The Mechanical Disposition Effect*

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Abstract

The disposition effect is widely viewed as evidence that investors prefer realizing gains to losses. We show that much of this pattern is mechanical: price-contingent trading styles alone can generate disposition-effect-like behavior. Using interlinked experimental and field data and a distinct traditional brokerage dataset, we find that the effect is up to nine times stronger for contrarian than momentum investors. This style is persistent across time and contexts, and so is the disposition effect. A zero-return discontinuity supports realization preference, yet it explains only about 10% of the effect. The disposition effect is therefore a noisy proxy for realization bias.

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1 Introduction

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

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

Our mechanical view has a simple intuition. Investors carrying different price-contingent trading rules mechanically generate different realized gain–loss patterns once cost basis evolves endogenously over time. As the simulation benchmark in Appendix C illustrates, contrarian investors buy after price declines and sell after increases, which depresses their cost basis and makes sales disproportionately likely to

[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., 2025), professional commodity traders (Locke and Mann, 2005), and in laboratory settings (e.g., Weber and Camerer, 1998; Talpsepp et al., 2014). In real estate markets, Genesove and Mayer (2001) show that homeowners are substantially more reluctant to sell at a loss, leading them to hold properties longer and set higher asking prices when facing potential losses.

occur in gain states. Momentum investors exhibit the opposite pattern. As a result, a disposition-effect-like pattern can emerge even when investors have no intrinsic preference for realizing gains or losses. The benchmark therefore yields a sharp empirical prediction: if the disposition effect is largely mechanical, it should vary systematically with investment style.

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

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

[2]Much of the classic literature relies on brokerage or administrative data from the 1990s, when trading frictions were substantially higher (e.g., Odean, 1998; Grinblatt and Keloharju, 2001; Kaustia, 2010; Ben-David and Hirshleifer, 2012; Chang et al., 2016). Only a small number of recent studies exploit data

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

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

We also examine whether investment style itself is stable. We find that style is highly persistent both over time and across contexts, echoing recent evidence on the stability of financial behavior among retail investors (Han et al., 2020; Sui and Wang, 2025) as well as mutual fund managers (Cohen et al., 2026). This stability naturally implies, and we later confirm, that the mechanically induced disposition effect should also appear persistent within individuals, offering a parsimonious explanation for a fact that has often been interpreted as evidence of a universal tendency to realize paper gains.

At the same time, our results do not imply that preference-based mechanisms are absent. Prospect Theory (Kahneman and Tversky, 1979) predicts greater risk-taking in

from modern digital trading platforms (e.g., Andersen et al., 2021, 2026; Andries et al., 2025). Modern platforms also provide investors with much more frequent and salient information on portfolio returns, which is important for identifying the disposition effect (e.g., Meng and Weng, 2018; Quispe-Torreblanca et al., 2024).

the loss domain, and realization utility models (Barberis and Xiong, 2009, 2012; Ingersoll and Jin, 2013) posit a direct utility gain from realizing profits. A key implication of realization utility is a discontinuous increase in selling at the zero-return threshold. Using the granularity of our experimental and FinTech data, we document a sharp and persistent increase in selling probability at exactly this threshold—providing field-level evidence for realization utility that has proved difficult to detect in prior administrative data.[3] Importantly, this discontinuity is present for both contrarian and momentum investors, indicating that realization preference is broadly shared rather than concentrated in particular styles. Quantitatively, however, this channel is modest: under our model-based decomposition, responses to return status *per se* account for only around 10% of the overall disposition effect.

Our paper contributes to a growing literature that combines experimental and field data to study investor behavior (e.g., An et al., 2024; Andersen et al., 2026). The broader implication of our findings is that the measured disposition effect is not a clean statistic for realization preference. Much of what is routinely identified as a primitive behavioral bias reflects instead the footprint of stable, price-contingent decision rules. This perspective shifts attention from documenting behavioral outcomes to understanding the underlying trading rules that generate them, with direct implications for how debiasing interventions should be targeted.

The remainder of the paper is organized as follows. Section 2 describes the experimental design and data. Section 3 develops our investment style measure and tests the central prediction that the disposition effect varies systematically with style across the experiment, the field, and an external brokerage dataset. Section 4 examines the stability of investment style and the resulting persistence of the disposition effect. Section 5 turns to realization preference. Section 6 concludes.

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

2 Experiment and Data

Our empirical strategy rests on two complementary datasets. First, we use a virtual trading experiment embedded in the Alipay platform, which provides a controlled, friction-free environment to measure investment style and disposition behavior. The experiment strips away confounds present in field data—transaction costs, liquidity needs, tax motives, and multi-asset portfolio complexity—that can generate disposition-effect-like patterns for reasons unrelated to trading style. Random assignment of price paths across participants further eliminates selection over market conditions. Second, we link these same participants to their real mutual fund holdings on Alipay over 2017–2021. This linkage is central to our identification: by measuring style in the clean experimental environment and disposition in real-world trading, we can test whether the style–disposition relationship reflects a genuine behavioral mapping rather than a statistical artifact of measuring both quantities in the same context. We describe each dataset in turn.

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. Originally designed to facilitate payments on Taobao, China's largest online shopping platform, Alipay now also features a broad suite of personal financial management tools, including mutual fund investment. As of mid-2020, Alipay serves over 1 billion annual active users. Notably, direct investment in common stocks is not possible via the platform; investors can only access equities through mutual funds, which determines the structure of our field dataset.

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 (11^{th}) active decision, the price will evolve for another period, then the experiment will conclude in accordance with the final asset price and present the eventual investment return rate of the player.

As a key component of the experiment design, the underlying risky asset reflects the real-world market index. More specifically, each and every price path that is randomly assigned to the participant is extracted from the historical prices of the China Shanghai Composite Stock Market Index (SSE Composite) spanning from 2011 to 2018. Each period in a game session is roughly equivalent to a month in real life, thus making a full game session approximately correspond to one year's market fluctuations. There are in total 160 alternative price paths in the experiment, facilitating substantial variations of market conditions among participants. Notably, the participant is not made aware of the source of the underlying price path, even after finishing the experiment.

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 trial 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.

[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.

Panel A of Table 1 summarizes the decision-level data. On average, it takes around six seconds between the two adjacent decisions, suggesting that the participants tend to digest the new information before making the investment decision. The participants seem to trade fairly frequently, and when they trade, they are more likely to buy instead of to sell: 41% of the time they increase the risky position, 13% of the time they do the opposite, while the remaining 46% belongs to not making active trading decisions. Furthermore, they usually do not trade substantially: the average turnover is about 7%, which is defined by the value of trade over current position in the risky asset (i.e., the market index) and is bounded on $[-1, 1]$. The participants in general exhibit meaningful exposure to risk, leading to an average of 55% risky share that is computed by current risky holding over total holdings. 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 a 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.

[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 certificates, 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 are 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

[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. Namely, 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.

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

3 The Role of Investment Style

The disposition effect is conventionally measured as an asymmetric selling response to return status: investors sell positions that are at a gain more readily than those at a loss. Our argument traces this pattern one step upstream. Return status at the moment of sale is itself a product of prior trading behavior: a contrarian investor who buys after price declines accumulates a depressed cost basis, making sales more likely to fall in the gain region; a momentum investor who buys after price increases generates an inflated cost basis, with the reverse implication. Investment style—the systematic response to price changes—thus shapes the distribution of unrealized returns at sale times, and therefore the measured disposition effect. The central prediction is sharp: the disposition effect should vary systematically with investment style. We test it across three distinct settings: the experimental game, real-life mutual fund trading on Alipay, and a traditional U.S. discount brokerage dataset.

