The Fixed Disposition Effect*

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Abstract

Using recently compiled individual-level data from both experimental and real-world trading settings, we provide robust evidence that the disposition effect arises independently from belief-driven and realization preference–driven motivations. We demonstrate that the disposition effect represents a stable, inherent characteristic at the individual investor level, accompanied by substantial cross-sectional heterogeneity. Specifically, our analysis shows that momentum traders exhibit minimal disposition biases, contrarian traders display the strongest disposition effects, and investors with other trading styles lie in between. These results highlight that, while most investors share an underlying preference for realizing gains, differences in belief-driven trading strategies amplify or mitigate the disposition effect.

Keywords: Disposition effect, Subjective beliefs, Realization preference, Household finance, 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 psychological 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 assets 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

[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).

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 trading data provided by Alipay, a globally leading financial services provider. The data covers a representative investor group, and facilitates identification of investment decisions from both online game-like experiments and real financial markets. The advantage of our approach is twofold. First, our real-life data spans the 2017-2021 period when the costs of monitoring real-time as well as historical asset price movements and making actual transactions have been sustainably reduced for retail investors. This feature is particularly relevant to the identification of disposition effect which could be mitigated by infrequent account checks. A large body of studies leverage similar US brokerage data collected in the early 1990s as in Odean (1998), ensuring comparability but implying notably high trading frictions (e.g., Ben-David and Hirshleifer, 2012; Chang et al., 2016). [2] [3] Second, the setup enables us not only to examine the relation between belief-driven investor types and the disposition effect in real-life and experimental contexts separately, but also to link experiment-elicited investor types to real-life investment outcomes. More specifically, we leverage a simple rule of classification

[2] In addition, Grinblatt and Keloharju (2001) and Kaustia (2010) exploit administrative data in Finland in late 1990s. A few recent studies use data collected after the mobile internet use dominates desktop use (e.g., Andersen et al., 2021; Andries et al., 2024).

[3] As pointed out by Ben-David and Hirshleifer (2012), attention-induced belief revision could potentially lead to the observed V-shape trading pattern that indicates investors are more likely to trade when the returns are salient.

for both setups: we examine individuals' active decisions with the respect to recent returns. Using a highly similar elicitation methodology is crucial for determining whether investment styles and the disposition effect are consistent *within* investors.

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 weakest overall disposition effect, whereas contrarian investors display the most pronounced bias. 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.

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 beliefs based on their early-stage decisions in the experimental context, and arguably preferences only play a minor role during that stage. The findings suggest that behavioral biases could be related to individual heterogeneity in beliefs about asset price movements. In a highly relevant study, Andersen et al. (2021) investigate how different beliefs about the expected returns of stock market could affect disposition effect on an individual basis, with a theoretical model proposed in 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.

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 a recently complied dataset. This implies that realization preference is not 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 heterogeneity in the disposition effect across different investor types, levels of sophistication, and contexts. Not all investors are equally prone to the bias. Dhar and Zhu (2006), for instance, show that wealthier and more educated investors exhibit a significantly weaker disposition 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. Locke and Mann (2005) found that even successful floor traders hold onto losing trades longer than winning trades, though at reduced levels relative to retail investors. 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. 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. By highlighting who is most susceptible to the disposition effect, this line of research suggests that the bias is not a universal constant but varies with experience, knowledge, and context. 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 reviews the theoretical and empirical literature related to the disposition effect, distinguishing clearly between belief-based and preference-based explanations. Section 3 describes the experimental and market datasets, our methodological framework, and empirical strategy for quantifying individual-level disposition tendencies. Section 4 presents our core empirical findings, including within-investor consistency and the decomposition into belief-driven and preference-driven components. Section 5 concludes.

2 The Experiment: A Virtual Investment Game

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 a 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.

The experiment setup 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.

3 Data

We construct the primary sample by starting with a randomly selected group of 100,000 experiment participants who played the virtual trading game. The sample time period spans from July 2019, the launch day to October 2021. With the help of Alipay, we link their experiment data to their real-world investment accounts if available. For each investor-month, we have access to their end-of-month asset allocation snapshots which describe all the investment made on the Alipay platform. As described earlier, although Alipay users could invest in various financial assets including mutual funds and deposit certificate, they cannot invest directly in common stocks. We 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. [4] 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 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. Furthermore, we compute the holding length for each investor-fund pair based on its first appearance. Finally, we obtain a sample consisting of 2,686,273 observations, of which the summary statistics are presented in Panel A of Table 1. Specifically, an average investor has a probability of 18% to sell a given fund within their portfolio. In contrast, Chang et al. (2016) documents a 5% probability of selling equity funds with a

[4] 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.

sample from the early 90's in the United States. The significant upward shift could be plausibly attributed to lower trading costs, mental and monetary. The average market value of fund holding is 4,537 CNY ($\sim$ 630USD) with an average return rate of 7%, and 62% of the observations carry a positive return which is denoted by the *Gain* dummy. This is in line with the positive average monthly return of 1.74% over all investor-fund-months.

