The Mechanical Disposition Effect*

Qinglin Ouyang Shumiao Ouyang

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Abstract

We propose that much of the disposition effect is mechanical: it arises from stable investment styles interacting with standard cost-basis accounting, rather than from a primitive preference for realizing gains. A simple benchmark shows that contrarian and momentum trading rules can generate sharply different disposition patterns even when investors never condition directly on return status. Using a unique linked dataset that combines a large-scale online experiment with real-world mutual fund transactions from Alipay, we confirm this prediction and document that the disposition effect is up to nine times stronger for contrarian than for momentum investors. We further show that investment style is highly stable across time and contexts, helping explain the persistence of the disposition effect, while a sharp zero-return discontinuity reveals a broadly shared but quantitatively modest residual role for realization preference.

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1 Introduction

Since the seminal work of Shefrin and Statman (1985), the tendency of investors to "sell winners too early and ride losers too long"—the so-called disposition effect—has become one of the most robust behavioral patterns in financial markets. A large body of evidence, from brokerage records to laboratory experiments, shows that investors are more likely to realize gains than losses.[1] This pattern persists even after accounting for rational considerations such as transaction costs, portfolio rebalancing, or tax optimization, and is therefore commonly interpreted as a primitive and broadly shared preference to realize gains rather than losses.

We challenge this canonical interpretation. We argue that a large share of the disposition effect is mechanical: it arises from stable investment styles interacting with standard cost-basis accounting, which endogenously determines whether sales occur in gain or loss states. If this channel is quantitatively important, then the measured disposition effect is not a clean statistic for realization preference. Instead, much of what is routinely interpreted as a behavioral bias may reflect the footprint of deeper and more stable decision rules. This distinction matters for both interpretation and policy: it implies that the canonical view overstates the preference-based component of the disposition effect, and that one-size-fits-all debiasing interventions may be misdirected.

Our mechanical view has a simple intuition. Investors carrying different price-contingent trading rules mechanically generate different realized gain–loss patterns once cost basis evolves endogenously over time. In a simple toy model, contrarian investors buy after price declines and sell after increases, which depresses their cost basis and makes sales disproportionately likely to occur in gain states. Momentum investors exhibit the opposite pattern. As a result, a disposition-effect-like pattern can

[1] Evidence of the 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), financial advisors (Andries et al., 2024), professional commodity traders (Locke and Mann, 2005), and in laboratory settings (e.g., Weber and Camerer, 1998; Talpsepp et al., 2014). In real estate markets, Genesove and Mayer (2001) show that homeowners are substantially more reluctant to sell at a loss, leading them to hold properties longer and set higher asking prices when facing potential losses.

emerge even when investors have no intrinsic preference for realizing gains or losses. The model therefore yields a sharp empirical prediction: if the disposition effect is largely mechanical, it should vary systematically with investment style.

To test this prediction, we measure investment style from responses to recent price changes while explicitly controlling for gain–loss status, ensuring that style is econometrically distinct from the disposition effect itself. We then test the model across three settings: a large-scale trading experiment, real-world mutual fund transactions on a major FinTech platform, and a traditional discount brokerage dataset. Crucially, our design links the first two settings at the individual level, allowing experimentally elicited style to predict the disposition effect in the field. This cross-context design provides a direct safeguard against the concern that we are merely relabeling realization patterns as "style." A further implication of the mechanical view is that, if investment style is stable within individuals, then the induced disposition effect should also appear persistent over time and across contexts.

Empirically, we combine a large-scale virtual trading experiment with detailed real-world mutual fund transactions from Alipay, one of the world's largest digital financial platforms. The experiment is embedded in a behavioral "financial personality" test, allowing us to match individuals' choices in the game to their subsequent mutual fund trading on Alipay over 2017–2021. This integrated design is unusual in the literature and delivers two key advantages. First, it allows us to test whether investment style elicited in a clean, low-stakes environment generalizes to high-stakes real-world financial decisions. Second, because the field setting is a modern mobile trading platform with low frictions and near real-time return visibility, it mitigates concerns that measured behavior mainly reflects inattention, stale account monitoring, or ambiguity about reference points.[2]

[2]Much of the classic literature relies on brokerage or administrative data from the 1990s, when trading frictions were substantially higher (e.g., Odean, 1998; Grinblatt and Keloharju, 2001; Kaustia, 2010; Ben-David and Hirshleifer, 2012; Chang et al., 2016). Only a small number of recent studies exploit data from modern digital trading platforms (e.g., Andersen et al., 2021, 2024; Andries et al., 2024). Modern platforms also provide investors with much more frequent and salient information on portfolio returns, which is important for identifying the disposition effect (e.g., Meng and Weng, 2018; Quispe-Torreblanca et al., 2024).

We estimate individual investment style using a regression-based approach that isolates how each investor adjusts her position in response to recent asset price changes, conditional on unrealized return status. Following the spirit of Liao et al. (2022), we construct an investor-level measure that we call the Contrarian Degree (CD), which places investors on a spectrum from momentum to contrarian. In both the experiment and the field, the majority of investors display contrarian trading behavior.

Investment style emerges as a central organizing force behind the disposition effect. Contrarian investors exhibit a much stronger disposition effect, whereas momentum investors display only a small, and sometimes even reversed, pattern. This style gradient appears consistently in the experimental data, in Alipay mutual fund trading, and in a traditional brokerage dataset (Barber and Odean, 2000), with magnitudes reaching up to nine-fold. In cross-sectional regressions, investment style explains substantially more variation in the disposition effect than standard demographic and socioeconomic characteristics. These findings, together with the toy model, indicate that much of the disposition effect reflects stable style-dependent mechanics rather than an independent behavioral primitive.

We also examine whether investment style itself is stable. We find that style is highly persistent both over time and across contexts, echoing recent evidence on the stability of investor behavior (Han et al., 2020; Sui and Wang, 2025). This stability naturally implies that the mechanically induced disposition effect should also appear persistent within individuals, offering a parsimonious explanation for a fact that has often been interpreted as evidence of a universal tendency to realize paper gains.

At the same time, our results do not imply that preference-based mechanisms are absent. Prospect Theory (Kahneman and Tversky, 1979) predicts greater risk-taking in the loss domain, and realization utility models (Barberis and Xiong, 2009, 2012; Ingersoll and Jin, 2013) posit a direct utility gain from realizing profits. A key implication of realization utility is a discontinuous increase in selling at the zero-return threshold. Using the granularity of our experimental and FinTech data, we document a sharp and persistent increase in selling probability at exactly this threshold.[3] Importantly, this discontinuity is present for both contrarian and momentum investors, indicating that realization preference is broadly shared rather than concentrated in particular styles. Quantitatively, however, this channel is modest: under our model-based decomposition, responses to return status *per se* account for only around 10% of the overall disposition effect.

More broadly, our paper contributes to a growing literature that combines experimental and field data to study investor behavior (e.g., An et al., 2024; Andersen et al., 2024). Our main contribution is to show that experimentally elicited investment styles generalize to real-world financial decisions and, in doing so, fundamentally reshape how the disposition effect should be interpreted. Rather than treating the disposition effect as a direct measure of a primitive realization bias, our findings suggest that it is, to a large extent, a reduced-form realization pattern generated by stable trading rules interacting with cost-basis mechanics. This perspective shifts attention from documenting behavioral outcomes to understanding the underlying decision rules that produce them.

The rest of the paper proceeds as follows. Section 2 introduces a simple mechanical benchmark in which price-contingent trading rules interact with endogenous cost-basis formation to generate a disposition-effect-like pattern even in the absence of any intrinsic preference for realizing gains or losses. Section 3 describes the experimental setting and the field data. Section 4 develops our measure of investment style and tests the central prediction that the disposition effect varies systematically with style across the experiment, the field, and an external brokerage dataset. Section 5 examines the stability of investment style and the resulting persistence of the disposition effect within individuals over time and across contexts. Section 6 turns to realization preference, documenting a sharp discontinuity in selling at the zero-return threshold but showing that this channel is broadly shared across styles and accounts for only a

[3] Neural and experimental evidence supports realization utility (Frydman et al., 2014; Frydman and Rangel, 2014), while Ben-David and Hirshleifer (2012) find little evidence of such discontinuities in historical brokerage data.

modest share of the overall disposition effect. Section 7 concludes.

2 A Mechanical View of the Disposition Effect

We now provide a simple mechanical benchmark that makes precise our main idea: a large share of the disposition effect can arise as a mechanical by-product of stable investment styles interacting with standard cost-basis accounting, even when investors never condition their trading decisions on whether a position is at a gain or a loss. The goal of this section is not to build a fully realistic model, but to offer a transparent thought experiment that clarifies how a persistent disposition pattern can mechanically emerge from price-based trading rules.

Consider a single risky asset whose price follows a geometric random walk:

$$P_t = P_{t-1} \exp(r_t), \qquad r_t \sim \mathcal{N}(\mu, \sigma^2), \tag{1}$$

where r_t denotes the log return at time $t = 1, 2, \ldots, T$. The investor is risk-neutral, cannot short-sell, and we abstract from portfolio choice to focus on the mechanics of trading and accounting. The platform reports a displayed cost basis C_t computed as a weighted-average purchase price. Consistent with our empirical setting, the cost basis is updated only upon purchases and remains unchanged during partial sales; it resets upon the next purchase after a full liquidation. Let $\Delta q_t \equiv q_t - q_{t-1}$ denote net share demand at time t, and let $\Omega = \{\tau < t : \Delta q_\tau > 0\}$ be the set of purchase periods since the most recent liquidation. The pre-sale cost basis is

$$C_{t^-} = \frac{\sum_{\tau \in \Omega} \Delta q_\tau P_\tau}{\sum_{\tau \in \Omega} \Delta q_\tau}, \tag{2}$$

which is simply a volume-weighted average of historical purchase prices.

Investment style is modeled as a deterministic response to contemporaneous price movements. For expositional clarity, we focus on two polar cases:

- **Contrarian**: buy iff $r_t < 0$ and sell iff $r_t > 0$,

- **Momentum**: buy iff $r_t > 0$ and sell iff $r_t < 0$.

Intuitively, contrarian investors accumulate when prices fall and trim positions when prices rise, while momentum investors do the opposite. Crucially, these trading rules depend only on the sign of the current return r_t, not on gain–loss status or the holding-period return of the position.

Given the cost-basis rule in Equation (2), these trading styles have asymmetric effects on the cost basis. Under contrarian trading, purchases concentrate in down states, placing larger weights on low prices and mechanically depressing C_{t^-}. Under momentum trading, purchases concentrate in up states, mechanically inflating C_{t^-}. At the same time, sale events occur in up (down) states for contrarian (momentum) investors by construction. The disposition effect is defined over the sample of realized sales: investors realize gains more frequently than losses. Accordingly, the relevant object in this benchmark is the unrealized return at the moment of sale, measured relative to the pre-trade cost basis:

$$U_t \equiv \frac{P_t}{C_{t^-}} - 1, \tag{3}$$

where C_{t^-} is evaluated after observing P_t but before any cost-basis update. A disposition-effect-like pattern corresponds to a distribution of U_t that is shifted toward positive values at sale times.

Two simple asymmetries jointly determine the sign and distribution of U_t at sale times: (i) contrarians sell only after up moves ($r_t > 0$), whereas momentum investors sell only after down moves ($r_t < 0$); and (ii) because the cost basis is a weighted average of past purchase prices and is invariant to partial sales, contrarian purchases in down states push C_{t^-} down, while momentum purchases in up states push C_{t^-} up. As a result, contrarian investors are mechanically more likely to realize gains than losses, while momentum investors tend to realize losses more often—even though neither type ever looks at $1\{U_t > 0\}$ when deciding whether to trade.

To gauge the magnitude of this channel, we simulate "zero-intelligence" agents who follow the contrarian or momentum rules above but never condition on gain–loss status. Prices follow a random walk with zero drift, and trading intensity scales with the absolute recent return, allowing for partial liquidations and re-entries. The cost basis is updated using the weighted-average rule upon purchases and remains fixed during partial sales. For each sale event, we compute the holding-period return $U_t = P_t/C_{t^-} - 1$ and focus on its distribution conditional on a sale.

Figure 1 visualizes the conditional-on-sale distribution under a representative parameterization. Consistent with the mechanism, contrarians sell predominantly in the gain region ($U_t > 0$), whereas momentum investors sell more often around or below zero. Table 1 reports the probability of realizing gains and losses conditional on sale, and the implied disposition effect, for a grid of volatilities and trading intensities. Across all configurations, contrarians exhibit a strongly positive disposition effect, while momentum investors exhibit a strongly negative effect. Varying parameters changes the magnitude but not the sign of the style-induced pattern.

