Retail Investing under Complexity: Field and Experimental Evidence

Preliminary, please do not circulate

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Abstract: This paper examines how complexity affects investment decisions of retail mutual fund investors. We develop a novel empirical approach to separate complexity's effect from beliefs and risk preferences. Using a Regression Discontinuity Design, we first identify a zero-crossing jump of 12.6% in purchase probability following a small asset price decline, which cannot be reconciled with a belief channel. We argue that decision complexity may cause investors to reduce continuous price changes to a binary signal. Indeed, we show that the discontinuity is stronger for larger consideration sets, less concentrated portfolios, uncertain environments, more complicated funds, and less-educated investors. Evidence from browsing behavior further reveals that the discontinuity arises not from inattention or low effort but from the cognitive demand of asset choices. Complementing these observational findings, controlled experiments demonstrate that when choices grow more difficult, individuals increase their reliance on direction-based cues, producing discrete shifts in behavior similar to those observed in the field. Finally, we find that while sell decisions also exhibit the zero-cross jump as performance turns positive, they are less susceptible to complexity-driven distortions than buy decisions. Our paper yields important implications for how investors react to small versus large variations in asset prices and underscore the importance of incorporating complexity into models of investment and asset demand elasticity.

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1. Introduction

Financial decision-making is a high-stakes puzzle, where investors must navigate an overwhelming flood of information, unpredictable markets, and conflicting objectives. Its complexity forces many to rely on mental shortcuts—simplifying their decisions in ways that often lead to costly mistakes. These errors may not be random; they could emerge systematically as complexity intensifies, shaping the very fabric of market behavior. But how exactly does complexity warp investment decisions and lead investors to systematic errors?

Recent research (e.g., Gabaix and Graeber, 2024) likens the human mind to a cognitive economy, where mental resources are allocated based on the difficulty of a task. The more intricate a problem—whether due to its many dimensions or the complexity within each dimension—the more strain it places on decision-making. A key consequence is that as complexity rises, decision errors grow larger, and behavioral attenuation toward the default strengthens. While experimental studies on tax systems and consumer behavior have shed light on how complexity influences choices, extending this understanding to financial markets presents a formidable challenge. Unlike controlled experiments, real-world trading is riddled with hidden variables—most notably, beliefs and risk preferences—that make it difficult to isolate the true effect of complexity on investor behavior. To unravel this mystery, we introduce novel pre-trading data that offers a rare glimpse into investors' thought processes before a trade and take an innovative approach to separate complexity's role from other decision-making factors.

We first identify, among retail investors, a novel zero-crossing jump in investors' purchase decisions—a discontinuity in purchase probability for a tiny asset price change—which *cannot* be reconciled with a belief channel (not Bayes-consistent). We rely on a Regression Discontinuity (RD) design to rule out the belief channel. Specifically, we utilize a granular dataset that traces investors' browsing activities at the product level on a mutual fund trading App, which allows us to directly observe what assets investors pay attention to prior to a trade. We show that purchase decisions exhibit a robust tendency of zero-crossing jump: for a small negative variation in an asset's price at the trading date from the price browsed one day before the trade, we detect a both visually and statistically significant surge in the probability of purchasing the asset by 12.6%. This discontinuous pattern of purchasing assets "on sale" cannot be explained by a mean-reverting belief that should involve continuous Bayesian updating: a rational decision upon observing a tiny

random change in price should predict an almost zero change in belief and thus the probability of purchasing the asset. As a result, we consider the jump in the probability of purchase by 12.6% as the deviation from the rational level, or the magnitude of the decision "error."

The observed jump can also be interpreted as a form of behavioral attenuation (Enke and Graeber, 2023; Gabaix and Graeber, 2024; Enke et al., 2024) from the default behavior, although explicitly characterizing the default probability of purchase is beyond the scope of this paper. The default level of an investor's response refers to reaction to a signal in the absence of any cognitive effort to process it. As market complexity increases or when the new information becomes difficult to interpret, investors are *more* likely to rely on the default behavior, exhibiting attenuation in their responses. In our setting, investors may have a default probability of purchasing an asset as long as they observe a drop in the asset's price. This behavior is exacerbated by the design of trading Apps, which prominently display positive or negative daily price movements. Analyzing more nuanced and continuous changes in price signals, however, presents a more complex cognitive challenge. As a result, investors may default to the baseline probability of purchase even when faced with minimal price changes—a phenomenon that can be seen as a form of behavioral attenuation.

In the second step, we demonstrate that the decision error is unlikely attributed to preferences, particularly those aligned with prospect theory. To test this idea, we investigate whether complexity increases erroneous decision-making — an outcome naturally predicted by complexity but not standard models on preferences. Drawing on insights from the concept of complexity as developed by Gabaix and Graeber (2024), we assess it from three aspects: dimensions of asset choice decisions, product-level complexity, and cognitive cost/capacity of investors.

First, when perceiving the decision as an asset choice problem, the higher dimension that an asset choice problem involves, the more complex the decision is. We proxy the dimension based on the size of investors' consideration set, which consists of the assets the investor browsed during the week prior to the trade date. A larger set indicates a higher dimension of an asset choice problem. In addition, since investors must consider the relationship between a new asset and the existing assets in their portfolio, we use portfolio concentration as a proxy for portfolio complexity. A lower level of concentration increases the number of interactions for investors to consider and thus makes the investment decision more complex. Furthermore, we measure dimension from

macro-economic uncertainty. We conjecture that investors have to consider more states of economy when the macroeconomic environment becomes more uncertain.

Second, when perceiving investors' decision as a purchase decision of a specific asset considered, higher product-level complexity may indicate the decision complexity. We measure product complexity using product types: equity funds, mixed funds, and bond funds. Equity funds are generally considered more complex than bond funds, because their value is influenced by a greater number of unpredictable factors, and thus it requires more sophisticated analysis to assess their potential returns and risks.

Third, for investors' cognitive cost or capacity, we look at their education levels. We conjecture that investors who completed a higher education degree possess lower cost of effort or greater cognitive capacity to analyze complex financial assets.

We show, indeed, that the discontinuity in purchase probability exhibits strong heterogeneity across these complexity measures: it is more pronounced for trades that involve larger consideration sets, for accounts that hold a less concentrated portfolio, during more uncertain macro environment, for equity funds, and among less educated investors. For example, the magnitude of the decision error in the subsample with larger consideration sets is twice as high as in the subsample with smaller consideration sets, while for less-educated investors, it is 2.5 times as high as that for more educated investors.

We conduct additional tests to enrich our understanding of trading under complexity by linking simplified decision-making to investors' cognitive effort. We show that investors exhibit a stronger tendency of zero-crossing jump for assets that they spend more time on and browse more frequently or earlier in the sequence. These results are largely consistent with a cognitive production function that induces attention sparsity (Gabaix, 2014). In other words, simplified decision-making manifests as a discontinuity in purchase behavior arises from complex problems that demand greater cognitive labor from investors, rather than from a lack of cognitive resources dedicated to these problems.

Complementing our main analysis, we conduct similar tests on sell decisions. We observe a similar zero-crossing pattern for sell decisions, suggesting that the disposition effect holds in both local and global samples. Complexity, however, appears to play a more limited role in explaining the discontinuity. This could be caused by sell decisions involving assets investors already hold or activating additional behavioral mechanisms because they realize gains or losses. In contrast, buy

decisions require evaluating a broader set of assets, potentially making them more complex for retail investors.

Next, we consider alternative explanations. One potential concern is that the measured complexity might be confounded by omitted variables that also influence investors' decisions, particularly through preferences and cognitive ability. Specifically, investors with certain preferences or levels of cognitive (in)ability may be more inclined to choose complex decision environments, and these characteristics could also amplify their discontinuity in purchase probability. To address concerns that individual differences drive the observed patterns, we incorporate individual fixed effects and partition our sample based on the individual median. Additionally, we explore alternative explanatory channels related to cognitive (in)ability and preferences (including loss aversion (Kahneman and Tversky, 1979), preference for simplicity (Puri, 2022), and salience-based modifications to loss aversion (Bordalo, Gennaioli, and Shleifer, 2012)). However, neither preference nor cognitive (in)ability provides a comprehensive explanation for our findings.

A caveat of our analysis is that decision complexity could be endogenous. Individuals choose what to look at, how much information to process, and which alternatives to consider. Therefore, more complex decision environments could be self-selected, making it difficult to isolate the causal effect of complexity on behavior. Moreover, field settings rarely provide a transparent normative benchmark, which complicates the measurement of behavioral distortions.

To overcome these challenges, we design a controlled experiment that exogenously varies decision complexity. In each trial, participants decide whether to invest in a focal asset or choose an outside option. One component of the focal asset's payoff, denoted A, is made visually salient and varies in both magnitude and sign, while the outside option provides an alternative benchmark. We manipulate decision complexity along two dimensions. First, we vary the size of the consideration set by changing the number of available outside options. Second, we vary the difficulty of the comparison by changing how close the returns of the focal asset and the best outside option are. Importantly, the experimental design ensures that, for every value of A, investing is objectively correct in exactly half of the trials and incorrect in the other half. Under full information processing, the investment rate should therefore be constant at 50 percent and independent of A.

Behavior deviates sharply from this benchmark. Investment decisions systematically co-move with the level of the salient component A, and display a pronounced discontinuity at the sign change of A. Both patterns become stronger as decision complexity increases with the size of the consideration set, especially when the returns of the focal asset and the outside option are close. By exogenously controlling complexity, the experiment establishes a causal link between decision complexity and reliance on salient and categorical cues. The results show that greater complexity induces systematic distortions in information processing, leading individuals to overweight easily processed signals and simplify their decision rules.

Our paper is most closely related to a burgeoning literature on decision-making under complexity. Gabaix and Graeber (2024) characterize a general framework of cognitive production function and provides a measure of complexity that applies to canonical economic models (e.g., consumption and tax theories).[3] Enke and Graeber (2023) argue that cognitively uncertainty could give rise to average behavior that is regressive to an intermediate option, which ties together a wide range of empirical regularities in behavioral economics that are typically viewed as distinct phenomena or even as reflecting preferences (e.g., probability weighting function in choice under risk, predictable over optimism and pessimism in forecasts of economic variables, etc.).

