The Fixed Disposition Effect*

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Abstract

We revisit the disposition effect and argue that it is best understood not as a primitive behavioral bias, but as a reduced-form outcome of stable investment styles. Using a unique inter-linked dataset that combines a large-scale experiment with real-world mutual fund transactions, we document strong within-investor persistence in disposition behavior across time and contexts. This persistence is largely driven by a fixed investment style: contrarian investors exhibit a substantially stronger disposition effect, while it is minimal for momentum investors. Investment style explains far more variation in the disposition effect than standard demographic and socioeconomic characteristics. By contrast, realization preference is generally shared. We provide some of the first field evidence that it accounts for roughly 10% of the bias via a sharp jump at the zero-return threshold. Overall, our findings suggest that the disposition effect often emerges as a structural outcome of price-based trading rules, rather than a generic behavioral bias.

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1 Introduction

Since the seminal work by Shefrin and Statman (1985), the tendency of investors to "sell winners too early and ride losers too long," the so-called disposition effect, has emerged as one of the most robust and widely documented behavioral patterns in financial markets. A vast body of evidence, from brokerage data to laboratory experiments, consistently shows that investors are more inclined to realize gains than losses.[1] This tendency persists even after accounting for rational considerations such as transaction costs, portfolio rebalancing, or tax optimization. As a result, the disposition effect is typically treated as a universal and systematic behavioral bias—an outcome variable to be explained by preferences, beliefs, or frictions.

We challenge this conventional perspective. Rather than viewing the disposition effect as a primitive bias, we argue that it is better understood as a stable, investor-specific behavioral trait that varies meaningfully across individuals yet remains highly persistent over time and across decision-making contexts. In this sense, the disposition effect behaves like an individual fixed effect. More importantly, we show that this fixed effect is largely a reduced-form manifestation of deeper and more fundamental heterogeneity in how investors respond to price changes.

We test this interpretation using newly compiled individual-level data from Alipay, one of the world's largest digital financial platforms. A key feature of Alipay is its integration of a behavioral FinTech product: a financial personality test built around a virtual trading game. The game elicits repeated investment decisions in a stylized environment, and participants' experimental behavior can be linked to their own real-world mutual fund trading on the platform over 2017–2021. This integrated design allows us to examine whether behavioral patterns identified in a clean experimental setting generalize to high-stakes real-world decisions—a task that has long been em-

[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 under experimental setups (e.g., Weber and Camerer, 1998; Talpsepp et al., 2014). In real estate markets, Genesove and Mayer (2001) show that homeowners are far more loss-averse in selling decisions than investors in the housing market, leading owner-occupants to hang on to houses longer and set higher asking prices when facing a potential loss.

pirically challenging due to the separation between laboratory and field data. We find strong evidence of such generalization: individual disposition tendencies are highly persistent over time and predictive across contexts.

Our two-setting framework offers several advantages. First, it enables a direct test of within-investor stability across two related but distinct environments: a low-stakes experimental game and a high-stakes, complex financial market. Second, the experimental setting isolates behavior from real-world confounds such as informational advantages, transaction costs, liquidity shocks, or tax considerations. Third, the real-world data capture investor behavior in a modern mobile trading environment with low frictions and frequent return visibility, mitigating concerns that measured behavior reflects inattention or delayed account checking.[2] Moreover, modern platforms provide near real-time return tracking, reducing ambiguity about reference points that is central to identifying the disposition effect (e.g., Meng and Weng, 2018; Pitkäjärvi et al., 2025; Quispe-Torreblanca et al., 2024).

If the disposition effect is stable yet heterogeneous, a natural question is what drives this heterogeneity. We focus on investors' responses to recent price movements—the fundamental source of gains and losses. Closely following Liao et al. (2022), we use a regression-based approach in both experimental and real-world data to isolate each investor's response to recent asset price changes, explicitly controlling for unrealized return status. This yields an investor-level measure of investment style, which we term the Contrarian Degree (CD), distinguishing contrarian from momentum investors. We find that the majority of investors, around 80%, exhibit contrarian trading behavior.

Investment style emerges as a central organizing force behind the disposition effect. Contrarian investors display a substantially stronger disposition effect, whereas their momentum counterparts exhibit only a minimal bias. This large style-based gap

[2] A large body of the literature relies on brokerage data from the early 1990s, reflecting substantially higher trading frictions (e.g., Odean, 1998; Ben-David and Hirshleifer, 2012; Chang et al., 2016). Similarly, administrative data from the late 1990s has been extensively studied (Grinblatt and Keloharju, 2001; Kaustia, 2010). Only a few recent studies exploit data from modern digital trading platforms (e.g., Andersen et al., 2021, 2024; Andries et al., 2024).

is consistently observed in the experimental data, in real-world mutual fund trading, and in a traditional discount brokerage dataset (Barber and Odean, 2000), reaching magnitudes of up to nine-fold. Importantly, investment style itself is highly persistent, echoing the findings of Han et al. (2020). Cross-sectional regressions further show that investment style explains substantially more variation in the disposition effect than standard demographic and socioeconomic characteristics. Taken together, these results indicate that the disposition effect is largely a reduced-form manifestation of investment style rather than an independent behavioral primitive. This relation is structural: as we demonstrate with stylized toy model and simulation, the interaction between price-contingent trading rules and standard cost-basis accounting mechanically generates a disposition pattern. Indeed, a strong disposition effect arises even for "zero-intelligence" agents free from any intrinsic gain–loss preferences

One potential concern is that investment style and the disposition effect may be observationally equivalent. For instance, if investors subjectively interpret holding-period returns as recent price changes. We address this concern in two ways. First, responses to price changes and to gain–loss status are conceptually and empirically distinct, and we explicitly control for return status in our estimation. Second, we exploit the cross-context structure of our data: investment style is cleanly elicited in the experimental setting, while the disposition effect is measured in real-world trading. The strong cross-context predictive power of experimentally elicited investment style alleviates concerns about mechanical equivalence.

While investment style accounts for the majority of heterogeneity in the disposition effect, more universally shared preference-based mechanisms may also contribute. Prospect Theory (Kahneman and Tversky, 1979) predicts greater risk-taking in the loss domain, which could delay loss realization. However, prospect theory alone struggles to quantitatively account for the disposition effect (Kaustia, 2010), motivating refinements such as realization utility (Barberis and Xiong, 2009, 2012; Ingersoll and Jin, 2013).

Although realization utility predicts a discontinuous increase in selling at the zero-return threshold, direct field evidence has remained limited.[3] Using the granular and low-friction nature of our FinTech data, we are among the first to document a sharp and persistent increase in selling probability at the zero-return threshold, consistent with realization preference. This discontinuity is present for both contrarian and momentum investors, indicating that realization preference is broadly shared. However, a model-based decomposition shows that responses to return status *per se* account for only around 10% of the overall disposition effect, rendering realization preference quantitatively secondary to investment style.

Beyond its substantive findings, our paper contributes to a growing methodological literature that integrates experimental and field data to study investor behavior (e.g., An et al., 2024; Andersen et al., 2024). By demonstrating that experimentally elicited behavioral traits generalize meaningfully to real-world financial decisions—consistent with evidence from other domains such as risk-preference elicitation (e.g., Falk et al., 2018)—our approach enables a shift in focus from documenting behavioral outcomes to studying the formation, stability, and distribution of deeper investment styles or beliefs about price changes. In this sense, the disposition effect emerges as a reduced-form manifestation of more fundamental behavioral heterogeneity.

Finally, our findings speak to how digital financial platforms may reshape retail investor behavior by enabling richer measurement of individual decision patterns. If behavioral tendencies such as investment style are stable rather than transient mistakes, one-size-fits-all debiasing interventions are unlikely to be effective. Instead, digital financial environments may facilitate more targeted forms of investor education and guidance that recognize persistent heterogeneity across investors, complementing emerging research on FinTech and household financial welfare (e.g., Agarwal et al., 2023; Barber et al., 2022; D'Acunto et al., 2019).