[Figure 1 and Table 1 around here.]

Beyond this mechanical channel, a large literature has emphasized preference-based motives for realizing gains, often summarized under the label "realization preference" or "realization utility". Such preferences predict a discrete jump in selling at the zero-return threshold even when trading rules are otherwise symmetric in prices. We return to this channel in detail in Section 6. Taken together, the mechanical benchmark and this preference-based perspective yield three key testable predictions that guide our empirical analysis:

- **Prediction 1 (Style–DE mapping).** Contrarian investors should exhibit a much stronger disposition effect than momentum investors, with the latter potentially displaying a reversed pattern.

- **Prediction 2 (Persistence as an implication).** If investment style is a stable individual trait, then the mechanically induced disposition effect should also appear stable over time and across contexts.

- **Prediction 3 (Residual preference component).** Even if realization preferences create an additional zero-return discontinuity that is shared across styles, this residual component should account for only a modest share of the overall disposition effect relative to the style-driven mechanical channel.

The next section describes our experimental and field settings and establishes that the disposition effect is pervasive in both environments. We then turn to the central prediction of the mechanical benchmark—Prediction 1—in Section 4, before testing Prediction 2 in Section 5 and isolating the residual realization-preference component in Section 6.

3 Experiment and Data

3.1 Platform Background

The experiment is designed and implemented as a virtual trading game by Alipay, one of the leading mobile payment platforms in China as well as around the globe. Before we elaborate the details about the virtual game, it is useful to provide a brief introduction of the platform. Originally designed to facilitate payments between customers and merchants on Taobao, China's Ebay-like online shopping platform, Alipay was first launched in late 2003. On top of payment businesses, Alipay now also features various personal financial management tools, enabling across-bank account management, credit card repayment, mortgage loan repayment, mutual fund investment and etc. As of mid-2020, Alipay serves over 1 billion annual active users and over 80 million monthly active merchants. Note that direct investment in common stocks is, however, impossible via the platform. With various kinds of mutual funds provided, Alipay documents a total asset under management (AUM) over 4.1 trillion CNY ($\sim$ 560 billion USD using current exchange rate) as of June 2020.

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

3.2 Experiment Description

3.2.1 Design

The experiment setup, following the spirit of Weber and Camerer (1998), is identical to the one used by Han et al. (2020). We summarize it as follows from the perspective of participant. Once in the experiment, the participant receives an endowment of imaginary 10,000 CNY as starting capital, and they will decide the initial allocation between a risky asset and a risk-free asset (cash). After the first decision, the participant will be directed to an interactive interface where they are presented a series of the risky asset's prices in a line chart. Along with the visualized price movement information, the participant will receive an extra inflow of 1,000 CNY cash in their game account to finance their next decision. One could choose to sell, hold or buy extra of the risky asset, but not short-sell. After the choice, the same procedure will repeat. In total, the participant has the opportunity to make 11 active decisions including one initial allocation without any price information and 10 consecutive decisions with historical price information. The idea of design is to mimic real-life trading processes with respect to a single risky asset. For every decision-period except for the first, the participant has the information on how the price evolves since the beginning, the total value of their portfolio (risky asset plus cash), the sum of capital inflows (10,000 + 1,000 $\times$ period number), the accumulated return rate, the accumulated profits/losses, the asset return rate during the past period, the risk-free balance, and the market value of risky asset holding. Figure B.1 shows an illustrative screenshot before a decision is to be made. After the final (11^{th}) 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.

3.2.2 Experimental data

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

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

Panel A of Table 2 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

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

they do the opposite, while the remaining 46% belongs to not making active trading decisions. Furthermore, they usually do not trade substantially: the average turnover is about 7%, which is defined by the value of trade over current position in the risky asset (i.e., the market index) and is bounded on $[-1, 1]$. The participants in general exhibit meaningful exposure to risk, leading to an average of 55% risky share that is computed by current risky holding over total holdings. To alleviate the concern that these multi-time participants might merely be the ones that are particularly interested in the game or the personality test, and play several times consecutively within a short time, we document that the average(median) interval between the two consecutive game sessions is 50(20) days. Furthermore, in Appendix Figure B.2, we visualize the decision-level features over experiment sessions, including the duration, the buy and sell dummies and the risky share: There seems no notable pattern that the participants behave systematically different across sessions, except that the session duration tends to be shorter as session progresses, which could be plausibly attributed to the increased familiarity with the game. Hence, we argue that, for a given player, each session is a fair representation of their general trading pattern.

In addition, the market performance is overall weakly positive: 0.33% return rate since the previous decision and 1.55% since the start of the experiment. Finally, we measure the participant's performance, before each decision, by their paper profits over accumulated cash inflow. Consistent with the generally positive market conditions, the average participant's return is positive at 0.38%.

Our Alipay dataset also allows us to connect most of the experiment participants to their demographic information as it is mandatory to upload a valid identification document before an user could enable payment- and investment-related services. The document contains several key features including age, gender and place of birth. Additionally, users can self-report other information, including but not limited to occupation and educational level in exchange for better customized Alipay services and functions. Panel B of Table 2 summarizes those important demographic characteristics in the cross-section of July 2021. The sample size varies across variables due to the nature of self-reporting. *Bachelor* is a binary dummy that equals one if the user holds at least a bachelor's degree. *Occupation* is a categorical dummy that covers three types: students, blue-collar workers and white-collar workers. *Total Alipay asset* refers to the average of end-of-month total market value of all financial products, primarily various kinds of mutual funds, that users hold directly on Alipay. We consider this as a proxy for wealth.

[Table 2 around here.]

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

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

3.3 Real-life Data

To serve the goal of investigating real-life disposition effect and within-investor consistency, we link the experiment participants to their actual financial holdings. For each investor-month, we have access to their end-of-month asset allocation snapshots which describe all the positions held on the Alipay platform. As described earlier, although Alipay users could invest in various financial assets including mutual funds, insurance and deposit certificate, they cannot invest directly in common stocks. We therefore focus solely on investors' equity mutual fund holdings, given the pivotal role of stocks and funds in households' balance sheet (Calvet et al., 2007) and the prevalence in the literature on households' stock market participation (e.g., Andersen et al., 2019).

The data is organized at investor-fund-month level, spanning over the period of January 2017 - October 2021. Each observation documents end-of-month details including but not limited to fund code, fund name, fund management company, the number of shares, market value (holding position), holding profit and holding return rate. [5] As such, the data enables us to construct a panel with which we could calculate the active change in number of shares. The key outcome variable, a *Sell* dummy, equals to one for an investor-fund-month if the number of shares is reduced when compared with that of previous month. This indicator by construction includes both partial and complete redemption. To ensure that the variable is meaningfully defined, we drop all positions that are opened during the given month, that is, we keep the ones with a positive market value as of previous month. With the *Sell* dummy, we follow Odean (1998) and exclude investor-month-fund observations if there is no selling record within the investor-month. Then, we keep investors with no less than 100 valid fund-month observations to ensure active participation. Furthermore, we compute the holding length for each investor-fund pair based on its first appearance.

As a result, we obtain a sample consisting of 12,071,776 observations, of which the summary statistics are presented in Panel C of Table 2. Notably, an average investor has a probability of 19% 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 enhanced attention. It also relates to the fact that our sample consists of investors

[5]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.

who participate the trading games multiple times, and they are expected to trade more actively. The average market value of fund holding is 4,097 CNY ($\sim$ 560 USD) with an average holding-period return rate of 5%, and the majority of the observations carry a positive return.

4 The Role of Investment Style

Having established a mechanical benchmark in which price-contingent trading rules and cost-basis accounting can generate a disposition-effect-like pattern even in the absence of realization preferences, we now bring this view to the data. We begin by confirming that the disposition effect is pervasive at the aggregate level, and then test the mechanical view's central prediction: that the disposition effect varies systematically with investment style. We do so across three distinct settings—the experimental game, real-life mutual fund trading on Alipay, and a traditional U.S. discount brokerage dataset. Following methods used in recent work on extrapolative beliefs (e.g., Andersen et al., 2024; Liao et al., 2022), we construct an individual-level measure that captures the extent to which investors trade against versus in line with recent market returns. We emphasize that this is a revealed investment style measure—a behavioral pattern that could be driven by beliefs, preferences, or other factors—and we do not aim to speak to the underlying psychological mechanisms. We classify individuals as either contrarian or momentum traders based on this measure, and then examine how investment style relates to the strength of the disposition effect.

4.1 Disposition effect at the aggregate level

Before turning to individual heterogeneity, we first evaluate whether the disposition effect is prevalent at the aggregate level in our data. To this end, we follow the classical measure proposed by Odean (1998), counting the number of sell and non-sell decisions under different return scenarios and calculating the proportions of gains realized (PGR) and losses realized (PLR):

$$PGR = \frac{\#Realized\ Gains}{\#Realized\ Gains + \#Paper\ Gains}, \tag{4}$$

$$PLR = \frac{\#Realized\ Losses}{\#Realized\ Losses + \#Paper\ Losses}. \tag{5}$$

The difference $PGR - PLR$ measures the disposition effect. Figure 2 presents aggregate disposition effects in both the experimental game and real-life trading. The left panel plots the probability of reducing risky holdings conditional on accumulated returns in the experimental game. When players face negative accumulated returns, the probability of decreasing risky holdings is below 5%, whereas it jumps to about 20% when accumulated returns are positive, and this pattern is stable across game periods. The magnitudes are very similar to recent experimental evidence based on representative US- and UK-based samples (Chapkovski et al., 2024), confirming that the disposition effect is still pervasive in modern experimental settings. They also indicate that our virtual investment game, although not conducted in a traditional laboratory environment, successfully captures standard investor behavioral biases as in previous studies (e.g. Talpsepp et al., 2014; Weber and Camerer, 1998). The right panel shows aggregate disposition effects based on real-life investor–fund–month observations. Following Odean (1998), we restrict the sample to investor–fund observations in months when the investor sold at least one fund, and compute PGR and PLR using realized and paper returns on the last trading day of each month. Compared with the experimental setting, PLR is substantially higher in the field, which is consistent with investors' liquidity needs and other practical motives for realizing losses. Nevertheless, we still document a sizable $PGR - PLR$ gap, indicating that the disposition effect remains a prominent feature of modern real-world trading behavior.

[Figure 2 around here.]

4.2 Evidence from the experiment

We begin with data from a cleaner and better-controlled environment—the virtual trading game. To measure investment style, we estimate the following decision-level regression separately for each investor i. The idea is to isolate how investors respond to recent price movements, while controlling for return-related components that may reflect preference-based responses, especially around the return break-even point. We also allow for an interaction between the gain and the absolute size of the player return, to capture the heterogeneous response to different depths of paper gains and losses:

$$\begin{aligned} Turnover_{i,d} = \alpha_i + \beta_i Recent\ return_{i,d} + \gamma_i Gain_{i,d} + \lambda_i |Player\ return_{i,d}| \\ + \eta_i Gain_{i,d} \times |Player\ return_{i,d}| + \varepsilon_{i,d} \end{aligned} \tag{6}$$

Here, $Turnover_{i,d}$ is the trading activity of investor i at decision d, defined as the traded amount divided by the current risky position, bounded between -1 and 1. $Recent\ return_{i,d}$ is the return since the last decision period of the market index. The variable $Gain_{i,d}$ indicates whether the investor has a positive accumulated return up to the decision point, and $|Player\ return_{i,d}|$ is the absolute size of that return. Our coefficient of interest, β_i, captures the sensitivity of trading to recent market movements. We define the *Contrarian Degree (CD)* as the opposite of β_i. A positive CD, or equivalently a negative β_i, suggests contrarian style, while a negative CD indicates momentum one. The left panel of Figure 3 shows the distribution of CD, revealing that approximately 86% of participants fall into the contrarian category.[6]

To get a general sense of how investment style relates to the disposition effect, we first follow Odean (1998) again and compute the difference in the propensity to realize gains versus losses. The right panel of Figure 3 plots the distribution of this difference

[6]Previous studies have shown mixed evidence, with various classification methods, in terms of whether an average retail investor exhibits contrarian or momentum style. In Nordic countries like Finland and Sweden, retail investors tend to be contrarians (Grinblatt and Keloharju, 2001; Jonsson et al., 2017), while in the U.S. they tend to be the opposite (Greenwood and Shleifer, 2014). Moreover, when the financial investment context is replaced by a more general forecasting task in order to measure extrapolative beliefs, Andersen et al. (2024) report a mildly higher prevalence of extrapolation among Danish retail investors.

for both contrarian and momentum investors, with the vertical line indicating no bias. We observe a stark contrast: most contrarian investors display a sizable disposition effect, while momentum traders exhibit little to none.