To measure investment style, we follow the spirit of Liao et al. (2022) and related work on individual-level heterogeneity in price responses (Andersen et al., 2026), constructing an individual-level measure that captures the extent to which each investor trades against versus in line with recent market returns. Unlike measures designed to capture momentum extrapolation specifically, this measure spans both directions and is signed so that positive values indicate contrarian behavior. We call this the *Contrarian Degree* (CD). We emphasize that CD is a revealed investment style measure—a behavioral pattern that could reflect beliefs, preferences, or rules of thumb—and we deliberately remain agnostic about its psychological origins; what matters for our argument is its predictive content and stability, not its source. We classify individuals as contrarian or momentum traders based on the sign of their CD, and examine how this maps to the strength of the disposition effect.

3.1 Disposition effect at the aggregate level

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

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

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

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.

[Figure 1 around here.]

3.2 Evidence from the experiment

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

$$\begin{aligned} Turnover_{i,d} &= \alpha_i + \beta_i Recent\ return_{i,d} + \gamma_i Gain_{i,d} + \lambda_i |Session\ return_{i,d}| \\ &\quad + \eta_i Gain_{i,d} \times |Session\ return_{i,d}| + \varepsilon_{i,d} \end{aligned} \tag{3}$$

Here, $Turnover_{i,d}$ is the trading activity of investor i at decision d, defined as the traded amount divided by the current risky position, bounded between -1 and 1. $Recent\ return_{i,d}$ is the return since the last decision period of the market index. The variable $Gain_{i,d}$

indicates whether the investor has a positive accumulated return up to the decision point, and $|Session\ return_{i,d}|$ is the absolute magnitude of the investor's accumulated return within the session up to decision point d. 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 style. The left panel of Figure 2 shows the distribution of CD, revealing that approximately 86% of participants fall into the contrarian category.[6]

To get a general sense of how investment style relates to the disposition effect, we first follow Odean (1998) again and compute the difference in the propensity to realize gains versus losses. The right panel of Figure 2 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.

[Figure 2 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 3 shows the resulting patterns. As expected, contrarian investors show a sharp difference in selling likelihood between gains and losses, while momentum investors 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

[6] Previous studies have shown mixed evidence, with various classification methods, in terms of whether an average retail investor exhibits contrarian or momentum style. In Nordic countries like Finland and Sweden, retail investors tend to be contrarians (Grinblatt and Keloharju, 2001; Jonsson et al., 2017), while in the U.S. they tend to be the opposite (Greenwood and Shleifer, 2014). Moreover, when the financial investment context is replaced by a more general forecasting task in order to measure extrapolative beliefs, Andersen et al. (2026) report a mildly higher prevalence of extrapolation among Danish retail investors.

utility theory (Barberis and Xiong, 2012).[7] We explore this preference-based explanation more closely in Section 5.

[Figure 3 around here.]

Up to this point, our evidence has aggregated the HPRs across all decision periods in a simple way. However, as Ben-David and Hirshleifer (2012) points out, this aggregation may not be the best way to capture the interaction between investment style and the disposition effect. To formally test the interaction between investment style and the disposition effect, we estimate the following regression similar to Andries et al. (2025) and Ben-David and Hirshleifer (2012):

$$\begin{aligned} 100 \times \mathit{Sell}_{i,y,p} &= \gamma \mathit{Gain}_{i,y,p} + \beta \mathit{Gain}_{i,y,p} \times \mathit{Contrarian}_i \\ &\quad + \mathit{FE}_i + \mathit{FE}_y + \mathit{FE}_p + \varepsilon_{i,y,p} \end{aligned} \tag{4}$$

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

[7] Both features observed from contrarian-style investors are highly similar to that in Kaustia (2010), but much less so for the extrapolators.

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 4, show highly consistent patterns. In the fully saturated specification (Column 4), the gain–loss asymmetry in selling probability is about 13 pps higher for contrarians, compared to momentum investors who have a baseline disposition effect of about 4 pps. In other words, investment style is a key, even determinant, predictor of the strength of the disposition effect.

[Table 3 around here.]

3.3 Evidence from the field

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

As in the experimental analysis, we classify investors based on their Contrarian Degree (CD), inferred using the same regression-based approach. While the core methodology remains similar to Equation 3, 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. Appendix Figure B.3 visualizes the distribution of the CD and the disposition effect by investor style in the field setting, confirming patterns analogous to those in the experiment.

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

$$
\begin{aligned}
100 \times \mathit{Sell}_{i,f,t} = {} & \delta\, \mathit{Gain}_{i,f,t-1} + \beta\, \mathit{Gain}_{i,f,t-1} \times \mathit{Contrarian}_i + \omega \log(\mathit{Holding\ months}_{i,f,t}) \\
& + \gamma \log(\mathit{Holding\ position}_{i,f,t-1}) + \eta \log(|\mathit{Holding\ period\ return}_{i,f,t-1}|) \\
& + \mathit{FE}_{i \times t} + \mathit{FE}_{f \times t} + \varepsilon_{i,f,t}, \qquad (5)
\end{aligned}
$$

where i, f, and t denote investor, fund, and month, respectively. The dependent variable $\mathit{Sell}_{i,f,t}$ equals one if investor i reduces their position in fund f during month t, and zero otherwise. The dummy variable $\mathit{Gain}_{i,f,t-1}$ indicates whether the holding shows a positive unrealized return at the end of month $t-1$. $\mathit{Contrarian}_i$ 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 pps less likely to sell when holding paper gains than losses.

[Table 4 around here.]

Importantly, these patterns—documented consistently across both the experimental and field settings—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 emerges as a reduced-form outcome of underlying price-based trading rules rather than an independent behavioral primitive.

3.4 External Validity: Evidence from a Traditional Brokerage Dataset

Having documented the style–disposition relationship in the experimental game and in real-life FinTech data, we now ask whether this pattern generalizes beyond the Alipay context. Our primary setting has features that could drive the results: it involves Chinese retail investors, a modern digital platform, and equity mutual funds rather than individual stocks. We address this concern using the canonical dataset of Barber and Odean (2000), which covers U.S. retail investors trading individual stocks at a large discount brokerage firm from January 1991 to December 1996—a different country, a different era, and a setting with substantially higher transaction costs and very different information conditions. 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 3, 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 4 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× and 9× stronger for contrarian investors than momentum ones.

[Figure 4 around here.]

A set of regression results that follows a simplified version of Equation 5 is presented in Table A.1. The pattern is qualitatively consistent with but weaker than the ones we observed in a more modern trading dataset: contrarian investors still exhibit a significantly stronger disposition effect than momentum ones. Taken together, the evidence from all three settings—the experiment, the FinTech platform, and the traditional brokerage—provides robust support for our central prediction: the disposition effect varies systematically with investment style, with contrarian investors displaying a much stronger bias than their momentum counterparts.

