

# Visual Saliency and Investment Decisions

Alfredo Desiato<sup>\*</sup>

[a.desiato1@aston.ac.uk](mailto:a.desiato1@aston.ac.uk)

Luca Enriques<sup>†</sup>

[luca.enriques@law.ox.ac.uk](mailto:luca.enriques@law.ox.ac.uk)

Alex Lee<sup>‡</sup>

[alex.lee@law.northwestern.edu](mailto:alex.lee@law.northwestern.edu)

Kenneth Khoo<sup>§</sup>

[kenneth.khoo@nus.edu.sg](mailto:kenneth.khoo@nus.edu.sg)

Alessandro Romano<sup>¶</sup>

[alessandro\\_romano@unibocconi.it](mailto:alessandro_romano@unibocconi.it)

## Abstract

Despite regulatory efforts to improve fee transparency, investors persistently underweight fees and overweight past performance—a phenomenon often attributed to cognitive biases and limited salience of cost information. We employ webcam-based eye-tracking technology in a large-scale online experiment to investigate how manipulating the visual saliency of fees shapes investment decisions. Participants allocated \$100 between pairs of equity funds differing in fees and historical returns, with treatments enhancing fee prominence through larger font sizes or strategic placement (top/left). We find that increasing fee saliency reduces time-to-first-fixation (TTFF) on past performance graphs by 47–75% and significantly increases dwell time on fees by 3–5.8%. These shifts in visual attention are associated with an 11.2% greater allocation to lower-fee funds in treatment groups compared to the control, with effects magnified for fund pairs exhibiting larger fee differentials. Our results demonstrate that interface design choices—such as prioritizing fee visibility over performance graphics—can meaningfully reduce biases in investor decision-making. By identifying the precise mechanisms of attention through which saliency interventions influence choices, we advance the saliency literature in behavioral finance and provide actionable insights for regulators and platforms aiming to improve fee transparency.

---

<sup>\*</sup>Aston University, School of Optometry.

<sup>†</sup>University of Oxford, Faculty of Law.

<sup>‡</sup>Northwestern University, Pritzker School of Law

<sup>§</sup>National University of Singapore, Faculty of Law.

<sup>¶</sup>Bocconi University, Department of Legal Studies.

# 1 Introduction

The Efficient Markets Hypothesis (EMH) posits that all publicly available information is quickly incorporated into asset prices, implying that past performance should not reliably predict future returns (Fama, 1970; Jensen, 1978; Beechey et al., 2000). Nevertheless, a substantial literature in behavioral finance shows that many investors persistently chase past performance and fail to minimize fees, despite clear evidence that both behaviors can undermine long-term returns (Barber et al., 2005; Fisch and Wilkinson-Ryan, 2014). For example, in the index fund market—where funds tracking a given index offer virtually identical portfolios prior to fees—the dispersion in fund prices remains comparable to that observed among actively managed funds (Hortaçsu and Syverson, 2004). In more recent years, DeHaan et al. (2021) show that many S&P 500 index funds have largely homogeneous returns and risks but continue to charge different fees. Moreover, empirical studies consistently find that investors favor funds with strong recent returns, exhibiting “performance-chasing” behavior even though regulatory disclaimers emphasize that past performance does not guarantee future results (Weiss-Cohen et al., 2022; Mercer et al., 2010).

Behavioral economists often attribute performance-chasing to several cognitive biases. In particular, recency bias and the representativeness heuristic have been hypothesized to induce investors to over-invest in well-performing stocks. Recency bias leads investors to overweight recent positive trends, assuming these will persist (Barberis et al., 1998). An empirical study by Bloomfield and Hales (2002) shows that investors overreact to earnings changes following similar patterns (i.e., a “continuation regime”), while Offerman and Sonnemans (2004) find that traders rely heavily on historical trends and thereby overestimate the autocorrelation of future prices. Similarly, the representativeness heuristic can cause investors to misinterpret a stock’s strong recent performance as evidence of its inherent quality, erroneously concluding it must be a “winning stock” going forward, even if future profits are already priced in (De Bondt and Thaler, 1985). For instance, drawing on 38,000 forecasts of stock prices and exchange rates, De Bondt (1993) reports that investors tend to “bet on trends,” extrapolating a stock’s recent performance as a stable attribute of the asset.

Another facet of this literature examines why investors fail to minimize fees, which may be driven by cognitive biases such as inattention and limited salience, or a misplaced belief that higher fees signal superior management. To explain the former, scholars argue that many investors regard fees as “small” relative to overall returns, reducing the perceived importance of choosing lower-cost funds (Hortaçsu and Syverson, 2004; Choi et al., 2010).<sup>1</sup> To make sense of the latter, one

---

<sup>1</sup>We turn to a more thorough discussion of salience in Section 2.1.

hypothesis is that some investors rationally seek non-portfolio services (e.g., financial advice or customer service) that accompany certain, often more expensive, funds ([Collins, 2005](#)). Yet empirical evidence offers limited support for this explanation: [Elton et al. \(2004\)](#) find no significant relationship between service quality and mutual fund inflows, and [Choi et al. \(2010\)](#) demonstrate in an experimental setting without ancillary services that participants—including Harvard MBA students—still fail to select the lowest-fee options among nearly identical S&P 500 index funds. Collectively, these findings underscore a persistent mismatch between investor decision-making and EMH predictions, highlighting how behavioral and psychological factors can shape both fund selection and fee minimization.