[Figure 3 around here.]

We then take a more granular view, plotting the probability of selling as a function of player's current holding period return (HPR), following Ben-David and Hirshleifer (2012) and Kaustia (2010). We restrict the return interval to $[-7\%, 7\%]$, approximately corresponding to the 5^{th} and 95^{th} percentiles of the sample. Figure 4 shows the resulting patterns. As expected, contrarian investors show a sharp difference in selling likelihood between gains and losses, while extrapolators show a much flatter pattern. Interestingly, for both groups, we observe a discrete jump in selling probability around the zero-return threshold, consistent with the prediction of realization utility theory (Barberis and Xiong, 2012).[7] We explore this preference-based explanation more closely in Section 6.

[Figure 4 around here.]

Up to this point, our evidence has aggregated the HPRs across all decision periods in a simple way. However, as Ben-David and Hirshleifer (2012) points out, this aggregation may not be the best way to capture the interaction between investment style and the disposition effect. To formally test the interaction between investment style and the disposition effect, we estimate the following regression similar to Andries et al. (2024) and Ben-David and Hirshleifer (2012):

$$\begin{aligned} 100 \times \mathit{Sell}_{i,y,p} = {} & \gamma \mathit{Gain}_{i,y,p} + \beta \mathit{Gain}_{i,y,p} \times \mathit{Contrarian}_i \\ & + \mathit{FE}_i + \mathit{FE}_y + \mathit{FE}_p + \varepsilon_{i,y,p} \end{aligned} \tag{7}$$

The dependent variable $\mathit{Sell}_{i,y,p}$ is an indicator for whether investor i reduces their risky position during period p in a game session based on the market path from year

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

y. $Contrarian_i$ is a dummy variable that equals one if investor i has a positive CD, and zero otherwise. We restrict the sample to observations with positive risky holdings to ensure the possibility of a sale—this filter reduces the sample by only about 4%. We include individual (FE_i), market-path-year (FE_y), and game-period (FE_p) fixed effects to control for unobserved heterogeneity. Standard errors are two-way clustered at the individual and game-period levels.

Table 4 reports the results. Column (1), without any fixed effects or style-related variables, confirms a strong and significant disposition effect: participants are about 16 percentage points (pps) more likely to sell when holding unrealized gains. Column (2) adds style-related variables but without fixed effects. The coefficient on *Gain* (4.901 pps) captures the disposition effect for momentum investors, while the interaction term *Gain* $\times$ *Contrarian* (13.208 pps) indicates that contrarian investors exhibit an additional 13 pps of disposition effect. Thus, contrarian investors display a total disposition effect of approximately 18 pps (4.901 + 13.208), which is substantially larger than the 5 pps effect for momentum investors. Columns (3) and (4), gradually adding fixed effects and style-related variables until the saturated specification of Equation 7, show highly consistent patterns. In the fully saturated specification (Column 4), the gain–loss asymmetry in selling probability is about 13 pps higher for contrarians, compared to momentum investors who have a baseline disposition effect of about 4 pps. In other words, investment style is a key, even determinant, predictor of the strength of the disposition effect.

[Table 4 around here.]

4.3 Evidence from the field

The experimental findings highlight the important role of investment style in shaping the strength of the disposition effect. While the experimental environment offers a clean and well-controlled setting, it deliberately abstracts from many real-world features, such as portfolio complexity, liquidity needs, and actual monetary stakes. In this section, we examine whether the relationship between investment style and the disposition effect extends to real-life trading decisions, and whether the patterns observed in the field are consistent with the mechanical interpretation proposed in the Introduction.

As in the experimental analysis, we classify investors based on their Contrarian Degree (CD), inferred using the same regression-based approach. While the core methodology remains similar to Equation 6, we adjust the specification to reflect the real-life context. Following Liao et al. (2022), we use the previous month's fund return as a proxy for recent price movements and additionally control for the logarithms of holding position and holding duration. The dependent variable is the percentage change in the number of fund shares held, restricted to the range of $[-1, 1]$. To ensure sufficient variation for identification, we retain only investors with more than 100 valid fund-month observations.

Using this approach, we identify approximately 76% of investors as contrarian, a proportion comparable to that observed in the experimental setting. This similarity suggests that the prevalence of contrarian trading behavior is not an artifact of the experimental design but reflects a broadly shared investment style among retail investors. Figure 5 visualizes the distribution of the CD as well as the disposition effect by investor style.

[Figure 5 around here.]

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

$$\begin{aligned} 100 \times \mathit{Sell}_{i,f,t} = {} & \delta\, \mathit{Gain}_{i,f,t-1} + \beta\, \mathit{Gain}_{i,f,t-1} \times \mathit{Contrarian}_i + \omega \log(\mathit{Holding\ months}_{i,f,t}) \\ & + \gamma \log(\mathit{Holding\ position}_{i,f,t-1}) + \eta \log(|\mathit{Holding\ period\ return}_{i,f,t-1}|) \\ & + \mathit{FE}_{i \times t} + \mathit{FE}_{f \times t} + \varepsilon_{i,f,t}, \end{aligned} \tag{8}$$

where i, f, and t denote investor, fund, and month, respectively. The dependent variable $\mathit{Sell}_{i,f,t}$ equals one if investor i reduces their position in fund f during month t, and zero otherwise. The dummy variable $\mathit{Gain}_{i,f,t-1}$ indicates whether the holding shows a positive unrealized return at the end of month $t-1$. *Contrarian*$_i$ equals one if investor i has a positive CD. We include investor-month and fund-month fixed effects to absorb time-varying heterogeneity across investors and funds, and standard errors are two-way clustered at the investor and month levels.

Table 5 presents the results. Despite the inclusion of saturated fixed effects, Columns (1)–(2) reinforce our experimental findings: the disposition effect is present for the average investor, and contrarian investors exhibit a significantly stronger disposition effect. In contrast, momentum investors display a significantly weaker—and even reversed—pattern, being 2.6 percentage points less likely to sell when holding paper gains than losses.

[Insert Table 5 around here.]

Importantly, these patterns do not require investors to derive utility directly from gains or losses. When reference points are anchored at purchase prices, a contrarian response to recent price increases mechanically implies a higher likelihood of selling positions with unrealized gains than those with unrealized losses. From this perspective, the disposition effect observed in the field emerges as a reduced-form outcome of underlying price-based trading rules rather than as an independent behavioral primitive.

Why the style–disposition relationship is not definitional

A natural concern is that investment style and the disposition effect may be observationally equivalent—that we are simply relabeling one price-based realization pattern as "style" and using it to explain another. Two features of our design directly address this concern.

First, investment style is estimated from responses to recent price changes, explicitly controlling for gain–loss status. The Contrarian Degree captures how investors trade in response to price movements *after* removing any direct response to whether a position is at a gain or a loss. Style and disposition behavior are thus conceptually and econometrically distinct objects.

Second—and most importantly—we exploit the two-setting design and use investment style estimated entirely from the experiment to predict real-life disposition behavior. The experimental style measure is elicited in a clean, low-stakes environment free of field-specific frictions, while the disposition effect is measured in real-world mutual fund trading with genuine financial stakes. If the style–disposition link were merely a definitional overlap, a style measure from one context should have no predictive power for realization patterns in another. We re-estimate Equation 8 using the experimentally inferred CD. Column (3) of Table 5 shows that the results remain qualitatively unchanged: experimentally classified contrarian investors exhibit a significantly stronger disposition effect in the field, while the effect for momentum investors is statistically insignificant. This cross-context predictive power is difficult to reconcile with a tautological interpretation, and instead supports a stable mapping from price-based decision rules to gain–loss realization patterns—precisely as the mechanical benchmark predicts.

These findings contrast with prior studies arguing that beliefs in mean reversion cannot explain the disposition effect. While our construct is not belief *per se*, it shares a similar methodological core. We attribute the discrepancy primarily to differences in how investment style is measured. Whereas prior studies often rely on performance relative to a benchmark index, we focus on absolute recent price movements. This choice is dictated by both the experimental design and the structure of the mutual fund data, where relative performance is difficult to observe and cognitively less salient for retail investors.

Furthermore, our findings stand in contrast to those of Chang et al. (2016), who report a generally reversed disposition effect for delegated assets such as mutual funds. They argue that investors shift blame for poor performance onto fund managers, which reduces the psychological cost of realizing losses. While we do not aim to dismiss this explanation, our results suggest that investment style heterogeneity may also play an important role in explaining the observed patterns. Several mechanisms could account for the discrepancy. First, differences in perceived delegation may matter: in our context, investors are able to closely monitor fund performance on a daily basis and submit orders conveniently at any time.[8] As a result, investors in our sample likely feel more responsible for their trading decisions and their portfolio outcomes, which may limit the psychological distancing that underpins the reverse-disposition pattern observed in other studies. Second, the very same investor might exhibit a different investment style when investing in mutual funds than when investing in stock markets. Put differently, the average mutual fund investor might shift from being largely contrarian (as we observe in our experimental setting) to being somewhat momentum-oriented, or there may be self-selection: momentum investors might be more likely to invest in mutual funds, while contrarian traders might prefer direct stock investments. Given that momentum investors in our sample exhibit a reversed disposition effect, such compositional differences could explain why Chang et al. (2016) observe an aggregate reversed pattern, while we document a positive average disposition effect that masks substantial heterogeneity across investment styles.

More generally, these findings help uncover the composition of retail investors in terms of investment style. This is especially important in emerging markets, where retail investors play a larger role in shaping asset prices (An et al., 2024; Liao et al., 2022). The fact that the majority of retail investors in our sample exhibit contrarian behavior complements previous findings on institutional investors in both U.S. and international markets (Badrinath and Wahal, 2002; De Haan and Kakes, 2011), as well as experimentally observed patterns (Weber and Camerer, 1998). This suggests that mean-reversion-based trading may be a broadly shared style across investor types, geographies, and contexts. Understanding the composition is particularly important as it provides micro-foundations for how heterogeneous behavioral tendencies shape aggregate return dynamics and pricing anomalies (e.g., Da et al., 2021; Frazzini, 2006; Greenwood and Shleifer, 2014; Grinblatt and Han, 2005).

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

4.4 Evidence from a traditional brokerage dataset

Having documented the style–disposition relationship in the experimental game and in real-life FinTech data, we now test whether this pattern extends to a traditional equity market setting, thereby completing our test of the mechanical prediction across three distinct environments. This also serves as an external validation, addressing the concern that our findings might be driven by features unique to the Alipay platform or to Chinese retail investors. We examine the style-disposition relationship using the classic dataset that includes individual-level transaction and holding records from a large discount brokerage firm over the period from January 1991 to December 1996 as in Barber and Odean (2000). We start with a random sample of 5,000 retail investors, and keep only the investor-stock pairs that we can identify their initial purchase and therefore track their lifecycle until a full liquidation or the end of the sample period. To ensure a meaningful classification of investment style, we restrict the investors to have at least 10 active trades.

We then use the same regression-based approach as specified in Equation 6, with some simplifying adjustments due to the relatively low trading frequency noticed in the classic dataset. Specifically, we use the past week's stock return before the trade as a proxy for recent price movement, without adding any additional controls. The dependent variable is again the percentage change in the number of shares held, restricted to the range of $[-1, 1]$. With the estimated CD, we document a fraction of 63% contrarian investors.

To shed light on the relative strength of the disposition effect across setups, we plot the average PGR and PLR for contrarian and momentum investors respectively, for our real-life and in-experiment as well as the classic dataset. Figure 7 shows the results. The magnitude differs across environments due to the nature of the context. However, we document a persistent disposition effect gap across style types: the disposition effect is between $3\times$ and $9\times$ stronger for contrarian investors than momentum ones.

[Insert Figure 7 around here.]

A set of regression results that follows a simplified version of Equation 8 is presented in Table A.1. The pattern is qualitatively consistent with but weaker than the ones we observed in a more modern trading dataset: contrarian investors still exhibit a significantly stronger disposition effect than momentum ones. Taken together, the evidence from all three settings—the experiment, the FinTech platform, and the traditional brokerage—provides robust support for the mechanical view's core prediction: the disposition effect varies systematically with investment style, with contrarian investors displaying a much stronger bias than their momentum counterparts.

