The Fixed Disposition Effect*

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First draft: March 2025
This draft: April 2025

Abstract

We examine whether the disposition effect—a tendency to sell winners and hold losers—reflects stable investor traits or context-dependent behavior. Using investor-level data from a large-scale trading experiment and matched real-world fund transactions, we document consistent disposition tendencies across settings. We find that both realization preferences and belief-driven trading styles independently contribute to this bias. While nearly all investors show a baseline tendency to realize gains, contrarian investors—who anticipate mean reversion—exhibit significantly stronger disposition effects than momentum traders. A robust discontinuity in selling behavior around zero returns further supports the role of realization utility. By isolating and validating both mechanisms within and across contexts, our study reconciles competing explanations in the literature and reframes the disposition effect as a behavioral trait shaped by heterogeneous beliefs and broadly shared preferences. These insights inform the modeling of investor behavior and the design of personalized financial interventions.

Keywords: Disposition effect, Subjective beliefs, Realization preference, Experimental finance

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"—a phenomenon known as the disposition effect—has emerged as one of the most robust and widely documented behavioral biases in financial markets. Extensive empirical studies, spanning data from brokerage accounts to laboratory trading experiments, consistently find that investors exhibit a systematic preference for realizing gains rather than losses.[1] This behavior persists even when controlling for rational motivations such as transaction costs, rebalancing needs, or tax optimization strategies (Odean, 1998). Despite its prevalence, the underlying mechanisms driving the disposition effect remain subjects of ongoing debate. In this paper, we aim to shed light on whether the disposition effect represents a stable, individual-specific trait, while reconciling competing explanations proposed in the literature.

Traditionally, explanations for the disposition effect have emphasized two broad channels: preferences and beliefs. Preference-based explanations focus primarily on investors' direct psychological utility from realizing gains or losses. The original explanation by Shefrin and Statman (1985), rooted in prospect theory (Kahneman and Tversky, 1979), attributes the disposition effect to loss aversion and mental accounting, suggesting that investors are naturally inclined to postpone the realization of painful losses and prematurely lock in pleasurable gains. Building on this insight, Barberis and Xiong (2012) introduced "realization utility," proposing that investors derive direct psychological satisfaction from the act of selling assets at a gain and experience distress when closing losing positions. Empirical support for realization utility comes from neural evidence, indicating immediate psychological rewards upon realizing gains (Frydman et al., 2014), and from experimental evidence showing that realized losses significantly alter investors' subsequent risk attitudes, leading them to retain losing as-

[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).

sets longer (Imas, 2016). However, despite their intuitive appeal, preference-based theories alone fail to comprehensively explain observed heterogeneity across investors and varying contexts, leaving substantial portions of the disposition effect unexplained (e.g., Dhar and Zhu, 2006; Kaustia, 2010; Meng and Weng, 2018).

Belief-based explanations, on the other hand, attribute the disposition effect to investors' biased expectations regarding future asset returns. For instance, Andersen et al. (2021) show that optimistic beliefs about the stock market's future performance can generate a strong disposition effect, as investors perceive sufficient upside potential to justify holding onto losing stocks while realizing modest gains early—a mechanism consistent with predictions by Barberis and Xiong (2009). A more intuitive illustration involves the belief in mean reversion, whereby investors sell winners and retain losers due to their expectation that returns will eventually revert to the mean. Indeed, experimental evidence by Weber and Camerer (1998) suggests that participants frequently exhibit mean-reversion expectations, providing a plausible rationale for their reluctance to realize losses. Nevertheless, empirical evidence often questions whether mean-reversion beliefs alone can fully explain the disposition effect. For example, Odean (1998) leverages an ex-post setup and finds that stocks investors refuse to sell subsequently underperform the stocks they sold, contradicting the notion of successful anticipation of price reversals. Kaustia (2010) further documents that investors consistently exhibit the disposition effect irrespective of whether their held stocks outperform or underperform the market, which suggests a more general phenomenon not fully explained by mean-reversion expectations. Moreover, Ben-David and Hirshleifer (2012) argue that mean-reversion beliefs, if truly playing a role, should apply broadly across all stocks in the market rather than exclusively affecting stocks investors currently own, which is supported by experimental evidence (Kadous et al., 2014).

Motivated by this theoretical ambiguity and the limited understanding of investor-level heterogeneity, this paper seeks to systematically investigate whether the disposition effect is primarily an individual-specific trait that remains stable across varying contexts. Specifically, we ask two related questions. First, is the disposition effect consistent within investors, such that individuals who exhibit the disposition bias in experimental settings also demonstrate similar behaviors in their real-world trading decisions? Second, if such individual consistency is found, what factors—belief-based or preference-based—underlie this behavioral stability?

To address these questions, our research leverages detailed individual-level data provided by Alipay, a globally leading financial services provider. We begin by examining a large-scale virtual investment experiment hosted on the Alipay platform, designed as an interactive trading simulation. The experimental setup, conceptually similar to Weber and Camerer (1998), enables us to identify and classify investors based on their reactions to recent price movements, isolating belief-driven behaviors from realization preference–driven motivations in a controlled environment. We then link these experimentally elicited investor types and disposition tendencies to the same investors' actual trading decisions in real financial markets. The advantage of our approach is threefold. First, the experimental setting allows us to capture investors' disposition effects and trading styles in an environment largely unaffected by confounding real-world factors such as transaction costs, liquidity constraints, and tax implications. Second, our corresponding real-life dataset spans the period 2017–2021, a recent era characterized by significantly reduced costs for retail investors to monitor real-time asset prices and execute transactions, ensuring that observed trading behaviors are minimally distorted by traditional frictions such as infrequent account checks or lack of attention.[2] Moreover, modern mobile trading platforms routinely provide investors with frequent, even real-time in many cases, updates on returns, minimizing ambiguity related to reference point definitions, which have posed challenges in prior studies (e.g., Meng and Weng, 2018; Pitkäjärvi et al., 2025).[3] Third and most importantly, this integrated design allows us to explicitly test the within-investor consistency of the disposition effect

[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), with only a few recent studies examining 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, potentially leading to heightened trading activity when returns become salient.

and investor types across controlled experimental and complex real-world settings. By using a highly consistent classification methodology—focusing on investors' active decisions in response to recent returns—we can robustly determine whether the observed disposition effect represents a stable, investor-specific characteristic that transcends context. Furthermore, our cross-context-validated evidence suggests that an investor's trading style in terms of reaction towards recent price movements is also a persistent and individual-specific trait.