The rest of the paper is structured as follows. Section 2 introduces the experimen-

[3] Neural evidence in laboratory settings, as well as behavior experiment evidence, supports realization utility (Frydman et al., 2014; Frydman and Rangel, 2014), whereas Ben-David and Hirshleifer (2012) find no such effect in historical brokerage data.

tal setting and data. Section 3 examines the persistence of the disposition effect across time and contexts. Sections 4 and 5 analyze investment style and realization preference, respectively. Section 6 concludes.

2 Experiment and Data

2.1 Platform Background

The experiment is designed and implemented as a virtual trading game by Alipay, one of the leading mobile payment platforms in China as well as around the globe. Before we elaborate the details about the virtual game, it is useful to provide a brief introduction of the platform. 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.

2.2 Experiment Description

2.2.1 Design

The experiment setup, following the spirit of Weber and Camerer (1998), is identical to the one used by Han et al. (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 (11th) active decision, the price will evolve for another period, then the experiment will conclude in accordance with the final asset price and present the eventual investment return rate of the player.

As a key component of the experiment design, the underlying risky asset reflects the real-world market index. More specifically, each and every price path that is randomly assigned to the participant is extracted from the historical prices of the China Shanghai Composite Stock Market Index (SSE Composite) spanning from 2011 to 2018.

Each period in a game session is roughly equivalent to a month in real life, thus making a full game session approximately correspond to one year's market fluctuations. There are in total 160 alternative price paths in the experiment, facilitating substantial variations of market conditions among participants.

2.2.2 Experimental data

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

To exploit the possibility of multi-participation, we randomly select a sample of 50,000 participants with 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 1 summarizes the decision-level data. On average, it takes around six seconds between the two adjacent decisions, suggesting that the participants tend to digest the new information before making the investment decision. The participants seem to trade fairly frequently, and when they trade, they are more likely to buy instead of to sell: 41% of the time they increase the risky position, 13% of the time they do the opposite, while the remaining 46% belongs to not making active trading decisions. Furthermore, they usually do not trade substantially: the average turnover

[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.

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

[Insert Table 1 around here.]

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

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

2.3 Real-life Data

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

The data is organized at investor-fund-month level, spanning over the period of January 2017 - October 2021. Each observation documents end-of-month details including but not limited to fund code, fund name, fund management company, the number of shares, market value (holding position), holding profit and holding return rate. [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 1. 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 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

[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.

average holding-period return rate of 5%, and the majority of the observations carry a positive return.

3 Is Disposition Effect Fixed?

3.1 Disposition effect at aggregate level

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

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

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

The difference *PGR* - *PLR* measures the disposition effect. Figure 1 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.

[Insert Figure 1 around here.]

3.2 The fixed disposition effect

3.2.1 Over-time persistence

The stylized fact outlined above 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). One potential explanation is that the disposition effect is not merely a universal bias that can be easily mitigated through awareness or experience, but rather a stable, investor-specific behavioral trait. In this section, we test this "fixed trait" hypothesis which has two testable predictions: (i) an individual's disposition effect should be stable over time, and (ii) it should also be consistent across different decision-making contexts.

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

To ensure meaningful identification of within-individual stability, we restrict the sample to investors who have at least 50 fund-month observations in both subperiods. We then compute the individual-level *PGR* and *PLR*, as well as the corresponding disposition effect. Figure 2 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).

[Insert Figure 2 around here.]

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

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

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

The results, presented in Table 2, closely mirror those from the real-life setting. Participants who exhibit stronger disposition bias in one session tend to do so again in the next. The 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 3, 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.

[Insert Figure 3 around here.]

3.2.2 Cross-context persistence

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 4 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.

[Insert Figure 4 around here.]

4 The Role of Investment Style

Having established that the disposition effect exhibits strong within-individual stability across both experimental and real-world settings, a natural and arguably more essential question arises: what drives this persistent behavioral pattern? To explore the underlying mechanisms, we focus on how investors react to price movements, namely, the fundamental source of both winning and losing positions. Specifically, we examine whether investors' trading responses to recent price changes can explain the cross-sectional variation in disposition effect strength. 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 which 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 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:

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

Here, $\textit{Turnover}_{i,d}$ 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. $\textit{Recent return}_{i,d}$ is the return since the last decision period of the market index. The variable $\textit{Gain}_{i,d}$ indicates whether the investor has a positive accumulated return up to the decision point, and $|\textit{Player return}_{i,d}|$ is the absolute size of that return. Our coefficient of interest, β_i, captures the sensitivity of trading to recent market movements. 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 5 shows the distribution of CD, revealing that approximately 86% of participants fall into the contrarian category.[6]

[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

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

[Insert Figure 5 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 6 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 5.

[Insert Figure 6 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 An-

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.

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

dries et al. (2024) and Ben-David and Hirshleifer (2012):

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

The dependent variable $\mathit{Sell}_{i,y,p}$ is an indicator for whether investor i reduces their risky position during period p in a game session based on the market path from year y. $Contrarian_i$ 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 3 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 5, 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.

[Insert Table 3 around here.]

4.2 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 structural 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 4, 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 7 visualizes the distribution of the CD as well as the disposition effect by investor style.

[Insert Figure 7 around here.]

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

$$
\begin{aligned}
100 \times \textit{Sell}_{i,f,t} = {} & \delta\, \textit{Gain}_{i,f,t-1} + \beta\, \textit{Gain}_{i,f,t-1} \times \textit{Contrarian}_i + \omega \log(\textit{Holding months}_{i,f,t}) \\
& + \gamma \log(\textit{Holding position}_{i,f,t-1}) + \eta \log(|\textit{Holding period return}_{i,f,t-1}|) \\
& + FE_{i\times t} + FE_{f\times t} + \varepsilon_{i,f,t}, \qquad (6)
\end{aligned}
$$

where i, f, and t denote investor, fund, and month, respectively. The dependent variable $\textit{Sell}_{i,f,t}$ equals one if investor i reduces their position in fund f during month t, and zero otherwise. The dummy variable $\textit{Gain}_{i,f,t-1}$ indicates whether the holding shows a positive unrealized return at the end of month $t-1$. $\textit{Contrarian}_i$ 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 4 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 4 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.

Up to this point, the experimental results demonstrate that investment style is strongly tied to the disposition effect in a clean and controlled environment. Yet the virtual game deliberately removes many real-world frictions, making it ideal for isolating investment style but raising concerns about external validity. By contrast, real-world trading involves genuine financial incentives, but any style measure inferred directly from field trades may be contaminated by constraints and frictions, creating endogeneity concerns.

To address this issue, we exploit the two-setting design and use the investment style estimated from the experiment to explain heterogeneity in real-life disposition behavior. This approach relies on the premise—supported by our earlier findings—that investment style is a stable individual trait. We re-estimate Equation 6 using the experimentally inferred CD. Column (3) of Table 4 shows that the results remain qualitatively unchanged: contrarian investors exhibit a significantly stronger disposition effect in the field, while the effect for momentum investors is statistically insignificant. The fact that experimentally elicited investment style predicts real-world realization behavior underscores that the style–disposition relationship is not mechanical or tautological, but reflects a stable mapping from price-based decision rules to gain–loss realization patterns.

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;

[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.

Greenwood and Shleifer, 2014; Grinblatt and Han, 2005).

4.3 Discussions on the style-disposition relationship

4.3.1 Is the investment style fixed?

Echoing earlier similar exercises, we provide a direct test of the stability of investment style itself by relating the real-life CD to the in-game CD. Figure 8 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. Combined with the findings from Section 3, these results suggest that the fixed disposition effect is largely a manifestation of a fixed investment style.

[Insert Figure 8 around here.]