To serve one of the key purposes of this paper, we elicit investors' investment strategy, or more specifically, whether one is a momentum trader or a contrarian trader, based on their real-life decisions. To alleviate the concern of noisy monthly fund return, we focus on investors' trading decisions following a month with drastically volatile price movement. Concretely, only the investors who have at least 50 fund-months with a monthly return rate lower than -20% or grater than 20% are kept. This restriction is to ensure the selected investors have reasonably sufficient investment history and have experienced significant market fluctuations so that we could obtain a more reliable classifying indicator. [5] For each investor, we evaluate their propensity to sell and to buy against an extremely negative or positive past monthly return. An investor is classified as a *Momentum* (*Contrarian*) trader if they tend to buy (sell) extra shares following a significant uptick AND to sell (buy) following a substantial drop. The remaining investors are labeled as mixed-strategy traders. As a result, we obtain 641 momentum investors, 1,092 contrarian investors and 1,780 mixed-strategy investors. Under the strict criteria, there are another 8,314 investors who cannot be classified into any of the above-mentioned groups due to insufficient investment history. We present the summary statistics of these unclassified investors in Table 1, but exclude them from the further analysis because of the study's scope.

[Insert Table 1 around here.]

Analogously, Panel B presents relevant numbers for at participant-period level. The first two columns depict the general distribution for all observations with a positive position in the risky asset so that it guarantees the possibility of making a sell decision at all. Then we split the participants based on the first price trend they see during the experiment session, as well as their response to the very first trend.[6] A participant belongs to either an up market where the exogenously determined first-period asset return is positive, or a down market where the return is negative. Like the real-life classification, a participant is considered a momentum (contrarian) player if they actively buy (sell) after a price uptick or sell (buy) after a price drop, regardless of the trading amount or the magnitude of return. The averages of key variables

[5] The classification remains similar when we vary restrictions on minimal number (30, 40 or 50) of observations and the cutoff of absolute return rate (10% or 20%).

[6] A natural concern is that the first movement affects experiment finish rate. Although we do not have information if one quits the game midway, we attempt to minimize the concern based on our representative sample extracted from those who finished. Among the 99,505 players that we obtain after basic data cleaning, 41,131 (41%) were assigned to a down market while 58,374 (59%) to an up market. Among all 160 possible market scenarios, 66 (41%) of them feature a price drop in the first period, while 96 (59%) of them indicate a price increase. With the highly matched fractions, we conclude that the first-period movement is, to a great extent, irrelevant to the probability of finishing the experiment.

are presented in the last four columns of Panel B. Note that, for this across-type comparison, we keep only the player-periods with a non-zero trade decision after witnessing the first price movement, and they do not include the first periods based on which we carry out the classification. Therefore, the number of observations do not add up to the one presented in the first column. In general, momentum players are less likely to sell, allocate substantially more in risky asset (the market index), and obtain a higher return. The distribution discrepancy of various variables advocate for more rigorous regression analysis, which is delivered in the following sections.

4 Empirical Analysis

4.1 Disposition effect and investor type in real life

Our empirical strategy relies on the assumption that investors classified as contrarian traders tend to exhibit stronger disposition effect than momentum investors. We test this assumption by leveraging data on investors' end-of-month mutual fund holdings and current profits. Specifically, we estimate the following regression model on the classified investors in the vein of Ben-David and Hirshleifer (2012):

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

where i, j, and t denote investor, fund and month, respectively. $Sell_{i,j,t}$ equals one if investor i reduces fund j'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 $t-1$. $Momentum_i$ ($Contrarian_i$) takes the value of one if investor i is more likely to sell (buy) following a price drop AND to buy (sell) following a price uptick, and the remaining investors are grouped as the benchmark. $Holding\ months_{i,j,t}$ documents the length since the most recent month that investor i opened position for fund j , and the variable will be reset to zero following a complete liquidation even for the same investor-fund pair. $Position_{i,j,t-1}$ is the value of investor i's holding on fund j at the end of month $t-1$. We further control for investor-month ($\lambda_{i,t}$) and fund-month($\eta_{j,t}$) 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. With the regression setup, we focus primarily on (1) β, namely, whether disposition effect is prevalent, and (2) the discrepancy between β_m and

β_c, that is, whether different types of investors have the same level of disposition effect.

Table 2 presents the result. Columns 1 and 2 suggest that our sample investors do exhibit the well-documented disposition effect after controlling for investor-month fixed effects.[7] On average, investors are 2.2 percentage points more likely to realize gains than losses, which is closely in line with previous findings on disposition effect (e.g., Kaustia, 2010; Odean, 1998). Column 3 compares how momentum and contrarian traders react to paper gains differently, with the other investors of mixed investment styles being the benchmark. With $\beta = 2.41$ and $\beta_m = -3.42$, it implies that disposition effect is no longer observed among momentum investors, and it exhibits a reverse disposition effect, if anything. In contrast, the disposition effect is even more pronounced for contrarian investors; they are approximately 7 percentage points more likely to realize gains versus losses. Furthermore, we document a positively significant relation between fund position and propensity to sell across all three specifications.

[Insert Table 2 around here.]

In addition, we follow the seminal methodology of Odean (1998) to confirm the above findings. To this end, we construct a subsample as follows; for every month in the sample, we keep investors' portfolios that consist of at least two risky mutual funds and feature at least one (partial or full) sell. We then calculate, for each investor at fund-month level, the number of paper gains and losses as well as the number of realized gains and losses. Gains and losses are determined by comparing the end-of-month net asset value to the fund's adjusted cost basis described in Section 3. Thereafter, we obtain the proportions of realized gains (PGR) and realized losses (PLR) for each investor i:

$$PGR_i = \frac{\sum_j \sum_t \#Realized\ Gains_{i,j,t}}{\sum_j \sum_t (\#Realized\ Gains_{i,j,t} + \#Paper\ Gains_{i,j,t})}, \tag{2}$$

$$PLR_i = \frac{\sum_j \sum_t \#Realized\ Losses_{i,j,t}}{\sum_j \sum_t (\#Realized\ Losses_{i,j,t} + \#Paper\ Losses_{i,j,t})}. \tag{3}$$

With individual-specific PGR and PLR, the alternative measure of investors' disposition effect (DE) is obtained from the difference PGR-PLR. We plot average PGR and PLR for the three investor types in Figure 1. The gap between two bars within the same type depicts the disposition effect. We find that the gap is most pronounced for contrarian investors, and it decays for investors of mixed strategies. For momentum investors, the gap virtually diminishes.