Our findings provide robust evidence that both belief-driven and realization preference–driven forces independently contribute to the disposition effect. With a recent sample, we observe a strong disposition effect both in the experiment and in the field, confirming the prevalence of this long-lasting bias. In addition, we show that, while a portion of the disposition effect arises from investor beliefs—for example, contrarians expecting mean reversion exhibit particularly strong reluctance to sell losers—there remains a significant "jump" in terms of probability of selling when a holding position crosses from a small loss into a small gain. This discontinuity around zero indicates a realization-based preference that is largely common to all investors, operating above and beyond any belief differences. Furthermore, we uncover pronounced cross-sectional variation that coincides with trading styles. Momentum investors exhibit the much lower overall disposition effect, compared to their contrarian counterparts. Thus, while nearly all investors exhibit some universal desire to "lock in" gains, the magnitude of the disposition effect depends strongly on whether their beliefs and strategies reinforce or counteract that innate preference. In addition to the suggestive evidence from the relation between unconditional probability of sell and return rate, we validate this finding with a carefully executed model in the spirit of regression discontinuity design, following Ben-David and Hirshleifer (2012).

Our paper, first and foremost, contributes to the literature of disposition effect by testing both belief- and preference-oriented motivations. Generally, the up-to-date literature has attributed this phenomena to preference-based explanations rather than subjective beliefs, potentially owing to the empirical challenges. Beliefs and preferences are particularly difficult to measure and disentangle based on transaction data for transactions could reflect investors' reactions to price movements as well as their current loss-gain status simultaneously. We provide a remedy that elicits investor's responses to price movements by using a regression-based approach which controls for gain-versus-loss status. The findings suggest that behavioral biases could be related to individual heterogeneity in beliefs about asset price movements. In a recent and relevant study, Andersen et al. (2021) empirically investigate how different beliefs about the expected returns of stock market could affect disposition effect on an individual basis, based on the theoretical model proposed by Barberis and Xiong (2009). Furthermore, Andersen et al. (2024) 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]

In terms of preference-based explanations, we are among the first to empirically support the realization preference proposed in Barberis and Xiong (2009). In contrast to Ben-David and Hirshleifer (2012) who argue that realization preference does not seem to explain the disposition effect, we identify a discontinuity around zero return by using the same identification strategy but exploiting a more recent dataset. This could imply that realization preference is too nuanced to be easily captured unless with sufficient investor attention which is enhanced by the nascent rise of mobile internat usage.

The findings also contribute to a strand of literature that examines cross-sectional heterogeneity in the disposition effect across different levels of sophistication and contexts. Not all investors are equally prone to the bias, and they make investment mistakes to a varying extent (Calvet et al., 2009). Dhar and Zhu (2006), for instance, show that wealthier and more educated investors exhibit a significantly weaker disposition

[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.

effect than their less sophisticated counterparts. Similarly, professional traders and institutional investors, who tend to be more experienced, still exhibit the disposition effect but to a lesser degree. Consistently, Feng and Seasholes (2005) document that as individuals gain trading experience, the disposition effect attenuates—up to about 70% of the bias is eliminated as an investor becomes seasoned, although even the most experienced investors may continue to sell winners more readily than losers. Furthermore, Locke and Mann (2005) reveal that even successful floor traders hold onto losing trades longer than winning trades, though at reduced levels relative to retail investors. In their recent study, Andries et al. (2024) suggest that professional financial advisors could actually enhance the disposition effect in their clients' portfolios when they have access to the portfolio performance.

Contextual factors play a role as well – 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. Building on these insights, our paper adds further evidence on cross-sectional variation and the persistence of the disposition effect. Specifically, we examine whether the same individuals display the bias consistently across an experimental task and their real-world trading, and investigate which investor characteristics—beyond basic demographic traits—predict a greater or lesser tendency to hold losers and sell winners. In line with Giglio et al. (2021), who document that investor beliefs and behaviors exhibit persistent individual heterogeneity not explained by simple demographic factors, our findings show that momentum-versus-contrarian trading styles play a more decisive role in accounting for the disposition effect than demographic characteristics alone. This contribution clarifies the role of investor heterogeneity in the disposition effect and suggests that the bias may be partially shaped by individuals' underlying beliefs and strategies, indicating important limits to its malleability.

The rest of the paper is structured as follows. Section 2 describes our experimental setup, data, and methodological approach for quantifying individual-level disposition tendencies. Section 3 analyzes the disposition effect within the experimental context, highlighting investor heterogeneity. Section 4 examines whether these experimental findings extend to real-world trading, and links experimental investor classifications to real-life behaviors, confirming within-investor consistency. Section 5 investigates the role of realization preferences around zero return thresholds. Section 6 concludes.

2 The Experiment: A Virtual Investment Game

2.1 Background of the platform

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 time of data extraction, around 2% of the users had participated in the investment game at least once.

2.2 Experimental 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 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 * 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.

2.3 Experimental data and variables

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.[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.

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). The participants in general exhibit meaningful exposure to risk, leading

[5]We do, however, acknowledge that this sample might not be a proper 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.

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%.

[Insert Table 1 around here.]

3 In-Experiment Disposition Effect

In this section, we leverage the experimental setup not only to investigate the existence of disposition effect at an aggregate level, but to reveal the varying extent to which investors exhibit disposition effect. With the arguably isolated virtual setup, we also attempt to explain the cross-sectional variations across investors.

3.1 Disposition effect at aggregate level

We start this part by examining whether disposition effect is prevalent at aggregate level. 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, including at individual level (e.g., see 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.

[Insert Figure 1 around here.]

3.2 Investor type and individual-level disposition effect

What contributes to the almost ubiquitous bias? A large body of literature has focused on preference-based explanations (e.g., Barberis and Xiong, 2012, 2009; Meng and Weng, 2018), whereas belief-driven attribute is rarely discussed. In this section, we attempt to construct a variable of *investor type* that is arguably highly related to investor's belief. More specifically, we run the following regression for each investor *i*. The idea of the specification is to extract the discrepancies in how they react to recent price movements, after controlling for return-relate response which could be associated with realization preference as indicated in Barberis and Xiong (2009).

$$Turnover_{i,d} = \alpha_i + \beta_i Market\ return_{i,d}^{t-1,t} + \gamma_i Gain_{i,d} + \lambda_i |Player\ return_{i,d}| + \varepsilon_{i,d} \qquad (3)$$