We argue that this link is structural rather than coincidental. A stable investment style can *mechanically* generate a persistent disposition pattern through its interaction with standard cost-basis accounting, even in the complete absence of intrinsic realization preferences. The mechanism operates through an endogenous shift in the reference point: a contrarian investor systematically accumulates positions on price dips, which mechanically suppresses their weighted-average cost basis. Consequently, when a subsequent price increase triggers a sale, the position is structurally more likely to be in a gain state. Conversely, a momentum investor accumulates on price spikes, inflating the cost basis, and thus realizes losses more frequently upon selling.

This structural perspective challenges the conventional view of the disposition effect as a primitive behavioral bias. Instead, the effect emerges as a reduced-form outcome of price-contingent trading rules. We formalize this intuition in Appendix C, where we show analytically and via simulation that a strong disposition pattern arises even for "zero-intelligence" agents who trade solely based on price trends without any awareness of gains or losses. Consequently, the aggregate disposition effect observed in the market is not a measure of universal irrationality, but largely a reflection of the underlying investor composition.

Our findings unify and extend recent literature on investor heterogeneity. First, the persistence of style aligns with Han et al. (2020), who document stable trading patterns across market scenarios. However, unlike their focus on aggregate buy/sell ratios, our regression-based approach explicitly disentangles the response to price trends from the response to holding-period returns, isolating the specific contribution of style. Second, our results complement Andersen et al. (2024), who find that extrapolators (contrarians) tend to sell stocks with lower (higher) capital gains. While they attribute this to differences in belief formation (forecast bias), our structural mechanism offers a more parsimonious explanation: heterogeneous trading rules mechanically map into heterogeneous realization patterns.

4.3.2 Comparison with other individual characteristics

Now that the investment style seems to be a fixed individual trait, a natural question is whether it is merely a repackaging of standard demographic and socioeconomic characteristics that are also fixed or somewhat stable. Our data allows us to connect the 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 then estimate the following cross-sectional OLS regression:

$$DE_i = \alpha + \beta\, \mathit{Contrarian}_i + \zeta X_i + \varepsilon_i, \tag{7}$$

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 5 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 5 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).

4.3.3 External validity test with the traditional dataset

Another immediate concern is that our findings might be driven by features unique to the Alipay users who are predominantly from China. As an external validation, we now 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 4, 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 9 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 9 around here.]

A set of regression results that follows a simplified version of Equation 6 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.

5 Beyond Investment Style: The Realization Preference

The previous section has suggested that the disposition effect is much less pronounced for momentum investors, and that the heterogeneous investment style is a key driver of the disposition effect. This section aims to empirically examine a leading explanation that is expected to be universally applicable regardless of the investment style.

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 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 the ones with returns slightly lower than 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 10 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 week to accommodate the more frequent data. The figure shares a largely similar pattern with the in-game counterpart (Figure 6). In general, both plots suggest that momentum investors have a higher propensity to sell than contrarians in the loss regime,

[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.

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.

[Insert Figure 10 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. 5 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 6, to account for the possibility that attention decays over time. The coefficients on *Gain* dummy capture the discontinuity around zero return. In contrast to Ben-David and Hirshleifer (2012), we document a statistically significant and economically meaningful jump up to six weeks since the position opening for a given investor-fund pair. 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 extrapolators 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).

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

[Insert Table 6 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 absence of the realization preference. Lastly, we compare the fitted disposition effect based on the two models, and report the difference in Table 7. The results, across in-experiment decisions and real-life transactions, consistently suggest that investors' response to the return status *per se*, arguably largely manifested by the realization preference, could potentially account for around 10% of the disposition effect among the sample investors.

[Insert Table 7 around here.]

6 Conclusion

This paper reconsiders the disposition effect not as a primitive behavioral bias, but as a reduced-form outcome of deeper and stable investment styles. By linking repeated decisions in a large-scale virtual trading experiment to real-world mutual fund transactions on a major digital platform, we document strong within-investor persistence in disposition behavior across time and across contexts. This persistence challenges the conventional view of the disposition effect as a homogeneous investment mistake and instead points to systematic and economically meaningful heterogeneity across investors.

A central finding of the paper is that heterogeneity in the disposition effect is largely driven by heterogeneity in investment style. Investors' responses to recent price movements—captured by persistent contrarian or momentum trading styles—account for the majority of variation in realization behavior. Contrarian investors exhibit a disposition effect that is up to nine times stronger than that of momentum investors, for whom the bias is economically small or even absent. Importantly, investment style itself is highly stable and generalizes from the experimental setting to real-world trading. As a result, the disposition effect observed at the aggregate level largely reflects the composition of investors in the market rather than a universally shared irrationality.

Beyond investment style, we revisit realization preference as a leading preference-based explanation of the disposition effect. Using granular, low-friction transaction data, we document a clear discontinuity in selling behavior around the zero-return threshold, consistent with realization utility. However, a model-based decomposition shows that this channel accounts for only a small fraction—around ten percent—of the overall disposition effect. Realization preference thus operates as a broadly shared but quantitatively secondary mechanism, complementing rather than dominating price-based trading behavior.

Taken together, our findings indicate that realization behavior responds more strongly to price dynamics than to gain–loss status *per se*. When reference points are anchored at purchase prices, price-based trading rules mechanically translate into differential realization of gains and losses. From this perspective, the disposition effect emerges as an outcome of how investors process and react to price changes, rather than as an independent behavioral preference. This interpretation provides micro-foundations for how stable behavioral heterogeneity can shape aggregate trading patterns, return dynamics, and pricing anomalies.

This reframing also has important welfare implications. The disposition effect has long been viewed as evidence of suboptimal trading. Our results suggest that its welfare consequences depend critically on the interaction between an investor's investment style and prevailing market conditions. Investors with little disposition bias may still trade excessively, while investors with a strong disposition effect may be responding coherently to price signals that align with their broader trading strategy. As such, evaluating investor behavior solely through the lens of the disposition effect risks conflating outcomes with underlying decision rules.

These insights have direct implications for investor education and guidance in digital financial environments. If behavioral tendencies such as investment style are stable rather than transient mistakes, 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. Modern FinTech platforms, which naturally generate rich and repeated behavioral data, are particularly well suited to support such targeted approaches.

Methodologically, this study underscores the value of combining experimental and field data to identify psychologically grounded components of investor behavior that are stable across contexts. By disentangling price-based trading rules from preference-based mechanisms, our approach shifts attention from documenting behavioral outcomes to understanding the deeper structures that generate them. More broadly, incorporating persistent behavioral heterogeneity is essential for understanding how individual decision-making aggregates into market-level outcomes in modern financial markets.

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Table 1: **Summary Statistics**

This table provides descriptive statistics on key variables. **Panel A** presents decision-level characteristics after excluding first-periods of each game session. *Duration* is the time spent before making investment decision, measured in seconds. *Buy* and *Sell* dummies indicate the trade decision during the period. *Risky share* is the pre-decision ratio of risky value over total value. *Turnover* is calculated by trade amount over pre-trade risky position, bounded on [-1, 1]. *Market return* refers the performance of risky asset, either during the recent period or since the beginning (namely, [t-1, t] or [0, t]). *Current player return* documents the return rate achieved by the player before making the investment decision. **Panel B** relates to individual demographic and socioeconomic features. *Bachelor* is a dummy capturing the highest completed education. *Total 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 2: **In-Experiment Disposition Effect over Sessions**

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

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

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

This table reports regression estimates based on Equation 5. The data are at the decision level. *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 4: **Real-Life Disposition Effect and Investment Style**

This table reports regression results examining the disposition effect using real-life investor–fund–month observations, based on Equation 6. 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 $\times$ *Sell*		
	(1)	(2)	(3)
Gain	3.147***	-2.563***	0.400
	(0.382)	(0.562)	(0.339)
Gain $\times$ RL Contrarian		7.558***	
		(0.689)	
Gain $\times$ 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 5: **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 4.1. *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 6: **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 6 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