4.5 Investment style versus demographics

A natural question is whether investment style is merely a repackaging of standard demographic and socioeconomic characteristics. Our data allows us to connect each investor to their basic socioeconomic information, including gender, age, education and occupation. Note that the former two are mandatory for users to be able to use the Alipay app, while the latter two are made available through self-reporting. We also include the investor's average total assets held via Alipay as a proxy for wealth.

We estimate the following cross-sectional OLS regression:

$$DE_i = \alpha + \beta \, \textit{Contrarian}_i + \zeta X_i + \varepsilon_i, \tag{9}$$

where DE_i denotes the disposition effect for investor i, and X_i is a vector of individual-level controls including gender, age, education, occupation, and total Alipay assets. Though we cannot directly measure investor's risk tolerance, we manage to proxy it by the average initial investment amount in the experiment. This is plausible due to the feature that the initial investment decision has to be made before any other information is revealed to the investor, namely, it is a blind investment decision. We define the *High risk tolerance* dummy as the investor's average initial investment amount, across all the games they have played, being above the median.

Table 6 reports cross-sectional regressions of individual disposition effects on investment style and standard individual characteristics. Columns (1) and (2), within the experimental setting, show the separate associations of investment style and demographics with the disposition effect. While several demographic characteristics—such as gender, age, and employment status—are statistically significant, their economic magnitudes are modest.

Column (3) includes both sets of variables simultaneously, and two results stand out. First, the coefficient on the contrarian dummy is large and highly significant, and it dominates traditional individual-level covariates in economic magnitude. Being a contrarian is associated with a 0.141 higher disposition effect, roughly six times the magnitude of the gender effect (-0.024). Likewise, wealth-based explanations are quantitatively small: a one–standard-deviation change in log total Alipay assets (1.419) translates into only about a 0.005 change in the disposition effect, which is negligible relative to the effect of investment style.

Second, this dominance is also reflected in explanatory power. Including investment style leads to a substantial increase in the adjusted R^2 relative to specifications with demographics alone, from 1.3% to 11.7%. Columns (4)–(6) report highly consistent results in the real-life setting, confirming that investment style plays a decisive role in explaining cross-sectional heterogeneity in the disposition effect.

[Insert Table 6 around here.]

More generally, these findings align with Giglio et al. (2021), who document that investor beliefs and behaviors exhibit persistent individual heterogeneity not explained by simple demographic factors. Our results suggest that investment style captures a fundamental behavioral dimension underlying realization behavior, rather than reflecting differences in gender, age, or wealth. A natural implication is that a more informative question is not which individual characteristics predict the disposition effect as a downstream outcome, but which forces shape individuals' investment styles in the first place.

While not the primary focus of our paper, it is noteworthy that the education and wealth proxies are both positively and significantly associated with the disposition effect. That is, investors with higher educational attainment or more financial assets tend to display a slightly stronger bias. This finding contrasts with earlier studies suggesting that financial sophistication mitigates the disposition effect (e.g., Calvet et al., 2009; Dhar and Zhu, 2006), but is broadly consistent with more recent evidence from Andersen et al. (2021).

5 Why the Disposition Effect Persists

The mechanical view developed in this paper carries a clear implication for persistence: if investment style is a stable within-individual trait, and price-contingent trading rules mechanically map into realization patterns via endogenous cost-basis formation, then the mechanically induced disposition effect should also appear stable over time and across decision-making contexts. We test this implication in two steps. First, we directly verify that investment style is persistent across the experimental and field settings. Then, we show that the disposition effect itself is likewise persistent—both over time within each setting and across the two markedly different environments.

5.1 Investment style as a stable individual trait

We provide a direct test of the stability of investment style by relating the real-life Contrarian Degree (CD) to the in-game CD. Figure 6 summarizes this relationship using a non-parametric bin-scatter. The figure displays a pronounced upward-sloping pattern: investors who trade more explicitly against price trends in the game also behave more contrarian in the field. Despite measurement noise arising from differences in context and data frequency, the cross-context correlation is 0.16 (significant at the 1% level). This persistence indicates that our investment-style measure captures a stable, within-individual trait.

[Insert Figure 6 around here.]

This evidence connects the empirical patterns back to the mechanical benchmark in

Section 2. There, stable contrarian and momentum rules interacting with cost-basis accounting mechanically generated a disposition-effect-like pattern even in the absence of realization preferences. Here, the cross-context persistence of CD shows that such trading rules are themselves stable traits in the data. If investment style is a stable trait, the mechanical channel predicts that the disposition effect should also appear persistent. We now test this prediction directly.

5.2 Over-time persistence of the disposition effect

The stylized fact that the disposition effect is pervasive in both experimental and field data might be a bit surprising, as we would expect retail investors to be more free from this particularly well-known behavioral bias since it was first documented by Shefrin and Statman (1985). Under the mechanical view, however, this persistence is not an independent puzzle but a natural consequence of the stability of the underlying investment styles documented above.

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

To ensure meaningful identification of within-individual stability, we restrict the sample to investors who have at least 50 fund-month observations in both subperiods. We then compute the individual-level *PGR* and *PLR*, as well as the corresponding disposition effect. Figure 8 presents a non-parametric bin-scatter plot of the measures from the two subperiods, which reveals a strong positive association between the pre- and post-2020 disposition measures, with a correlation coefficient of 0.355 (significant at the 1% level).

[Figure 8 around here.]

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

$$DE_{i,j} = \beta \cdot DE_{i,j-1} + FE_n + FE_y + FE_m + \varepsilon_{i,j} \tag{10}$$

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

The results, presented in Table 3, closely mirror those from the real-life setting. Participants who exhibit stronger disposition bias in one session tend to do so again in the next. The coefficient on lagged disposition effect in Column (1) is 0.219 (significant at the 1% level), indicating substantial persistence. While this coefficient may appear modest at first glance, it should be interpreted as a lower bound on the true persistence parameter. This is because measurement error in individual-level disposition measures—arising from the limited number of trading decisions per session—attenuates the estimated coefficient toward zero. The R^2 of 4.9% in the baseline specification should be evaluated in this context: given the substantial measurement error inherent in session-level disposition measures, this explanatory power actually reflects a meaningful degree of persistence. Moreover, the sizable intercept of 0.211 confirms that the disposition bias is prevalent at the aggregate level. Columns (2) through (4) present increasingly saturated specifications, all of which continue to show a robust relationship between past and current disposition effects.

To further explore the possibility of learning over repeated trading experiences, we examine session order fixed effects more closely. This analysis is motivated by prior studies suggesting that investor experience and sophistication may attenuate the disposition effect (e.g., Calvet et al., 2009; Costa et al., 2013; Feng and Seasholes, 2005). While the existing literature focuses primarily on cross-sectional differences across individuals, we depart from this approach by investigating the within-individual evolution of disposition behavior across experimental sessions. As plotted in Figure 9, we find no economically meaningful evidence that later sessions are associated with systematically higher or lower levels of the disposition effect. For instance, the disposition effect in Session 5 is roughly 0.006 higher than the benchmark (Session 2), which is economically negligible given the average disposition effect of 0.166 over the first sessions.

[Figure 9 around here.]

5.3 Cross-context persistence of the disposition effect

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

To test this hypothesis, we merge the two datasets and focus on a subsample of investors for whom both experimental and real-life disposition effect measures are available and well defined. Figure 10 presents a non-parametric bin-scatter with 20 bins, showing the relationship between each investor's experimental and real-life disposition effects. The plot reveals a clear, positive, and monotonic association: investors who exhibit a stronger disposition effect in the experimental setting also tend to display a stronger effect in real-life trading. Despite possible measurement noise stemming from the monthly frequency and multi-asset aggregation of real-life data as well as the rather simple experiment setting, we still find a statistically significant cross-context correlation of 0.187 (significant at the 1% level). To benchmark our estimate, Sui and Wang (2025) document a correlation of 0.132 in a setting where investors trade stocks both in real and simulated environments under the same information set, which is somewhat lower but qualitatively similar. Altogether, these findings indicate that the disposition effect is a persistent and stable individual trait that generalizes across markedly different (experimental and real-world) decision environments. Combined with the cross-context stability of investment style documented in Section 5.1, these results support the interpretation that the persistent disposition effect is largely the mechanical footprint of a deeper and stable investment style, consistent with the benchmark in Section 2.

[Figure 10 around here.]

6 Beyond Mechanical: the Realization Preference

The previous sections have identified investment style as the first-order source of heterogeneity in the disposition effect: it accounts for the vast majority of cross-sectional variation and, because style is stable, explains why the bias appears persistent. This section isolates the residual, preference-based component that operates *on top of* the mechanical channel. Rather than offering a competing explanation of the disposition effect, our goal is to quantify how much of the bias remains once the style-driven mechanical component is accounted for.

More specifically, we leverage our comprehensive and granular data to re-visit the role of realization preference (Barberis and Xiong, 2012; Ingersoll and Jin, 2013). The idea is that investors gain a burst of 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 greater than zero should be significantly more inclined to sell their holdings than those with returns slightly below zero. Despite the straightforward intuition, there is limited field evidence supporting this notion—non-traditional neural data manages to do so (Frydman et al., 2014), while virtually no effect is detected in the trading history data (Ben-David and Hirshleifer, 2012).

The no-effect finding in the field could possibly be driven by confounding factors' masking out investors' response to returns switching from loss to gain. There are at least three such factors. First, trading with the discount brokerage firm comes with frictions primarily caused by commission costs. Barber and Odean (2000) document an average of 3% costs for round-trip transactions as well as a 1% costs for bid-ask spread. Second, the reference point is not explicitly defined in the canonical dataset—as well as how it is communicated with the investors, especially for holdings that are built throughout a series of purchases and sales. Third and somewhat related to the second, it is not feasible for the investors at earlier time to track stock prices in a nearly real-time manner.

We alleviate these concerns thanks to our modern setup. However, the investor-fund-month dataset used in previous sections, despite the relatively large sample size, does not fit our needs. This much nuanced test calls for more granular data, for which we introduce an additional transaction-level dataset. The randomly selected sample covers a distinct and smaller group of Alipay investors from our baseline sample, and it records all the mutual fund transactions including, but not limited to, purchases and redemptions. We then construct a sample consisting of investor-fund-day observations, and we limit the observations to the ones with a holding length shorter than 10 weeks for the sake of a sufficient level of attention. Furthermore, we filter out investors with less than 100 fund-day observations to ensure statistical power.[9]

With the more frequent data, we first present in Figure 11 the relation between holding return rate and unconditional probability of sell for both types of investors. 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

[9]Note that, however, we do not link this extra sample to the experiment because the sample was extracted from the Alipay investor population, and only a small fraction of the sample has an experiment participation record.

week to accommodate the more frequent data. The figure shares a largely similar pattern with the in-game counterpart (Figure 4). In general, both plots suggest that momentum investors have a higher propensity to sell than contrarians in the loss regime, while this pattern reverses in the gain regime; it persistently exhibits a somewhat distorted X-shape. More intriguingly, we notice a similar discontinuity of probability around the zero-return cutoff.

[Figure 11 around here.]

The evidence of unconditional selling probability distribution implies that the realization preference and belief-driven investment style seem to work separately in affecting retail investor's selling decision. We implement a more rigorous regression discontinuity design to examine the hypothesis, following Ben-David and Hirshleifer (2012). The specification is largely close to Eq. 7 except for the inclusion of third-degree polynomials and their interaction with holding length as well as the style.[10] The return interval is restricted to [-10%, 10%] to better capture the effect of zero-return threshold. 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. The discontinuity lessens as holding length extends, which is not surprising and could potentially be justified by less attention and arrival of liquidity shocks. As Welch (2022) puts it, the data used in Ben-David and Hirshleifer (2012) comes from 1990s, "a different era in a time before the Internet, social media, and low transaction costs".

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* $\times$ *Contrarian*. Our results suggest that contrarian beliefs are not significantly associated with the discontinuity around the zero-return threshold. Put differently, both extrap-

[10]We have also altered the degree of polynomials to fourth and fifth, and the results, available upon request, remain highly stable.

olators and contrarians 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).

[Table 7 around here.]

As a final exercise, we carry out a model-based decomposition to further quantify the contribution of the realization preference to the disposition effect. The idea is to manually shut down the channel that is directly associated with response to return status. Put differently, we remove all the terms related to the *Gain* dummy from the RDD specification, and then fit the return-status-free model to estimate the probability of sell, thus calculating the disposition effect in the absence of the realization preference. Lastly, we compare the fitted disposition effect based on the two models, and report the difference in Table 8. Across in-experiment decisions and real-life transactions, under our specification, investors' response to the return status *per se*, arguably largely manifested by the realization preference, accounts for on the order of 10% of the disposition effect among the sample investors.