The outcome variable $Turnover_{i,d}$ refers to the turnover of participant *i*'s decision *d*. $Market\ return_{i,d}^{t-1,t}$ captures the market return rate after the most recent decision. $Gain_{i,d}$ indicates whether the player has accumulated a positive return before making decision *d*, while $|Player\ return_{i,d}|$ is the magnitude of the return. Our coefficient of interest is investor-specific β_i, which we name *Degree of Extrapolation (DOX)* because it is expected to be associated with whether one holds more of an extrapolative or a contrarian belief. A positive β_i indicates that the investor tends to trade *in* the direction of recent market movement, hence, we label such investors *Momentum* investors. On the contrary, a negative coefficient would imply the investor's trades are normally *against* the recent market dynamics, and we label them *Contrarian* investors. Figure B.2 presents the distribution of DOX, and among all the game participants we identify around 86% of them to be contrarians.[6]

We proceed to show how the prevalence of disposition effect varies between two types of investors in the experiment. Figure 2 plots the distribution, with a vertical line indicating the scenario where there is no difference in the propensity of realizing gains versus losses, namely, no disposition effect. The figure shows a clear discrepancy between two types of investor; the vast of majority of contrarian investors exhibit disposition effect, whereas an average momentum trader carries virtually no disposition effect. To further validate this finding, we follow the literature (e.g., Ben-David and Hirshleifer, 2012; Kaustia, 2010) and take a more granular look at the relation between investor's probability of sell and their paper return rate before the decision. We restrict the return interval to [-7%, 7%], roughly representing the range between 5-th and 95-th percentile across all decision-level observations. Figure 3 presents the scatters. In line with the distribution presented in Figure 2, we notice a gap of propensity to sell between cases with a positive return and those with a negative return for contrarian investors, while the gap almost vanishes for momentum investors. Interestingly, we document a jump of probability of sell around zero return (indicated by the dashed line) for both groups, although the jump seems less pronounced for momentum investors. This discontinuity supports the realization utility theory in Barberis and Xiong (2012), which argues that investors obtain a jolt of utility only when they *realize* profits or losses. We investigate this preference-based hypothesis more rigorously in Section 5.

[Insert Figures 2 and 3 around here.]

To further establish the relation between investor type and disposition effect, we

[6] Our classification result of the majority of retail investors being more inclined to exhibit contrarian trading style is consistent with previous studies (e.g., Grinblatt and Keloharju, 2001; Jonsson et al., 2017). However, it is worth noting that when the financial concept is replaced by a more general setup, Andersen et al. (2024) find that the average DOX is 0.14 among Danish retail investors, implying a larger fraction of momentum traders. Revealing the actual distribution of contrarian-versus-momentum traders is, nevertheless, out of the scope of this paper.

evaluate the following linear regression:

$$
\begin{aligned}
100 \times \mathit{Sell}_{i,g,p} = \gamma \mathit{Gain}_{i,g,p} + \beta \mathit{Gain}_{i,g,p} \times \mathit{Momentum}_i \\
+ FE_i + FE_g + FE_p + \varepsilon_{i,g,p}
\end{aligned}
\tag{4}
$$

where $\mathit{Sell}_{i,g,p}$ indicates whether participating investor i chooses to actively lower risky position during period p within the game session which displays market index price history of year g. To ensure that sell action is possible, we restrict the sample to observations with a positive risky position before the decision. Such a constraint does not seem to cause serious selection bias, as the sample size shrinks by only approximately 4%. Furthermore, various fixed effects are staggered in the regressions in order to account for unobserved heterogeneity. Our findings in Table 2 consistently suggest that the disposition effect is in general strong and unignorable among the investment game players: they are approximately 16 percentage points more likely to realize gains than losses. More importantly, Column 4 shows that the effect of investor type remains substantial even after controlling for various fixed effects, and momentum trading style largely offsets the disposition effect. Taken together, our findings imply that investor's response to price movements, in addition to the response to current return status, has strong explanatory power on the disposition effect.

[Insert Table 2 around here.]

Our findings somehow contradict previous literature which refutes that the belief-based factors, especially the belief in mean-reversion, could explain the disposition effect, which could arguably attributed to the discrepancy in how mean-reversion is interpreted. The evidence against the belief-driven explanations usually measures the relative-to-market-index performance of the underlying assets (e.g., Grinblatt and Keloharju, 2001; Kaustia, 2010; Talpsepp et al., 2014), while we leverage the absolute recent performance without considering the market performance. Our reasoning is threefold. One is that the measurement is more compatible with our experimental setup where relative performance does not exist. For the later sections that exploit mutual fund holding data, we argue that relative performance could be less effective, compared to stock-based scenario, since mutual funds serve various needs and they do not always aim at overperforming the market portfolio. The fact that mutual funds usually contain a small but non-negligible fraction of cash holdings also affect the relative performance directly (Chernenko and Sunderam, 2016). The other reason, applicable mainly for the later investigations, is that mutual fund investors cannot observe accurate real-time absolute performance during the trading hours, instead, they are provided an estimate with error. Determining whether a given mutual fund out performs the market is therefore virtually infeasible. Lastly, it is conceptually simpler to consider absolute rather than relative performance for an average retail investor who is generally not highly financially sophisticated.

3.3 Other factors beyond investor type

Is investor type simply a re-packaging or a compilation of certain individual characteristics? This is a valid concern as earlier studies find that disposition effect is negatively associated with financial sophistication (e.g., Calvet et al., 2009; Dhar and Zhu, 2006).

To test the hypothesis, we leverage the demographics information registered on Alipay platform which requires uploading a valid identification document before an user could enable payment- and investment-related functions. This helps link investors correctly to their age, gender and city of birth. In addition, users can self-report other information, including but not limited to occupation and educational level in exchange for better customized services and functions. Panel A of Table 3 summarizes relevant demographic as well as trading characteristics in the cross-section of July 2021. Note, however, that the sample size shrinks greatly after dropping missing values of demographics due to self-reporting. *Bachelor* is a binary dummy that equals one if the user is a current college student or hold at least a bachelor's degree. *Occupation* is a categorical dummy that covers three types: students, blue-collar workers and white-collar workers. *Total asset* refers to the average of end-of-month total market value of all financial products, primarily various kinds of mutual funds, that an investor holds directly on

Alipay. We consider this as a proxy for wealth.

The summary statistics suggest a self-selection in self-reporting: roughly one-third of users in the baseline sample provide detailed education and occupation information. The vast majority of the reporting ones are younger than 28 years old and well-educated. While two-thirds of them have a white-collar job, only a tiny fraction of them are blue-collar workers. This sample, despite the selection bias, works in our favor because these investors tend to have higher financial sophistication, thus to exhibit weaker disposition effect in general. As a result, this should hinder our identification of the gap in disposition effect between two types of investors, which is implemented by the following simple cross-sectional OLS regression:

$$DE_i = \alpha + \beta Momentum_i + \zeta Z_i + \varepsilon_i, \tag{5}$$

where Z_i is a vector of demographic controls as described above. Panel B of Table 3 shows relevant results. We first examine how investor type and demographic characteristics are individually related to the disposition effect. Columns 1 and 2 document that momentum-chasing, female, better-educated, and wealthier investors are correlated with significantly lower disposition effect. With controlling for two sets of variables, Column 3 consistently shows that momentum investors exhibit weaken disposition effect, implying that investor type contributes to disposition in addition to other common individual attributes. Although not the primary focus of this paper, it is worth noting that the negative and significant coefficients on the wealth proxy (average total assets) and the education indicator do not support the notion that financial sophistication reduces the disposition effect. Despite the disagreement with findings in, for instance, Dhar and Zhu (2006) and Calvet et al. (2009), our findings are somewhat in line with those in Andersen et al. (2021), shedding light on the need of further future investigation on the role of financial literacy.