3.5 Why the Style–Disposition Relationship Is Not Definitional

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

First, investment style is estimated from responses to recent price changes, explicitly controlling for gain–loss status. Equation 3 isolates how investors adjust their position in response to recent market movements after removing any direct response to whether a position is at a gain or a loss. The Contrarian Degree is therefore conceptually and econometrically distinct from the disposition effect.

Second, we exploit the two-setting design and use investment style estimated entirely from the experiment to predict real-life disposition behavior. The experimental style measure is elicited in a clean, low-stakes environment free of field-specific frictions, while the disposition effect is measured in real-world mutual fund trading with genuine financial stakes. If the style–disposition link were merely a definitional overlap, a style measure from one context should have no predictive power for realization patterns in another. Column (3) of Table 4 shows that the results remain qualitatively unchanged when using the experimentally inferred CD: experimentally classified contrarian investors exhibit a significantly stronger disposition effect in the field, while the effect for momentum investors is statistically insignificant.

Third, the relationship replicates in an entirely different institutional environment. The Barber–Odean dataset covers U.S. retail investors trading individual stocks in the 1990s—a different country, asset class, era, and information environment than the Alipay platform. Despite this, a CD measure constructed from the same methodology identifies the same qualitative pattern (Section 3.4). The consistency across such different environments makes it implausible that the style–disposition link is a statistical artifact of any specific feature of our primary data.

Taken together, the style–disposition relationship reflects a genuine behavioral mapping: investment style, as a systematic response to price movements, propagates through cost-basis accounting into the distribution of return status at sale times, generating the disposition effect as a downstream outcome. Appendix C formalizes and simulates this mechanism, confirming that it generates quantitatively large disposition-effect differences across styles even under simple zero-intelligence trading rules.

Our 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.

Our results also speak to Chang et al. (2016), who report a generally reversed disposition effect for delegated assets such as mutual funds and attribute it to investors shifting blame for poor performance onto fund managers. While we do not dismiss this explanation, investment style heterogeneity may also play an important role. In our context, investors can closely monitor fund performance on a daily basis and submit orders at any time,[8] which likely limits the psychological distancing that underpins the reversed pattern elsewhere. Additionally, if momentum investors self-select into mutual funds while contrarian traders prefer direct stock investment, the aggregate reversed pattern documented by Chang et al. (2016) may partly reflect compositional differences in investment style rather than a universal delegation effect.

More broadly, these findings help characterize the composition of retail investors in terms of investment style. The predominance of contrarian behavior in our sample complements evidence on institutional investors in U.S. and international markets (Badrinath and Wahal, 2002; De Haan and Kakes, 2011) and experimentally observed patterns (Weber and Camerer, 1998), suggesting that mean-reversion-based trading is a broadly shared tendency across investor types and contexts. This composition matters because it provides micro-foundations for how heterogeneous behavioral tendencies shape aggregate return dynamics and pricing anomalies (e.g., Da et al., 2021; Frazzini, 2006; Greenwood and Shleifer, 2014; Grinblatt and Han, 2005), and is especially relevant in emerging markets where retail investors play an outsized role (An et al., 2024; Liao et al., 2022).

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

4 Stable Styles, Persistent Biases

The estimation of CD in Section 3 implicitly treats investment style as a stable individual trait: pooling decisions across sessions assumes that each investor's response to price movements reflects a persistent characteristic rather than a transient state. This section examines whether that assumption is borne out, and traces what it implies for the disposition effect if it is. The mechanical argument makes a sharp prediction: if CD is a stable within-individual trait, then the induced disposition effect should appear persistent too, both over time and across decision contexts. We proceed in three steps: we first verify that CD is stable on both dimensions, then show that this stability carries through to the disposition effect, and finally assess whether the persistence of investment style is merely a reflection of stable demographic characteristics.

The disposition effect is well established as a pervasive cross-sectional pattern, but its within-individual persistence—whether the same investor exhibits it consistently across time and contexts—is a separate and less-documented phenomenon. Under the canonical view, such persistence would reflect a deeply rooted preference for realizing gains, stable because preferences are stable. Our mechanical view offers a different reading: the disposition effect persists within individuals because the underlying investment style persists. This distinction has a direct implication for financial education and debiasing: if the bias is a downstream outcome of stable trading rules, interventions targeted at the realization decision itself are likely to be ineffective. The more productive lever is the upstream response to price movements that drives cost-basis dynamics in the first place.

4.1 Investment Style as a Stable Individual Trait

Figure 5 presents evidence on two dimensions of investment style stability. Panel (a) examines over-time stability within each setting. In the real-life setting, we split each investor's transaction history at January 2020 and estimate CD separately for each subperiod. In the experimental setting, we pool all in-game decisions for each investor across sessions, rank them by chronological order, and divide them into two equally-sized halves; CD is then estimated separately from each half. This design avoids relying on a specific date cutoff and instead exploits the full within-investor time variation from repeated participation. The strong positive association between early- and late-period CD estimates—over-time correlation of 0.30, significant at the 1% level—confirms that an investor's style classification is not sensitive to when in their history it is measured.

Panel (b) plots the cross-context relationship between experimentally and field-estimated CD using a non-parametric bin-scatter. Despite substantial differences in context, asset type, and data frequency, investors who trade more contrarian in the game also do so in real-life mutual fund trading, with a cross-context correlation of 0.16 (significant at the 1% level).

[Figure 5 around here.]

Together, the two panels establish that investment style is stable both across contexts and over time—precisely the condition required for the mechanical channel to generate persistent disposition effects. This evidence connects back to the formal benchmark in Appendix C: the stable contrarian and momentum rules assumed there are themselves empirically documented features of investor behavior. We now test whether this stability carries through to the disposition effect.

4.2 Persistence of the Disposition Effect

We now test whether the stability of investment style documented above carries through to the disposition effect itself. Figure 6 presents non-parametric bin-scatter evidence on two dimensions. Panel (a) examines over-time stability in the real-life setting. We split each investor's transaction history at January 2020, a cutoff that provides a roughly even split of the 2017–2021 sample period and coincides with the COVID-19 outbreak—a plausibly large shock to investor behavior and market sentiment. Restricting to investors with at least 50 fund-month observations in both subperiods, we compute individual-level DE for each half. The strong positive association between pre- and post-2020 DE, with a correlation of 0.355 (significant at the 1% level), indicates that the bias persists within individuals even across a period of substantial macroeconomic disruption.

Panel (b) plots each investor's experimentally elicited disposition effect against their real-life counterpart. The experiment and field settings differ substantially—single risky asset versus a multi-fund portfolio, low stakes versus real money, controlled price paths versus actual market conditions—so cross-context predictive power is a demanding test of individual-level stability. Nevertheless, the association is clear, positive, and monotonic, with a cross-context correlation of 0.187 (significant at the 1% level). As a benchmark, Sui and Wang (2025) document a correlation of 0.132 in a setting where investors trade in real and simulated environments under the same information set; our estimate is somewhat higher, likely reflecting the more distinct decision contexts in our design.

[Figure 6 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 and estimate:

$$DE_{i,j} = \alpha_i + \beta \cdot DE_{i,j-1} + FE_n + \varepsilon_{i,j} \tag{6}$$

where $DE_{i,j}$ denotes the disposition effect of investor i in their j^{th} experimental session, α_i is an individual fixed effect, and FE_n denotes session-order fixed effects. Standard errors are clustered at the investor level. Column (1) estimates the univariate specification without fixed effects; Column (2) adds individual fixed effects; Column (3) further adds session-order fixed effects.