[Table 8 around here.]

7 Conclusion

This paper proposes that a large share of the disposition effect is mechanical: it arises from the interaction of stable investment styles with standard cost-basis accounting, rather than from a primitive preference for realizing gains. Contrarian investors—who buy after price declines and sell after increases—exhibit a disposition effect up to nine times stronger than momentum investors, for whom the bias is economically small or even absent. This pattern is consistently observed across three distinct settings: a large-scale virtual trading experiment, modern FinTech mutual fund data, and a traditional U.S. discount brokerage. Because investment style itself is a stable individual trait, the mechanically induced disposition effect also appears persistent within individuals over time and across contexts. A residual, broadly shared realization preference—visible as a discontinuity in selling at the zero-return threshold—accounts for only a modest share (on the order of ten percent under our decomposition) of the overall bias.

These findings reframe what the disposition effect *is*. Rather than an independent behavioral preference, it emerges as the mechanical footprint of how investors process and react to price changes. When reference points are anchored at purchase prices, price-based trading rules mechanically translate into differential realization of gains and losses. The aggregate disposition effect thus largely reflects the composition of investment styles in the market rather than a universally shared irrationality. This interpretation provides micro-foundations for how stable behavioral heterogeneity can shape aggregate trading patterns, return dynamics, and pricing anomalies.

The reframing also has welfare and policy implications. If the disposition effect is driven by stable investment styles rather than transient mistakes, evaluating investor behavior solely through this lens risks conflating outcomes with underlying decision rules. One-size-fits-all debiasing interventions are unlikely to be effective; instead, financial education and advisory tools may benefit from recognizing persistent heterogeneity and tailoring guidance to investors' underlying responses to price changes.

Methodologically, this study underscores the value of combining experimental and field data to disentangle price-based trading rules from preference-based mechanisms, shifting attention from documenting behavioral outcomes to understanding the deeper decision structures that generate them.

References

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

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

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

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

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

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

Barber, B.M., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. The journal of Finance 55, 773–806.

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

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

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

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

Calvet, L.E., Campbell, J.Y., Sodini, P., 2009. Measuring the financial sophistication of households. American Economic Review 99, 393–398.

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

Chapkovski, P., Khapko, M., Zoican, M., 2024. Trading gamification and investor behavior. Management Science .

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

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

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

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

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

Frazzini, A., 2006. The disposition effect and underreaction to news. The Journal of Finance 61, 2017–2046.

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

Frydman, C., Rangel, A., 2014. Debiasing the disposition effect by reducing the saliency of information about a stock's purchase price. Journal of economic behavior & organization 107, 541–552.

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

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

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

Grinblatt, M., Han, B., 2005. Prospect theory, mental accounting, and momentum. Journal of Financial Economics 78, 311–339.

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

Han, L., Luo, X., Ouyang, S., 2020. Investor's responses to market fluctuations: Evidence from experiment and real trading. Working Paper.

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

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

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

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

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

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

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

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

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

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

Sui, P., Wang, B., 2025. Stakes and investor behaviors. Journal of Financial Economics 172.

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

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

Welch, I., 2022. The wisdom of the robinhood crowd. Journal of Finance 77, 1489–1527.

Table 1: **Mechanical Disposition Effect under Zero-Intelligence Simulation**

`CD_factor`	σ	Type	N_{gain}	N_{loss}	PGR	PLR	DE
1	0.1	Contrarian	35,182	14,858	0.703	0.297	0.406
1	0.1	Momentum	15,498	34,301	0.311	0.689	−0.378
2	0.1	Contrarian	36,115	13,946	0.721	0.279	0.443
2	0.1	Momentum	14,690	35,462	0.293	0.707	−0.414
3	0.1	Contrarian	36,073	13,492	0.728	0.272	0.456
3	0.1	Momentum	14,614	35,123	0.294	0.706	−0.412
1	0.2	Contrarian	36,252	13,632	0.727	0.273	0.453
1	0.2	Momentum	15,051	35,088	0.300	0.700	−0.400
2	0.2	Contrarian	35,497	12,717	0.736	0.264	0.472
2	0.2	Momentum	14,184	35,775	0.284	0.716	−0.432
3	0.2	Contrarian	32,170	11,993	0.728	0.272	0.457
3	0.2	Momentum	13,632	34,604	0.283	0.717	−0.435

Notes: The table reports outcomes conditional on a sale decision. N_{gain} and N_{loss} count sale events with $U_T > 0$ and $U_T \leq 0$, respectively, where $U_T = P_T/C_{T^-} - 1$ is evaluated at the sale price using the pre-trade cost basis. Simulations fix $\mu = 0$ and vary σ and `CD_factor` (Contrarian Degree factor, proxying for trade intensity). Note that in this setting where sales are strictly price-driven, the standard denominator of paper gains/losses is less relevant; we thus focus on the conditional probabilities PGR and PLR (which sum to one) and report DE = PGR − PLR.

Table 2: **Summary Statistics**

This table provides descriptive statistics on key variables. **Panel A** presents decision-level characteristics after excluding first-periods of each game session. *Duration* is the time spent before making investment decision, measured in seconds. *Buy* and *Sell* dummies indicate the trade decision during the period. *Risky share* is the pre-decision ratio of risky value over total value. *Turnover* is calculated by trade amount over pre-trade risky position, bounded on [-1, 1]. *Market return* refers the performance of risky asset, either during the recent period or since the beginning (namely, [t-1, t] or [0, t]). *Current player return* documents the return rate achieved by the player before making the investment decision. **Panel B** relates to individual demographic and socioeconomic features. *Bachelor* is a dummy capturing the highest completed education. *Total Alipay assets* (in CNY) is the average monthly value of all types of assets held via Alipay. Finally, **Panel C** focuses on real-life investor-fund-month observations, over the period of January 2017 to October 2021. *Months since first purchase* documents the number of months since the initial purchase. *Holding position*, *Holding profit*, and *Holding period return* refer to the end-of-month holding amount, the displayed profits or losses, and the displayed rate of return for a given fund-month, respectively. These three variables are lagged for one month.

	Panel A: Decision level in experiment					
	N	Mean	SD	p25	Median	p75
Duration	4,527,250	6.26	6.81	2.54	4.37	7.60
Buy dummy	4,527,250	0.41	0.49			
Sell dummy	4,527,250	0.13	0.33			
Risky share (%)	4,527,250	55.09	35.57	25.50	59.06	88.94
Turnover (%)	4,527,250	6.94	40.91	0	0	13.88
Market return [t-1, t]	4,527,250	0.33	6.19	-3.05	0.72	3.78
Market return [0, t]	4,527,250	1.55	11.89	-5.54	0.73	7.79
Current player return (%)	4,527,250	0.38	4.94	-1.67	0.13	2.35
	Panel B: Individual level					
	N	Mean	SD	p25	Median	p75
Age	48,266	31.25	8.99	25	29	35
Gender	48,266	0.67	0.47			
Total Alipay assets	48,266	72500	154947	10009	29993	78316
Bachelor	34,680	0.31	0.46			
Occupation	30,785					
Student	30,785	0.17	0.38			
White collar	30,785	0.65	0.48			
Blue collar	30,785	0.18	0.38			
	Panel C: Individual-fund-month level in real life					
	N	Mean	SD	p25	Median	p75
Sell dummy	12,071,776	0.19	0.39			
Months since first purchase	12,071,776	7.15	7.69	2	5	10
Holding position	12,071,776	4097.07	18749.48	36.97	558.92	2846.00
Holding profit	12,071,776	194.17	4294.74	-4.83	0.37	51.52
Holding period return (%)	12,071,776	5.27	20.10	-1.93	4.72	8.49

Table 3: **In-Experiment Disposition Effect over Sessions**

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

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

Table 4: **In-Experiment Disposition Effect and Investment Style**

This table reports regression estimates based on Equation 7. The data are at the decision level. *Sell* is a dummy equal to one if the participant reduced their risky asset holdings, and zero otherwise. *Gain* equals one if the participant's accumulated return before the decision is positive. *Contrarian* is a dummy indicating the sign of investor's degree of extrapolation. *Period* is the sequence of the decision period within a given session. *Market year* corresponds to the historical market index path shown in the session. Standard errors are two-way clustered at the individual and game-period levels and reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: 100 × *Sell*			
	(1)	(2)	(3)	(4)
Gain	16.043***	4.901***	15.152***	4.276***
	(1.037)	(0.670)	(1.112)	(0.781)
Contrarian		-4.348***		
		(0.511)		
Gain × Contrarian		13.208***		12.888***
		(1.171)		(1.131)
Constant	4.262***	7.832***		
	(0.249)	(0.406)		
Period FE	No	No	Yes	Yes
Market year FE	No	No	Yes	Yes
Individual FE	No	No	Yes	Yes
Observations	4,527,250	4,527,250	4,527,250	4,456,280
Adj. R^2	0.056	0.063	0.112	0.117

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

This table reports regression results examining the disposition effect using real-life investor–fund–month observations, based on Equation 8. The dependent variable *Sell* equals one if the investor reduced their fund holdings during the month, and zero otherwise. *Gain* equals one if the fund's return by the end of the previous month was positive. *Contrarian* is a dummy variable indicating the sign of investor's investment style, measured in either the experiment or the real-life setting. *Months since first purchase* is the number of months since the most recent initial purchase, and resets to zero after full liquidation. *Holding position*, *Holding profit*, and *Holding period return* refer to the end-of-month market value, displayed profit or loss, and return rate, respectively. These three variables are lagged by one month. Standard errors are two-way clustered at the investor and calendar-month levels. *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable: 100 × *Sell*		
	(1)	(2)	(3)
Gain	3.147***	-2.563***	0.400
	(0.382)	(0.562)	(0.339)
Gain × RL Contrarian		7.558***	
		(0.689)	
Gain × Exp. Contrarian			3.059***
			(0.295)
Log(Months since first purchase)	0.372***	0.400***	0.373***
	(0.114)	(0.114)	(0.114)
Log(Holding position)	2.456***	2.496***	2.457***
	(0.165)	(0.165)	(0.165)
|Holding period return|	-0.785	-0.679	-0.778
	(0.689)	(0.652)	(0.686)
Investor-month FE	Yes	Yes	Yes
Fund-month FE	Yes	Yes	Yes
Observations	9,927,327	9,927,327	9,927,327
Adj. R^2	0.360	0.361	0.360

Table 6: **Disposition Effect and Individual Characteristics**

This table presents individual-level evidence of the relation between disposition effect and individual characteristics, in both the experimental (Panel (a)) and the real-life settings (Panel (b)). *Disposition effect* is measured according to Odean (1998). *Contrarian* dummy is defined according to the methodology detailed in Section 4.2. *High risk tolerance* dummy is a proxy for risk tolerance, defined by whether the individual has an above-median average initial investment amount in the experiment. *Bachelor* is a dummy capturing the highest completed education. *Total Alipay assets* (in CNY) is the average monthly value of all types of assets held via Alipay. The demographic characteristics are measured in the cross-section of July 2021. *p<0.1, **p<0,05, ***p<0.01.

	Dependent Variable: *Disposition Effect*					
	(a) In-experiment			(b) Real-life		
	(1)	(2)	(3)	(4)	(5)	(6)
Contrarian	0.134***		0.141***	0.099***		0.094***
	(0.002)		(0.003)	(0.002)		(0.003)
High risk tolerance		0.004*	0.008***		-0.017***	-0.010***
		(0.002)	(0.002)		(0.003)	(0.003)
Male		-0.030***	-0.024***		-0.013***	-0.013***
		(0.002)	(0.002)		(0.003)	(0.003)
Log(Age)		-0.050***	-0.047***		0.009	0.016
		(0.011)	(0.011)		(0.014)	(0.014)
Bachelor		0.013**	0.011**		0.016**	0.014**
		(0.005)	(0.005)		(0.007)	(0.007)
Occupation						
Blue-collar		-0.022**	-0.029***		-0.007	-0.003
		(0.009)	(0.009)		(0.012)	(0.011)
White-collar		-0.018***	-0.017***		-0.014*	-0.014*
		(0.006)	(0.006)		(0.007)	(0.007)
Log(Total Alipay assets)		0.006***	0.003***		0.002	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	0.059***	0.318***	0.208***	0.013***	0.064	-0.029
	(0.002)	(0.034)	(0.032)	(0.002)	(0.042)	(0.040)
Observations	47,300	16,844	16,844	21,712	7,494	7,494
Adj. R^2	0.115	0.013	0.117	0.121	0.010	0.115

Table 7: **The Role of Realization Preference: Regression Discontinuity Design**

This table presents regression discontinuity results based on an investor–fund–day panel. The specification extends Equation 8 by introducing polynomial controls for holding return rates around the zero-return threshold. **Panel A** summarizes the sample used in the analysis. *Holding period return* is the accumulated return since the most recent purchase, measured as of the previous day. *Holding position* is the market value of the holding as of the previous day. **Panel B** reports regression estimates. The dependent variable, *Sell*, equals one if the investor partially or fully redeems the mutual fund on a given day, and zero otherwise. *Gain* is a dummy equal to one if the holding return as of the previous day is positive. Control variables include lagged holding position and holding length (in days), both in logarithmic form. *p<0.1, **p<0.05, ***p<0.01.