Empirical evidence on risky choice is largely based on experiments. For example, Frydman and Jin (2022) test a theory of risky choice in which the perception of a lottery payoff is noisy due to information processing constraints in the brain. Enke and Shubatt (2023) study the complexity of binary choice between lotteries. Charles et al. (2024) show that cognitive noise causally and substantially increases the pass-through from beliefs to actions. Oprea (2024) provides experimental evidence showing that much of the behavior motivating some important behavioral theories of risk (e.g., loss aversion) derive from complexity-driven mistakes rather than true risk preferences. Enke et al. (2024) show that many widely-studied decision anomalies (including low sensitivities of investment to expected returns and savings to interest rates) represent special cases of behavioral attenuation induced by complexity.

Empirical evidence outside laboratory settings has been scarce. For example, Graeber et al. (2025) use stock market reaction to earnings announcements as the empirical setting and find an

[3] Other models may feature the cost of cognitive effort in the form of communicating (entropy, Sims (2003)), attention (Caplin et al. (2020)), understanding one's own preference (Ortoleva (2013)), etc., but do not endogenize task complexity.

S-shaped response pattern around category threshold. Our study is among the first to provide causal evidence for complexity-induced decision errors made by individual investors in financial markets. Leveraging a novel RD design and rich cross-sectional variations in complexity, we rigorously disentangle complexity-driven effects from alternative explanations based on belief formation and risk preferences. Furthermore, by directly linking complexity to trading patterns and cognitive effort, we offer compelling new insights into how investors process information under complexity, shedding light on the mechanisms driving systematic decision errors.

Second, our paper contributes to the trading literature that studies reference-dependent behaviors, such as the disposition effect (Odean, 1998; Quispe-Torreblanca et al., 2025). We find such heuristics are more pronounced when investors' decisions involve greater complexity, casting doubt over a pure preference-based explanation or, at the very least, their external validity in simpler decision environments. For example, complexity could induce investors to resort to comparative assessment that is cognitively easier (Kahneman et al., 1982) than absolute assessments (e.g., Stewart et al., 2005). Moreover, by differentiating buy decisions from sell decisions, we show that complexity has differing impacts on the two types of trades, a perspective ignored by the existing literature.

Finally, our paper is related to the literature on attention and salience (Kahana, 2012a; Bordalo, Gennaioli, and Shleifer, 2012, 2020) and the studies on investor attention using login data (Karlsson et al. 2009; Sicherman et al. 2015; Quispe-Torreblanca et al., 2024). While the attention and salience models do not explicitly feature complexity, our findings suggest that under greater complexity, investors are more likely to rely on flawed intuitions in the sense of "what comes to mind." In other words, *observed* price changes serve as a prominent metric that shapes behavioral attenuation.

Our paper is organized as follows. In Section 2, we explain data sources and sample construction. Empirical methodology is presented in Section 3. We provide main findings in Section 4 and additional analysis in Section 5. We conduct an experiment and structural estimation in Section 6. Section 7 concludes.

2. Data and Sample Construction

Our proprietary data is from a professional third-party financial institution in China, spanning from December 1, 2021 to October 31, 2022 with over 13,000 investors. The institution has obtained an

independent fund sales license and its trading app facilitates transactions of both public and private funds and offers also retail services of financial products. Our data consists of only public not private fund investors. We have access to individual investors' browsing records on the institution's trading app, which capture the start and end time of each instance in which an investor views a fund's information page. Additionally, the dataset contains details on investors' fund holdings and trading activities on the platform, including transaction timestamps, trade types, and trade values. Lastly, we observe investors' demographic characteristics, such as gender, age, education level, and profession.

We aim to study whether investors choose to trade a specific asset on a given day. Thus, we need to construct a sample that consists of actual trades and counterfactual potential trades. To construct the sample, we first identify all potential trading dates for each investor based on their activity within the app. Specifically, we define a *potential trading date* as any date when an investor interacts with the app, such as browsing certain assets or executing trades. Next, we match each investor's potential trading dates with their prior browsing history for each asset and calculate both the frequency and duration (in seconds) of asset views up to the given active date. In particular, we focus on assets browsed one day before an investor's potential trading date, capturing assets that they are most likely to be interested in and spend deliberation effort on. Doing so also makes the trading decisions more comparable across assets. Each observation in the sample is constructed at the level of investor × potential trading date × potential tradable asset, and represents an investor's trading opportunity on a particular day. Finally, we match each observation to short-term price changes and relevant asset-specific and investor-specific information. Since our analysis focuses on mutual funds, the price information available to investors is updated only after the market closes each day. Consequently, on any potential trading day, investors can observe only the prices from the previous trading day. Accordingly, for each potential trading date in our sample, we match each fund with its price data from the prior day. In addition, investors have continuous access to all historical price data and basic fund information through the app's interface.

Our constructed sample consists of 11,713 investment accounts, each of which has at least one potential trading date within the sampling period. Summary statistics is provided in Table 1. The average age of account holders is 46.2 years (median: 40), and 44% of them are female. The average account balance is RMB 198,208 (median: RMB 51,769.9). On average, each account

holds 8.9 assets (median: 5) and executes 7.2 trades per month (median: 4). In terms of online browsing activity, investors view assets 21.5 times on average per month (median: 5).

[Insert Table 1]

Each observation in this sample represents a combination of an investor, an asset, and a potential trading date, totaling 605,724 observations. For these observations, the average price change between the trading day and the previous day is 0 (median: 0), with a standard deviation of 0.043. Among them, approximately 3% of cases result in an actual buy transaction. The average transaction amount for these purchases is RMB 4,818.3.

Additionally, we observe investors' browsing activity both on and before the potential trading day. Specifically, we define the set of assets viewed within the week leading up to and including the potential trading day as the investor's consideration set. We find that, on average, an investor's consideration set contains 48.9 assets (median: 22). The average number of views per asset is 7.3, with an average viewing duration of 91.5 seconds. At the set level, investors view all assets in the set 142.6 times, with a total browsing length of approximately 1,600 seconds.

3. Empirical Methodology

Consider on date t, an investor i observes an asset j's price changes from the previous day's browsed price $p_{j,t-1}$ to $p_{j,t}$. For a rational investor who possesses unlimited cognitive capacity, she is able to update her belief ($L(\cdot)$) of asset value ($V_{j,t}$) following Bayes' rule. Assuming that the asset's price changes by an arbitrarily small amount of $\Delta p_{j,t}$ (i.e., from $p_{j,t-1}$ to $p_{j,t}$) without other contemporaneous changes, the investor should change her belief about the asset value by an amount from $L(V_{j,t} \mid p_{j,t-1})$ to $L(V_{j,t} \mid p_{j,t})$, proportional to the change in likelihood also by a sufficiently small amount following a continuous likelihood function ($L(p_{j,t}|V_{j,t}) - L(p_{j,t-1}|V_{j,t})$). In other words, a rational response to observing a small price change should lead to a negligible adjustment in the probability of making a purchase.

3.1. A Regression Discontinuity Design

Investors, however, may deviate from the rational response when decision-making involves complexity. In this subsection, we describe the methodology to detect possible erroneous behavior, specifically, reference dependency in purchase decisions, by implementing a Regression Discontinuity (RD) design. RD designs can be used to measure treatment effects when a treatment

is based on whether an underlying continuous forcing variable (or running variable) crosses a threshold. Under the condition that there is no other source of discontinuity, the treatment effect induces a discontinuity in the outcome of interest at the threshold. Thus, the outcomes on the two sides of the threshold are unequal, and the difference between these two directional limits measures the treatment effect. A necessary condition for the validity of the RD design is that the forcing variable itself is continuous at the threshold (Hahn, Todd, and Van der Klaauw, 2001).

In our setting, we construct a forcing variable which is the deviation of the asset's price today from its previous-day price browsed by the investor. When such a deviation is small, we consider it as almost random, especially in light of a typical retail mutual fund investor has no market impact. Consider a case in which we wish to test whether on date *t*, an investor *i* who observes a drop in an asset *j*'s price ($p_{j,t}$) from the previous day's browsed price ($p_{j,t-1}$) has a significantly different probability of purchasing the asset from observing a price increase. Let $y_{i,j,t}$ refer to the purchase response (or not) for the investor *i*, and let $\Delta p_{j,t}$ be the one-day price change. We select bandwidth θ for the maximum absolute value of $\Delta p_{j,t}$. The bandwidth can be an arbitrarily small value, and different values can be used in the robustness checks. The RD design compares observations for which $0 < \Delta p_{j,t} < \theta$ with those for which $-\theta < \Delta p_{j,t} < 0$. Thus, we retain observations for which $|\Delta p_{j,t}| < \theta$. Finally, we estimate the effect of observing a price change on purchase behavior by utilizing a subsample in which the price changes are within a specified bandwidth. In robustness tests, we also use one-day return as the running variable.

We follow Lee and Lemieux (2010) to approximate the underlying relationship between investors' purchase response $y_{i,j,t}$ (the dependent variable) and one-day price change $\Delta p_{j,t}$ with the inclusion of four polynomials of the first and second order that are different for each side. The treatment effect is represented by coefficient β in Equation (1) below.

$$y_{i,j,t} = \alpha + \beta \cdot 1(\Delta p_{j,t} \geq 0) + P(\Delta p_{j,t}, r) + P(\Delta p_{j,t}, l) + \lambda_i + \gamma_j + \nu_m + \varepsilon_{i,j,t.} \quad (1)$$

In Equation (1), β is the coefficient of interest. The term $1(\Delta p_{j,t} \geq 0)$ is an indicator variable for whether the observed price change is nonnegative. $P(\Delta p_{j,t}, r)$ includes two polynomials of the first and second order of the price changes for the observations on the right-hand side of the price changes (i.e., the positive price changes), and $P(\Delta p_{j,t}, l)$ includes two polynomials of the first and second order of the price changes for observations on the left-hand side of the price changes (i.e., the negative price changes). The polynomials capture any continuous relationship between $\Delta p_{j,t}$

and $y_{i,j,t}$. In our setting, this approach controls for the other determinants of purchase behavior that vary across price changes using a sufficiently flexible polynomial function of p (Imbens and Lemieux 2008; Lee and Lemieux 2010). λ_i, γ_j, and ν_m refer to investor, product and yearmonth fixed effects, respectively. We cluster the standard errors at the investor level.

Because the RD design is identified only at the discontinuity, in the empirical estimation of equation (1), the bandwidth θ should be chosen to balance the goal of staying as local to the zero cutoff as possible with that of ensuring that there are enough data to yield informative estimates. We follow the approach of Calonico, Cattaneo, and Titiunik (2014) to calculate the optimal bandwidth that remarkably improves on alternative nonparametric estimators in consistency and robustness. For robustness, we also employ a practical implementation of RD within various pre-specified bandwidths. Our results are robust across these estimation approaches using different bandwidths.