[Insert Figure 1 around here.]

[7] In an unreported exercise, we control for investor, fund, month fixed effects separately, and document similar results.

We further examine whether investor types could help explain disposition effect beyond investor's demographic characteristics by estimating a simple cross-sectional regression as follows,

$$DE = \alpha + \beta_m Momentum_i + \beta_c Contrarian_i + \beta Z_i + \varepsilon_i, \tag{4}$$

where Z_i is a vector of demographic and socioeconomic controls including gender, age, bachelor, occupation and total asset invested via Alipay. *Occupation* is a categorical dummy that covers three types: students (the omitted benchmark), blue-collar workers and white-collar workers. *Average 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. [8] We present the results in Table 3 which suggest that momentum-versus-contrarian investment types provide strong predictive power on the extent of disposition effect after controlling for various demographic controls. Although the relation between disposition effect and demographic characteristics is out of the scope of our paper, we find no consistent evidence indicating that more sophisticated investors (measured by total investment amount and education level) are less prone to the disposition effect bias, which echo with the inconsistency among earlier studies (e.g., Andersen et al., 2021; Dhar and Zhu, 2006).

[Insert Table 3 around here.]

The findings presented so far suggest that there is an interplay between the disposition effect and investor's inherent trading strategy. However, one concern is that the interplay is merely mechanical. Put differently, it could be that momentum (contrarian) traders tend to sell(buy) more often when facing paper losses and to buy(sell) when facing paper gains, which directly leads to the observed disposition effect. Although this concern seems plausible, we argue that momentum-versus-contrarian investment style is by definition determined by the previous price trend, thus independent of paper gains and losses. To further support the argument, we implement the following two-step exercise. The first step is to estimate the following decomposition regression for each and every investor i :

$$\begin{aligned} 100 \times Sell_{i,j,t} = {} & \beta_{1,i} Gain_{i,j,t-1} + \beta_{2,i} \mathbb{I}[Ret_{j,t-1} > 0] + \beta_{3,i} \mathbb{I}[Ret_{j,t} > 0] + \beta_{4,i} \mathbb{I}[Ret_{j,t+1} > 0] \\ & + \alpha_i + \gamma Sqrt(Holding\ months_{i,j,t}) + \delta Log(Position_{i,j,t-1}) + \varepsilon_{i,j,t}, \end{aligned} \tag{5}$$

where $\mathbb{I}[Ret_{j,t} > 0]$ equals one if the monthly return of fund j during month t is positive and zero otherwise.

[8] To enable payment and investment functions, Alipay users must submit a valid identification document, which help link investors to their age, gender and city of birth. In addition, users can self-report their occupation and education information for more customized services.

β_1 reflects the disposition effect after controlling for the reactions to recent price movements, captured by β_2 and β_3. We further estimate β_4 to account for the possibility of private information regarding future performance. Finally, α_i captures investor i's base probability of selling. To ensure statistical power, the estimation consists of investors who have at least 50 valid fund-months observations. With the vector of estimated coefficients, we implement the second step that tests whether investor types relate to the characteristics extracted from real-life holding changes:

$$Coef_i = \delta + \theta_m Momentum_i + \theta_c Contrarian_i + \varepsilon_i, \tag{6}$$

where $Coef_i$ is one of the five investor-specific parameters $[\beta_1, \beta_2, \beta_3, \beta_4, \alpha]$. This cross-sectional specification compares momentum and contrarian investors with other investors being the benchmark, of which the results are presented in Table 4. In line with previous findings, Column 1 documents strong disposition effect for contrarian traders while essentially no effect $(-0.033 + 0.029 = -0.004)$ for momentum traders. Columns (2-4) suggest that momentum-versus-contrarian differences are only significant for the most recent monthly returns (captured by β_3). Intuitively, momentum investors exhibit lower propensity to sell their shares after a month with price uptick. The final Column 5 suggests that momentum investors trade more actively.

[Insert Table 4 around here.]

4.2 Disposition effect in experiment

Real-world financial markets are full of information which affects investors' judgment and decision-making process. To disentangle the effects of our interest, we leverage the experiment-like virtual investment game where price is the only information available and exogenously given. The aim is to investigate whether the interplay between investor types and disposition effect identified from the previous exercises still holds.

The first test focuses on whether the disposition is a fixed individual-specific feature, namely, whether the *same* investor would exhibit similar investment strategy in real life *vis-à-vis* in the investment game. In order to classify game participants in a similar manner to the real-life setup, we exploit the random assignment of game condition. Specifically, we split the players based on the direction of their specific market's first price movement, which we denote up-market or down-market. Subsequently, a player will be labeled "game-momentum" ("game-contrarian") if they trade in the same (opposite) direction with the first market movement. Analogously, we check how the remaining investors' react following different fund

performances, for instance, whether one is more likely to sell when the performance during the past month is negative, and label them accordingly. As such, we obtain two conceptually similar indicators both in game and in real life, which facilitates a correlation test. Presented in Table 5, the results show that the two measures across setups are positively significant, suggesting that investors tend to exhibit a consistent trading style and the virtual investment game setup is a relevant proxy to the real world.