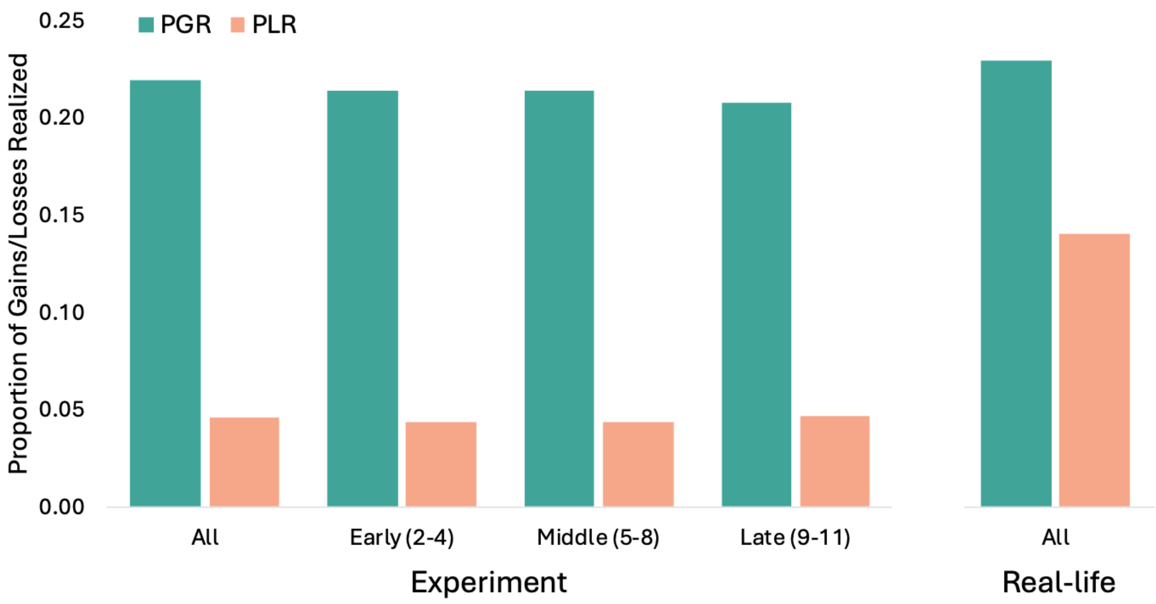
	Dependent Variable: 100 × *Sell*		
Holding length	1 to 21 (1)	22 to 42 (2)	43 to 70 (3)
Gain	0.363*** (0.105)	0.354*** (0.124)	0.148 (0.117)
Contrarian	0.061 (0.086)	0.144 (0.103)	0.270*** (0.098)
Gain × Contrarian	0.108 (0.135)	0.086 (0.160)	0.028 (0.151)
Controls	Yes	Yes	Yes
3rd Polynomials of holding 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 7: **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 4.1. 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.

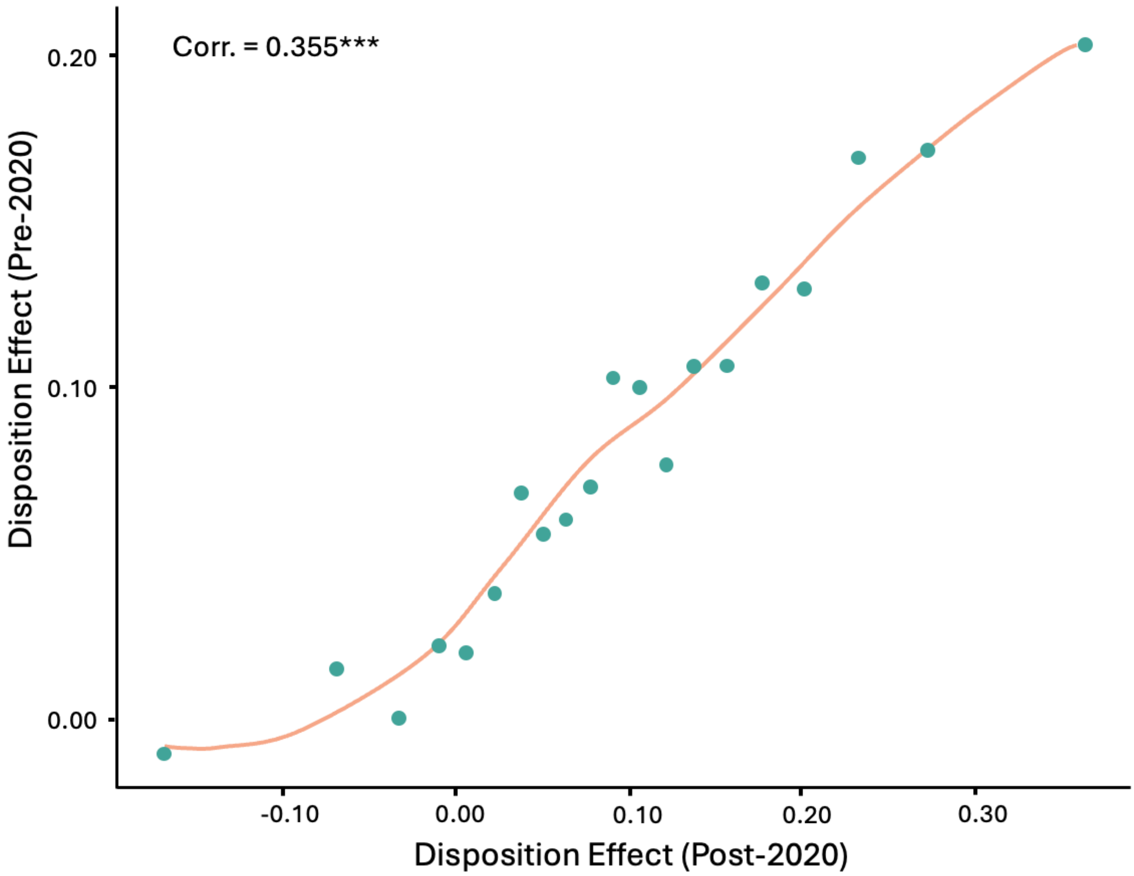
	Experiment		**Real-life**	
Investment style	Contrarian	Momentum	Contrarian	Momentum
DE w/ jump	16.955	4.114	0.539	0.128
DE w/o jump	15.212	3.769	0.504	0.114
Diff. in DE	1.743***	0.346***	0.035***	0.014***
Effect	11.46%	9.17%	6.94%	12.28%

Figure 1: **Aggregate Disposition Effect**



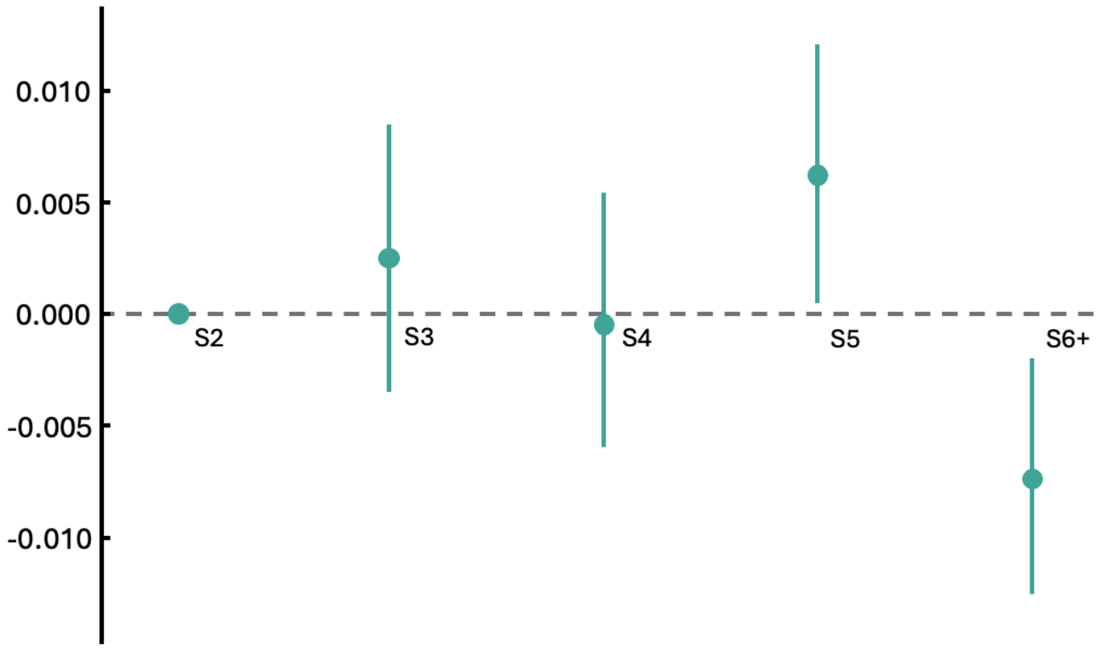
Notes: This figure shows aggregate disposition effect in both experimental and real-life settings. The left panel displays how the prevalence of disposition effect varies over different experiment stages. The sample further restricts the pre-decision risky position to be positive to guarantee the possibility 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. 1 and 2.