3.2. Validation

There are two important conditions for the validity of the RD design. First, the sole source of discontinuity should be the treatment (in our case, price changes). In other words, other observable and unobservable characteristics of the investors and products the left and to the right of the cutoff should be similar. We compare a set of covariates between observations to the left and right of the cutoff, namely, the annual standard deviation of the asset price, the investor's browsing frequency and length of the asset one week prior to the potential trading date, as well as the investor's average holding value of the month. We present the results in Table 2, which show no significant jump in these variables at the cutoff.

[Insert Table 2]

The second condition for the RD design's validity is a lack of manipulation or self-selection near the cutoff. In other words, potential outcomes by treatment status should be continuous functions of the running variable as that running variable crosses the cutoff. Otherwise, it would raise the concern that agents can endogenously manipulate their observed running variable values to opt themselves into or out of treatment. In our analysis, we focus on retail mutual fund investors who have relatively limited capital for investment. As a result, they should be considered as having no price impact and acting solely as price takers in the mutual fund market. In addition, we provide in Figure 1, a visual representation of the continuity of the density of the running variable around

the cutoff of zero. Specifically, we implement manipulation testing procedures of one-day price changes of traded assets using the second-order local polynomial density estimators with a triangular kernel function proposed in Cattaneo, Jansson and Ma (2014). Black curve represents the point estimates and grey area indicates 95% confidence intervals. Our analysis shows a P-value of 0.86 around the cutoff, implying smoothness in the density function. The result is robust to using one-day return as the running variable.

[Insert Figure 1]

4. Results

In this section, we first present a novel form of behavioral response that deviates from the rational level. We then explore the heterogeneity in this pattern across various measures of complexity.

4.1. Discontinuity in Buy Decisions

As argued in Section 3, a rational response to observing a small price change should lead to a negligible adjustment in the probability of making a purchase. Using the RD design, we, however, find that purchase decisions exhibit a robust tendency of zero-crossing jump for a tiny change in asset prices. Specifically, we detect a both visually and statistically significant discontinuity in the probability of purchasing a mutual fund around the zero cutoff when comparing the asset's price at the trading date to the price browsed one day before the trade.

Table 3 presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in asset price since the previous day is greater than or equal to zero. Investor, product, and yearmonth fixed effects are included in all specifications. We control polynomials, different for each side, of order two in columns (1) – (3), no polynomials in columns (4) – (5), and order one in columns (6) – (7). We show the RD regressions at the optimal and other bandwidths: column (1) uses optimal bandwidth of 0.014, while columns (2) uses a wider bandwidth of 0.017 for robustness. Columns (4) and (6) adopt bandwidths of 0.002 and 0.008, optimal under respective polynomial functions. Columns (3), (5), and (7) use a global support of 0.5 for an examination of external validity.

[Insert Table 3]

When optimal bandwidth is used for our preferred specification (column (1)), we find that the probability to purchase the asset increases by 12.6% (0.3%/2.38%) relative to the mean of 2.38% when the asset price drops compared to the previous day browsed price. This baseline finding is robust to both local and global bandwidths as shown in columns (2) and (3), and the magnitude is comparable across different specifications. We interpret the magnitude of 12.6% as the deviation from the rational level of purchase probability.

In Figure 2, we provide a visual representation of the discontinuity. Observations are sorted, based on the price change, into bins of size 0.02. Five bins on each side of zero are shown on the x-axis. Points on the left (right) side of zero represent observations from negative (positive) price changes. The graph plots the average purchase likelihood on the y-axis, where each point represents for observations within their respective bin (with 95% confidence intervals). We use polynomials of order two, different for each side. Consistent with the findings in Table 3, we observe a notable visual discontinuity in the probability of purchasing a mutual fund around the zero cutoff.

[Insert Figure 2]

Next, we refine the construction of counterfactuals of the no trade sample. To do so, we include only potential trading dates on which the investor made a trade on any assets on that day. Therefore, the counterfactuals do not include investors who completely refrain from any trading on the potential trading day. Rather, we focus on the instances in which the investors did trade some assets but not other assets browsed before a potential trading date. In other words, we restrict counterfactuals to assets in the consideration set of the traded assets. In Table 4, we repeat the analysis in Table 3 and observe a similar pattern of treatment effect. That is, out of all the assets browsed before a trade, the one that experiences a price drop, even though slight, is more likely to be purchased.

[Insert Table 4]

In conclusion, we find a robust pattern that investors' response to a tiny price change deviates from the rational level. The observed jump can also be interpreted as a form of behavioral attenuation from the default behavior. In our context, investors may have a default likelihood of purchasing an asset whenever they observe a price drop. However, interpreting more nuanced changes in price signals presents a greater cognitive challenge. Consequently, investors may revert to their baseline probability of purchase, even in the presence of minor price fluctuations.

4.2. Heterogeneity across Complexity

Complexity theory predicts that erroneous decision-making increases with complexity. In this section, we test whether the observed jump diminishes as complexity reduces. This is not naturally predicted by the prospect theory, as reference-dependent preference is embedded in the utility function and should therefore persist even as decisions become more complex. According Gabaix and Graeber (2024), the macro complexity of a decision involves at least four aspects: the dimension of the decision, the complexity of analyzing each dimension, the cognitive capacity of the decision maker, and the relative importance of each dimension. We focus our analysis on the first three aspects to develop our proxies for complexity.

4.2.1. Dimensions of Asset Choice Problems

The higher dimension of an asset choice problem involves, the more complex the decision is. We proxy the dimension of an asset choice problem in three ways. First, we conjecture that the more assets that investors consider, the more complex the asset choice problem is. We measure the size of investors' consideration set by the number of assets the investor browsed during the week prior to the trade. We divide the sample based on whether the size of the consideration set is above or below the median of each investor. We then conduct the analysis specified in Equation (1) separately for each subsample.

Second, when making investment decisions, investors need to consider how a new asset relates to the existing assets in their portfolio. Therefore, the more complex the composition of their current holdings, the more complex the decision to purchase a new asset becomes. We use the Herfindahl-Hirschman Index (HHI) of an investor's portfolio to measure this complexity. A lower HHI indicates that the investor must take into account a greater number of existing assets when evaluating the new asset, and thus a higher level of complexity in the investment decision process. As the portfolio HHI does not exhibit much time-series variation for individuals, we divide the sample based on whether the HHI calculated for each account by month is above or below the sample median in the same month.

Third, we hypothesize that increased uncertainty in the macro economy may lead investors to consider a broader range of economic states when making asset allocation decisions, thus resulting in greater complexity in the decision-making. To test this hypothesis, we divide the 12 months in

our sample period into two groups based on the volatility index (VIX) of the CSI 300 Index[4], a widely used measure of uncertainty in China's stock market. One group consists of the six months with relatively high average VIX levels, and the other includes the six months with relatively low VIX levels. In particular, the high-VIX group includes March through June and October through November of 2022. The first four months correspond to the spread of the Omicron variant and the lockdown of Shanghai, one of China's most important commercial and industrial hubs, which raised significant concerns about macroeconomic disruption. The latter two months coincide with the period around the 20th National Congress of the Chinese Communist Party, a time of increased speculation and uncertainty about future economic policies. These months capture periods of heightened macroeconomic uncertainty. We then perform the analysis specified in Equation (1) separately for each subsample.

We present the results in Table 5. Columns (1) and (2) analyze the subsamples with small and large consideration sets, respectively. We find that that the discontinuity is only pronounced when investors' consideration sets are large. The observed jump is –0.004 (significant at 5% level) in the subsample with large consideration sets, but only –0.002 (insignificant at conventional levels) in the subsample with small consideration sets. Columns (3) and (4) present results for subsamples with low and high portfolio HHIs, respectively. The observed jump is more pronounced among investors with low portfolio concentration—i.e., those with more complex portfolios—showing a magnitude of –0.004, significant at the 10% level. In contrast, for investors with highly concentrated portfolios, the effect is smaller at –0.002 and not statistically significant at conventional levels.

Columns (5) and (6) report the results for the high- and low-VIX subsamples. We find that the observed jump is more pronounced during periods of higher market volatility. Specifically, the jump is –0.004 and statistically significant at the 5% level during high-VIX months, whereas it is –0.003 and statistically insignificant during low-VIX months.

[Insert Table 5]

[4] The CSI 300 Index is a capitalization-weighted stock market index designed to replicate the performance of the top 300 stocks traded on the Shanghai and Shenzhen stock exchanges, and serves as a key benchmark for the Chinese stock market.

In a nutshell, our findings in this subsection suggest that the observed jump or the deviation from the rational level is stronger when the asset choice decision involves higher dimension to analyze.

4.2.2. Product Complexity

If we perceive investors' decision as a purchase decision of a specific asset rather than asset choices out of multiple assets, investors are more likely to make mistakes as the complexity at the product level grows. To measure product-level complexity, we examine product types. Specifically, we compare equity funds, mixed funds, and bond funds. Equity funds are generally considered more complex than bond funds. This is because fixed-income securities generate predictable income through interest payments, and their prices are primarily influenced by interest rates and credit quality. In contrast, stocks' growth prospect of cash flow involves more uncertainty, and their prices are influenced by a wider range of factors, including company performance, industry trends, macroeconomic conditions, and market sentiment, which are harder to predict.

We present the results in Table 6. Columns (1) to (3) analyze the subsamples of equity, mixed and bond funds, respectively. We find that that, as the asset price goes down, the observed magnitude of jump exhibits a monotonic decline across the three types of assets, with the largest magnitude observed for equity funds (–0.014, significant at 1% level), a moderate jump for mixed funds (–0.003, insignificant at conventional levels), and even a decline for bond funds (0.002, insignificant at conventional levels).

[Insert Table 6]

In conclusion, our findings in this subsection suggest that the observed jump or the deviation from the rational level is stronger when the product-level complexity grows.

4.2.3. Cognitive Cost/Capacity

We conjecture that investors who are more educated or financially literate have greater cognitive capacity or lower cost of effort when analyzing asset choice problems, thus rendering decision mistakes less likely to occur. To measure investors' cognitive capacity, we look at investors' education degree and profession. We separate our sample investors into having an education degree below and above (including) the college level. When looking at professions, we separate the sample into investors in the finance profession and in others. As the data contains a lot of

missing values associated with profession, we mainly focus on the magnitude rather than statistical significance.