Within the full sample of players, we estimate the following regression that mimics the real-life baseline model Eq. 1,

$$\begin{aligned} 100 \times Sell_{i,t} = \gamma Gain_{i,t-1} + \beta^{up}\mathbb{I}[Ret_{i,1} \geq 0]\{Gain_{i,t-1} \times Momentum_i^{up}\} \\ + \beta^{down}\mathbb{I}[Ret_{i,1} < 0]\{Gain_{i,t-1} \times Momentum_i^{down}\} + \lambda_i + \eta_t + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $Ret_{i,1}$ refers to the market return during the first period within a game session, therefore, $\mathbb{I}[Ret_{i,1} \geq 0]$ equals one if the player belongs to the "up-market" group. Since the first period is used for classification, the regression only uses observations with a $t \geq 2$. λ_i and eta_t capture investor and game-period fixed effects, respectively. The standard errors are two-way clustered at investor and game-period level. Table 6 presents the results, echoing with our previous findings. Column 1 suggests that disposition effect widely exists among the player population. Columns (2-3), with two sub-samples, consistently suggest that momentum investors exhibit much lower (or virtually no) disposition effect compared to their contrarian counterparts.

We close this belief-oriented investigation episode by interacting real-life data with game-elicited investor types, to eliminate the concern that the absence of disposition effect for momentum investors is purely mechanical and determined intrinsically by the classification method in real life. We replace the real-life-elicited momentum indicator with the game-elicited one in the regression model Eq. 1, and re-estimate it. The results are presented in Table 7. Repeatedly, the sample is divided into two groups according to the in-game first-period condition. With different samples, Columns (1-2) document highly similar findings as the ones presented above. As such, we could safely conclude that disposition effect is closely related to individual-specific belief-based investment style.

[Insert Table 7 around here.]

4.3 Discontinuity

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 data to test the effect of

realization preference which is first modeled by Barberis and Xiong (2012). 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 free from various confounding factors. More specifically, we compile all observations except for the first-periods, and keep 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. We plot the average probability of selling for momentum, contrarian and all traders in Figure 2.[9] There exists a consistent and substantial gap of propensity to sell between the ones in gain regime and the ones in loss regime. This finding motivates our further investigation using a real-life dataset that could support external validity.

[Insert Figure 2 around here.]

To examine the potential jump around zero holding return, we introduce an additional transaction-level dataset and evaluate the regression discontinuity model as used in Ben-David and Hirshleifer (2012). The specification is largely close to the baseline model Eq. 1 except for the inclusion of polynomials and their interaction with holding length. This extra sample covers a different and much smaller group of Alipay users, 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, except that this is a more granular setup that enables us to identify more nuanced trading patterns. We present the estimation results with varying degree of polynomials and varying holding-length windows in Table 8.[10] The coefficients in the first row describe the discontinuity around zero return. In contrast to Ben-David and Hirshleifer (2012), we document a statistically significant and economically meaningful jump up to 50 days since the position opening for a given investor-fund pair. We conclude from the table that the realization preference accounts for up to 57% of disposition effect among the sample investors. The discontinuity decays as holding length extends, which is not surprising and could potentially be justified by less attention and arrival of liquidity shocks. A visualization of the jump is presented in Figure 3, where we aggregate all the investor-fund-day observations with a holding return rate of [-20%, 20%] and a holding

[9] We disregard whether the player is assigned to an up market or a down market, and pool them together based on whether they are momentum or contrarian traders.

[10] We exclude the observations with a holding length shorter than five days in this analysis to allow for interactions between fund's daily returns and investor's holding returns. Otherwise, the coefficient of interest could be interpreted as a price-trend-related effect (up-versus-down) instead of a return-related effect (gain-versus-loss).

length not exceeding 50 days.

[Insert Table 8 around here.]

[Insert Figure 3 around here.]

In order to shed light on the relative independence of realization preference from belief, we extend the regression discontinuity analysis by interacting investor types with the polynomials. Table 9 presents the essence of the results using the 3rd-degree polynomial specification. We consistently document positively significant and meaningful jumps around zero return, but find no evidence suggesting that investment styles affect the jump to a significant extent.

[Insert Table 9 around here.]

5 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

This table reports key descriptive statistics for both the real-life and in-experiment decisions. Starting with a randomly selected group of 100,000 experiment participants, we keep the ones who have active fund investment records during the period of January 2017 - October 2021. At aggregate investor-fund-month level, Panel A presents the mean and standard deviation of the variables collected from real-life investment record. *Sell* equals to one if the number of fund shares is reduced compared to the previous month and zero otherwise. *Position* is the market value of the currently held fund shares. *Holding profit* is the accumulated profit that calculated by Alipay and provided to the investor, while *Holding return* is calculated by profit divided by the total cost. *Gain* indicates whether current holding profit is positive. *Holding months* refer to the holding length since the most recent position opening. *Monthly return* measures the fund's return rate during the past month. The sample divided into four groups, (1) *Momentum* contains investors who tend to trade in the same direction as the recent monthly return, (2) *Contrarian* consists of investors who tend to trade in the opposite direction to the recent performance, (3) *Mixed* includes the ones who exhibit inconsistent trading patterns and (4) *Unclassified* covers all the investors that we cannot group due to lack of sufficient investment histories. Panel B is constructed at player-game-period level, but otherwise in a similar way for the decisions made during experiments. *Risky position* refers to the amount held in risky asset. *Asset return* relates to the risky asset. The sample is divided into two groups (up- vs. down-market) based on the first-period performance of the risky asset assigned to the investor.