Table 2 presents the results. The most informative contrast is the jump from Column (1) to Column (2): raw R^2 rises from 4.9% to 41.9%, and adjusted R^2—which penalizes for the large number of individual fixed-effect parameters—from 4.9% to

21.0%. Even after this penalty, the fourfold increase confirms that stable individual-level differences in DE account for the dominant share of explainable variation across sessions—the individual fixed effects themselves are the persistence result. The univariate coefficient of 0.219 (significant at the 1% level) confirms that past DE positively predicts future DE across sessions. The coefficient flips to -0.136 in Column (2), a reversal that reflects Nickell (1981) bias rather than genuine mean reversion: with a median panel length of 7 sessions, the bias is of order $-1/(T-1) \approx -0.17$, sufficient on its own to account for the observed negative sign.

Column (3) examines whether the disposition effect systematically trends over repeated participation—a within-individual test for learning. Prior evidence suggests that investor experience and financial sophistication may attenuate the disposition effect (e.g., Calvet et al., 2009; Costa et al., 2013; Feng and Seasholes, 2005), though this is based largely on cross-sectional comparisons. Here we can test it directly within individuals. The R^2 is unchanged relative to Column (2), and the session-order coefficients are economically negligible: the largest is 0.008 for Session 5, against an average DE of 0.166 among participants' first sessions. If anything, the disposition effect edges marginally upward in later sessions—the opposite of what learning would predict.

4.3 Investment Style versus Demographics

The evidence above establishes that investment style is a stable individual trait, and that this stability propagates into a persistent disposition effect. A natural follow-up question is whether this stability simply reflects the persistence of standard socioeconomic characteristics. Demographics such as age, gender, and wealth are themselves relatively stable over time, so if investment style were merely a proxy for these factors, the persistence documented above would carry no additional insight beyond what standard heterogeneity models already imply. Our data allow us to assess this directly by connecting each investor to their basic socioeconomic information: age and gender (mandatory for Alipay account activation), as well as self-reported education, occupation, and average total assets held on the platform as a proxy for wealth.

We 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 investors' risk tolerance, we proxy it by the average initial investment amount in the experiment—a plausible measure given that the initial decision is made before any price information is revealed. We define the *High risk tolerance* dummy as this average 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. Two results stand out. First, the coefficient on the contrarian dummy is large, highly significant, and 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). Wealth-based explanations are quantitatively small: a one-standard-deviation change in log total Alipay assets translates into only about a 0.005 change in the disposition effect. Second, this dominance is reflected in explanatory power: including investment style raises the adjusted R^2 from 1.3% to 11.7% relative to demographics alone. Columns (4)–(6) report highly consistent results in the real-life setting.

[Table 5 around here.]

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. Investment style captures a behavioral dimension that is stable within individuals and not reducible to observable socioeconomic characteristics, reinforcing the interpretation that the persistence of the disposition effect reflects a genuine underlying trait rather than a demographic artifact. 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.

One further pattern deserves mention: education and wealth proxies are both positively and significantly associated with the disposition effect. Investors with higher educational attainment or more financial assets tend to display a slightly stronger bias—a finding that 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).

Having established that the disposition effect is a persistent individual trait driven by stable investment style rather than demographics, Section 5 asks whether any residual preference for realizing gains operates beyond the mechanical channel.

5 Beyond Mechanical: the Realization Preference

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

More specifically, we leverage our comprehensive and granular data to re-visit the role of realization preference (Barberis and Xiong, 2012; Ingersoll and Jin, 2013). The idea is that investors gain a burst of utility from realizing gains instead of keeping paper gains, making them refrain from realizing losses unless facing a liquidity shock. Following this, we would expect a discontinuity around zero return: investors with returns incrementally greater than zero should be significantly more inclined to sell their holdings than those with returns slightly below zero. Despite the straightforward intuition, there is limited field evidence supporting this notion—non-traditional neural data manages to do so (Frydman et al., 2014), while virtually no effect is detected in the trading history data (Ben-David and Hirshleifer, 2012).

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

We alleviate these concerns thanks to our modern setup. However, the investor-fund-month dataset used in previous sections, despite the relatively large sample size, does not fit our needs. This more 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]

[9]Note that, however, we do not link this extra sample to the experiment because the sample was ex-

With the more frequent data, we first present in Figure 7 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 3). In general, both plots suggest that momentum investors have a higher propensity to sell than contrarians in the loss regime, while this pattern reverses in the gain regime; it persistently exhibits a somewhat distorted X-shape. More intriguingly, we notice a similar discontinuity of probability around the zero-return cutoff.

[Figure 7 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 investors' 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. 4 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)

tracted from the Alipay investor population, and only a small fraction of the sample has an experiment participation record.

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

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". To quantify the economic magnitude following Ben-David and Hirshleifer (2012), the final row of Panel B reports the ratio of the *Gain* coefficient to the unconditional sell probability. For holdings up to six weeks, this ratio reaches 27–28%, indicating that crossing from loss into gain territory raises the daily sell probability by more than a quarter relative to the baseline. The ratio declines to 11% for longer holding horizons, consistent with the attention-decay pattern noted above.

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 momentum and contrarian investors exhibit a jump of selling probability when the holding return rate crosses the return border from the loss to the gain regime, which we interpret as a piece of evidence in favor of the realization utility theory (Barberis and Xiong, 2012).

[Table 6 around here.]

As a final exercise, we carry out a model-based decomposition to further quantify the contribution of realization preference to the disposition effect. The idea is to manually shut down the channel that is directly associated with response to return status. Put differently, we remove all the terms related to the *Gain* dummy from the RDD specification, and then fit the return-status-free model to estimate the probability of sell, thus calculating the disposition effect in the absence of the realization preference. We compare the fitted disposition effects from the two models and report the difference in Table 7.

The 10% share reported there should be read alongside the up-to-28% ratio from Table 6, as the two statistics measure different objects. The 28% figure is the *local* marginal effect of crossing the zero-return threshold on the daily sell probability, estimated among investors with holding periods of up to six weeks—precisely the attentive, short-horizon cases where the discontinuity is sharpest. The 10% figure in Table 7 integrates the gain-response effect over the full distribution of holding-period returns and the entire 10-week sample window, including longer horizons where the discontinuity is economically small. Together, the two exercises bracket the importance of realization preference: meaningful at the margin for attentive investors, but averaging to roughly 10% of the overall disposition effect once aggregated across all investors and holding horizons.

[Table 7 around here.]

6 Conclusion

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

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

The reframing also has welfare and policy implications. If the disposition effect is driven by stable investment styles rather than transient mistakes, evaluating investor behavior solely through this lens risks conflating outcomes with underlying decision rules. One-size-fits-all debiasing interventions are unlikely to be effective; instead, financial education and advisory tools may benefit from recognizing persistent heterogeneity and tailoring guidance to investors' underlying responses to price changes. Our combined experimental-and-field design is essential for this conclusion: it allows investment style to be elicited in a setting free of the gain-status confound, and then validated against real financial decisions—a separation that purely observational data cannot provide.

More broadly, this paper illustrates that behavioral patterns in financial markets are not always what they appear to be: what looks like a primitive bias may be the predictable outcome of deeper, stable decision rules. Understanding which behavioral regularities are genuine primitives and which are derived consequences of more fundamental traits is, we believe, an important and underexplored question for behavioral finance.