We present the results in Table 7. Columns (1) and (2) analyze the subsamples of investors with a highest degree below and above college, respectively. We find that that the zero-crossing jump is only present for those who did not receive college education: the observed jump is –0.005 (significant at 5% level). In contrast, the magnitude is –0.002 (insignificant at conventional levels) for the other subsample. Columns (3) and (4) analyze the subsamples of investors for whom we have occupation information, separately examining those who work in the finance industry and those who do not. We find that that the observed jump is only –0.001 for the former, but –0.003 for the latter (both insignificant at conventional levels).

[Insert Table 7]

Overall, our findings in this subsection suggest that the observed jump or the deviation from the rational level is stronger when investors' cognitive capacity is more limited.

5. Additional Tests

In this section, we conduct additional tests to enrich our understanding of investing under complexity. We examine the role of cognitive effort, repeat the main analysis for sell decisions, and conduct robustness analysis.

5.1. Cognitive Effort

In this subsection, we analyze the amount of cognitive effort investors put into solving the asset choice problem and its relation to the discontinuity in purchase probability at the zero-crossing of price changes. Examining it helps us isolate the complexity channel from the inattention channel. One might argue that deviations from the rational level of behavior could result from a lack of attention or cognitive effort. However, a crucial prediction derived from the cognitive production function in Gabaix and Graeber (2024) is that when the function induces sparsity (i.e., some dimensions of a decision are not attended at all), complexity increases cognitive effort. In this section, we investigate if the observed jump varies across cognitive effort levels.

First, we utilize the browsing data to calculate the total browsing time and frequency that investors spend on each asset in the week prior to date *t,* as a proxy for cognitive effort. We then split the sample based on whether the browsing time or frequency is above or below the median

of each investor. Columns (1) – (4) of Table 8 show a greater discontinuity for products that investors browse more frequently or spend more time on.

[Insert Table 8]

Second, we use browsing sequence to measure investors' potential interest in the asset. We hypothesize that the earlier investors browse an asset in the week leading up to the trade, the more interested they are in the asset and the longer they have considered it, indicating a higher level of deliberation in their decision-making process. We divide the sample based on when the assets first enter the investor's consideration set within the week leading up to the potential trading day. Columns (5) – (8) of Table 8 show that the discontinuity is more pronounced in the subsamples of assets that attract greater investors' interest.

In Table A.1, we construct a different sample to further investigate this effect. In Panel A, we present the same tests as in the main specification (Table 3) but restrict the sample to investors who did not browse the asset on the previous day but did so two days ago, indicating less interest. Panel B incorporates an interaction term to compare the effect of one-day price change on purchase decisions between investors who viewed the asset one day before the potential trading day and those who viewed it earlier. Across both panels, we find that the purchase probability discontinuity is primarily driven by investors who viewed the asset specifically on the day before the potential trading day.

To sum up, these findings suggest that erroneous decision-making arises from complex problems that demand greater cognitive labor from investors, rather than from a lack of cognitive resources dedicated to these problems.

5.2. Discontinuity in Sell Decisions

Within the behavioral literature, reference dependency associated with sell decisions, known as the disposition effect, has been extensively studied. However, most research examines this effect across the global support of price changes rather than focusing on local variations. Consequently, it becomes challenging to differentiate between preferences consistent with prospect theory and mean-reverting beliefs. From the perspective of complexity theory, we revisit the disposition effect by investigating the local effect for small changes in asset prices and see whether the zero-crossing discontinuity exists within a local support of trading gains.

In Table 9, we replicate the analysis of Table 3 for sell decisions. When constructing counterfactuals for sell trades, we largely follow the same approach as for buy trades. Specifically, we first identify all potential trading dates for each investor based on dates in which the investor is active on the app. In addition, because we use the original purchase price as the reference point when constructing directional cues, we allow for a longer horizon of investor interest in sell decisions by considering browsing activity within the three weeks—rather than just the one day—prior to the trade. Column (1) of Table 9 shows, within the optimal bandwidth, evidence consistent with disposition effect around the cutoff. Specifically, as the cumulative gain (in thousands) increases, the probability to sell the asset increases by 17% (i.e., 0.0009/0.0052) relative to the mean. The pattern is robust under a more local bandwidth of 0.5 (column (2)) and a more global bandwidth of 10 (column (3)). Appendix Figure A.1 visualizes the discontinuity.

[Insert Table 9]

In Appendix Tables A.3 to A.5, we repeat the same cross-sectional analyses for sell trades along different dimensions of complexity. We find that discontinuity is more pronounced among larger consideration sets, less concentrated portfolios, and non-financial professionals. But the difference becomes indistinguishable in magnitudes partitioning the sample based on the VIX index or even reversed for product types. Overall, although we observe a similar zero-crossing pattern for sell decisions, complexity appears to play a more limited role in explaining the discontinuity. We see at least two reasons for this difference. First, sell decisions concern assets that investors already hold, whereas buy decisions require investors to search for and evaluate a broader set of alternatives, often including unfamiliar assets. Second, because sell trades involve the realization of gains or losses, they may activate additional behavioral mechanisms that operate independently of or interact only weakly with complexity. Consequently, the channels through which complexity affects retail investors' buy decisions may differ from those relevant for their sell decisions.

5.3. Robustness Tests

In addition, we use the one-day return rate instead of the one-day price change in level as the running variable in our RD test. We experiment with the optimal and larger bandwidths and apply second-order, first-order, and no polynomial specifications. As shown in Table A.2, all regressions

except the specification with a global bandwidth under second-order polynomial exhibit a statistically significant discontinuity. Moreover, the magnitude of the effect of positive price change on purchase probability remains consistent with our main specification (Table 3), suggesting the robustness of our RD design results.

5.4. Alternative Explanations

Previous cross-sectional evidence suggests that as choice complexity increases, investors' behavior becomes more likely to display a jump in purchase probabilities as price decreases. However, one may concern that the complexity that we measure may not be exogenous to investors' asset choices or purchase decisions. Rather, it might be confounded with omitted variables that also have an impact on investors' decisions, most notably, preferences and cognitive ability. Specifically, investors with certain preferences or cognitive (in)ability may be more likely to choose complex decision environments, and these characteristics may also make them more prone to display a jump in purchase probabilities.

To alleviate this concern, we include individual fixed effects in our empirical analysis, and our classification of high versus low volatility assets and large versus small consideration sets is partitioned for each investor rather than across all investors in the sample. This ensures that our analysis compares behavioral responses to price changes of different assets within each investor, mitigating concerns that individual differences drive the observed patterns.

We next discuss the alternative channels, specifically, via preferences and cognitive ability. Possible candidates of preferences are loss aversion and preference for simplicity. According to loss aversion, reference-dependent preference may take the form of reduced purchasing probability if investors view increases in asset prices as an opportunity loss. We, however, find that the discontinuity in purchase probability is more pronounced for riskier assets and absence of such discontinuity for less risky assets, contradicting the prediction that loss averse investors should be less inclined to take on riskier assets.

While the canonical prospect theory may fail to reconcile with the heterogeneity in the purchase probability discontinuity with respect to complexity, one may argue that simple modifications that incorporate *salience* may do. For example, Frydman and Rangel (2014) found that investors became less prone to the disposition effects when the purchase prices were made less salient. In our setting, as assets exhibit more volatility, price changes may become a more

salient factor. But it is unclear why greater volatility would lead to greater salience of even tiny price movements. Nevertheless, this theory does not consistently explain why under other complex decision environments (e.g., with large consideration sets and less concentrated portfolios), the discontinuity pattern is more pronounced. In addition, as prices changes should be more salient for sell decisions due to the realization of trading performance, the absence of a discontinuity in sell probability around the cutoff associated with sell decisions provides additional evidence against this alternative explanation.

One may also interpret the jump in the probability of purchasing an asset following a tiny price decline as reflecting a preference for simplicity (Puri, 2022). However, the observation that the purchase probability increases with complexity suggests a heightened, rather than diminished, preference for risky assets as complexity grows. This contradicts the positive complexity premium predicted by the theory of preference for simplicity.

A second alternative explanation is that the observed patterns are driven by cognitive ability rather than decision complexity. Investors with lower cognitive ability or who are more cognitively constrained are more likely to display behavioral heuristics, and they might also be more likely to self-select into complex decision environments, as they struggle with decision-making. To further test whether the observed discontinuity is driven by variations in cognitive ability, we focus specifically on low-ability investors, using education level as a proxy. In Table 10, we examine the low-education individuals' behavior in large versus small consideration sets and find that even among low-ability investors, the discontinuity remains significantly more likely in large than in small consideration sets. This suggests that complexity itself, rather than the difference in cognitive ability, plays a key role in driving these patterns.

[Insert Table 10]

In short, we believe that neither preference nor cognitive (in)ability can provide a unifying explanation for our findings.

6. Experiment

Using field data, we establish a robust "zero-crossing discontinuity" in investor purchase decisions: investors are substantially more likely to buy an asset following a small negative price change than after a small positive one. However, these findings are observational and thus potentially subject to endogeneity concerns. In real-world settings, investors endogenously choose which assets to

view and when to trade, and their information sets, beliefs, and preferences are not directly observable. Moreover, the complexity of real investment environments makes it difficult to define a clear normative benchmark for rational behavior.

To complement the observational analysis, we therefore conduct a controlled experiment designed to isolate the cognitive mechanism behind the discontinuity. The experiment aims to test whether individuals rely on directional (up vs. down) rather than magnitude-based information when evaluating investment opportunities under complexity. Specifically, we examine whether subjects simplify the decision environment by categorizing small positive and negative changes as distinct signals and whether such categorical thinking leads to discrete jumps in investment rates around the zero threshold.

6.1. Design and Implementation

6.1.1. Experimental Design

The Decision Problem

We construct a simplified investment task that mirrors key features of the empirical setting while allowing precise control over information and payoffs. In each decision problem or a trial, participants are asked whether to invest in a focal asset or not. The return from investing in the focal asset is determined by two deterministic numbers, A and B, such that the total value equals $A+B$. A captures the direction and magnitude of a salient cue—analogous to a daily price change. The parameter A takes eight possible values: ±15, ±35, ±65, and ±90. Positive values of A are displayed in green, while negative values are displayed in red. The second component B, analogous to asset value, is a two-digit positive integer that varies randomly across trials and provides a baseline level of value common across assets.

Each focal asset is matched with a set of outside options. The outside options follow the same payoff rule as the focal asset (i.e., the returns are determined by the sum of two numbers), but the value of the highest outside option equals the focal asset's value minus a deviation term Δ: ±10, ±20, and ±30. A positive Δ means the focal asset is better than the outside option, whereas a negative Δ means the outside option is better.