Panel A: Real-life monthly data

Sample	All		Momentum	Contrarian	Mixed	Unclassified
Investor-Fund-Month Obs	2,842,873		325,514	395,532	680,789	1,441,038
	Mean	SD	Mean	Mean	Mean	Mean
Sell dummy	0.18	0.39	0.18	0.22	0.18	0.17
Position	4537.57	17169.07	4099.34	4556.04	4521.11	4639.27
Holding profit	223.13	3020.51	243.60	121.92	208.07	253.40
Holding return (%)	6.88	14.41	8.50	4.73	7.37	6.89
Gain dummy	0.62	0.49	0.64	0.57	0.63	0.62
Holding months	8.20	8.03	8.55	8.62	8.67	7.79
Monthly return (%)	1.74	7.73	1.81	1.91	1.92	1.58

Panel B: Virtual investment game

Sample	All		Up-market		Down-market	
Player type	All		Momentum	Contrarian	Momentum	Contrarian
Player-period Obs	939,975		161,798	99,623	17,149	165,050
	Mean	SD	Mean	Mean	Mean	Mean
Sell dummy	0.14	0.35	0.14	0.20	0.15	0.21
Risky position	8131.57	5237.49	9835.36	6937.89	9337.63	6789.36
Player return (%)	0.16	0.50	0.17	-0.07	0.22	-0.17
Gain dummy	0.53	0.50	0.54	0.52	0.52	0.48
Asset return past period (%)	0.27	0.61	0.03	-0.45	0.68	0.49
Asset return since start (%)	0.97	0.12	2.94	1.19	-1.50	-1.68

Table 2: Real-life disposition effect and investor types

The table presents the results from estimating Eq. 1 and alike. The dependent variable, *Sell*, indicates whether an investor sells a mutual fund holding partially or completely during a given month. *Gain* is a dummy that takes the value of one when the investor-fund-month has a positive accumulated return in the end of the previous month. Columns (1-2) cover all active investors in the sample, while Column 3 keep only the classifiable ones with sufficient investment experience. Investors are classified into three groups: (1) *Momentum*, those who are more likely to buy when prices go up and more likely to sell when prices go down, (2) *Contrarian*, those who are more likely to sell when prices go up and more likely to buy when prices go down, and (3) the rest of mixed investment patterns (benchmark group). *Holding months* document the number of months since the most recent position opening for investor-fund pairs, and *Position* is the market value of the fund holding as of the end of previous 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	-0.887	2.196***	2.412***
	(0.643)	(0.394)	(0.462)
Gain × *Momentum*			-3.422***
			(0.626)
Gain × *Contrarian*			4.591***
			(0.687)
Sqrt(Holding months)	-2.946***	-0.042	0.019
	(0.176)	(0.072)	(0.085)
Log(Position)	1.805***	2.317***	2.551***
	(0.134)	(0.143)	(0.173)
Fund-Month FE	Yes	Yes	Yes
Investor-Month FE	No	Yes	Yes
Adj. R^2	0.094	0.372	0.370
Observations	2,842,873	2,842,873	1,401,835

Table 3: Disposition effect, investor types, and demographics

The table presents whether investor types and demographic characteristics predict disposition effect using Eq. 4. The dependent variable, *Disposition Effect*, is defined as the difference between proportion of realized gains (PGR) and proportion of realized losses (PLR) based on Eq. 2 and Eq. 3. Investors are classified into three groups: (1) *Momentum*, those who are more likely to buy when prices go up and more likely to sell when prices go down, (2) *Contrarian*, those who are more likely to sell when prices go up and more likely to buy when prices go down, and (3) the rest of mixed investment patterns (benchmark group). *Occupation* is a categorical dummy that covers three types: students (the omitted benchmark), blue-collar workers and white-collar workers. *Average asset* refers to the average of end-of-month total market value of all financial products that an investor holds directly on Alipay. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: *Disposition Effect*		
	(1)	(2)	(3)
Momentum	-0.051***		-0.084***
	(0.008)		(0.014)
Contrarian	0.067***		0.050***
	(0.006)		(0.011)
Male		-0.008	-0.013
		(0.010)	(0.010)
Log(Age)		0.001	0.023
		(0.052)	(0.050)
Bachelor		-0.008	-0.016
		(0.019)	(0.018)
Occupation			
Blue-collar		-0.057	-0.060
		(0.049)	(0.047)
White-collar		-0.024	-0.027*
		(0.015)	(0.014)
Log(Avg. asset)		0.013***	0.008*
		(0.005)	(0.004)
Constant	0.055***	-0.092	-0.076
	(0.004)	(0.151)	(0.146)
Adj. R^2	0.060	0.004	0.065
Observations	3,430	1,218	1,218