4 Disposition Effect in Real Life

4.1 Data description

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. [7] 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 smaller than the 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 last 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. Furthermore, we compute the holding length for each investor-fund pair based on its first appear-

[7] 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.

ance. As a result, we obtain a sample consisting of 6,680,923 observations, of which the summary statistics are presented in Panel A of Table 4. 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 could be plausibly attributed to lower trading costs, simpler trading executions as well as stronger 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 return rate of 6%, and the majority of the observations carry a positive return.

As with experimental data, we divide the sample by the investor type that is determined by the same regression-based approach described in Section 3.1. While the approach remains the same, we adjust the specification by using the previous month's fund return rate as a proxy of price movement, and further including holding position and holding length, both in logarithmic terms. The dependent variable of trading activity is the percentage change of number of held shares, bounded on [-1, 1]. To ensure the power of regression, we exclude investors with less than 100 valid fund-month observations. As a result, we identify a fraction of around 76% investors being contrarians, in line with the finding from the experimental setup that suggests the vast of majority of retail investors tend to invest against the recent price trend. We also plot the distribution of the DOX in Figure B.3.

4.2 Real-life disposition effect and investor type

Following the literature (e.g., Andries et al., 2024; Ben-David and Hirshleifer, 2012), we leverage the following regression to examine real-life disposition effect more rigorously:

$$
\begin{aligned}
100 \times Sell_{i,f,t} = & \beta Gain_{i,f,t-1} + \omega Sqrt(Holding\ months_{i,f,t}) + \gamma Log(Position_{i,f,t-1}) \\
& + \beta_m \{Gain_{i,f,t-1} \times Momentum_i\} + \beta_c \{Gain_{i,f,t-1} \times Contrarian_i\} \\
& + FE_{i \times t} + FE_{f \times t} + \varepsilon_{i,j,t}, \qquad (6)
\end{aligned}
$$

where i, f, and t denote investor, fund and month, respectively. $Sell_{i,f,t}$ equals one if investor i reduces fund f's shares during month t and zero otherwise. $Gain_{i,j,t-1}$ is a binary dummy that indicates whether the investor-fund pair records a positive holding profit at the end of month *t-1*. $Holding\ months_{i,f,t}$ documents the length since the most recent month that investor i opened position for fund f, and the variable will be reset to zero following a complete liquidation even for the same investor-fund pair. $Position_{i,f,t-1}$ is the market value of investor i's holding on fund f at the end of month *t-1*. We further control for investor-month and fund-month fixed effects to alleviate the concern that certain trading patterns could be time-specific. Standard errors are two-way clustered at investor and month levels.

Columns 1-3 in Panel B of Table 4, despite the saturated fixed effects, echo the findings we document in the experimental setup : the disposition effect is reduced significantly, even reversed, among momentum investors. Column 4 presents the results from a simple uni-variate regression, with the level of disposition effect being the outcome variable. The significant and negative coefficient indicates that investor type could to a great extent explain the cross-sectional variation of disposition effect among retail investors. It is worth noting that our findings contradict those of Chang et al. (2016) who document a reverse-disposition for delegated assets, i.e., mutual funds, via the channel of cognitive dissonance. Investors tend to blame the fund manager, instead of themselves, for the fund's poor performance, thus making it more acceptable to realize losses than in the non-delegated context such as dealing with individual stocks. It could be rationalized by the reduced level of perceived delegation in the sense that our settings allow investors to closely monitor fund performance on a daily basis and to submit an order fairly easily around the clock.[8] As a consequence, the investors in our sample could feel more responsible for their investment decisions and the performance thereof.

[Insert Table 4 around here.]

4.3 When experimental data meets real-life decisions

So far we have confirmed that momentum-chasing investors exhibit much weaker disposition effect, in both experimental and real-life setups. However, it could remain concerning that the regression-based classification method cannot fully distinguish investor's response to price movement from that to return status, even after controlling for two return-related variables. This potentially vital issue implies that our previous findings could be largely mechanical because *both* the disposition effect and investor type are elicited within the same data, either in-game or real-life. We address this concern by introducing game-elicited investor types to the real-life disposition effect.

More specifically, we alter the regression model Eq. 6 by replacing the real-life-based momentum dummy by the experiment-based one. As such, the two key variables of our interest are determined separately in two contexts. The results are presented in Table 5. We persistently document that, both at investor-fund-month level (Column 1) and at investor level (Column 2), momentum-chasing investment style substantially offsets the disposition effect.

[Insert Table 5 around here.]

In addition to the relation between investor type and the disposition effect which we try to shed light on, results in Table 5 imply that investor type, as well as the disposition effect, is stable within-individual. Put differently, the same individual tends to exhibit similar trading style in terms of how they react to price movement, and also

[8] During our sample period, estimated real-time performance of domestic mutual fund was made available to the Alipay users. The estimates were based on mutual funds' quarterly reports, hence not fully accurate. The feature was removed in July 2023.

similar level of unwillingness to realize losses. We implement a straightforward cross-context correlation test on the disposition effect and the DOX, and present the results in Table 6. Both correlation coefficients are significantly positive, highlighting one of the key findings of this paper as the title suggests, namely, the disposition effect works like a fixed effect at investor level. Moreover, the tendency to chase price momentum, measured by the DOX, also remains persistent within investor. To sum up, our findings demonstrate that retail investors tend to react to price movement and return status in their own specific, but consistent, way over time.

[Insert Table 6 around here.]

5 The Role of Realization Preference

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 Figure 3 provides 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 4. 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 4 around here.]

The investor-fund-month dataset used in Section 4, 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.[9]

With the more frequent data, we first present in Figure 6 the relation between holding return rate and unconditional probability of sell for both types of investors.[10] 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 3). 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.

[9]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.

[10]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.

[Insert Figure 6 around here.]

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. 6 except for the inclusion of third-degree polynomials and their interaction with holding length as well as investor type.[11] We present the estimation results with varying holding-length windows in Table 7, 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 7 around here.]