Subjects receive performance-based incentives tied to the correctness of their decisions. In each decision round, a choice is defined as objectively correct if the subject selects the focal asset when Δ is positive and selects the outside option when Δ is negative.

Complexity Conditions

We consider two sources of decision complexity in our experimental design. First, we vary the size of the outside option set. In the *Small Set Condition*, participants compare a focal investment asset with a single outside option. In the *Large Set Condition*, participants compare the same focal asset with five outside options. Importantly, the highest outside option is identical across the two conditions. The additional four outside options in the Large Set condition are generated to be strictly worse than both the focal asset and the best outside option. These inferior alternatives are included solely to increase cognitive load and to mimic the presence of competing alternatives in complex financial environments, without introducing superior investment opportunities. Therefore, under full and correct integration of payoff information, optimal choices are identical across the two conditions; the only difference is the complexity of the decision environment.

Second, we vary the payoff gap between the focal asset and the best outside option. The payoff of the best outside option equals the focal asset's payoff minus a deviation term Δ, where $\Delta \in \{\pm 10, \pm 20, \pm 30\}$. A positive Δ indicates that the focal asset dominates the outside option, while a negative Δ indicates that the outside option dominates the focal asset. This variation captures a second dimension of decision complexity: smaller absolute values of Δ make the comparison more cognitively demanding, as subjects must process payoff information more precisely to identify the dominant alternative.

Rational Benchmark

The task is designed such that the rational decision rule is straightforward to characterize. A rational participant with unlimited cognitive capacity should always invest in the focal asset whenever its value exceeds that of the outside option, and choose the outside option otherwise. That is, the rational decision depends solely on the difference between the value of the focal asset and the outside option Δ: subjects should invest in the focal asset if and only if Δ is positive and not otherwise. Because Δ is evenly distributed around zero, a fully rational decision-maker would

invest in exactly half of the cases, yielding an average investment rate of 50% across all problems. Conditional on a positive Δ (i.e., the focal asset dominates), subjects should always invest in the focal asset; and conditional on a positive Δ (i.e., the outside option dominates), subjects should always not invest in the focal asset. Figure A.2 plots the rational benchmarks.

[Insert Figure A.2]

Hypotheses

While the rational benchmark implies that investment decisions should be independent of the salient component A, this prediction relies on individuals' ability to fully integrate all payoff-relevant information. We conjecture that this ability deteriorates as decision complexity increases. When cognitive demands are higher, individuals may place disproportionate weight on information that is easier to process or more salient, even if it is normatively irrelevant.

In our setting, increased complexity may therefore lead investors to rely more strongly on the salient component A, and to adopt simplified, categorical decision rules based on its sign rather than its precise magnitude. These considerations motivate the following hypotheses.

H1. Under the Large Set Condition, investment decisions are more sensitive to the level of the salient payoff component A.

H2. Under the Large Set Condition, investment decisions rely more on the sign of A, indicating increased categorical processing.

H3. These effects are stronger when the payoff gap Δ between the focal asset and the best outside option is small.

6.1.2. Implementation

Each participant completes 48 independent decision problems, corresponding to all possible combinations of 8 focal assets and 6 outside option values. Each decision screen presents six assets: one focal asset, one outside option, and four distractors. The order of problems and the position of the alternative options on the screen are randomized across participants to prevent learning or positional biases. No feedback is provided after each decision to avoid reinforcement effects or dynamic updating. Before the main task, subjects complete several practice trials to ensure they

understand the payoff rule and the decision interface. The time limit for each decision is 20 seconds, with a short break after 24 trials.[5]

Subjects are recruited through Prolific, an established online participant pool widely used for behavioral and experimental research. We recruited 100 subjects in total, with 50 subjects assigned to each of the high- and low-complexity conditions. The experiment took approximately 12–18 minutes to complete. Participants receive a base payment of $3.00, plus a performance-based bonus of up to $2.00, determined by the outcome of a randomly selected decision problem from those they completed.

6.2. Results

Figure 3 displays the main experimental results. Panel A reports the average investment rate across different values of A for the full sample, while Panel B breaks down the investment rate by levels of Δ. Vertical bars represent standard errors.

[Insert Figure 3]

In Panel A, we find that investment rates increase monotonically in rather than a constant 50%, indicating A as a salient cue. Importantly, the investment rate exhibits an obvious jump at $A = 0$ for both Small and Large Set Conditions. Moreover, the discontinuity at $A = 0$ is visibly larger in the Large Set condition than in the Small Set condition. This pattern suggests that when the decision environment becomes more complex, participants rely more heavily on the salient and categorical information conveyed by the sign of A. In addition, investment rates in the Large Set Condition display a steeper relationship with the level of A on both sides of the cutoff, indicating a stronger overall sensitivity to this salient cue.

Panel B further shows that the jump is particularly pronounced when the focal asset and the outside option have similar payoffs—that is, when Δ is small. Quantitatively, the magnitude of the experimental discontinuity is substantial. The investment rate jumps by over 100% when Δ equals ± 10 in the Large Set Condition.

[Insert Table 11]

In Table 11, we report regression results examining how decision-environment complexity affects reliance on the salient payoff component A. Columns (1)–(4) present specifications that

[5] On average, participants spend about 5–10 seconds per decision, and the entire experiment lasts approximately 15 minutes, including instructions and practice rounds.

focus on sensitivity to the level of A. Across all observations and within each payoff-gap subsample ($|\Delta| = 10, 20, 30$), the interaction between A and the Large Set treatment is positive and statistically significant. This pattern indicates that, relative to the Small Set Condition, investment decisions in the Large Set Condition respond more strongly to changes in the value of A. The magnitude and significance of this interaction are broadly stable across different values of $|\Delta|$.

Columns (5)–(8) extend the analysis by incorporating an indicator for whether A is positive (*A_pos*), allowing us to test for categorical (sign-based) processing. The coefficient on *A_pos* is positive and statistically significant across all specifications, implying that participants are more likely to invest when A is positive than when it is negative, which reflects the jump observed in our retail investor data.

We next examine whether high complexity strengthens this sign-based reliance. The interaction between *A_pos* and the Large Set treatment is not statistically significant in the full sample. However, it is positive and significant in the subsample with the smallest payoff gap ($|\Delta| = 10$). This finding suggests that when the decision problem is most difficult—i.e., when payoff differences are small—greater complexity further increases reliance on categorical sign information. Together, these results indicate that higher complexity amplifies both sensitivity to salient payoff levels and, in more demanding environments, dependence on simplified categorical cues.

Overall, the experiment provides clean causal evidence that the zero-crossing heuristic can arise from perceptual and cognitive simplification rather than from preferences or belief distortions.

7. Conclusion

This paper examines the impact of complexity on investment decisions using granular trading and browsing data of retail mutual fund investors. We integrate large-scale observational evidence with controlled experimentation and structural estimation to show how decision complexity systematically shapes investor behavior. Across settings, individuals deviate from fully rational benchmarks in predictable ways: when choices become harder or information is more cognitively demanding to process, people increasingly rely on simplified, direction-based cues rather than evaluating full underlying values. This generates discrete shifts in behavior—such as sharp changes around category boundaries—that mirror patterns observed in real financial markets.

We first develop a novel empirical strategy to isolate the effect of complexity from beliefs and risk preferences. We identify a discontinuity in purchase behavior at the zero-crossing of price changes, using a regression discontinuity design that rules out the belief channel. We find that a small negative change in an asset's price from the price browsed one day before a trade induces a surge in the probability of purchasing the asset by 12.6%. This discontinuity cannot be explained by a belief change that should involve continuous Bayesian updating. Thus, we consider the jump in the probability as the deviation from the rational level. In the second step, we demonstrate that complexity increases erroneous decision-making — an outcome not naturally predicted by the prospect theory. We show that the zero-crossing discontinuity varies substantially with various complexity measures: it is more pronounced for trades that involve larger consideration sets, accounts that hold a less concentrated portfolio, during more uncertain macro environment, for equity funds and funds with higher volatility, and among less educated investors.

By investigating investors' cognitive effort through their browsing activities, we show that investors exhibit a stronger discontinuity in purchase probability for assets that they spend more time on and browse more frequently or earlier in the sequence. This finding implies that simplified decision-making process arises from complex problems that demand greater cognitive effort rather than a result of a lack of cognitive effort.

Results from the controlled experiment further demonstrates that these deviations arise not from preferences but from cognitive frictions that lead individuals to compress continuous information into coarse categories. Together, the evidence provides a unified account of how complexity influences decision-making: as environments become more demanding, investors economize on cognitive effort by leaning on heuristics, producing systematic and measurable departures from rational choice.