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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]). *Session return* is the investor's accumulated return within the current game session up to the point of the 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
Session 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 persistence in the experimentally measured disposition effect across sessions. The dependent variable is the individual-level disposition effect in session j. *Lagged Disposition Effect* is the disposition measure from the participant's most recent prior session. *Individual FE* are investor fixed effects. *Session order FE* are dummies for the third, fourth, fifth, and sixth-or-later sessions, with session 2 as the reference category; session 1 observations are excluded because no lagged value is available. 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)
Lagged Disposition Effect	0.219***	−0.136***	−0.136***
	(0.004)	(0.003)	(0.003)
Session 3			0.004
			(0.003)
Session 4			0.004
			(0.003)
Session 5			0.008**
			(0.003)
Session 6+			0.006**
			(0.003)
Constant	0.211***		
	(0.002)		
Individual FE	No	Yes	Yes
Session order FE	No	No	Yes
Observations	148,199	148,199	148,199
R^2	0.049	0.419	0.419
Adj. R^2	0.049	0.210	0.210

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

This table reports regression estimates based on Equation 4. 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 5. The dependent variable *Sell* equals one if the investor reduced their fund holdings during the month, and zero otherwise. *Gain* equals one if the fund's return by the end of the previous month was positive. *Contrarian* is a dummy variable indicating the sign of investor's investment style, measured in either the experiment or the real-life setting. *Months since first purchase* is the number of months since the most recent initial purchase, and resets to zero after full liquidation. *Holding position*, *Holding profit*, and *Holding period return* refer to the end-of-month market value, displayed profit or loss, and return rate, respectively. These three variables are lagged by one month. Standard errors are two-way clustered at the investor and calendar-month levels. *p<0.1, **p<0.05, ***p<0.01.

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

Table 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 3.2. *High risk tolerance* dummy is a proxy for risk tolerance, defined by whether the individual has an above-median average initial investment amount in the experiment. *Bachelor* is a dummy capturing the highest completed education. *Total Alipay assets* (in CNY) is the average monthly value of all types of assets held via Alipay. The demographic characteristics are measured in the cross-section of July 2021. *p<0.1, **p<0,05, ***p<0.01.

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

Table 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 5 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. The final row reports the ratio of the *Gain* coefficient to the unconditional sell probability, following Ben-David and Hirshleifer (2012), and expresses the discontinuity at the zero-return threshold as a share of the baseline daily sell probability. *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

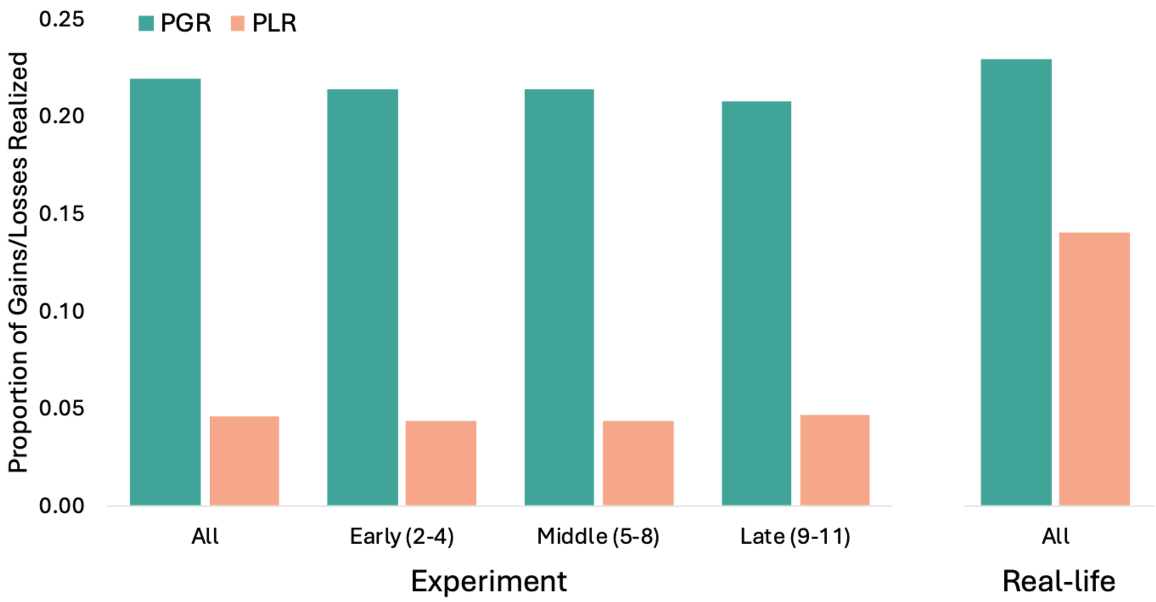
	Dependent Variable: 100 × *Sell*		
Holding length	1 to 21	22 to 42	43 to 70
	(1)	(2)	(3)
Gain	0.363***	0.354***	0.148
	(0.105)	(0.124)	(0.117)
Contrarian	0.061	0.144	0.270***
	(0.086)	(0.103)	(0.098)
Gain × Contrarian	0.108	0.086	0.028
	(0.135)	(0.160)	(0.151)
Controls	Yes	Yes	Yes
3rd Polynomials of holding period return	Yes	Yes	Yes
Polynomials × Contrarian	Yes	Yes	Yes
Polynomials × Log(Holding length)	Yes	Yes	Yes
Observations	373,537	276,498	265,028
Adj. R^2	0.001	0.001	0.001
Gain coef. / uncond. sell prob.	27.7%	27.0%	11.3%

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 3.2. *DE with Gain response* and *DE without Gain response* are the fitted disposition effects including and excluding the *Gain* dummy and the associated interaction terms, respectively. *Difference in DE* is the gap between the two. *Share explained* is the difference in DE divided by the DE without Gain response, expressing the contribution of realization preference as a fraction of the mechanical baseline.

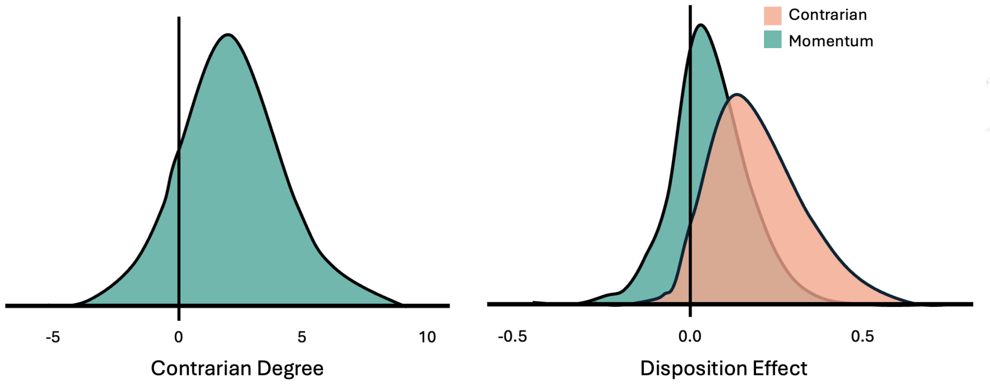
	Experiment		**Real-life**	
Investment style	Contrarian	Momentum	Contrarian	Momentum
DE with Gain response	16.955	4.114	0.539	0.128
DE without Gain response	15.212	3.769	0.504	0.114
Difference in DE	1.743***	0.346***	0.035***	0.014***
Share explained	11.46%	9.17%	6.94%	12.28%