[11] We alter the degree of polynomials to fourth and fifth, the results remain highly stable.

6 Concluding Remarks

In this paper, we investigate whether the disposition effect is a stable individual-specific trait and explore the relative roles of belief-based and preference-based explanations. By leveraging unique data from a virtual trading experiment integrated with real-world trading data from Alipay, we provide robust empirical evidence that the disposition effect indeed represents a stable, individual-specific behavioral characteristic. Specifically, we find significant consistency in investors' disposition tendencies across experimental and real-market settings, validating the trait-like interpretation of this behavioral bias.

Moreover, our findings reveal that both subjective beliefs and realization preferences independently and significantly drive the disposition effect. In particular, we document substantial cross-sectional heterogeneity associated with investors' inherent trading styles. Contrarian investors display the strongest disposition effect, whereas momentum investors exhibit minimal to no disposition bias. Crucially, we identify a clear discontinuity in selling probability around the zero-return threshold, supporting the realization preference theory proposed by Barberis and Xiong (2012). This discontinuity, previously questioned by Ben-David and Hirshleifer (2012) among others, becomes visible in our analysis likely due to increased investor attention facilitated by modern mobile trading platforms.

More broadly, our results highlight the critical importance of accounting for investor heterogeneity, especially individual differences in beliefs and trading strategies, when examining behavioral biases. By demonstrating that investment behavior traditionally viewed as a behavioral anomaly can be substantially explained by stable individual differences in beliefs and realization preferences, our findings underscore the necessity of considering both factors simultaneously. This insight not only enhances our understanding of the disposition effect but also suggests important limitations to interventions that exclusively target belief formation or preferences separately.

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Table 1: **Summary Statistics: The Virtual Investment Experiment**

This table summarizes 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* depicts 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. N = 4,527,250.

	Mean	SD	Q1	Median	Q3
Duration	6.26	6.81	2.54	4.37	7.60
Buy dummy	0.41	0.49			
Sell dummy	0.13	0.33			
Risky share (%)	55.09	35.57	25.50	59.06	88.94
Turnover(%)	6.94	40.91	0	0	13.88
Market return(%) [t-1, t]	0.33	6.19	-3.05	0.72	3.78
Market return(%) [0, t]	1.55	11.89	-5.54	0.73	7.79
Current player return (%)	0.38	4.94	-1.67	0.13	2.35

Table 2: **In-Experiment Disposition Effect and Investor Type**

This table presents estimated coefficients according to Eq.4. The observations are at decision-level, covering all game-periods with a positive pre-decision risky position. *Sell* is a dummy that equals one if the decision is to reduce risky position, and zero otherwise. *Gain* takes the value of one if pre-decision player return is positive, and zero otherwise. *Momentum* is a dummy that indicates investor type. *Game year* refers to the actual year of market index path that is assigned to the participant. Standard errors are two-way clustered at investor and game-period level and presented in the parentheses. *p<0.1, **p<0,05, ***p<0.01.

	Dependent Variable: $100 \times$ *Sell*			
	(1)	(2)	(3)	(4)
Gain	16.745***	16.161***	15.912***	17.945***
	(1.073)	(1.217)	(1.193)	(1.314)
Gain $\times$ Momentum				-14.587***
				(1.230)
Constant	4.429***			
	(0.271)			
Period FE	No	Yes	Yes	Yes
Game year FE	No	No	Yes	Yes
Investor 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 3: **In-Experiment Disposition Effect and Demographics**

This set of tables presents individual-level evidence of the relation between disposition effect and demographic characteristics. **Panel A** summarizes the two samples used in the regressions. *Disposition effect* is measured according to Odean (1998). *Momentum* dummy is defined based on *Degree of extrapolation* which is described in Section 3.2. *Bachelor* indicates education level, including on-going bachelor studies. *Total assets* (in CNY) is the average monthly value of all types of assets held via the Alipay platform. **Panel B** presents regression results. *p<0.1, **p<0,05, ***p<0.01.

Panel A: Summary Statistics

	N	Mean	SD	Q1	Median	Q3
Disposition effect	48,266	0.17	0.14	0.07	0.16	0.26
Momentum dummy	48,266	0.13	0.34			
Degree of extrapolation	48,266	-1.89	1.92	-2.99	-1.83	-0.71
Age	17,197	25.88	3.54	23	26	28
Male dummy	17,197	0.64	0.48			
Bachelor dummy	17,197	0.85	0.32			
Occupation dummy	17,197					
Student		0.31				
Blue-collar		0.02				
White-collar		0.67				
Total assets	17,197	47,513.19	86,618.00	7,845.10	21,790.06	54,208.23

Panel B: Regressions

	Dependent Variable: *Disposition Effect*		
	(1)	(2)	(3)
Momentum	-0.147***		-0.154***
	(0.002)		(0.003)
Male		-0.028***	-0.023***
		(0.002)	(0.002)
Log(Age)		-0.054***	-0.046***
		(0.002)	(0.011)
Bachelor		0.019***	0.016***
		(0.004)	(0.004)
Occupation (Base group: Student)			
Blue-collar		-0.004	-0.016*
		(0.010)	(0.009)
White-collar		-0.006*	-0.008***
		(0.003)	(0.003)
Log(Avg_asset)		0.013***	0.008*
		(0.005)	(0.004)
Constant	0.194***	0.312***	0.340***
	(0.001)	(0.034)	(0.032)
Observations	48,266	17,197	17,197
Adj. R2	0.127	0.013	0.126

Table 4: **Real-Life Disposition Effect and Investor Type**

This set of tables report results of the investigation of disposition effect with real-life fund-month observations. **Panel A** summarizes the sample. *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 B** presents regression results. For all specifications, *Momentum* indicates investor types. Columns 1-3 use fund-month observations, and the dependent variable *Sell* dummy indicates whether the number of shares is reduced during the month. *Gain* equals one if the fund-month documents a positive return by the end of last month. Standard errors are two-way clustered at investor and month level. Column 4 leverages a uni-variate regression on individual level, with the dependent variable of disposition effect that follows Odean (1998). *p<0.1, **p<0,05, ***p<0.01.