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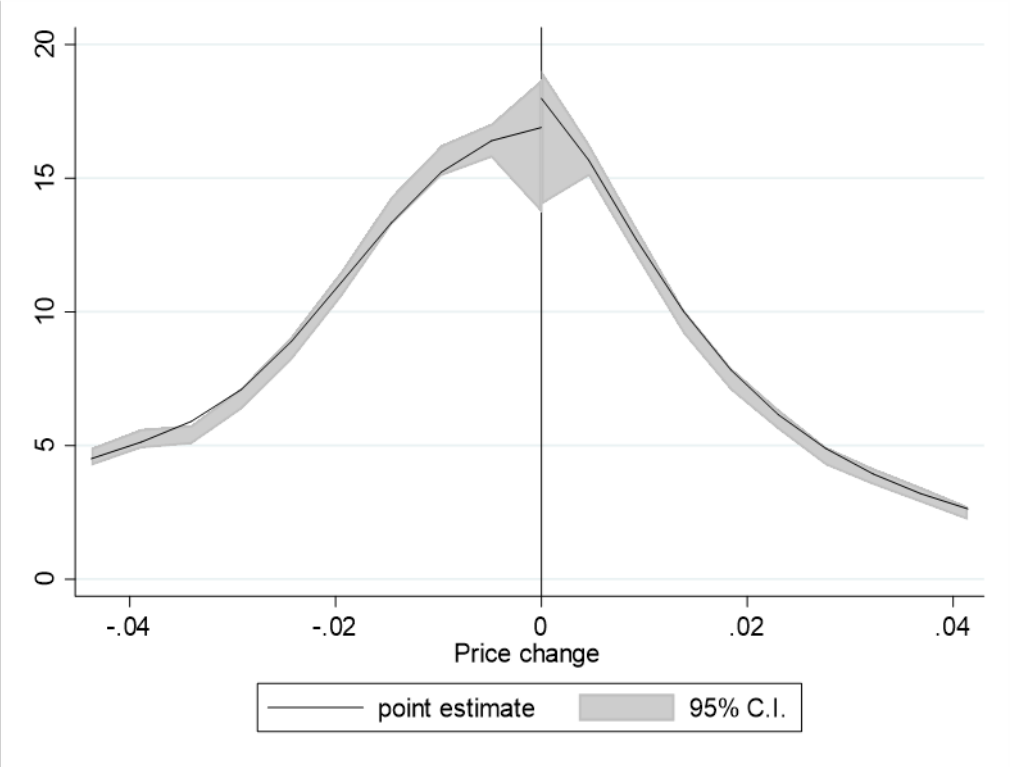
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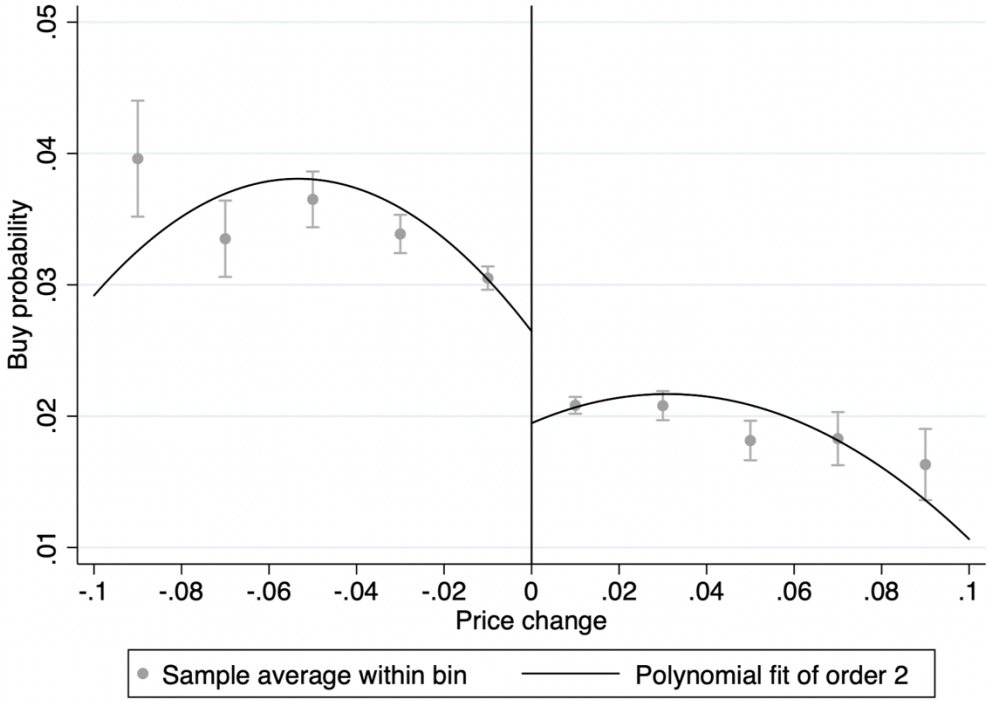
Figures

Figure 1: Validation Test: Detecting Possible Manipulation at the Cutoff



Note: In this figure, we provide a visual representation of the continuity of the running variable around the cutoff of zero. Specifically, we implement manipulation testing procedures of one-day price changes of traded assets using the second-order local polynomial density estimators with a triangular kernel function proposed in Cattaneo, Jansson and Ma (2014). For a review on manipulation testing see McCrary (2008). Black curve represents the point estimates and grey area indicates 95% confidence intervals. P-value in this test is reported to be 0.86.

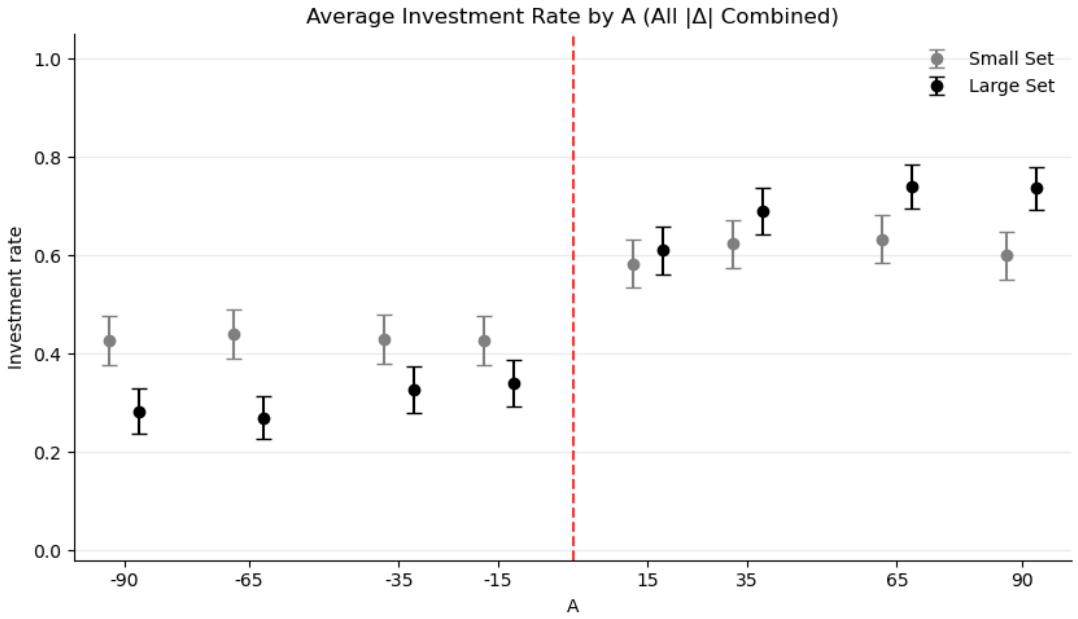
Figure 2: Price Changes and Trading



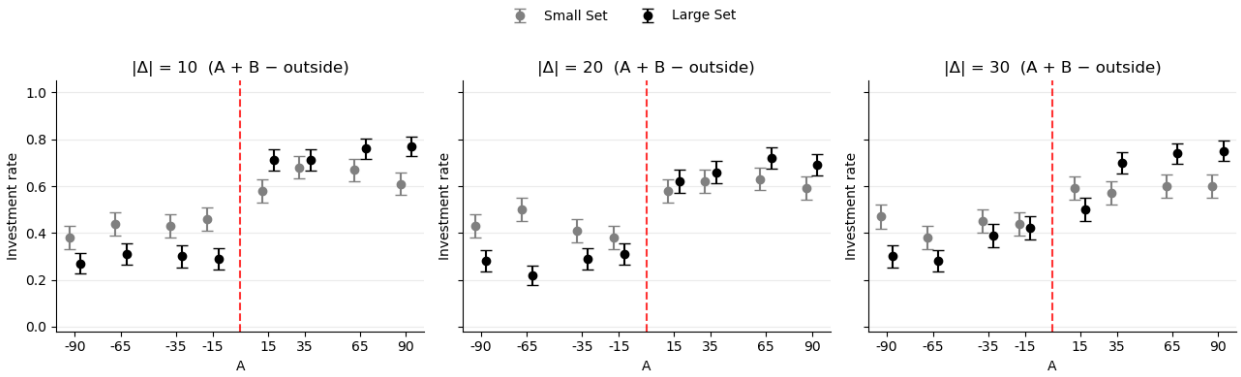
Note: In this figure, we provide a visual representation of the discontinuity in the treatment effect. Observations are sorted, based on the price change, into bins of size 0.02. Five bins on each side of zero are shown on the x-axis. The graph plots purchase likelihood on the y-axis, where each point represents for observations within their respective bin (with 95% confidence intervals). We use polynomials of order two, different for each side. Points on the left (right) side of zero represent observations from negative (positive) price changes.

Figure 3. Experiments

Panel A: Full Sample



Pane B: Results by Δ



Note: This figure presents the experimental results. Panel A reports the average investment rate across different values of *A* for the full sample under Large and Small Set Conditions, while Panel B breaks down the investment rate by levels of Δ. Vertical bars represent standard errors.

Tables

Table 1: Summary Statistics

Panel A. Account level

Variable	N	mean	sd	p5	p50	p95
Age	11713	46.16	12.59	30	40	70
Gender (F)	11713	0.44	0.5	0	0	1
Holding RMB	11713	198208.62	562774.8	1314.25	51769.88	818988.38
Number of products	11713	8.86	23.51	1	5	25
Monthly transaction	11713	7.2	15.66	0	4	23
Monthly browsing frequency	11713	21.46	72.49	1	5	87

Panel B. Investor×asset×trading day level

Variable	N	mean	sd	p5	p50	p95
1-day price change	605724	0	0.043	-0.077	0	0.075
Positive 1-day price change (≥ 0)	605724	0.54	0.5	0	1	1
Buy dummy	605724	0.03	0.16	0	0	0
Transaction amount	16190	4818.32	39646.9	3	400	14250
Consideration set (one week prior to the potential trading day)						
Consideration set size	605724	48.89	90.93	3	22	172
Browse freq of the asset	605724	7.27	14.08	1	3	24
Browse length of the asset (in seconds)	605724	91.46	134.73	3	36	357
Total browse freq	605724	142.64	282.35	3	49	590
Total browse length (in seconds)	605724	1608.46	3459.11	40	644	5546

Note: The table presents the summary statistics of the variables used in our analysis.

Table 2: Validation Test

	(1)	(2)	(3)	(4)
Dep. var.:	Annual std	Browse Freq	Browse Length	Holding
Pos Price Chg	0.000	0.044	-0.559	-1503.360
	(0.000)	(0.085)	(0.956)	(3525.029)
Bandwidth	0.014 (opt)	0.014 (opt)	0.014 (opt)	0.014 (opt)
Polynomial	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y
R-squared	0.739	0.453	0.298	0.384
N	269527	270237	270237	270237

Note: This table verifies that there is no jump in the property of the asset or the investors' browsing behavior prior to the potential trading date around the cutoff of the running variable, namely the price change of the asset within a single day. *Annual std* is the annual standard deviation of the asset price. *Browse Freq* and *Browse Length* are the browsing frequency and length (in seconds) of the asset one week prior to the potential trading date. *Holding* is the mean holding of the investor in that month. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * $p<0.1$, * $p<0.05$, *** $p<0.01$.