Figure 2: **Over-time Persistence of Disposition Effect**



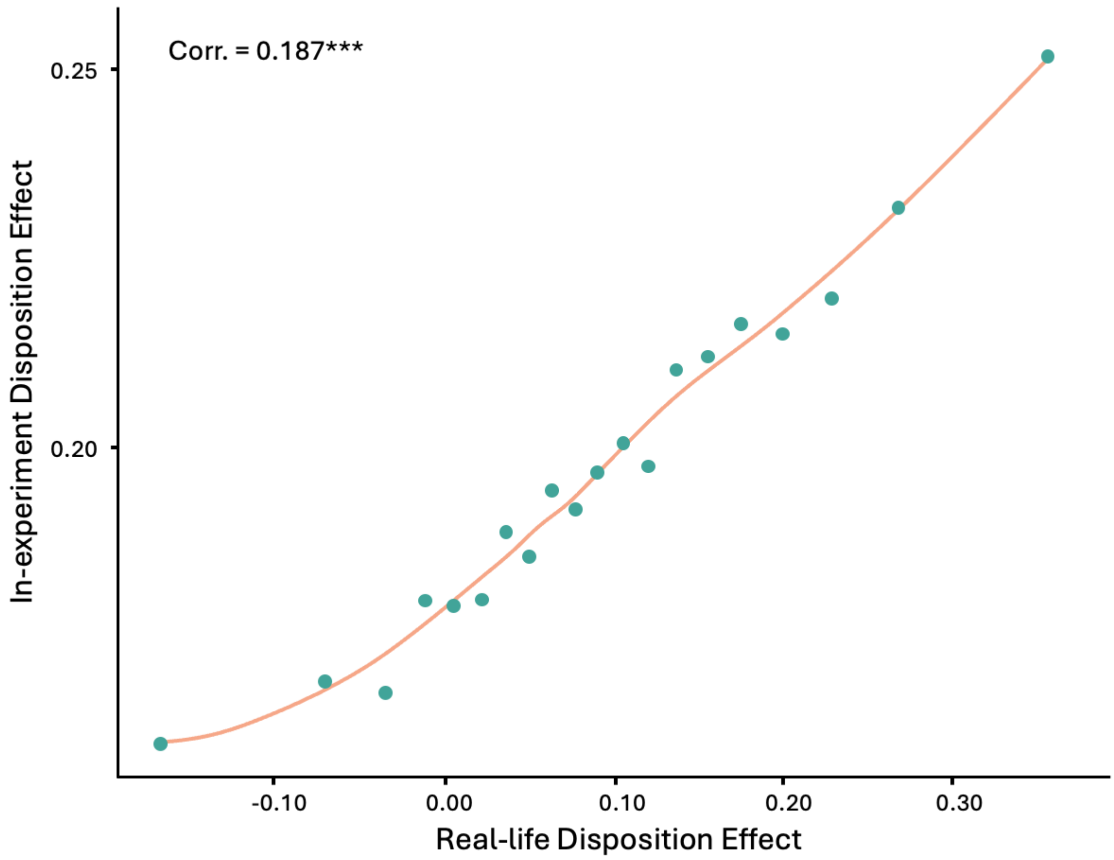
Notes: This figure plots the relation between investors' disposition effects before and after 2020, based on their real-life mutual fund holding changes via Alipay. The figure uses a non-parametric bin-scatter approach with 20 bins, where each point represents the average disposition effect within each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

Figure 3: **Learning over Repeated Trading Experiences**



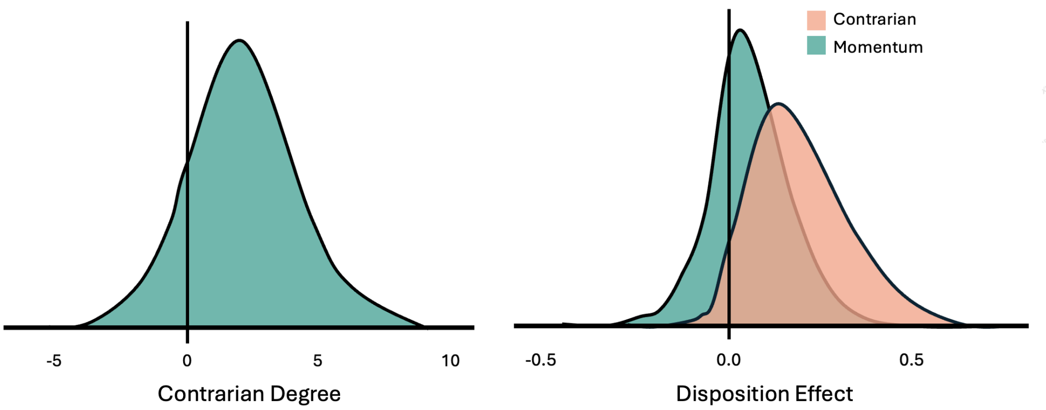
Notes: This figure plots the session order fixed effects on the disposition effect, as specified in Equation 3. The sample includes all the decision-level observations in the experiment. Session 2 is the benchmark session.

Figure 4: **Cross-Context Consistency of Disposition Effect**



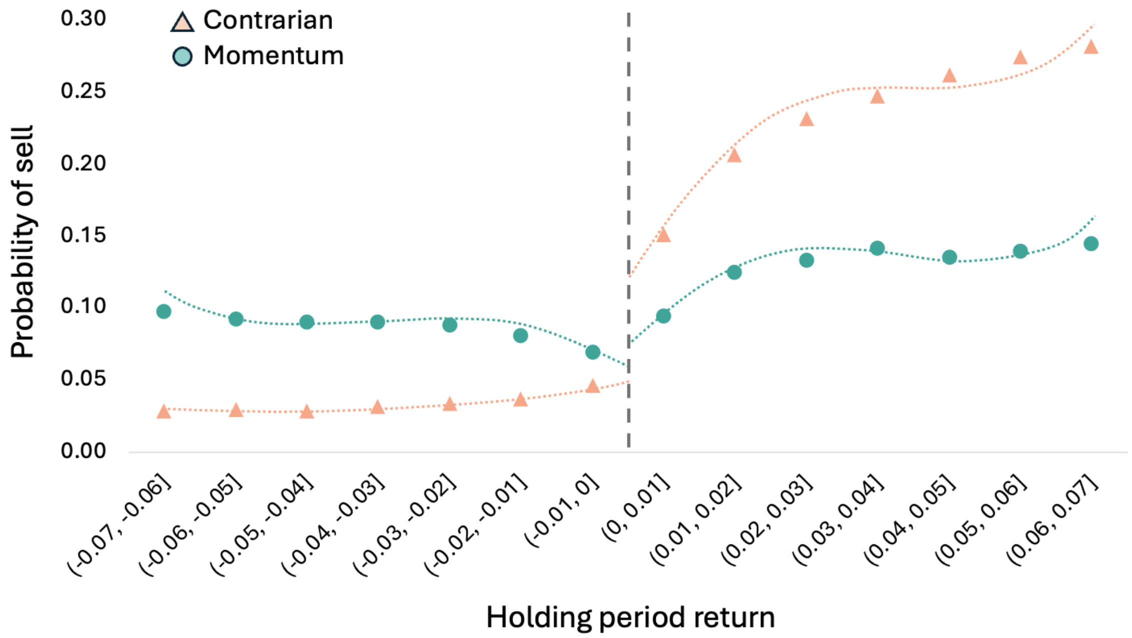
Notes: This non-parametric bin-scatter figure plots the relation between disposition effects measured in the virtual investment game and in real-life mutual fund trading. Each point represents a bin out of 20 equal-sized bins in total. The orange line is a LOESS fit.