Panel A: Summary Statistics (N = 6,680,923)

	Mean	SD	Q1	Median	Q3
Sell dummy	0.29	0.45			
Holding length	7.84	7.58	2	5	11
Holding position	4240.31	15579.05	137.32	907.55	3298.14
Holding profit	167.80	3022.58	-9.60	2.96	72.85
Holding return rate (%)	5.81	20.19	-2.55	2.00	9.80

Panel B: Regression

	Dependent Variable:			
	(1)	(2)	(3)	(4)
		100 × *Sell*		*DE*
Gain	0.625	4.274***	6.148***	
	(0.828)	(0.479)	(1.193)	
Momentum				-0.102***
				(0.002)
Gain × 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. R2	0.114	0.313	0.314	0.115

Table 5: **Real-Life Disposition Effect and Experiment-Elicited Investor Type**

This table presents the results after connecting experimental measures to real-life transactions. For both specifications, *Momentum* indicates investor types that are elicited from the virtual investment game. Column 1 uses fund-month observations, and the dependent variable *Sell* dummy indicates whether the number of shares is reduced during the month. *Gain* equals one if the fund-month documents a positive return by the end of last month. Standard errors are two-way clustered at investor and month level. Column 2 leverages a uni-variate regression on individual level, with the dependent variable of disposition effect that follows 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. R2	0.312	0.007

Table 6: **Measurement Consistency between Two Setups**

This table presents the cross-sectional correlation of two key measures between experiment and real-life. *Degree of Extrapolation* is calculated according to Section 3.2, while *Disposition Effect* follows the definition of Odean (1998). *p<0.1, **p<0,05, ***p<0.01.

		Real-Life	
		Degree of Extrapolation	Disposition Effect
In-Game	Degree of Extrapolation	0.188***	
In-Game	Disposition Effect		0.163***

Table 7: **Regression Discontinuity Design**

This set of results relates to regression discontinuity specification which introduces varying polynomials of holding returns to the baseline specification Eq.6 at investor-fund-day level. **Panel A** summarizes the sample. *Holding return rate* and *Holding position* are measured as of the previous day. *Panel B* presents regression results. The dependent variable, *Sell*, indicates whether an investor sells a mutual fund holding partially or completely during a given day. *Gain* is a dummy that equals to one if the investor-fund pair documents a positive holding return as of the end of previous day. Controls including holding position and holding length in days, lagged for one day and in logarithmic terms. *Effect* is calculated by the coefficient of *Gain* over unconditional probability of sell over all observations falling within the holding day window. *p<0.1, **p<0.05, ***p<0.01.

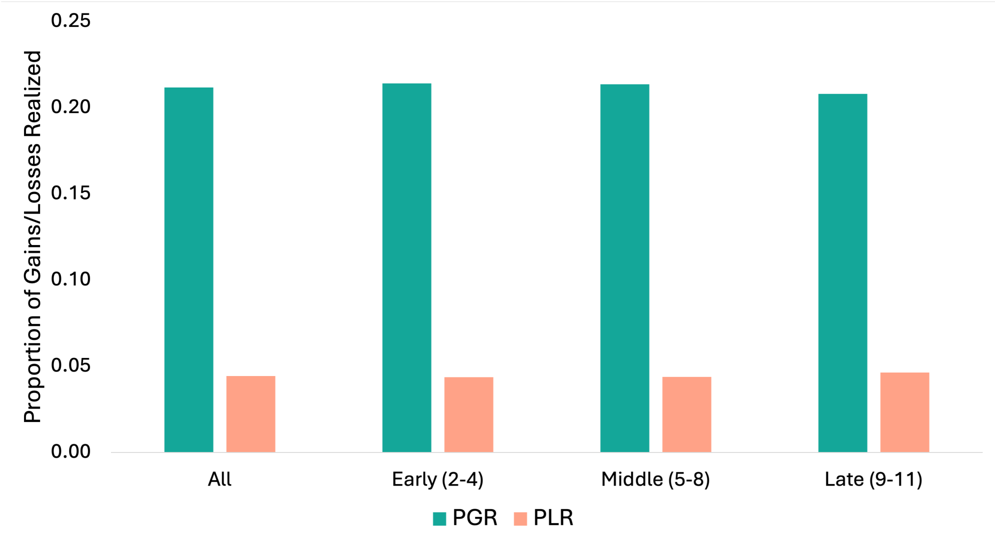
Panel A: Summary Statistics (N = 891,193)

	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

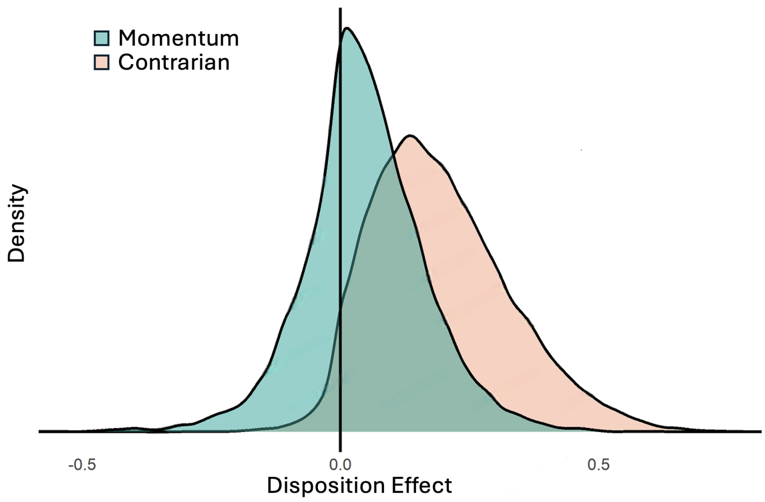
	Dependent Variable: 100*Sell		
Holding days	1 to 21 (1)	22 to 42 (2)	43 to 70 (3)
Gain	0.432*** (0.083)	0.429*** (0.100)	0.125 (0.094)
Momentum	-0.120 (0.086)	-0.161 (0.103)	-0.323*** (0.098)
Gain × Momentum	-0.013 (0.132)	-0.110 (0.157)	0.113 (0.147)
Controls	Yes	Yes	Yes
3rd Polynomials of holding return 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 R2	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**