Figure 1: **Aggregate Disposition Effect**



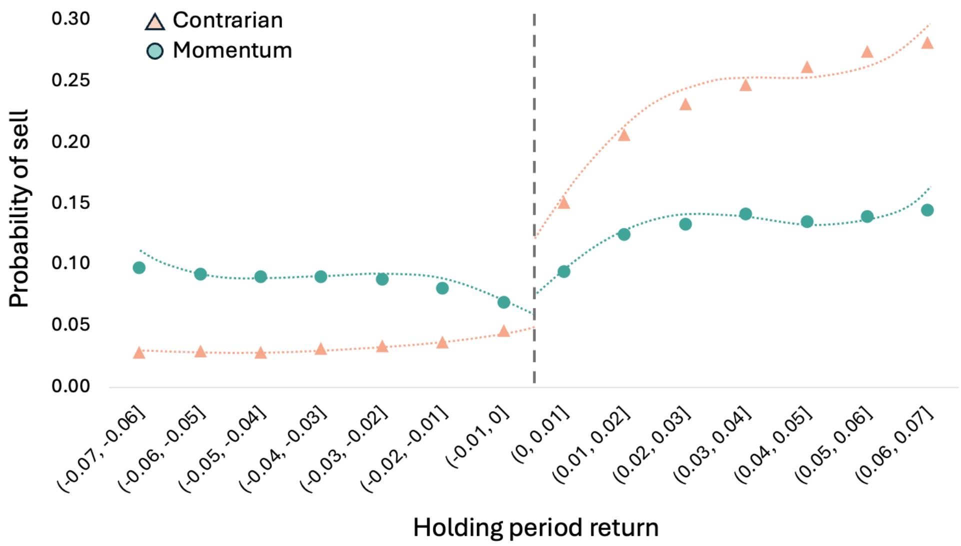
Notes: This figure shows aggregate disposition effect in both experimental and real-life settings. The left panel displays how the prevalence of disposition effect varies over different experiment stages. The sample further restricts the pre-decision risky position to be positive to guarantee the possibility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



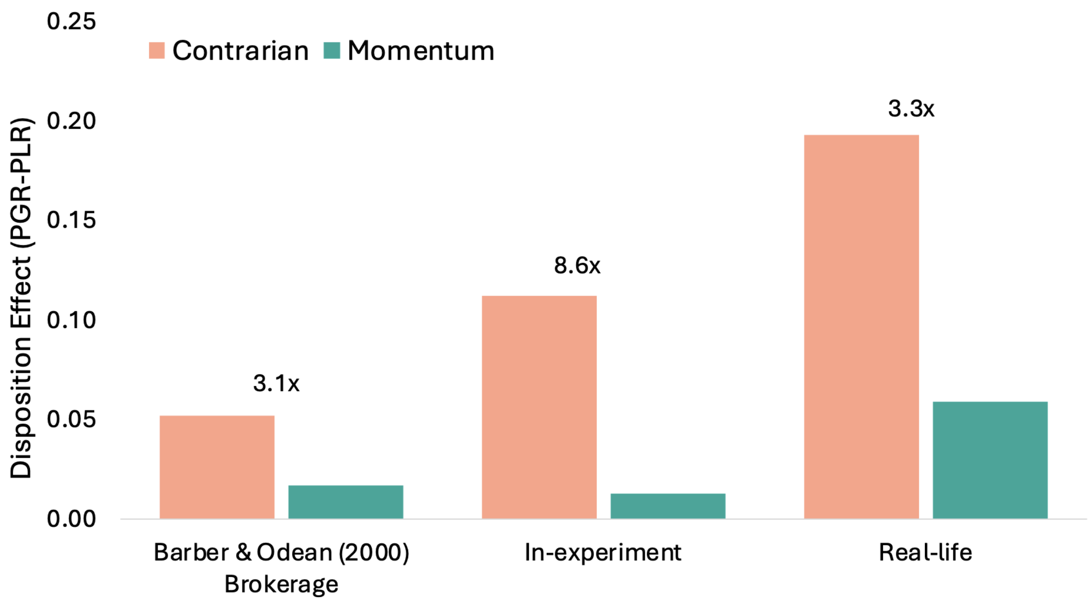
Notes: This figure plots the distribution of Contrarian Degree (CD, left panel) and Disposition Effect (DE, right panel) by investor style in the experiment. The CD is measured according to the methodology detailed in Section 3.2. The DE is measured according to Odean (1998).

Figure 3: **In-Experiment: Holding Period Return, Probability of Sell, and Investment Style**



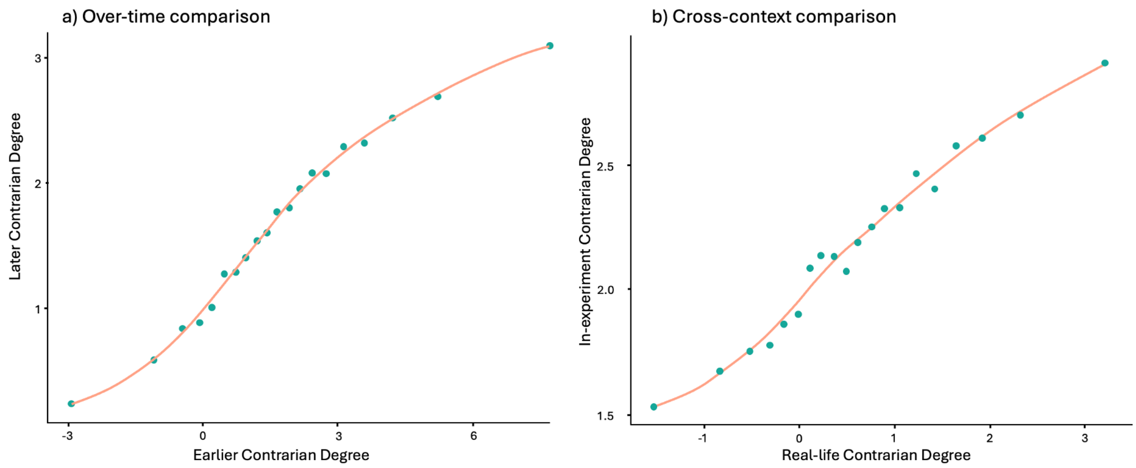
Notes: This figure depicts the relation between current in-game holding period return and probability of selling, covering all decision-level investment decisions except for the first of each game session. The classification method of investor type is described in Section 3.2. The dashed curves are third-order polynomial fits. The dashed vertical line indicates zero return.