Figure 5: **In-experiment: Distribution of CD and DE by Investor Style**



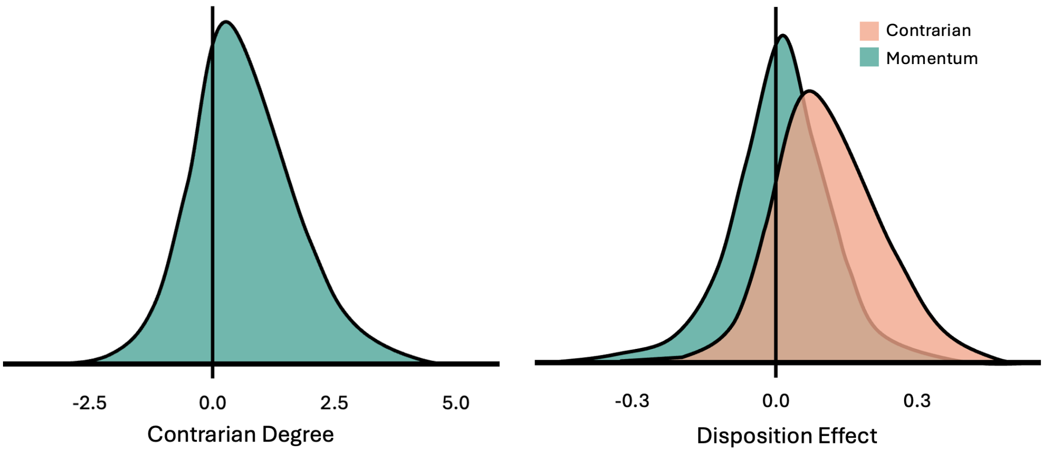
Note: This figure plots the distribution of Contrarian Degree (CD, left panel) and Disposition Effect (DE, right panel) by investor style in the experiment. The CD is measured according to the methodology detailed in Section 4.1. The DE is measured according to Odean (1998).

Figure 6: **In-Experiment: Holding Period Return, Probability of Sell, and Investment Style**



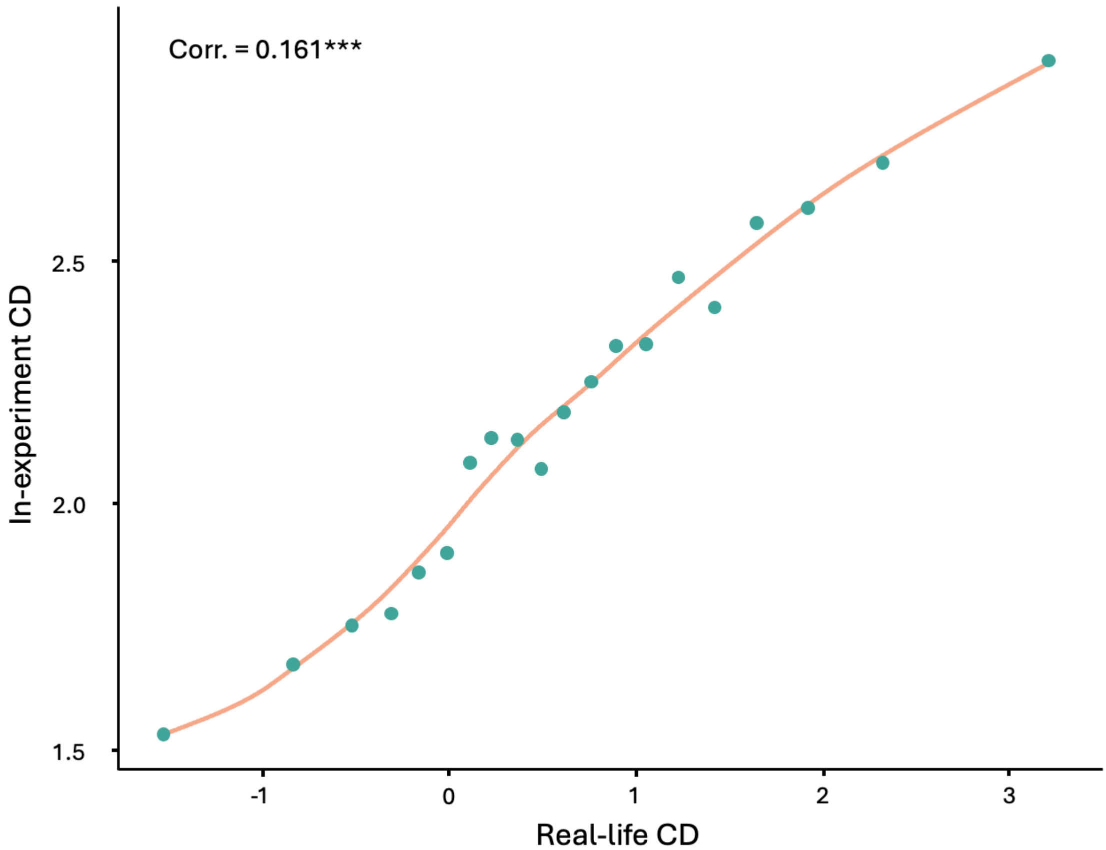
Notes: This figure depicts the relation between current in-game holding period return and probability of selling, covering all decision-level investment decisions except for the first of each game session. The classification method of investor type is described in Section 4.1. The dashed curves are third-order polynomial fits. The dashed vertical line indicates zero return.

Figure 7: **Real-life: Distribution of CD and DE by Investor Style**



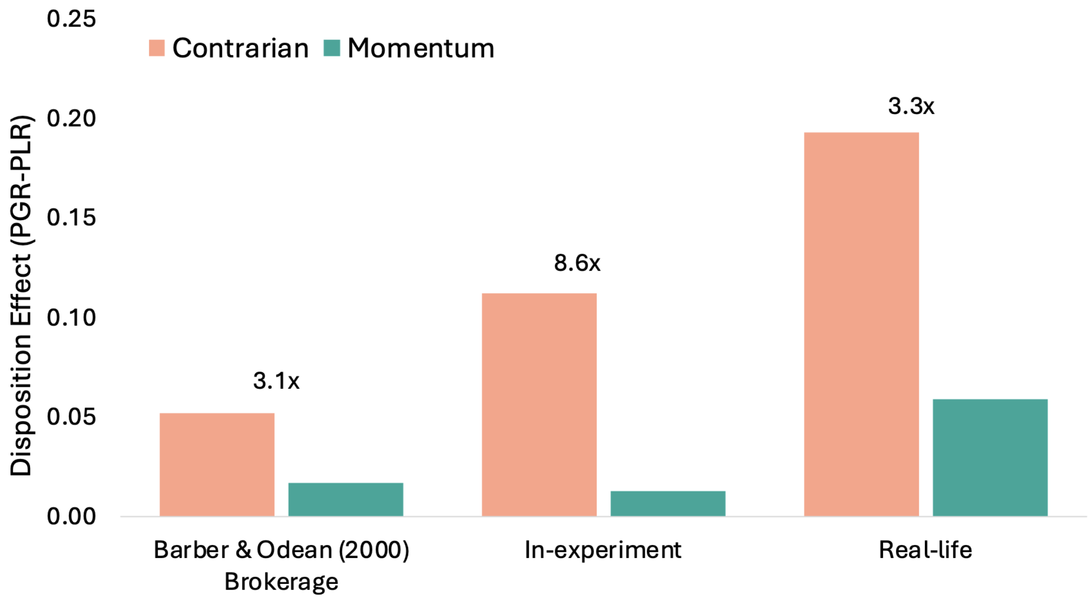
Note: This figure plots the distribution of Contrarian Degree (CD, left panel) and Disposition Effect (DE, right panel) by investor style in the real-life setting. The CD is measured according to the methodology detailed in Section 4.1. The DE is measured according to Odean (1998).