Table 4: Return, profit and propensity to sell

This table reports the estimation results of the cross-sectional decomposition Eq. 6. The dependent variables are coefficients obtained from estimating Eq. 5 independently at investor level. The sample covers only investors who have sufficient investment experience that allows for investor-type identification. *Momentum* indicates investor's tendency to trade in the same direction as the fund recent return, *Contrarian* indicates investor's tendency to trade in the opposite direction as the fund recent return, and the omitted benchmark group contains those who do not exhibit a consistent trading pattern. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: *Estimated coefficients*				
	β_1 *Gain*	β_2 $\mathbb{I}[Ret_{t-1} > 0]$	β_3 $\mathbb{I}[Ret_t > 0]$	β_4 $\mathbb{I}[Ret_{t+1} > 0]$	α *Intercept*
	(1)	(2)	(3)	(4)	(5)
Momentum	-0.038***	-0.010**	-0.065***	-0.006	0.078***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.026)
Contrarian	0.038***	0.011***	0.084***	0.004	-0.065***
	(0.004)	(0.004)	(0.005)	(0.003)	(0.022)
Constant	0.026***	0.037***	0.055***	-0.007***	-0.170***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.014)
Adj. R^2	0.049	0.006	0.168	0.001	0.007
Observations	3,500	3,500	3,500	3,500	3,500

Table 5: Real-life versus in-experiment: Consistency of investor type

This table shows the Pearson correlation between investor types identified from real-life versus experimental setups, for the investors with sufficient investment experience. All presented variables are binary dummies. The superscripts *up* and *down* indicate whether the dummies are obtained from records with positive or negative past returns. *p<0.1, **p<0.05, ***p<0.01.

		Real-life	
		$Momentum^{up}$	$Momentum^{down}$
Experiment	$Momentum^{up}$	0.082***	0.087***
	$Momentum^{down}$	0.047**	0.115***

Table 6: In-experiment disposition effect and investor types

The table presents the results from estimating Eq. 7 and alike with the sample of virtual investment game players during the September 2019 - October 2021 period. The sample is restricted to active buy and sell decisions, thus excluding hold decisions. The dependent variable, *Sell*, indicates whether an investor lowers the position during a given game period excluding the first two periods. *Gain* is a dummy that takes the value of one in case of positive in-game returns before the given period's decision. Column 1 uses the full sample, while Column 2 and 3 use subsample that consist of those who are assigned a market with the first period return being positive (an up market) and negative (a down market), respectively. $Momentum^{up}$ ($Momentum^{down}$) is a binary dummy that indicates whether the player is classified as a momentum or a contrarian player based on the decision after witnessing the first-period asset return. *Holding months* document the number of months since the most recent position opening for investor-fund pairs, and *Position* is the market value of the fund holding as of the end of previous month. Standard errors are two-way clustered at investor and period level. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: $100 \times Sell$		
	(1)	(2)	(3)
Gain	13.161***	19.534***	16.914***
	(1.223)	(2.785)	(1.684)
$Gain \times Momentum^{up}$		-11.589***	
		(2.473)	
$Gain \times Momentum^{down}$			-15.333***
			(1.999)
First-period market move	All	Up	Down
Game Period FE	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes
Observations	443,620	261,421	182,199
Adj. R2	0.155	0.157	0.171

Table 7: Real-life disposition effect and experiment-elicited investor types

The table presents the how the disposition effect interacts with investor type which is elicited from in-experiment decisions. The dependent variable, *Sell*, indicates whether an investor sells a mutual fund holding partially or completely during a given month. *Gain* is a dummy that takes the value of one when the investor-fund-month has a positive accumulated return in the end of the previous month. Columns 1 and 2 use, respectively, sub-samples that consist of those who are assigned a market with the first period return being positive (an up market) and negative (a down market). $Momentum^{up}$ ($Momentum^{down}$) is a binary dummy that indicates whether the investor is classified as a momentum or a contrarian trader based on the in-experiment decision after witnessing the first-period asset return. Standard errors are two-way clustered at investor and month level. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: $100 \times Sell$	
	(1)	(2)
Gain	3.706***	1.873***
	(0.532)	(0.241)
$Gain \times Momentum^{up}$	-2.516***	
	(0.636)	
$Gain \times Momentum^{down}$		-3.145***
		(0.897)
Sqrt(Holding months)	-0.073	0.040
	(0.076)	(0.076)
Log(Position)	2.190***	2.240***
	(0.079)	(0.081)
In-game first-period market move	Up	Down
Fund-Month FE	Yes	Yes
Investor-Month FE	Yes	Yes
Adj. R^2	0.378	0.377
Observations	1,003,070	820,216

Table 8: Regression Discontinuity

This table estimates a regression discontinuity specification which introduces varying polynomials of holding returns to the baseline specification Eq. 1 with a separate sample at investor-fund-day level. The dependent variable, *Sell*, indicates whether an investor sells a mutual fund holding partially or completely during a given trading 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. *p<0.1, **p<0.05, ***p<0.01.