Panel A: Summary Statistics (N = 915,063)

	Mean	SD	Q1	Median	Q3
Sell dummy	0.01	0.11			
Gain dummy	0.53	0.50			
Holding period return (%)	-0.07	0.42	-2.52	0.08	2.34
Holding length (days)	30.19	19.64	13	27	46
Holding position	4219.32	16063.28	100.27	710.34	2953.15

Panel B: Regression Results

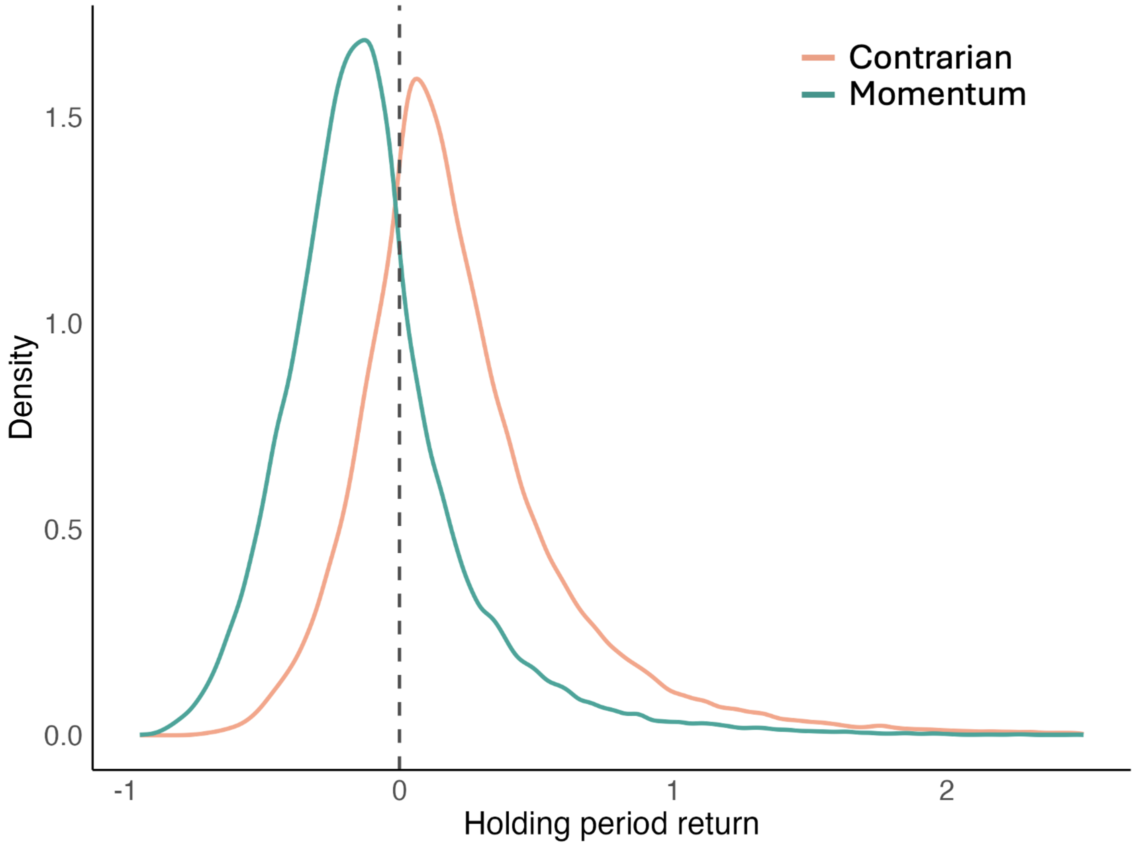
	Dependent Variable: 100 × *Sell*		
Holding length	1 to 21 (1)	22 to 42 (2)	43 to 70 (3)
Gain	0.363***	0.354***	0.148
	(0.105)	(0.124)	(0.117)
Contrarian	0.061	0.144	0.270***
	(0.086)	(0.103)	(0.098)
Gain × Contrarian	0.108	0.086	0.028
	(0.135)	(0.160)	(0.151)
Controls	Yes	Yes	Yes
3rd Polynomials of holding period return	Yes	Yes	Yes
Polynomials × Contrarian	Yes	Yes	Yes
Polynomials × Log(Holding length)	Yes	Yes	Yes
Observations	373,537	276,498	265,028
Adj. R^2	0.001	0.001	0.001

Table 8: **Model-Based Decomposition**

This table presents the model-based decomposition of the disposition effect, in both the experimental decision-level and the real-life transaction-level settings. The disposition effect is measured according to Odean (1998). The investment style is measured according to the methodology detailed in Section 4.2. The *DE w/ jump* and *DE w/o jump* are the fitted disposition effects including and excluding the *Gain* dummy and the associated interaction terms, respectively. The *Effect* is the difference in DE divided by the DE w/o jump.

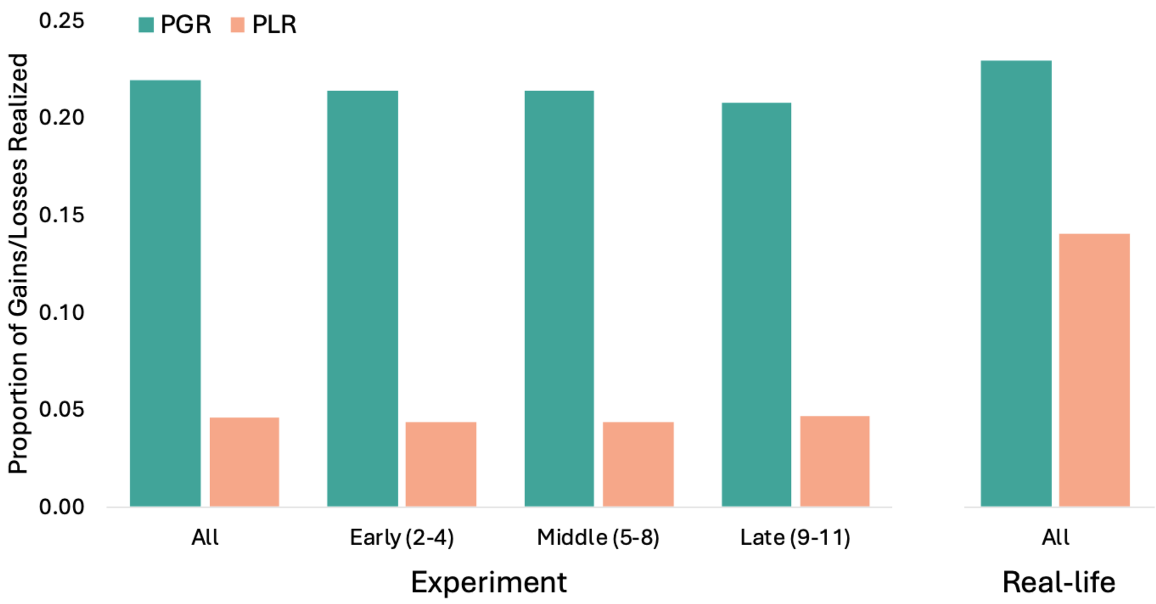
	Experiment		**Real-life**	
Investment style	Contrarian	Momentum	Contrarian	Momentum
DE w/ jump	16.955	4.114	0.539	0.128
DE w/o jump	15.212	3.769	0.504	0.114
Diff. in DE	1.743***	0.346***	0.035***	0.014***
Effect	11.46%	9.17%	6.94%	12.28%

Figure 1: **Toy Model Simulation**



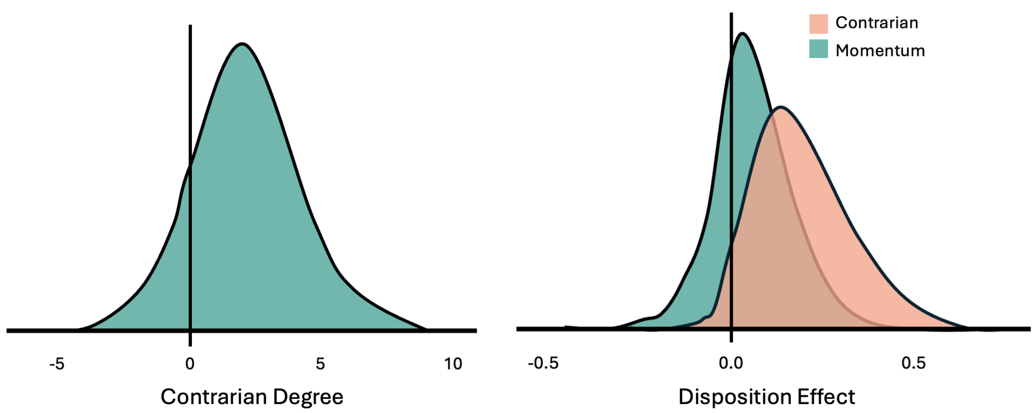
Notes: This figure plots the density of the holding period return $U_t = P_t/C_{t^-} - 1$ conditional on a sale, separately for contrarian and momentum investors, from the mechanical benchmark in Section 2. Agents follow price-based trading rules but never condition on gain–loss status. Prices follow a geometric random walk with zero drift; the cost basis is a volume-weighted average of past purchase prices (Eq. 2). The dashed line indicates zero return.

Figure 2: **Aggregate Disposition Effect**



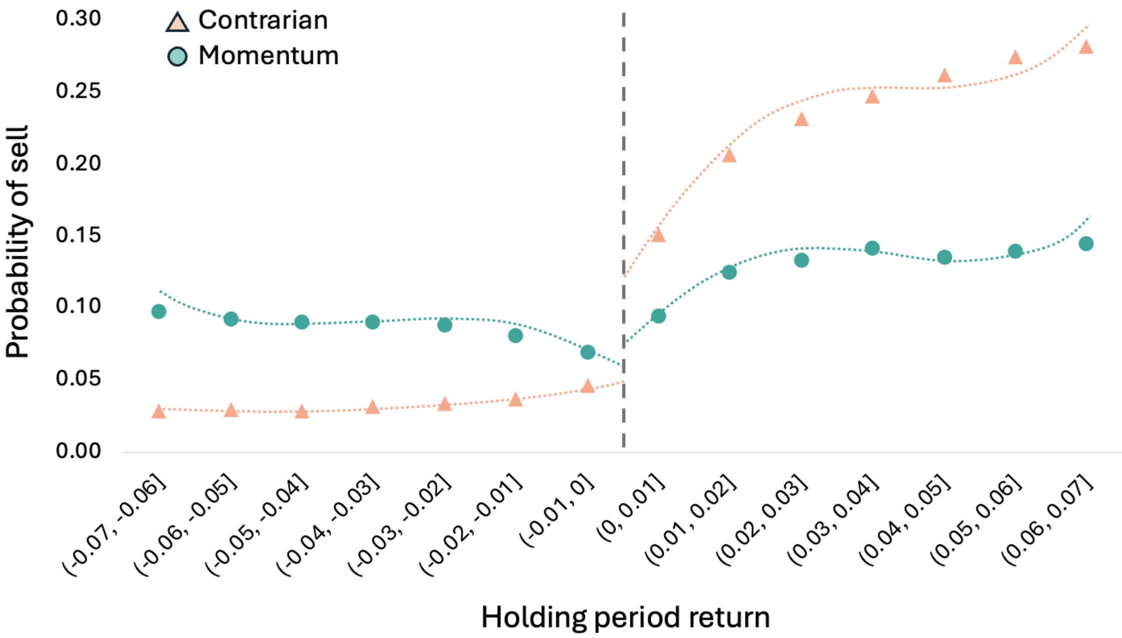
Notes: This figure shows aggregate disposition effect in both experimental and real-life settings. The left panel displays how the prevalence of disposition effect varies over different experiment stages. The sample further restricts the pre-decision risky position to be positive to guarantee the possibility 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. The right panel shows aggregate disposition effect based on real-life investor-fund-month observations. PGR and PLR are defined following Eq. 4 and 5.