Figure 8: **Cross-Context Consistency of Contrarian Degree**



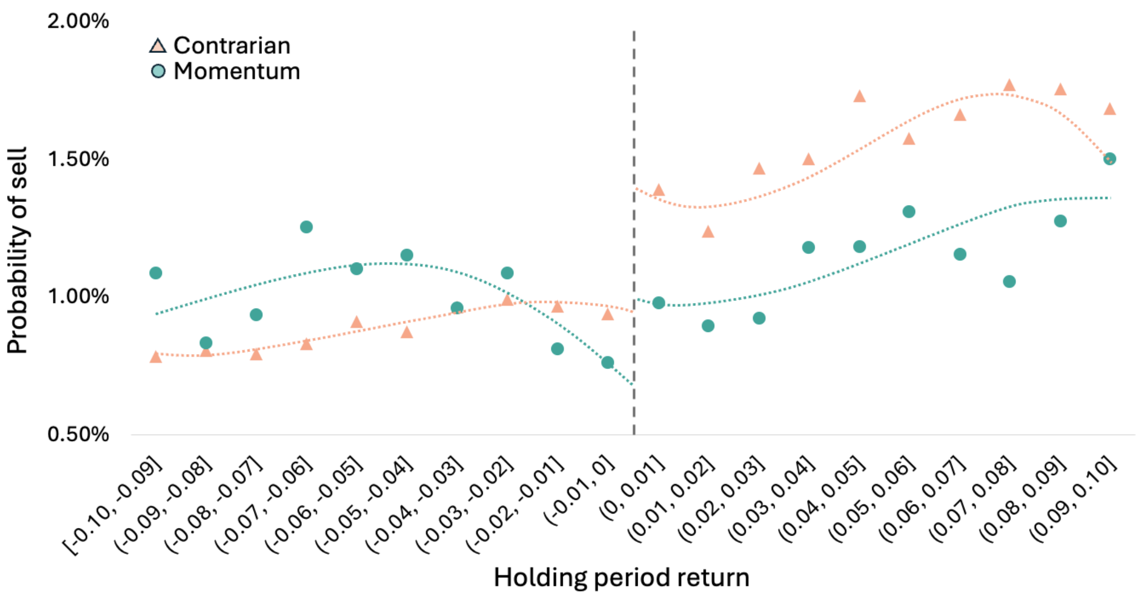
Notes: This non-parametric bin-scatter figure plots the relation between Contrarian Degree (CD) measured in the virtual investment game and in real-life mutual fund trading. Each point represents a bin out of 20 equal-sized bins in total. The orange line is a LOESS fit.

Figure 9: **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 10: **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 4.1. 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 6. 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.

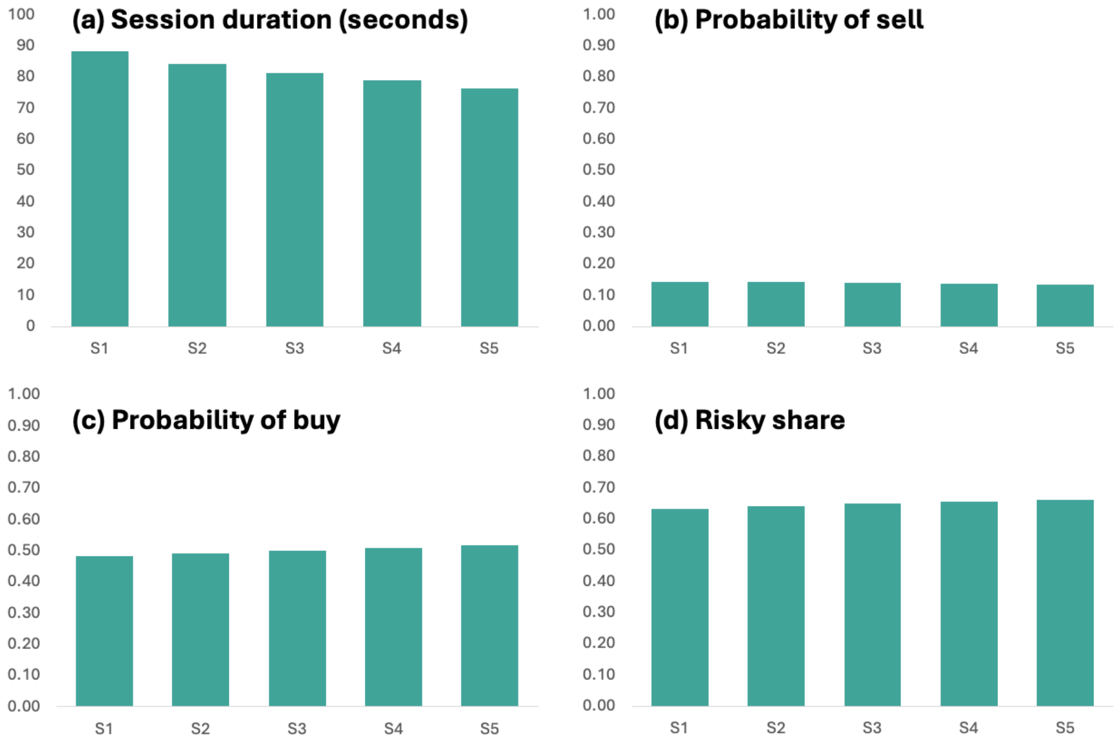
	Dependent Variable: 100 × *Sell*				
	(1)	(2)	(3)	(4)	(5)
Gain	18.247***	18.379***	14.727***	20.269***	20.259***
	(0.247)	(0.247)	(0.358)	(0.401)	(0.401)
Contrarian		3.435***	-0.204	-1.002**	
		(0.247)	(0.357)	(0.468)	
Gain × Contrarian			6.949***	6.950***	6.469***
			(0.493)	(0.535)	(0.537)
Constant	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.

C A Toy Model: Endogenous Cost Basis and Mechanical Disposition

This appendix formalizes the structural intuition that the disposition effect can emerge as a mechanical by-product of investment style once trading flows interact with a platform's cost-basis accounting rule. The key message is simple: even if investors never condition their trading decisions on whether a position is at a gain or a loss, a stable, price-contingent trading rule can endogenously shape the distribution of unrealized returns at *sale times*, generating a disposition-effect-like pattern in reduced form.

C.1 Environment

Time is discrete, $t = 0, 1, \ldots, T$. A risk-neutral investor trades a single risky asset whose price follows a geometric random walk:

$$P_t = P_{t-1} \exp(r_t), \qquad r_t \sim \mathcal{N}(\mu, \sigma^2), \tag{8}$$

where r_t denotes the log return. The investor holds $q_t \geq 0$ shares and cannot short-sell. We abstract from portfolio choice and focus on the mechanics of trading and accounting.

C.2 Investment Style as a Price-Contingent Trading Rule

Investment style is modeled as a deterministic response to contemporaneous price movements. Let $\Delta q_t \equiv q_t - q_{t-1}$ denote net share demand at time t.

We consider two canonical styles:

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

Crucially, the trading rule depends only on the sign of the current return r_t, not on gain–loss status or the holding-period return of the position.

C.3 Endogenous Cost Basis Formation

The platform reports a displayed cost basis C_t computed as a weighted-average purchase price. Consistent with the accounting convention in our empirical setting, the cost basis is updated *only upon purchases* and remains unchanged during partial sales[cite: 11, 202]. If the investor fully liquidates the position, the cost basis resets upon the next purchase.