Table 3: Price Changes and Trading

Dep. var.: Buy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pos Price Chg	-0.003**	-0.003**	-0.003***	-0.002*	-0.006***	-0.002*	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bandwidth	0.014 (opt.)	0.017	0.5	0.002 (opt.)	0.5	0.008 (opt.)	0.5
Polynomial	Y	Y	Y	N	N	Linear	Linear
Individual FE	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.113	0.116	0.114	0.115	0.114	0.109	0.114
N	269102	301903	601454	81072	601454	188172	601454

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to zero. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 4: Restricting to Dates with a Buy Trade

Dep. var.: Buy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pos Price Chg	-0.012**	-0.009*	-0.010***	-0.011**	-0.023***	-0.011**	-0.016***
	(0.005)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)
Bandwidth	0.014 (opt.)	0.018	0.5	0.003	0.5	0.01	0.5
Polynomial	Y	Y	Y	N	N	linear	linear
Individual FE	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.156	0.159	0.158	0.172	0.158	0.156	0.158
N	73249	86909	169777	24818	169777	59370	169777

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. Sample selection: the dates are restricted to the ones on which the investor has made a purchase. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 5: Decision Dimensions: Consideration Set Size, Portfolio Concentration and Macroeconomic Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)
	Large set	Small set	Low	High	Large VIX	Small VIX
Dep. var.: Buy			concentration	concentration		
Pos Price Chg	-0.004**	-0.002	-0.004*	-0.002	-0.004**	-0.003
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Bandwidth	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)
Polynomial	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y
R-squared	0.119	0.126	0.108	0.129	0.098	0.128
N	149860	116887	138437	129118	101436	165399

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. The consideration set consists of assets the investor viewed on the trade day and during the preceding week. *Small Set* refers to the investor×date with the consideration set size that is below the median of the investor's set size in the sample, and *Large Set* otherwise. *Low concentration* refers to the sample in which the HHI of the investor's portfolio is below the median of the observations in the same month, and *High concentration* otherwise. *Large VIX* includes samples from March to June and October to November 2022, which correspond to the six months in the sample with relatively higher VIX of the CSI 300, and *Small VIX* includes samples from the other six months with relatively lower VIX. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 6: Product Complexity

Dep. var.: Buy	(1) Equity funds	(2) Mixed funds	(3) Bond funds
Pos Price Chg	-0.014***	-0.003	0.002
	(0.004)	(0.002)	(0.002)
Bandwidth	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)
Polynomial	Y	Y	Y
Individual FE	Y	Y	Y
Product FE	Y	Y	Y
Year Month FE	Y	Y	Y
R-squared	0.108	0.131	0.116
N	84680	112796	30952

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. Columns (1) to (3) analyze the subsamples of equity, mixed and bond funds, respectively. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 7: Cognitive Capacity: Education

	(1)	(2)	(3)	(4)
Dep. var.: Buy	High EDU	Low EDU	Fin Prof	Non Fin Prof
Pos Price Chg	-0.002	-0.005**	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Bandwidth	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)
Polynomial	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y
R-squared	0.121	0.097	0.121	0.090
N	167738	98928	20893	141813

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. *High EDU* refers to the investors with a college degree or higher, and *Low EDU* otherwise. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 8: Cognitive Effort

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: Buy	Freq High	Freq Low	Length High	Length Low	Enter late	Enter early	Enter% late	Enter% early
Pos Price Chg	-0.005*	-0.001	-0.004*	-0.001	-0.001	-0.006**	-0.001	-0.005**
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
Bandwidth	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)	0.014 (opt.)
Polynomial	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.162	0.092	0.141	0.090	0.097	0.150	0.109	0.123
N	113259	152368	132814	132330	173159	93994	138388	126955

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. If an investor views an asset more frequently than their average weekly views in the sample before a potential trading day, it is *Freq High*; otherwise, *Freq Low*. If the viewing time exceeds their average weekly duration, it is *Length High*; otherwise, *Length Low*. An asset is *Enter Early* if first viewed at least four days before the potential trading day; otherwise, *Enter Late*. If it enters the consideration set later than 40% of other assets, it is *Enter % Early*; otherwise, *Enter % Late*. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 9: Selling Decisions

Dep. var.: Sell	(1)	(2)	(3)
Pos. Cum. Perf.	0.0009***	0.0007*	0.0011***
	(0.0003)	(0.0004)	(0.0003)
Bandwidth	1 (opt.)	0.5	10
Polynomial	Y	Y	Y
Individual FE	Y	Y	Y
Product FE	Y	Y	Y
Year Month FE	Y	Y	Y
R-squared	0.026	0.024	0.027
N	1,413,161	1,174,625	2,049,548

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and cumulative gain of sell trades. *Sell* is a dummy variable that equals one if the asset is sold and zero if it is not. *Pos. Cum. Perf.* is a dummy variable that equals one if cumulative gain is greater than or equal to 0. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 10: Consideration Set Size (Low Education Sample)

	(1)	(2)
Dep. var.: Buy	Small set	Large set
Pos Price Chg	-0.003	-0.008**
	(0.004)	(0.003)
Bandwidth	0.014 (opt.)	0.014 (opt.)
Polynomial	Y	Y
Individual FE	Y	Y
Product FE	Y	Y
Year Month FE	Y	Y
R-squared	0.132	0.091
N	41875	55549

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. The sample is limited to the investor with education level below college (not inclusive). *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. The consideration set consists of assets the investor viewed on the trade day and during the preceding week. *Small Set* refers to the investor×date with the consideration set size that is below the median of the investor's set size in the sample, and *Large Set* otherwise. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table 11: Experiment Result

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var: Invest	all	|Δ|=10	|Δ|=20	|Δ|=30	all	|Δ|=10	|Δ|=20	|Δ|=30
A_value	0.001***	0.002***	0.001**	0.001***	0.000	0.001**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Large_set	-0.021	-0.019	-0.040	-0.005	-0.052	-0.121**	-0.074	0.038
	(0.019)	(0.023)	(0.025)	(0.021)	(0.034)	(0.051)	(0.049)	(0.045)
Large_set × A_value	0.002***	0.002***	0.002***	0.002***	0.001***	0.000	0.001*	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
A_pos					0.172***	0.135**	0.217***	0.160***
					(0.047)	(0.066)	(0.061)	(0.050)
Large_set × A_pos					0.060	0.205**	0.068	-0.086
					(0.065)	(0.093)	(0.084)	(0.085)
N	4,762	1,591	1,582	1,589	4,762	1,591	1,582	1,589
R-sq	0.077	0.095	0.075	0.062	0.086	0.110	0.091	0.066
adj. R-sq	0.076	0.093	0.073	0.061	0.085	0.107	0.088	0.063

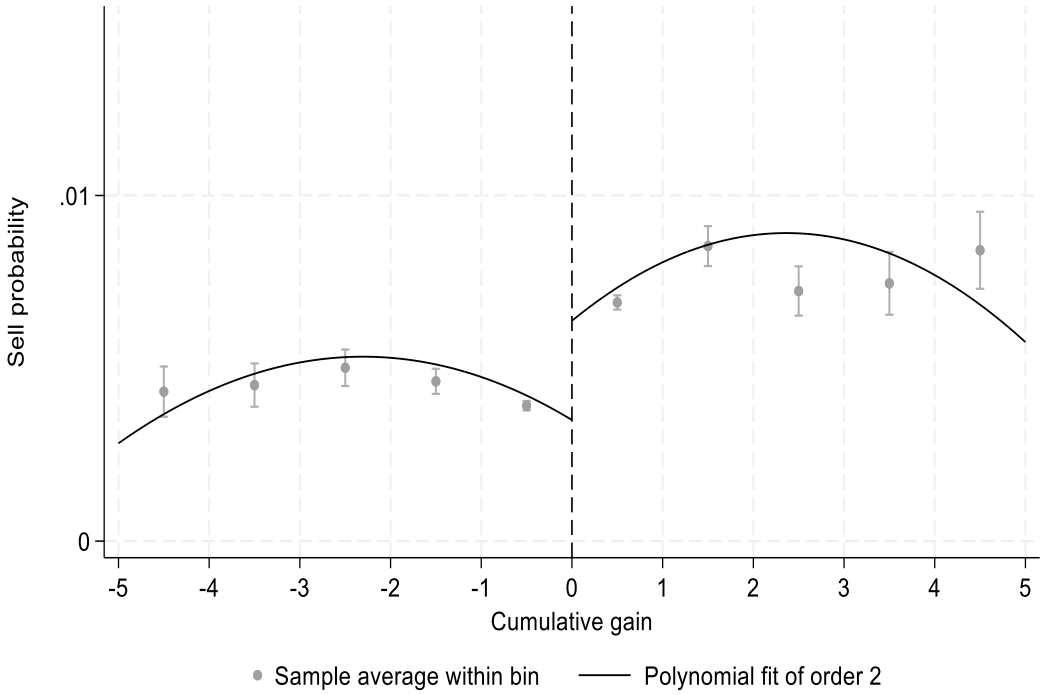
Note: This table presents the regression of participants investment decision on the A values and the treatment High complexity. *Invest* is a dummy variable that equals one if the participant decides to invest in the focal asset and zero if it is not. *A_value* is the value of A. *A_pos* is a dummy variable that equals one if *A_value* greater than or equal to 0. *High* is a dummy variable that equals one the participant is from the High complexity condition. Standard errors are clustered at the participate level. * p<0.1, * p<0.05, *** p<0.01.

Appendix 1: Variable Definition

Variable	Definition
Pos Price Chg	An indicator variable that takes the value of 1 if the price change from the day before the potential trading day to the potential trading day is greater than or equal to 0, and 0 otherwise.
Buy	An indicator variable that equals 1 if the asset is purchased on the potential trading day, and 0 otherwise.
Annual std	The standard deviation of the asset's price over the one-year period up to the potential trading day.
Brows Freq	The number of times the asset was viewed in the week up to the potential trading day.
Brows Length	The total duration (in seconds) spent viewing the asset in the week lup to the potential trading day.
Holding	The average value of portfolio held by the investor during the observed sample period.
Small/large set	An investor's Consideration Set is the number of assets viewed in the week before a potential trading day. If this number is below the investor's median Consideration Set size, it is Small; if above or equal, it is Large.
Small/large HHI	*Small HHI* refers to the Herfindahl-Hirschman Index of the investor's portfolio is below the median of the observations in the same month, and *Large HHI* otherwise. If the investor does not hold any asset in that month, the HHI is set to 1 in that month.
High/low volatility	If an asset's price standard deviation in the year before the potential trading day is above the median of the assets browsed by the investor in the sample, it is classified as High Volatility; Low Volatility otherwise.
High /low EDU	If the investor has a college degree or higher, they are classified as High EDU; otherwise, Low EDU.