Figure 3: **In-experiment: Distribution of CD and DE by Investor Style**



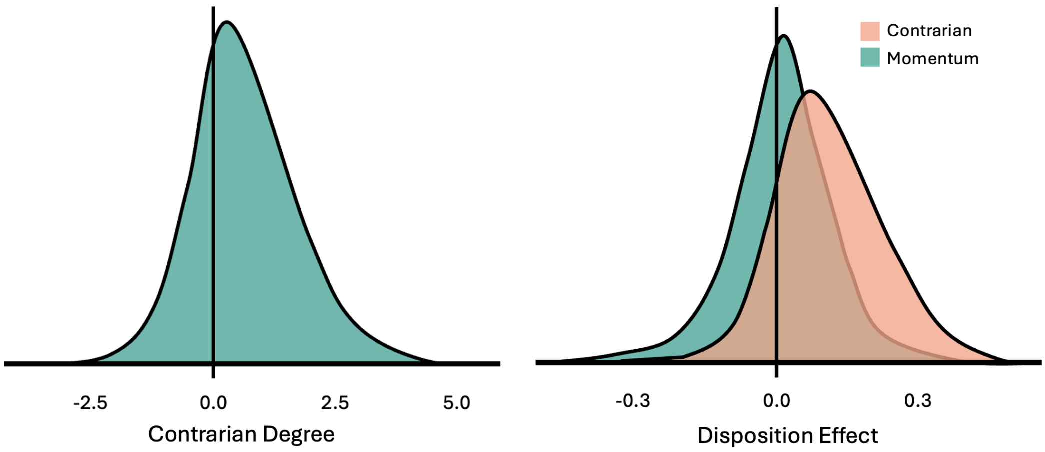
Note: This figure plots the distribution of Contrarian Degree (CD, left panel) and Disposition Effect (DE, right panel) by investor style in the experiment. The CD is measured according to the methodology detailed in Section 4.2. The DE is measured according to Odean (1998).

Figure 4: **In-Experiment: Holding Period Return, Probability of Sell, and Investment Style**



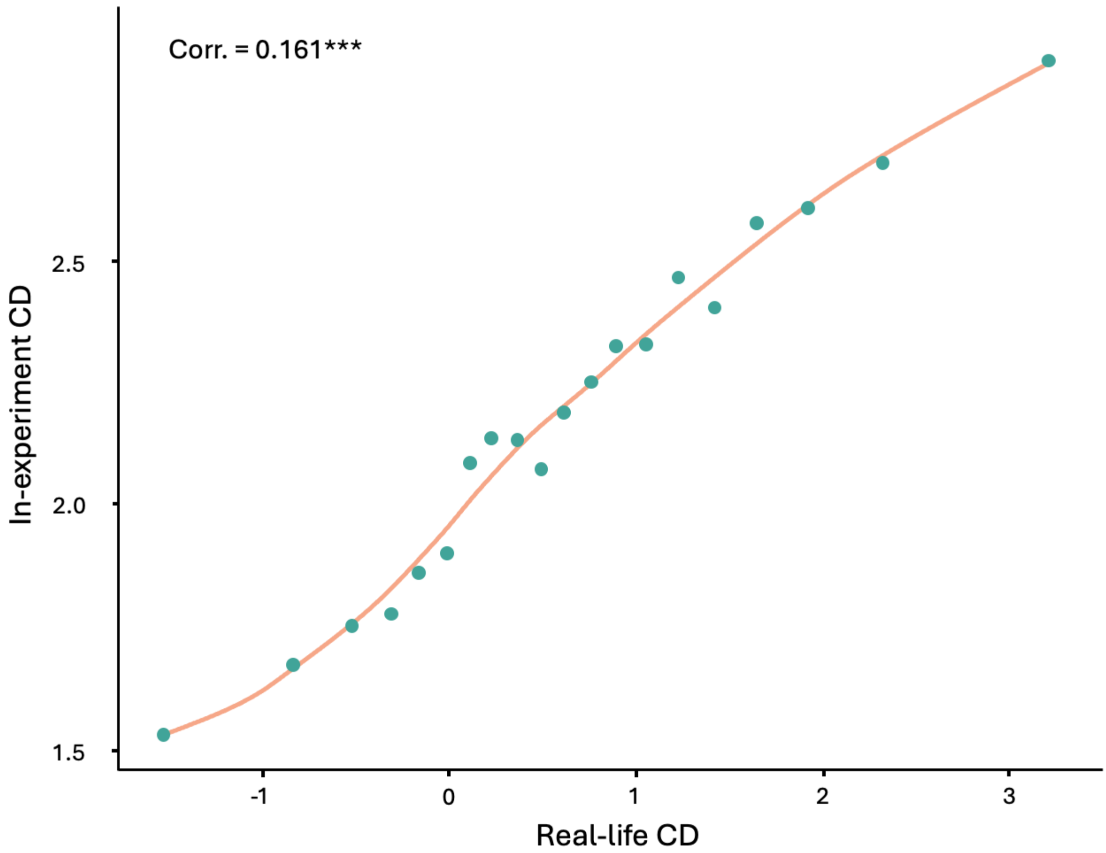
Notes: This figure depicts the relation between current in-game holding period return and probability of selling, covering all decision-level investment decisions except for the first of each game session. The classification method of investor type is described in Section 4.2. The dashed curves are third-order polynomial fits. The dashed vertical line indicates zero return.

Figure 5: **Real-life: Distribution of CD and DE by Investor Style**



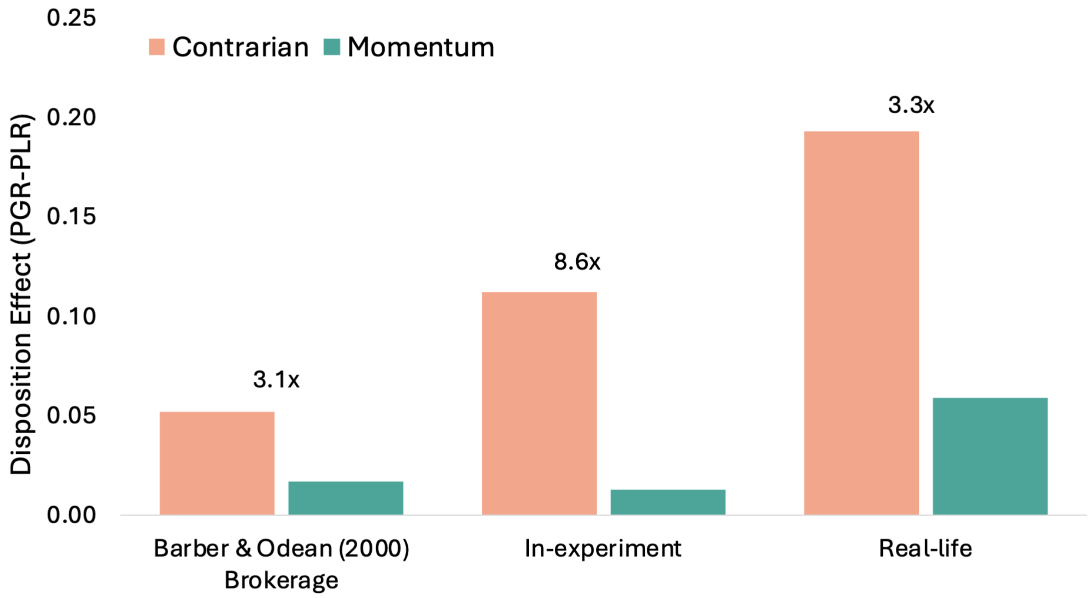
Note: This figure plots the distribution of Contrarian Degree (CD, left panel) and Disposition Effect (DE, right panel) by investor style in the real-life setting. The CD is measured according to the methodology detailed in Section 4.2. The DE is measured according to Odean (1998).

Figure 6: **Cross-Context Consistency of Contrarian Degree**



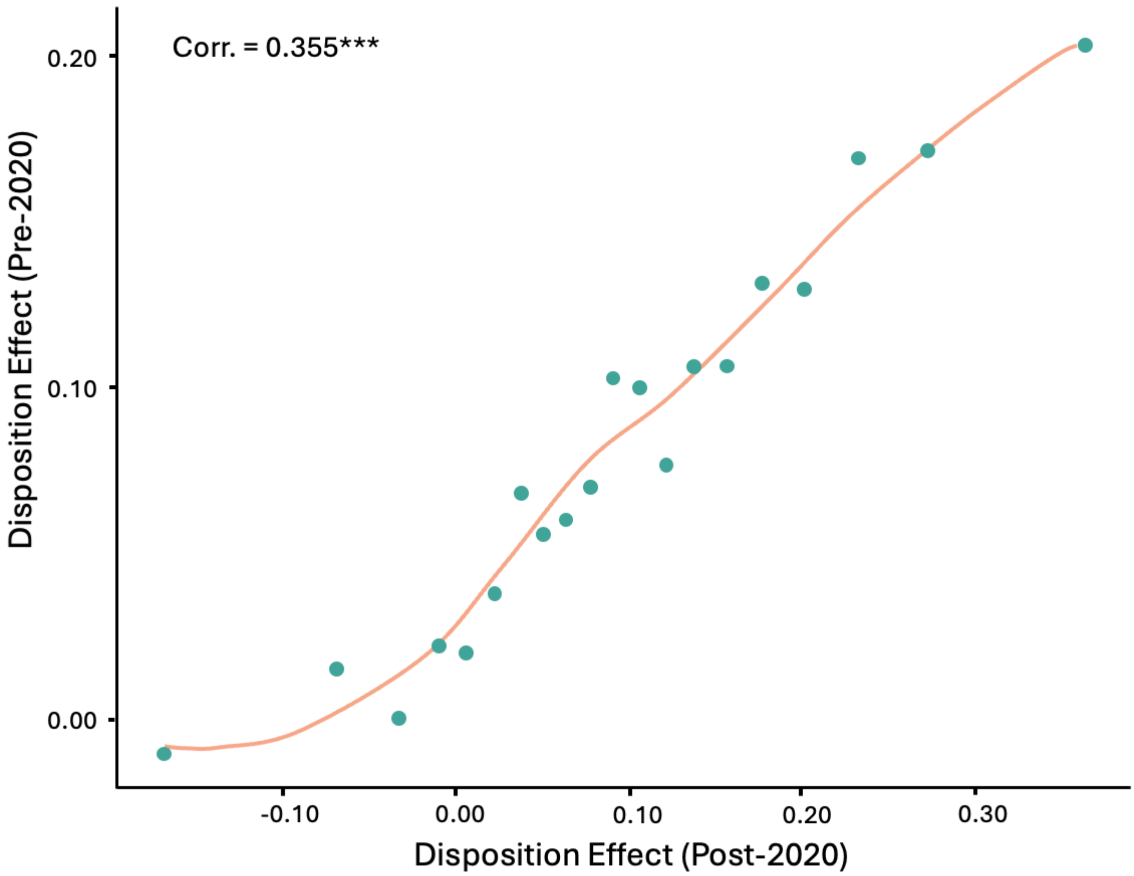
Notes: This non-parametric bin-scatter figure plots the relation between Contrarian Degree (CD) measured in the virtual investment game and in real-life mutual fund trading. Each point represents a bin out of 20 equal-sized bins in total. The orange line is a LOESS fit.

