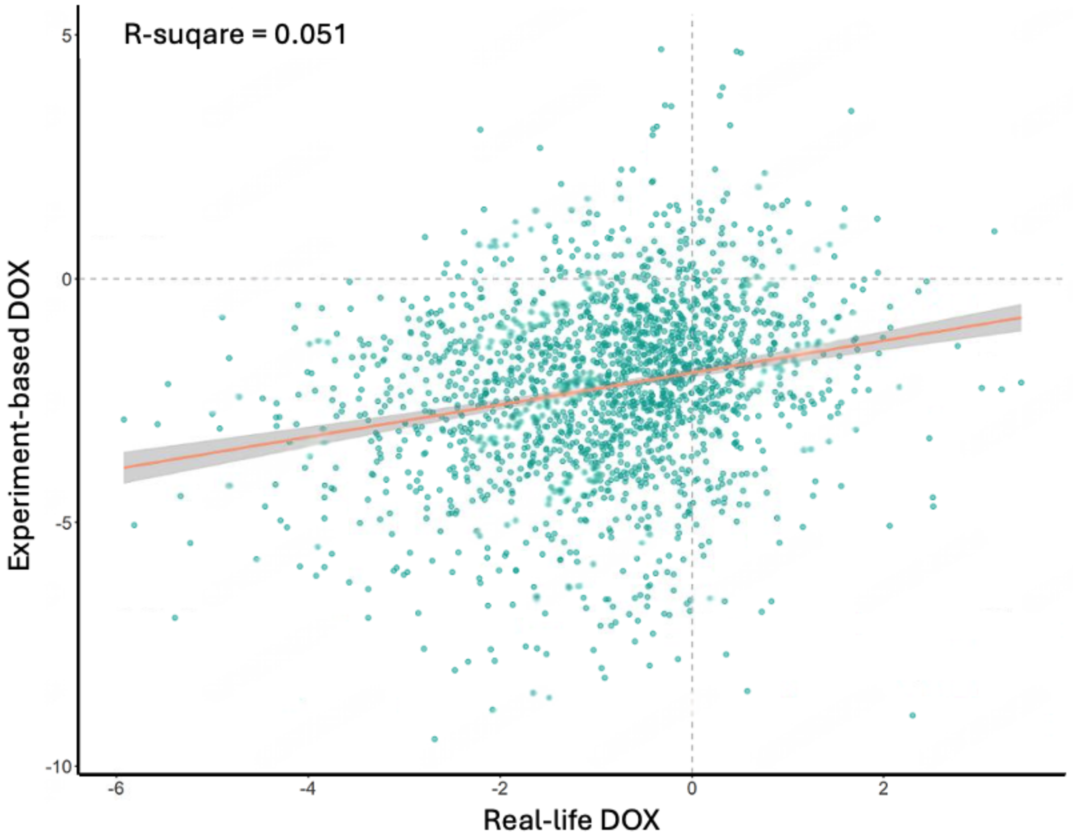
Note: This figure plots the distribution of degree of extrapolation (DOX) elicited from experimental data. The DOX is measured based on the regression-based approach outlined in Section 4.1.

Figure B.3: Distribution of Real-Life Degree of Extrapolation



Note: This figure plots the distribution of degree of extrapolation (DOX) obtained according to the regression-based approach described in Section 4.1, with real-life observations at investor-fund-month level.

Figure B.4: **Cross-context Consistency of Degree of Extrapolation**



Notes: This figure plots the relation between Degree of Extrapolation (DOX) measured in the virtual investment game and in real-life mutual fund trading. The DOX is obtained from a regression-based approach described in Section 4. Each point represents one investor. The orange line is a linear fit.