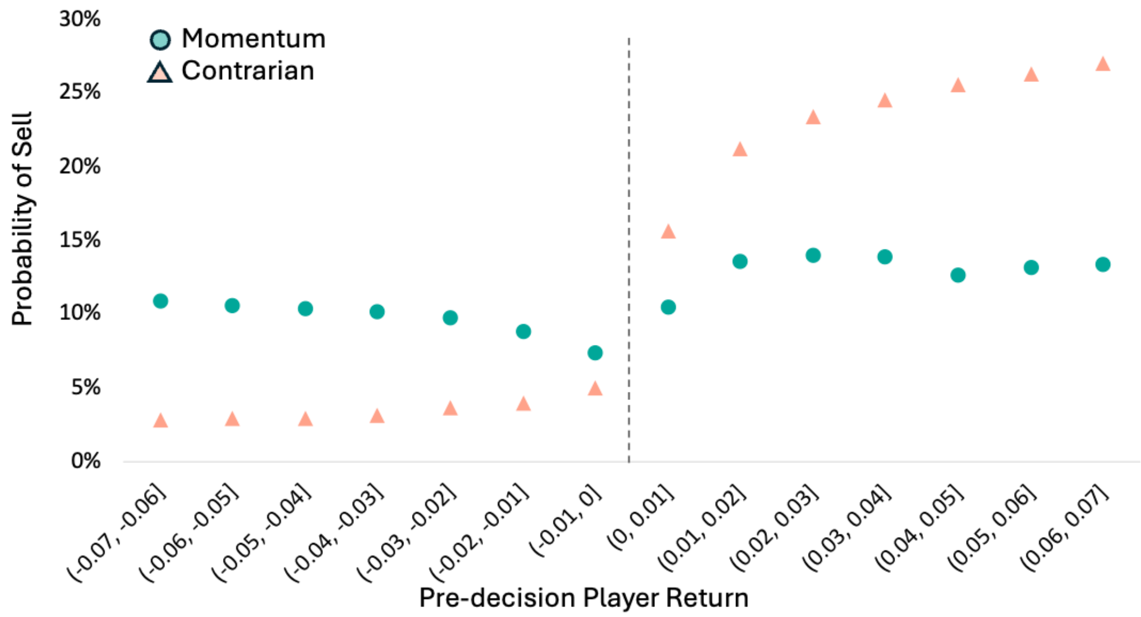
Notes: This figure shows aggregate disposition effect, and how the prevalence of disposition effect varies over different experiment stages. The sample further restricts the pre-decision risky position to be positive to guarantee the possibility of selling decision. *Early* stage pools all the investment 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: **Distribution of In-Experiment Disposition Effect by Investor Type**



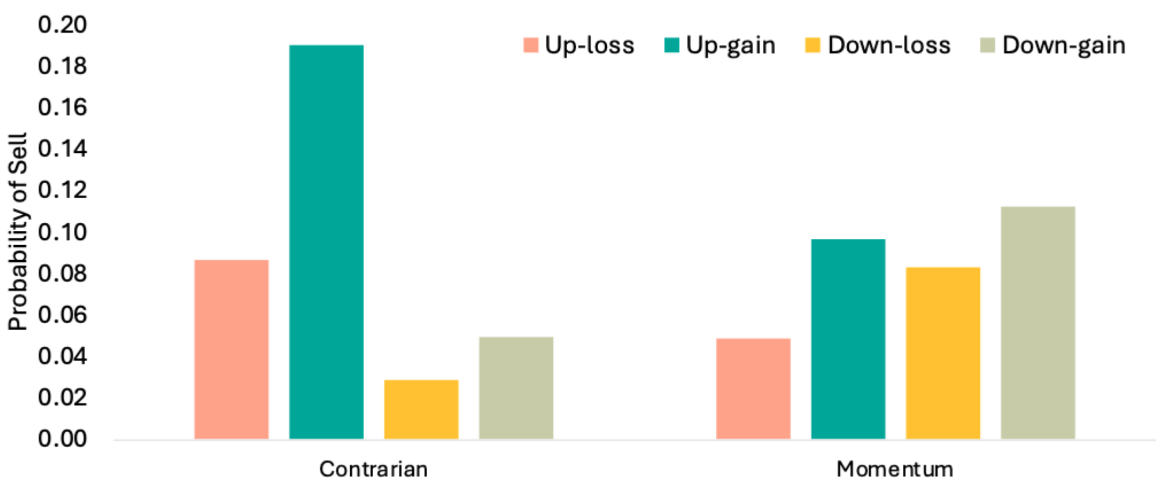
Notes: This figure compares the distribution of individual-level disposition effect between two types of investor. The classification method is described in Section 3.2. Disposition effect is measured by *PGR - PLR* following Odean (1998) with in-experiment decision-level observations.

Figure 3: **Game Return, Probability of Selling and Investor Type**



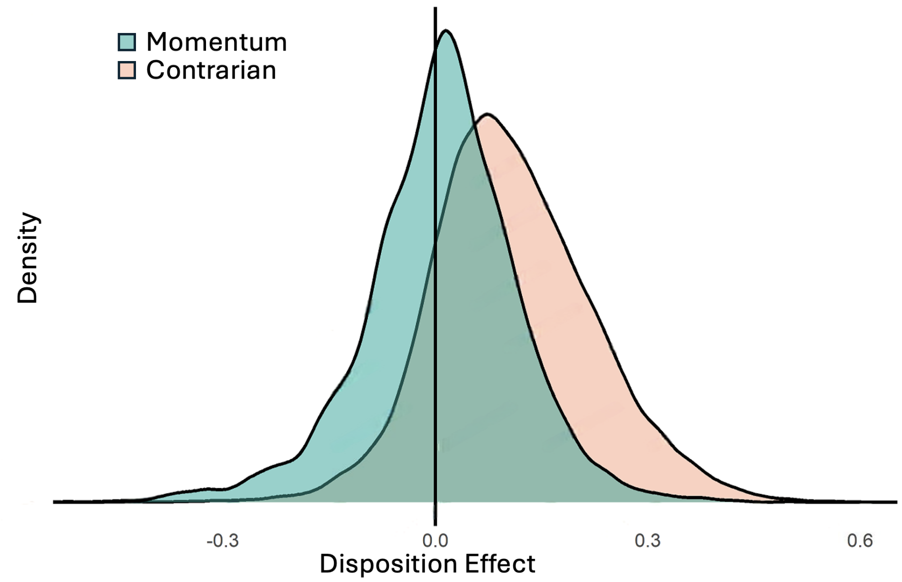
Notes: This figure depicts the relation between current in-game return and probability of selling, covering all decision-level investment decisions except for the first of each game session. The sample excludes observations with a zero pre-decision risky position. The classification method of investor type is described in Section 3.2. The dashed vertical line indicates zero return.