Figure 4: **Cross-style Gap in Disposition Effect**



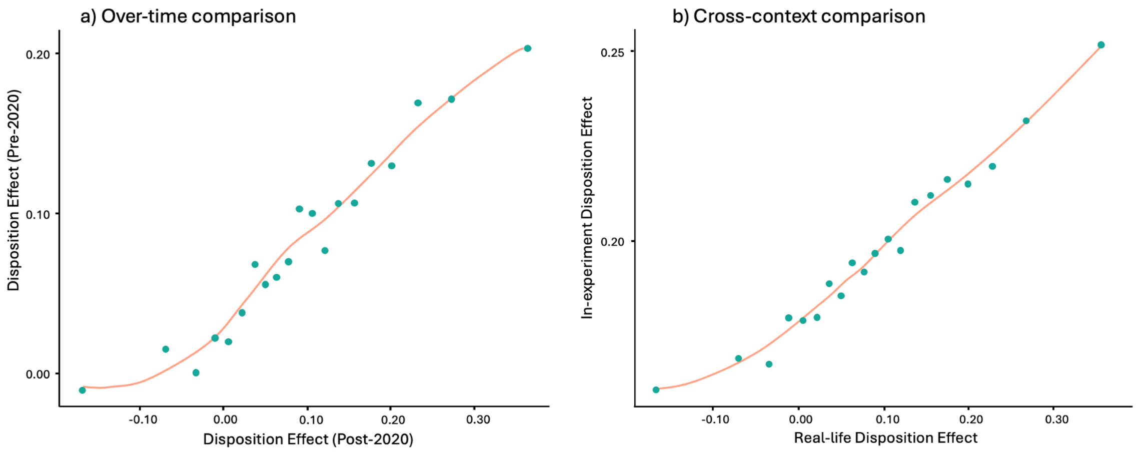
Notes: This figure plots the average disposition effect for contrarian and momentum investors in three different settings as indicated.

Figure 5: **Stability of Investment Style**



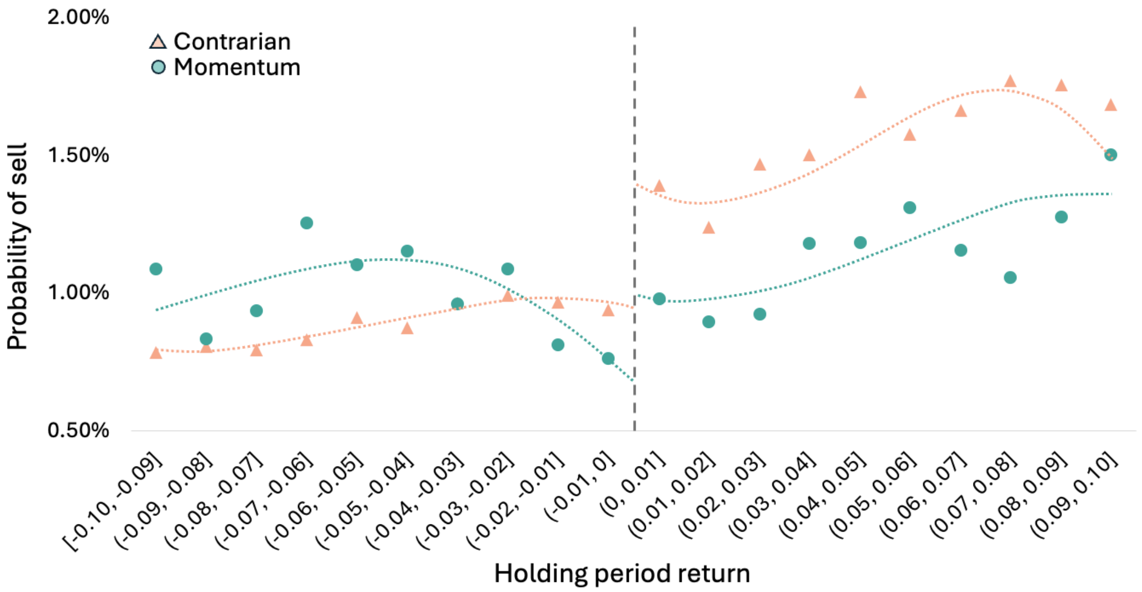
Notes: This figure presents evidence on the stability of Contrarian Degree (CD) across two dimensions. Panel (a) plots early-period CD against late-period CD separately for the real-life and experimental settings. In the real-life setting, early and late periods are defined by a January 2020 split. In the experimental setting, each investor's in-game decisions are ranked chronologically and divided into two equally-sized halves, with CD estimated separately from each half. Panel (b) plots each investor's experimentally estimated CD against their field-estimated CD. All scatter plots use a non-parametric bin-scatter approach with 20 equal-sized bins; the orange line is a LOESS fit.

Figure 6: **Persistence of the Disposition Effect**



Notes: This figure presents evidence on the persistence of the disposition effect across two dimensions. Panel (a) plots each investor's pre-2020 disposition effect against their post-2020 counterpart, based on real-life mutual fund transactions. The sample is restricted to investors with at least 50 fund-month observations in both subperiods. Panel (b) plots each investor's experimentally elicited disposition effect against their field-estimated counterpart. Both panels use a non-parametric bin-scatter approach with 20 equal-sized bins; the orange line is a LOESS fit.

Figure 7: **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 3.2. The dashed curves are third-order polynomial fits. The dashed vertical line indicates zero return.

A Supplementary Tables

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

Using the traditional dataset from Barber and Odean (2000), this table presents the regression estimates of the disposition effect and the investment style, largely following Equation 5. 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.

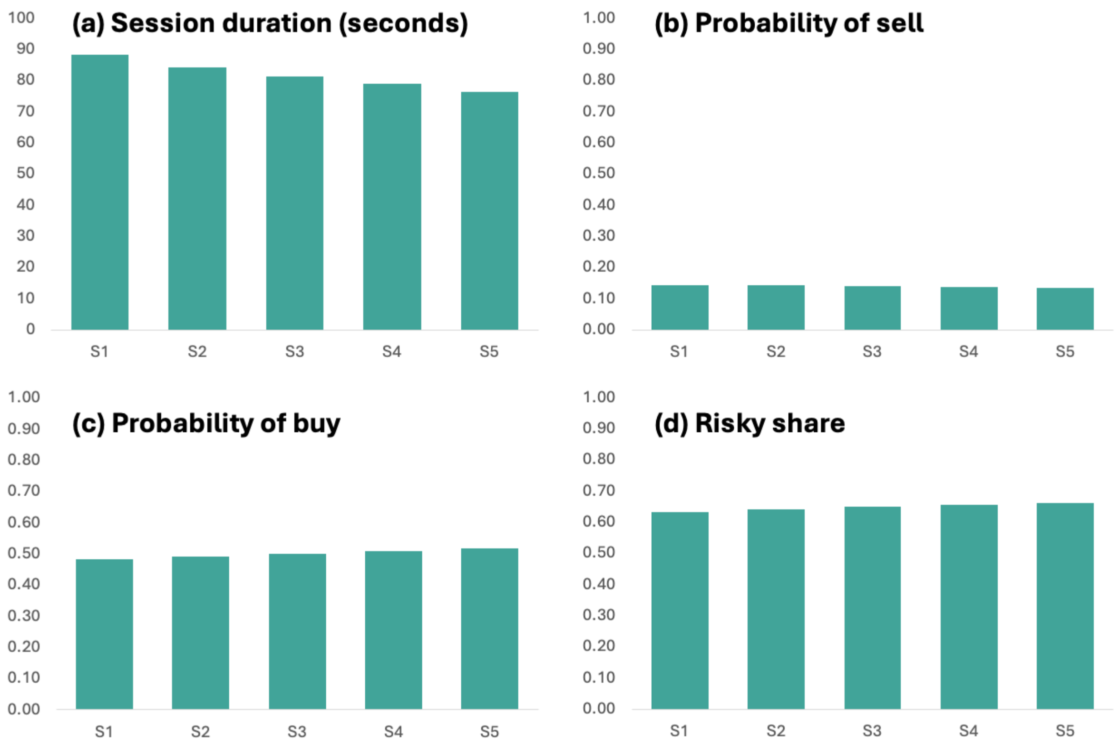
	Dependent Variable: 100 × *Sell*				
	(1)	(2)	(3)	(4)	(5)
Gain	18.247***	18.379***	14.727***	20.269***	20.259***
	(0.247)	(0.247)	(0.358)	(0.401)	(0.401)
Contrarian		3.435***	-0.204	-1.002**	
		(0.247)	(0.357)	(0.468)	
Gain × Contrarian			6.949***	6.950***	6.469***
			(0.493)	(0.535)	(0.537)
Constant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