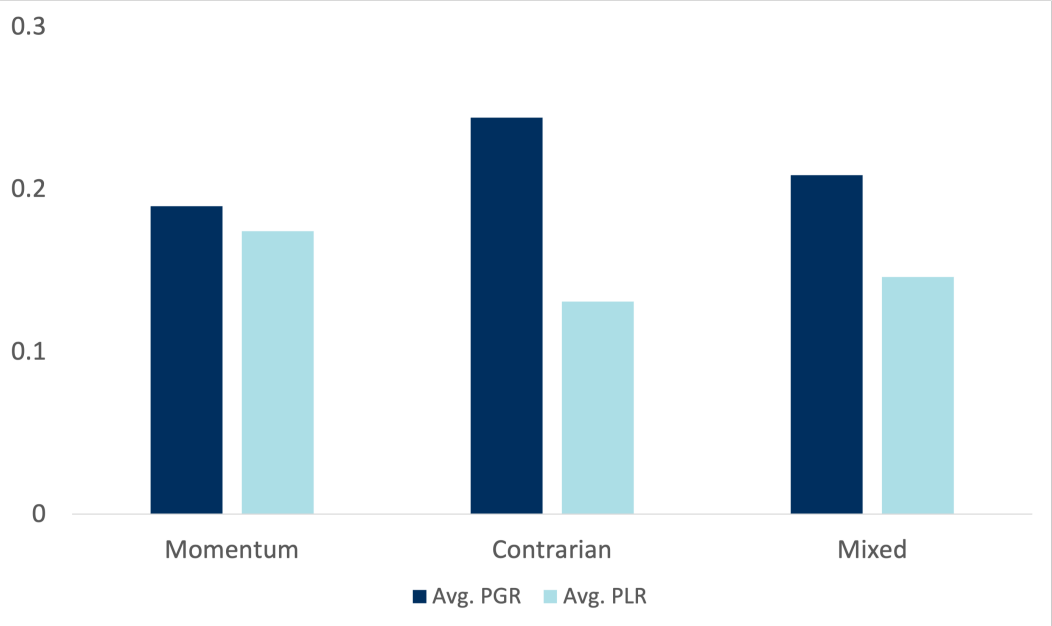
	Dependent variable:100 x *Sell*								
Holding days	5 to 15			16 to 50			51 to 90		
Degree of polynomial	3rd	4th	5th	3rd	4th	5th	3rd	4th	5th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gain	0.743***	0.780***	0.892***	0.359***	0.399***	0.316***	0.010	0.022	-0.040
	(0.120)	(0.122)	(0.134)	(0.079)	(0.081)	(0.090)	(0.086)	(0.088)	(0.097)
Polynomials and interactions with Sqrt(Holding days)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.001	0.001	0.001	0.002	0.002	0.002	0.002	0.002	0.002
Observations	137,766	137,766	137,766	260,627	260,627	260,627	182,430	182,430	182,430
Unconditional probability (%)	1.574	1.574	1.574	1.128	1.128	1.128	0.768	0.768	0.768
Effect (%)	47.20	49.56	56.67	31.83	35.37	28.01	1.30	2.86	-5.21

Table 9: Regression Discontinuity with Different Investor Types

This table shows how the discontinuity around zero investor return is different for various types of investors. A 3rd-degree polynomial as well as its interactions with investor types are used. The dependent variable, *Sell*, indicates whether an investor sells a mutual fund holding partially or completely during a given trading 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. *Momentum* equals to one if the investor tends to trade in the direction of fund recent performance, while *Contrarian* equals to one if the investor tends to trade against the direction of performance. The benchmark group consists of investors who do not exhibit a consistent trading pattern in terms of their reaction to recent fund returns. *p<0.1, **p<0.05, ***p<0.01.

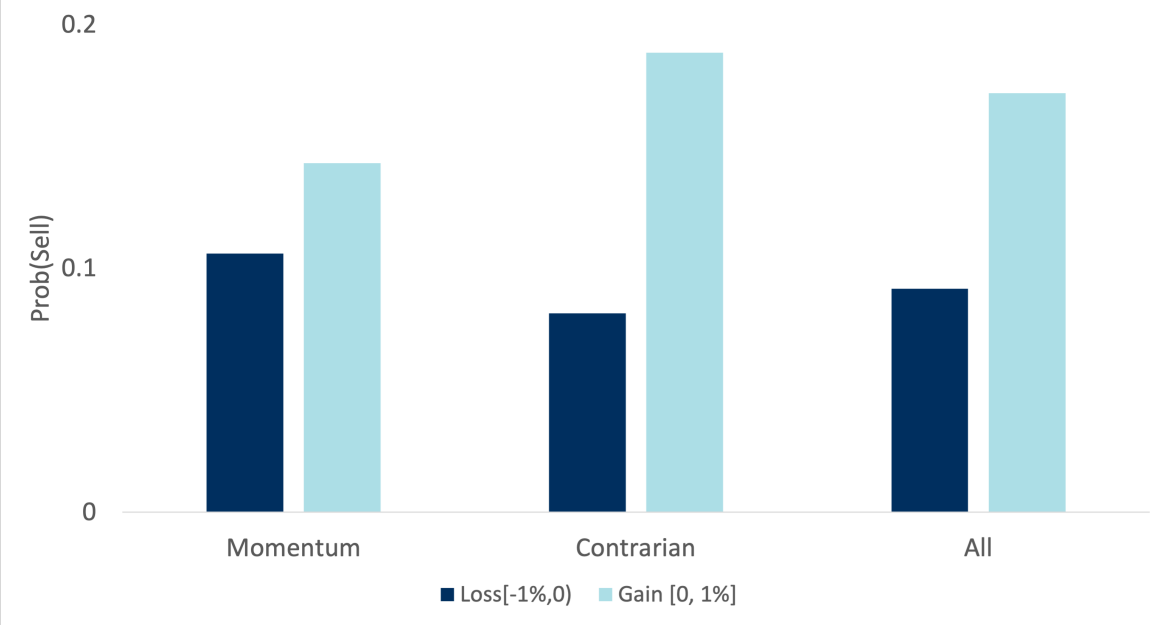
	Dependent Variable: $100 \times Sell$		
Holding days	5 to 15	16 to 50	51 to 90
	(1)	(2)	(3)
Gain	0.426**	0.554***	0.170
	(0.212)	(0.159)	(0.176)
Gain × *Momentum*	0.441	-0.024	-0.117
	(0.402)	(0.300)	(0.336)
Gain × *Momentum*	-0.134	-0.396	0.274
	(0.540)	(0.389)	(0.427)
Polynomials and interactions with investor types	Yes	Yes	Yes
Adj. R^2	0.001	0.002	0.002
Observations	80,597	148,334	101,410