Figure 7: **Cross-style Gap in Disposition Effect**



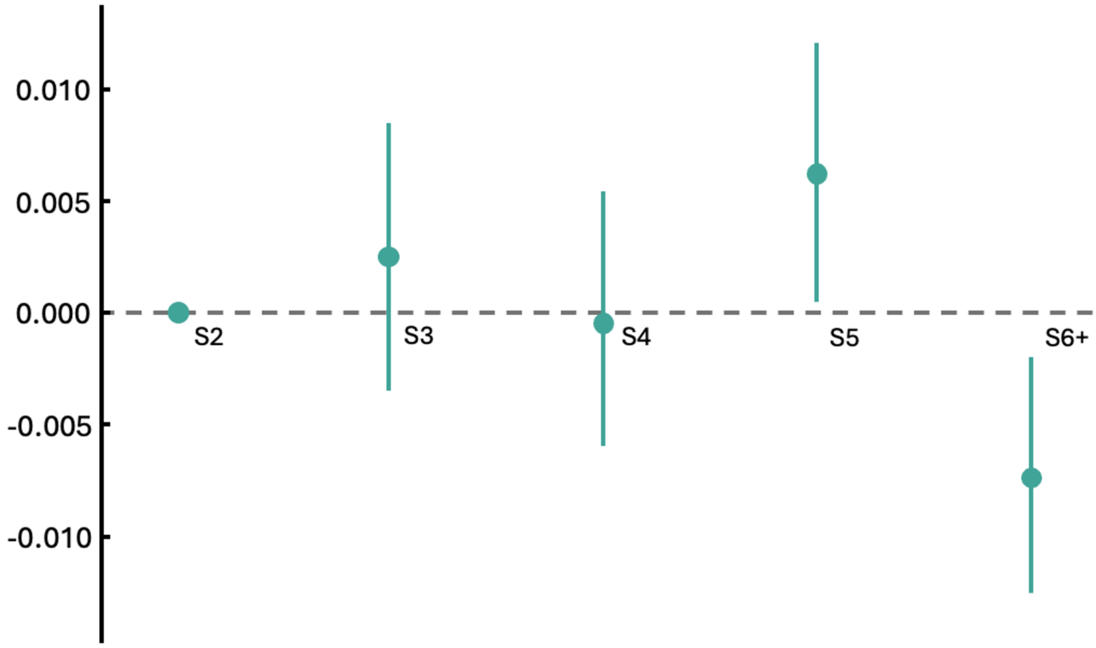
Notes: This figure plots the average disposition effect for contrarian and momentum investors in three different settings as indicated.

Figure 8: **Over-time Persistence of Disposition Effect**



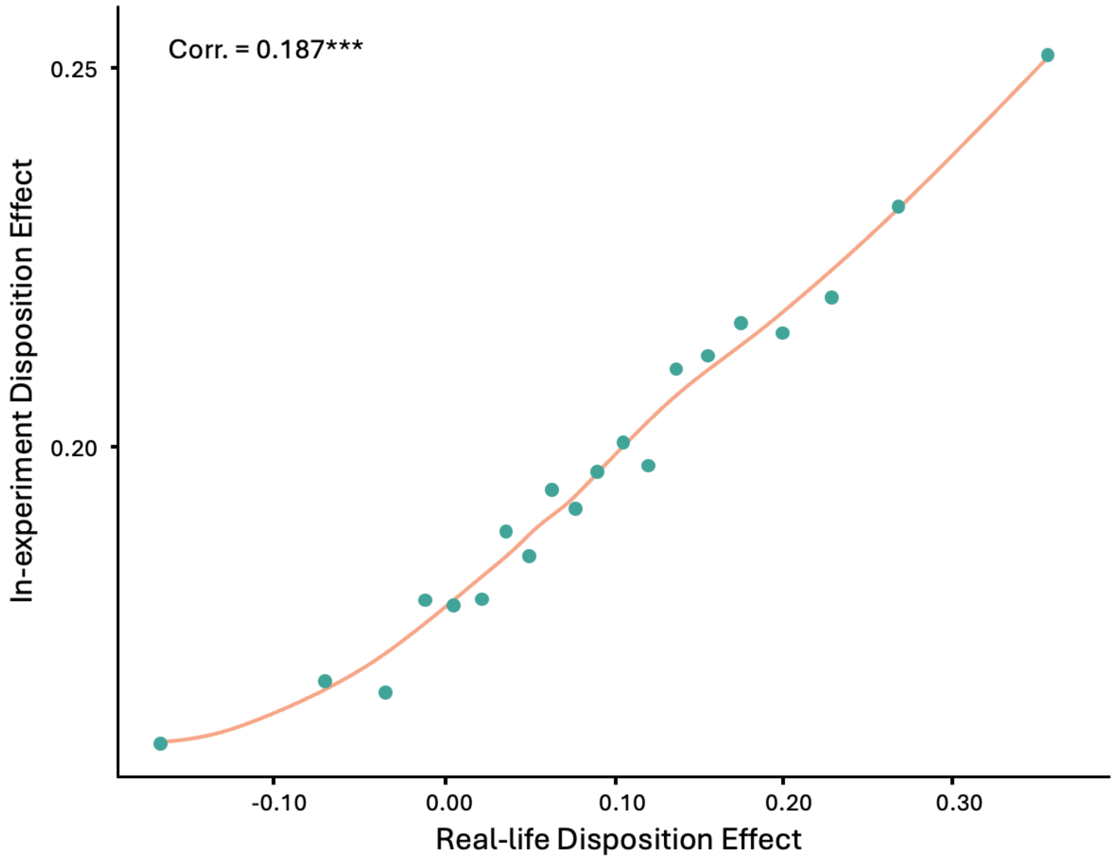
Notes: This figure plots the relation between investors' disposition effects before and after 2020, based on their real-life mutual fund holding changes via Alipay. The figure uses a non-parametric bin-scatter approach with 20 bins, where each point represents the average disposition effect within each bin. The orange curve is a LOESS fit. The sample includes investors with at least 50 monthly observations in both subperiods.

Figure 9: **Learning over Repeated Trading Experiences**



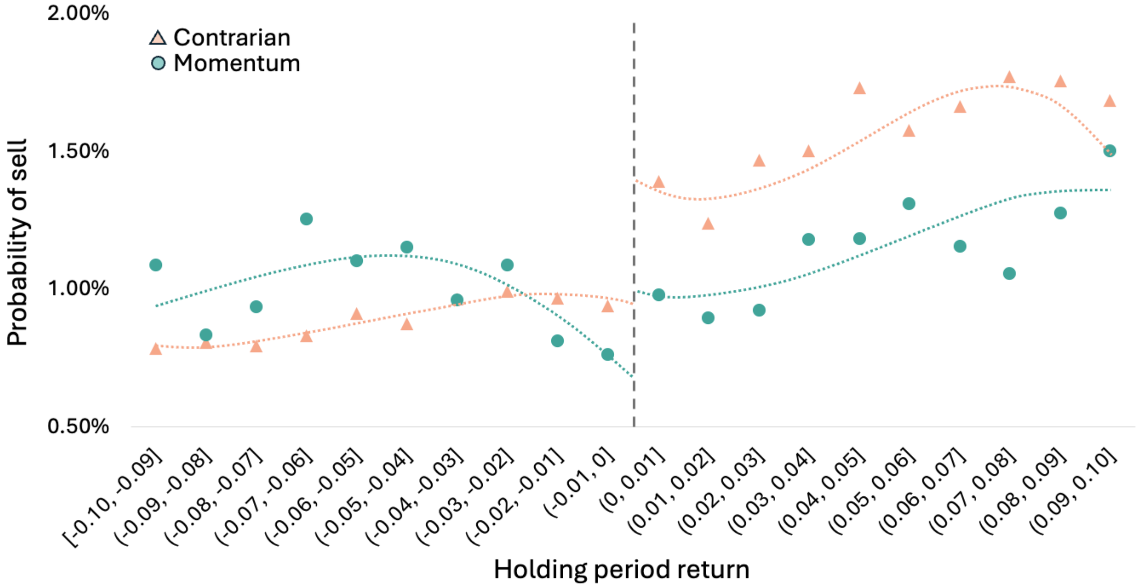
Notes: This figure plots the session order fixed effects on the disposition effect, as specified in Equation 10. The sample includes all the decision-level observations in the experiment. Session 2 is the benchmark session.

Figure 10: **Cross-Context Consistency of Disposition Effect**



Notes: This non-parametric bin-scatter figure plots the relation between disposition effects measured in the virtual investment game and in real-life mutual fund trading. Each point represents a bin out of 20 equal-sized bins in total. The orange line is a LOESS fit.

Figure 11: **Real-life: Holding Period Return, Probability of Sell, and Investment Style**



Notes: This figure depicts the relation between holding period return and probability of sell for pooled observations at investor-fund-day level. The sample excludes observations with a zero position in the previous day, to ensure the possibility of executing a sell order. The classification of investor type follows essentially the description in Section 4.2. The dashed curves are third-order polynomial fits. The dashed vertical line indicates zero return.

A Supplementary Tables

Table A.1: **Disposition Effect and Investment Style among U.S. Retail Investors**

Using the traditional dataset from Barber and Odean (2000), this table presents the regression estimates of the disposition effect and the investment style, largely following Equation 8. The dependent variable *Sell* is a dummy equal to one if the participant reduced their risky asset holdings, and zero otherwise. The *Gain* dummy is equal to one if the participant's accumulated return before the decision is positive. The *Contrarian* dummy is a dummy indicating the sign of investor's investment style, measured in either the experiment or the real-life setting. *p<0.1, **p<0.05, ***p<0.01.

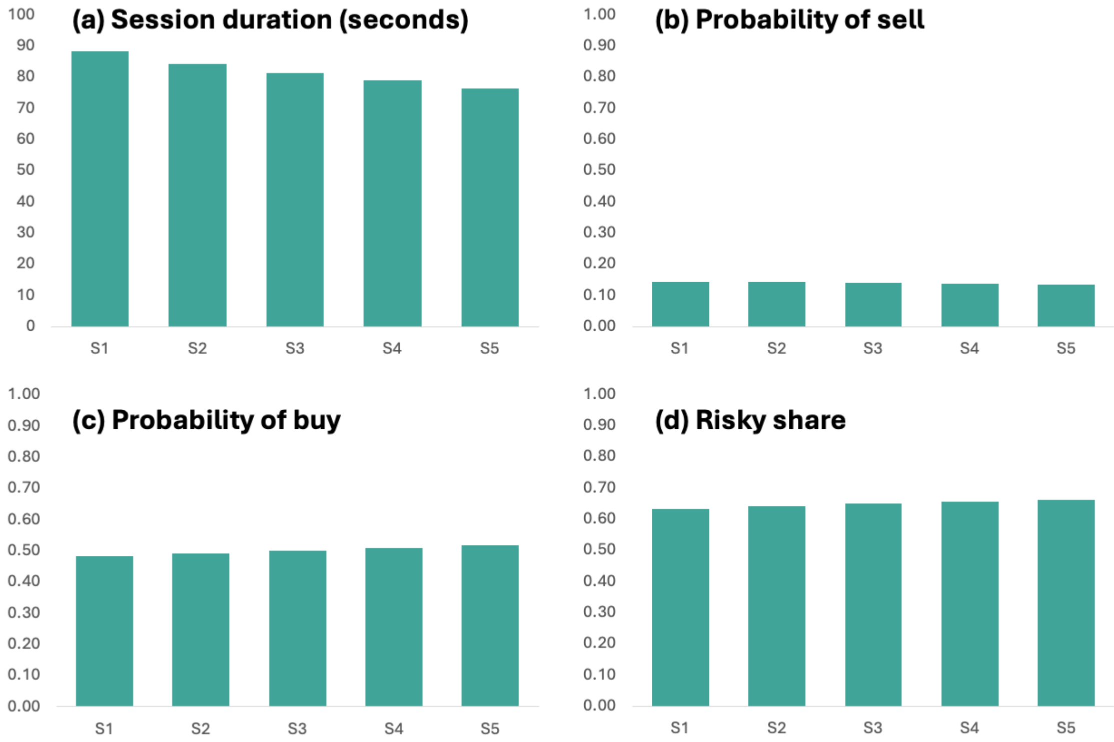
	Dependent Variable: 100 × *Sell*				
	(1)	(2)	(3)	(4)	(5)
Gain	18.247***	18.379***	14.727***	20.269***	20.259***
	(0.247)	(0.247)	(0.358)	(0.401)	(0.401)
Contrarian		3.435***	-0.204	-1.002**	
		(0.247)	(0.357)	(0.468)	
Gain × Contrarian			6.949***	6.950***	6.469***
			(0.493)	(0.535)	(0.537)
Constant	1.155***	-0.713***	1.266***		
	(0.178)	(0.223)	(0.263)		
Stock FE	No	No	No	Yes	Yes
Date FE	No	No	No	Yes	Yes
Investor FE	No	No	No	No	Yes
Observations	57,228	57,228	57,228	57,228	57,228
Adj. R^2	0.087	0.090	0.093	0.173	0.209

B Supplementary Figures

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

Notes: This figure illustrates the interface of the virtual trading game. The participant is presented with a series of price movements in a line chart, and they are given an extra inflow of 1,000 CNY cash in their game account to finance their next decision. They can choose to sell, hold or buy extra of the risky asset, but not short-sell.

Figure B.2: **Decision-level Features over Experiment Sessions**



Notes: This figure plots the game session features, by aggregating over all the decision-level observations for participants' first, second, ..., fifth sessions respectively. These features include (a) the duration of the whole gaming session, (b) the probability of selling, (c) the probability of buying, (d) the risky share. This figure covers their first five game sessions for each participant.