Consider a sale occurring at time T. Let $\Omega = \{\tau < T : \Delta q_\tau > 0\}$ denote the set of purchase periods since the most recent liquidation. The pre-sale cost basis is

$$C_{T^-} = \frac{\sum_{\tau \in \Omega} \Delta q_\tau P_\tau}{\sum_{\tau \in \Omega} \Delta q_\tau}, \tag{9}$$

a volume-weighted average of historical purchase prices. Under contrarian trading, purchases concentrate in down states, placing larger weights on low prices and mechanically suppressing C_{T^-}; under momentum trading, purchases concentrate in up states, mechanically inflating C_{T^-}.

C.4 Mechanical Mapping from Style to Disposition

The disposition effect is defined over the *sale sample*: investors realize gains more frequently than losses. Accordingly, the relevant object in this toy model is the unrealized return at the moment of sale, measured relative to the *pre-trade* cost basis:

$$U_T \equiv \frac{P_T}{C_{T^-}} - 1, \tag{10}$$

where C_{T^-} is evaluated after observing P_T but before any cost-basis update.

The mechanical channel operates through two interacting asymmetries:

1. **Timing of sales.** Contrarians sell only after up moves ($r_T > 0$), whereas momentum investors sell only after down moves ($r_T < 0$).

2. **Asymmetric cost-basis updating.** The cost basis C_{T^-} is shaped by past purchase prices but is invariant to sales. Since contrarians buy in down states, C_{T^-} is tilted downward; since momentum investors buy in up states, C_{T^-} is tilted upward.

These two forces jointly determine the sign and distribution of U_T at sale times.

Proposition C.1 (Style-induced shift in unrealized returns at sale times) *Conditional on a sale occurring, the distribution of U_T differs systematically by investment style. For contrarian investors, the conditional distribution of U_T is shifted toward positive values; for momentum investors, it is shifted toward negative values.*

Proof sketch. Write the pre-sale cost basis as a weighted average of historical purchase prices, $C_{T^-} = \sum_{\tau \in \Omega} w_\tau P_\tau$ where $w_\tau \geq 0$ and $\sum_{\tau \in \Omega} w_\tau = 1$. Under contrarian trading, w_τ loads on down-state purchase prices, lowering C_{T^-}, and the sale event requires $r_T > 0$, raising P_T relative to P_{T-1}; together these push P_T / C_{T^-} up and shift U_T right. The momentum case follows symmetrically with signs reversed. □

C.5 Simulation evidence: a zero-intelligence agent

We illustrate Proposition C.1 using a "zero-intelligence" simulation in which agents never condition on $1\{U_T > 0\}$, yet a disposition-effect-like pattern emerges mechanically.

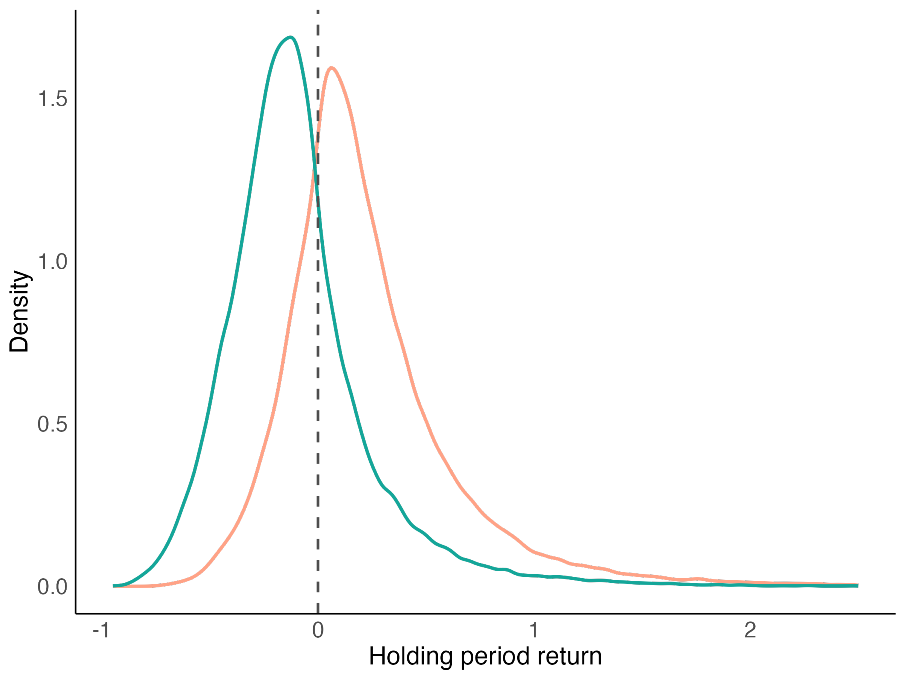
Design choice. We fix the drift at $\mu = 0$ to isolate the interaction between trading style and cost-basis accounting. We then vary volatility and trading intensity to show that these parameters affect the magnitude, but not the direction, of the style-induced pattern.

Setup. We simulate $N = 10{,}000$ independent investors over $T = 20$ periods. Prices follow the log-return process above with $\mu = 0$ and $\sigma \in \{0.1, 0.2\}$. Half of investors are contrarian and half are momentum. Trading intensity scales proportionally with the absolute simple return (denoted `CD_factor` $\in \{1, 2, 3\}$), allowing for partial liquidations and re-entries. For example, a `CD_factor` of 2 suggests that contrarians will invest (liquidate) 2% of their cash (risky holdings) for every 1pp decrease (increase) in the asset price. The opposite applies for momentum investors. The cost basis is updated using the weighted-average method upon purchases and remains fixed during partial sales, resetting only after full liquidation. Each period includes an exogenous cash inflow (1000), and investors start with initial risky-asset wealth and cash of 5000 each, mirroring the lab-in-the-field setting explored in our main text.

Measurement. For each sale event, we compute the holding-period return $U_T = P_T/C_{T^-} - 1$, evaluated at the trade price and prior to any cost-basis update. Because the disposition effect is defined over realized sales, we focus on the distribution of U_T conditional on a sale.

Illustration. Figure C.1 visualizes the conditional-on-sale distribution under a representative parameterization (`CD_factor`$= 2$, $\sigma = 0.2$). Consistent with the mechanism, contrarians sell predominantly in the gain region ($U_T > 0$), whereas momentum investors sell more often around or below zero.

Figure C.1: **Conditional-on-sale distribution of holding period return**



Notes: The unrealized holding period return is defined by $U_T = P_T/C_{T^-} - 1$. The dashed vertical line marks $U_T = 0$. The figure illustrates a representative parameterization with `CD_factor`$= 2$ and $\sigma = 0.2$. Contrarians (in orange) sell disproportionately in the gain region, while momentum investors (in cyan) sell more frequently in the loss region.

Table C.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.

Robustness across volatility and trading intensity. Table C.1 reports the probability of realizing gains and losses conditional on sale, and the implied disposition effect, for a small grid of (σ, CD_factor) values. Define

$$\text{PGR} \equiv \Pr(U_T > 0 \mid \text{Sell}), \qquad \text{PLR} \equiv \Pr(U_T \leq 0 \mid \text{Sell}), \qquad \text{DE} \equiv \text{PGR} - \text{PLR}.$$

Across all configurations with $\mu = 0$, contrarians exhibit a strongly positive DE, while momentum investors exhibit a strongly negative DE. Varying σ and CD_factor affects the magnitude but not the sign of the effect, consistent with the mechanical channel.

Takeaway. The toy model and simulation clarify why, in our setting, a stable investment style can manifest as a stable disposition tendency: the disposition effect is an outcome variable induced by trade timing and cost-basis accounting, rather than a primitive preference for realizing gains. As a result, the aggregate disposition effect observed in the market is not a measure of universal irrationality, but largely a reflection of the underlying investor composition.