Figure 1: Real-life disposition effect across investor types



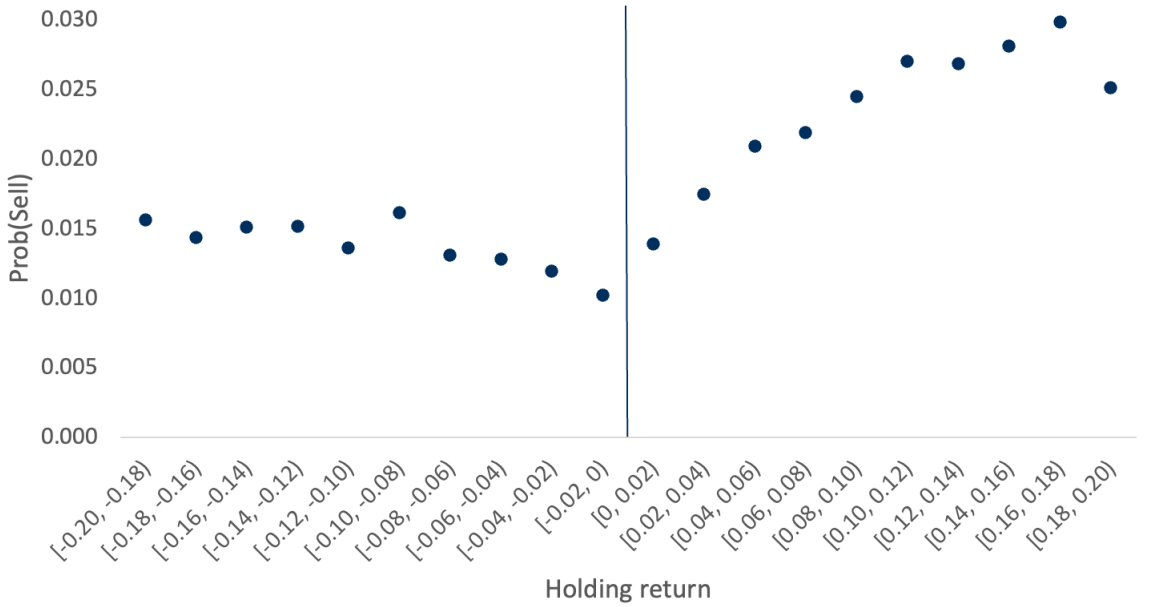
Notes: Using the investor-fund-month baseline sample, this figure compares real-life average proportion of realized gains (PRG) and average proportion of realized losses (PRL) according to Eq. 2 and Eq. 3 and across different types of investors. The gap between two bars indicate the level of disposition effect as in Odean (1998). See Section 3 for classification details of investor types.

Figure 2: In-experiment disposition effect across investor types



Notes: This figure exploits all periods in the virtual investment game except for the first two periods. The unit of analysis is participant-period, and the observations are limited to those with a current game return within the range of [-1%, 1%]. Investor types are determined based on the market movement and the decision made during the second period of the experiment. See Section 3.

Figure 3: Holding return and selling probability



Notes: This figure exploits individual-fund-day observations that are constructed based on transaction-level data. The sample is restricted to a maximum holding length of 50 days, and trading days only. Holding returns for investor-fund pairs are pooled, binned with a 2% interval, and presented on the x-axis. The vertical line indicates a cutoff of zero holding return.

A Supplementary Tables

Table A.1: Real life: Disposition effect and investor types

The table presents the results from estimating Eq. 1 and alike with the sample covering eligible investors during the period of Jan 2017-Sep 2021. After examining all investor-month observations, we keep portfolios that have at least two funds and feature at least one fund sale(partial or complete). The dependent variable, *Sell*, indicates whether an investor sells a mutual fund holding partially or completely during a given month. *Gain* is a dummy that takes the value of one when the investor-fund-month has a positive accumulated return in the end of the previous month. Columns (1-2) cover all active investors in the sample, while Column 3 keep only the classifiable ones with sufficient investment experience. Investors are classified into three groups: (1) *Momentum*, those who are more likely to buy when prices go up and more likely to sell when prices go down, (2) *Contrarian*, those who are more likely to sell when prices go up and more likely to buy when prices go down, and (3) the rest of mixed investment patterns (benchmark group). *Holding months* document the number of months since the most recent position opening for investor-fund pairs, and *Position* is the market value of the fund holding as of the end of previous month. Standard errors are two-way clustered at investor and month level. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: $100 \times Sell$		
	(1)	(2)	(3)
Gain	0.026	3.321***	3.465***
	(0.747)	(0.561)	(0.611)
Gain × *Momentum*			-5.072***
			(0.916)
Gain × *Contrarian*			5.857***
			(0.817)
Sqrt(Holding months)	-2.256***	0.124	0.190
	(0.155)	(0.114)	(0.127)
Log(Position)	2.496***	3.568***	3.604***
	(0.145)	(0.185)	(0.209)
Fund-Month FE	Yes	Yes	Yes
Investor-Month FE	No	Yes	Yes
Adj. R^2	0.109	0.313	0.320
Observations	1,683,293	1,683,293	933,857

B Supplementary Figures

Figure B.1: Virtual Trading Game: An Illustration