Figure 4: **Game Return, Probability of Sell and Investor Type**



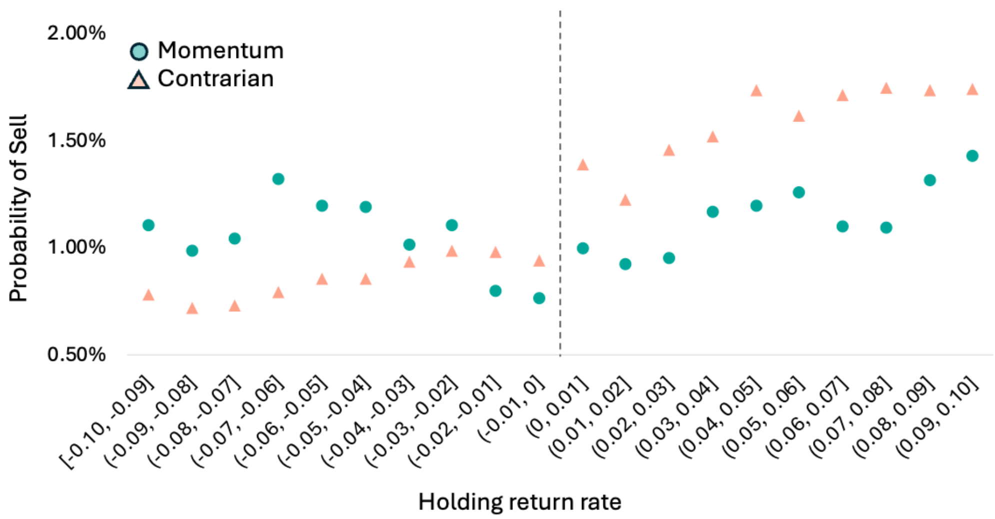
Notes: This figure leverages a sub-sample consisting of decision-level observations with a positive pre-decision risky position and an in-game return rate within a narrow interval of [-1%, 1%], and compares probability of sell under different scenarios between two types of investor. The scenario is defined based on the most recent price movement (up or down) and player's current in-game return (loss or gain), yielding a total of four scenarios.

Figure 5: **Distribution of Real-Life Disposition Effect by Investor Type**



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 3.2. Disposition effect is computed by *PGR - PLR* following Odean (1998) with real-life fund-month-level observations.

Figure 6: **Holding return, Probability of Sell, and Investor Type**



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 submitting a sell order. The classification method of investor type follows essentially the description in Section 3.2. The dashed vertical line indicates zero return.

A Supplementary Tables

Table A.1: **Real-Life Disposition Effect and Investor Type**

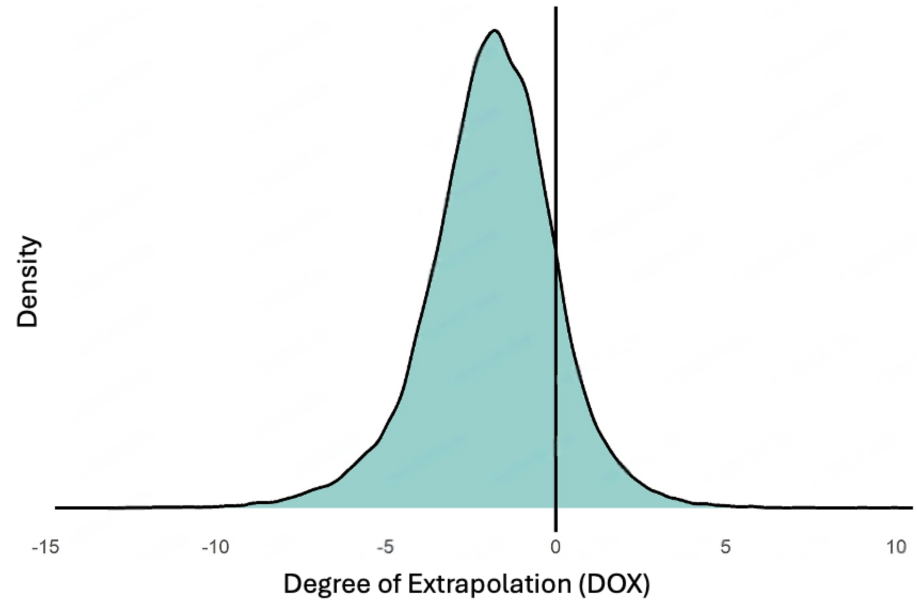
This table uses the same set of specifications as Columns 1-3 of Table 4, except that it relaxes the sample restriction used in Odean (1998) that the fund-month must belong to an investor who made an active sell during that month. Standard errors are two-way clustered at investor and month level. *p<0.1, **p<0,05, ***p<0.01.

	Dependent Variable: 100 × *Sell*		
	(1)	(2)	(3)
Gain	-0.253	3.112***	4.685***
	(0.742)	(0.386)	(0.442)
Gain × Momentum			-7.617***
			(0.703)
Log(Holding length)	-3.186***	0.355***	0.382***
	(0.206)	(0.125)	(0.125)
Log(Holding position)	1.877***	2.486***	2.519***
	(0.121)	(0.165)	(0.165)
Investor-month FE	No	Yes	Yes
Fund-month FE	Yes	Yes	Yes
Observations	10,170,142	10,170,142	10,170,142
Adj. R2	0.101	0.356	0.357

B Supplementary Figures

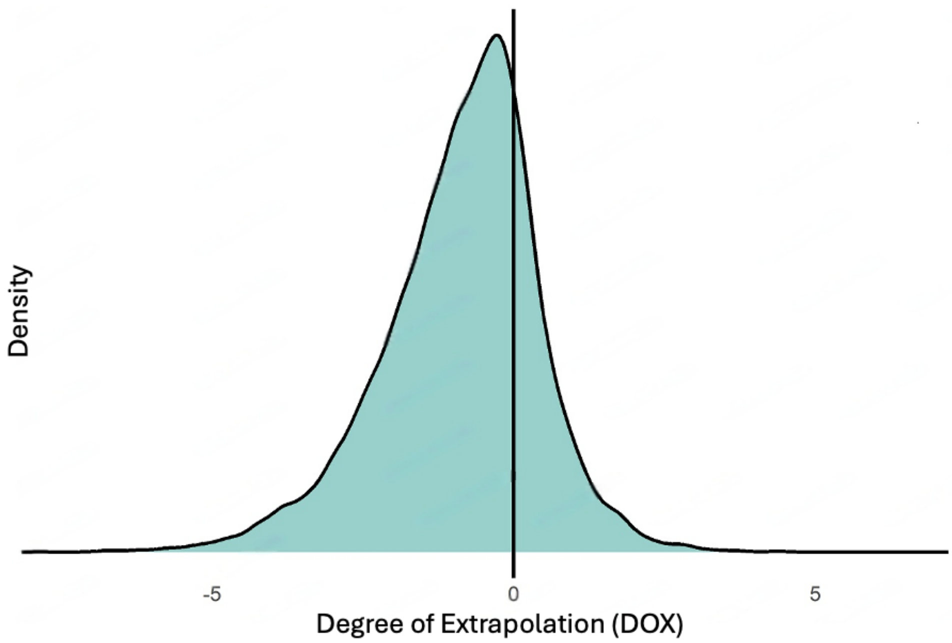
Figure B.1: Virtual Trading Game: An Illustration

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 3.2.

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 3.2, with real-life observations at investor-fund-month level.