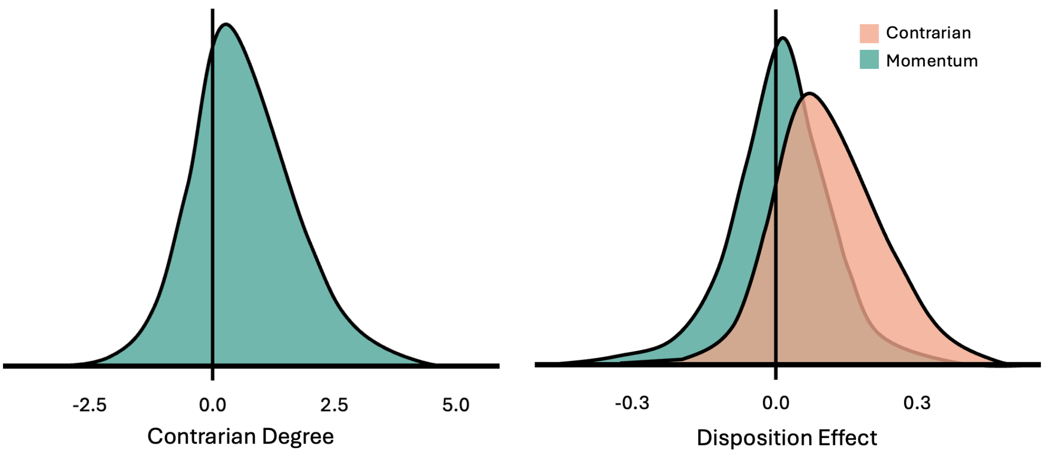
Notes: This figure illustrates the interface of the virtual trading game. The participant is presented with a series of price movements in a line chart, and they are given an extra inflow of 1,000 CNY cash in their game account to finance their next decision. They can choose to sell, hold or buy extra 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.

Figure B.3: **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 3.2. The DE is measured according to Odean (1998).

C A Simulation Benchmark: 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 goal is to show as transparently as possible how a persistent disposition pattern can arise from price-based rules alone—without any conditioning on gain–loss status—and to quantify its magnitude via simulation. The key message is simple: a stable, price-contingent trading rule endogenously shapes 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. Contrarian investors accumulate when prices fall and trim when prices rise; momentum investors do the opposite.

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; it resets upon the next purchase after a full liquidation.

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. The relevant object 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. A disposition-effect-like pattern corresponds to a distribution of U_t that is shifted toward positive values at sale times.

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

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 $C_{t^-} = \sum_{\tau \in \Omega} w_\tau P_\tau$ 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

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. We fix the drift at $\mu = 0$ to isolate the interaction between trading style and cost-basis accounting, and 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. A `CD_factor` of 2 means contrarians invest (liquidate) 2% of their cash (risky holdings) for every 1 pp decrease (increase) in the asset price; momentum investors apply the opposite rule. 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 of 1,000, and investors start with risky-asset wealth and cash of 5,000 each, mirroring the experimental setting in the main text.

Measurement. For each sale event, we compute $U_t = P_t/C_{t^-} - 1$, evaluated at the trade price and prior to any cost-basis update. We focus on the distribution of U_t conditional on a sale, since the disposition effect is defined over realized transactions.

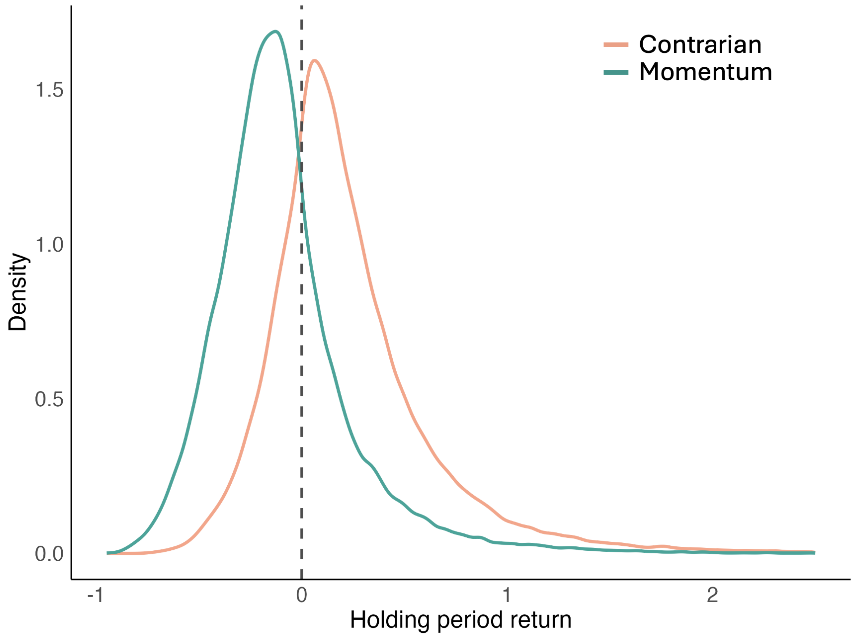
Results. Figure C.1 plots the conditional-on-sale distribution under a representative parameterization (`CD_factor`$= 2$, $\sigma = 0.2$). Consistent with Proposition C.1, contrarians sell predominantly in the gain region ($U_t > 0$), whereas momentum investors sell more often around or below zero.

Robustness. Table C.1 reports PGR, PLR, and DE for a grid of (σ, `CD_factor`) values, where

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

Across all configurations, contrarians exhibit a strongly positive DE and momentum investors exhibit a strongly negative DE. Varying σ and `CD_factor` changes the magnitude but not the sign, confirming that the style-induced pattern is a structural feature of the mechanism rather than an artifact of any particular parameterization.

Figure C.1: **Conditional-on-Sale Distribution of Holding Period Return**



Notes: The holding period return is $U_t = P_t/C_{t^-} - 1$, evaluated at the sale price using the pre-trade cost basis. The dashed vertical line marks $U_t = 0$. The representative parameterization uses `CD_factor`$= 2$ and $\sigma = 0.2$.

Takeaway. The benchmark clarifies why a stable investment style manifests 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. The aggregate disposition effect observed in the market is therefore not a measure of universal irrationality but largely a reflection of the composition of investment styles among investors.

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` (trading intensity). Because sales are strictly price-driven in this benchmark, the standard PGR/PLR denominator of paper positions is less relevant; we focus on conditional probabilities (which sum to one) and report DE = PGR − PLR.