Freq high/low	If the number of times an investor views an asset in the week before a potential trading day is above their own average weekly views in the sample, it is High Frequency; otherwise, Low Frequency.
Length high/low	If the total time an investor spends viewing an asset in the week before a potential trading day is above their own average weekly viewing time in the sample, it is High Length; otherwise, Low Length.
Enter late/early	If an asset was first viewed at least four days before the potential trading day, it is Enter Early; otherwise, Enter Late.
Enter% late/early	If an asset entered the consideration set later than 40% of the other assets in the set, it is Enter % Early; otherwise, Enter % Late.

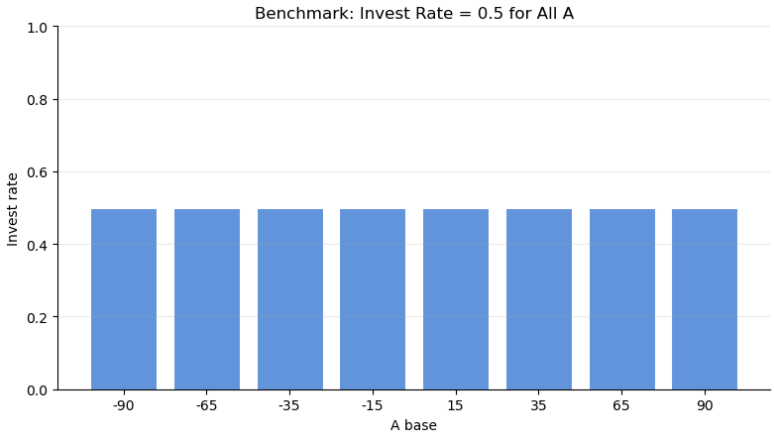
Figure A.1: Price Changes and Trading: Sell



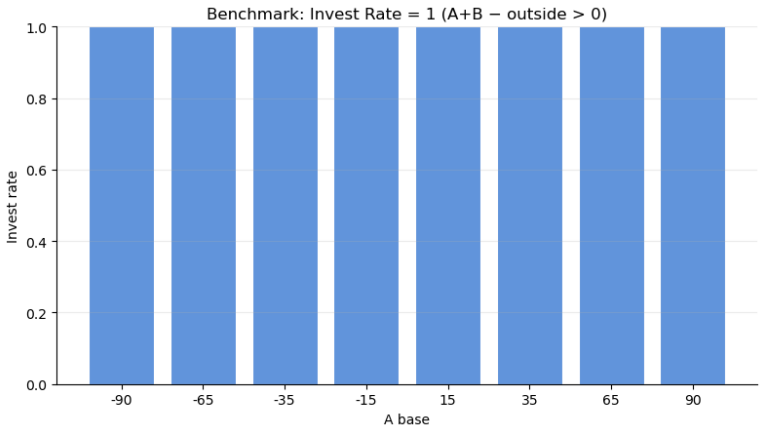
Note: In this figure, we provide a visual representation of the discontinuity in the treatment effect on sell probability. Observations are sorted, based on the cumulative gain, into bins of size 1. Five bins on each side of zero are shown on the x-axis. The graph plots purchase likelihood on the y-axis, where each point represents for observations within their respective bin (with 95% confidence intervals). We use polynomials of order two, different for each side. Points on the left (right) side of zero represent observations from negative (positive) cumulative gain.

Figure A.2. Rational Benchmarks for Experiments

Panel A: Rational Benchmark for all Decision Problems



Panel B: Rational Benchmark when Focal Asset Dominants (Positive Δ)



Panel C: Rational Benchmark when Focal Asset Dominants (Negative Δ)

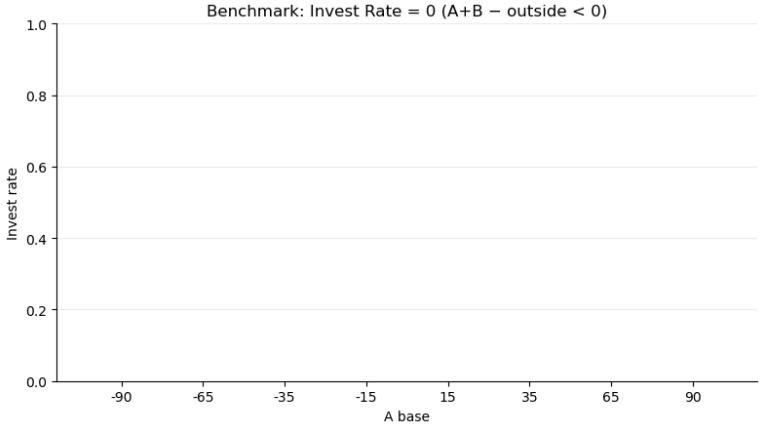


Table A.1: Assets Investors Less Interested in

Panel A. Effect of one-day pos price change on the investors who viewed on two days not one day before the trade date

Dep. var.: Buy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pos Price Chg	-0.001	-0.001	0.001	-0.001	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bandwidth	0.014 (opt.)	0.017	0.5	0.002	0.5	0.008	0.5
Polynomial	Y	Y	Y	N	N	linear	linear
Individual FE	Y	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.078	0.077	0.075	0.100	0.075	0.076	0.075
N	185205	206239	379305	60751	379305	132977	379305

Panel B. Effect of one-day price change on the investors who viewed on previous day vs. not on previous day

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Buy	d1 vs. d2	d1 vs. d2d3	d1 vs. d2-d7	d2Only	d2d3Only	d2-d7Only
Pos Price Chg	-0.001	0.000	0.001**	-0.001	0.000	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pos Price Chg × View D-1	-0.002*	-0.003**	-0.004***			
	(0.001)	(0.001)	(0.001)			
Bandwidth	0.014 (opt)	0.014 (opt)	0.014 (opt)	0.014 (opt)	0.014 (opt)	0.014 (opt)
Polynomial	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y
R-squared	0.101	0.097	0.091	0.078	0.080	0.083
N	459642	584072	968806	185205	310374	695130

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. Sample selection: the investor viewed the asset page at least once during the previous 3 days. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. *View D-1* is a dummy that equals 1 if the investor viewed the asset page on the previous day and 0 otherwise. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table A.2: Price Changes and Trading based on Asset Returns

Dep. var.: Buy	(1)	(2)	(3)	(4)	(5)	(6)
Pos Price Chg	-0.003**	-0.001	-0.004***	-0.006***	-0.003**	-0.002**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Bandwidth	0.007 (opt.)	0.05	0.001	0.05	0.004	0.05
Polynomial	Y	Y	N	N	Linear	Linear
Individual FE	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y
R-squared	0.117	0.114	0.125	0.114	0.114	0.114
N	249586	601454	75240	601454	171607	601454

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day, using return rate as the running variable. *Buy* is a dummy variable that equals one if the asset is bought and zero if it is not. *Pos Price Chg* is a dummy variable that equals one if the change in price since the previous day is greater than or equal to 0. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table A.3: Decision Dimensions: Consideration Set Size, Portfolio Concentration and Macroeconomic Uncertainty (Sell)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Sell	Large set	Small set	Low concentration	High concentration	Large VIX	Small VIX
Pos. Cum. Perf.	0.0011***	0.0009***	0.0011**	0.0005	0.0009*	0.0009**
	(0.0004)	(0.0003)	(0.0005)	(0.0003)	(0.0005)	(0.0004)
Bandwidth	1 (opt.)	1 (opt.)	1 (opt.)	1 (opt.)	1 (opt.)	1 (opt.)
Polynomial	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y	Y	Y
R-squared	0.029	0.027	0.026	0.035	0.028	0.029
N	775,399	636,445	699,777	712,525	771,045	640,769

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Sell* is a dummy variable that equals one if the asset is sold and zero if it is not. *Pos. Cum. Perf.* is a dummy variable that equals one if cumulative gain is greater than or equal to 0. The consideration set consists of assets the investor viewed on the trade day and during the preceding week. *Small Set* refers to the investor×date with the consideration set size that is below the median of the investor's set size in the sample, and *Large Set* otherwise. *Low concentration* refers to the sample in which the HHI of the investor's portfolio is below the median of the observations in the same month, and *High concentration* otherwise. *Large VIX* includes samples from March to June and October to November 2022, which correspond to the six months in the sample with relatively higher VIX of the CSI 300, and *Small VIX* includes samples from the other six months with relatively lower VIX. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table A.4: Product Complexity (Sell)

	(1)	(2)	(3)
Dep. var.: Sell	Equity funds	Mixed funds	Bond funds
Pos. Cum. Perf.	0.0008*	0.0009**	0.0018**
	(0.0005)	(0.0004)	(0.0008)
Bandwidth	1 (opt.)	1 (opt.)	1 (opt.)
Polynomial	Y	Y	Y
Individual FE	Y	Y	Y
Product FE	Y	Y	Y
Year Month FE	Y	Y	Y
R-squared	0.024	0.031	0.034
N	532,110	690,832	84,191

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Sell* is a dummy variable that equals one if the asset is sold and zero if it is not. *Pos. Cum. Perf.* is a dummy variable that equals one if cumulative gain is greater than or equal to 0. Columns (1) to (3) analyze the subsamples of equity, mixed and bond funds, respectively. Columns (4) and (5) analyze assets with high and low volatility, respectively. H*igh std* refers to the asset with a standard deviation of daily returns over the past year above the median of the assets browsed by the investor, and *Low std* otherwise. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.

Table A.5: Cognitive Capacity: Education (Sell)

	(1)	(2)	(3)	(4)
Dep. var.: Sell	High EDU	Low EDU	Fin Prof	Non Fin Prof
Pos. Cum. Perf.	0.0011	0.0005	0.0003	0.0009**
	(0.0009)	(0.0004)	(0.0005)	(0.0004)
Bandwidth	1 (opt.)	1 (opt.)	1 (opt.)	1 (opt.)
Polynomial	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y
R-squared	0.018	0.034	0.028	0.029
N	385,974	791,030	87,379	710,478

Note: This table presents the relationship between the likelihood of an investor purchasing an asset and the price change of that asset within a single day. *Sell* is a dummy variable that equals one if the asset is sold and zero if it is not. *Pos. Cum. Perf.* is a dummy variable that equals one if cumulative gain is greater than or equal to 0. *High EDU* refers to the investors with a college degree or higher, and *Low EDU* otherwise. Investor, product, year, and month fixed effects are controlled in all specifications. Standard errors are clustered at the investor level. * p<0.1, * p<0.05, *** p<0.01.