While U.S. regulators are fully aware of investors' under-sensitivity to fees, it is fair to say they have not been effective in tackling the problem so far. Mutual funds must prepare a “statutory prospectus” in accordance with Form N-1A,<sup>2</sup> containing 13 Items prescribed by the SEC. They may also prepare a “summary prospectus”,<sup>3</sup> which must contain information about fees, in the form of a table, and about investments, risks and performance, including a bar chart “showing the Fund’s annual total returns for each of the last 10 calendar years (or for the life of the Fund if less than 10 years).”<sup>4</sup> Fees disclosure is required to precede performance disclosure in both the prospectus and the summary prospectus, apparently in an (undoubtedly timid) effort to make the former more salient than the latter.<sup>5</sup>

In 2020, the SEC proposed substantial reforms to mutual fund prospectus fees disclosures ([SEC, 2020](#)). Most relevantly, the SEC proposed the creation of a “simplified fee summary”, which would replace the fee table that currently appears in the summary section prescribed by Item 3 of Form N-1A. The statutory prospectus would also include the current fee table prescribed by Item 3, in addition to the simplified summary (a new Item 8A would require the fee table in the statutory prospectus). The regulator’s goal was “to streamline the presentation of fees and provide an easier-to-understand presentation that includes fewer data points to help provide a clearer picture of the total costs of investing in a fund” ([SEC, 2020](#)). Its motivation was the awareness that, despite the importance of fees as a factor that investors should consider in making their choices, “the degree to which investors understand fund fees and expenses remains a significant source of focus and attention, and the Commission and staff have continually sought to improve investors’

---

<sup>2</sup>SEC rules require the use of this form for securities of open-end management investment companies: 17 C.F.R. § 239.15A (2024).

<sup>3</sup>17 C.F.R. § 230.49 (2024).

<sup>4</sup>Securities and Exchange Commission, Form N-1A (11 December 2023), 2–3.

<sup>5</sup>More precisely, Form N-1A requires that the prospectus place Items 2–8 immediately after the Cover Page (Item 1) and any table of contents, and to place them in numerical order Securities and Exchange Commission, Form N-1A (11 December 2023).

understanding in this area” ([SEC, 2020](#)). Such reforms were never adopted.

Yet even if they had been, the SEC’s focus on mandated disclosure documents—namely, the statutory and summary prospectuses—undermines their efficacy. The fundamental problem is that investors do not necessarily read, or even browse through, prospectuses ([Palmeter and Taha, 2008](#); [Mercer et al., 2010](#)). Instead, they often turn to their brokerage providers’ websites or apps, which, under FINRA Rule 2210(d)(5),<sup>6</sup> must present standardized fee and expense data whenever performance information is disclosed. Nevertheless, in practice, these platforms may still exploit investors’ inclination to overweight past performance and underweight fees: they frequently highlight performance data—often in graphical form—while fee information, though not strictly hidden, is rarely made highly visible.<sup>7</sup>

## 2 Background literature

### 2.1 Saliency

In principle, changes in framing that do not alter the information set should not affect decisions. However, research shows that the way in which information is framed and presented can have a significant impact on choices ([Tversky and Kahneman, 1981](#)). A straightforward way to alter the frame in which the information is presented is by changing the relative saliency of the information.

In behavioral economics and psychology, a stimulus is salient when it attracts the decision maker’s attention “bottom up”, that is, “automatically and involuntarily” ([Bordalo et al., 2022](#)). Given that attention is both a scarce and rivalrous resource ([Loewenstein and Wojtowicz, 2023](#)), the relative saliency of an attribute plays a crucial role in determining whether people consider that attribute when making decisions ([Bordalo et al., 2022](#)).

A rich body of literature has investigated the role of saliency in decision-making. In a series of papers, [Bordalo et al. \(2012; 2013; 2020\)](#) develop theoretical models centered on attribute saliency and demonstrate that these models provide a powerful explanation for many choice instabilities contrary to standard rational-choice axioms in an expected utility framework ([Von Neumann](#)

---

<sup>6</sup>Under Section 15(b) of the Securities Exchange Act of 1934, broker-dealers must register with the SEC and affiliate with a self-regulatory organization (SRO). FINRA, as the largest SRO, serves as the default choice for most firms.

<sup>7</sup>The lack of fee prominence is exemplified by the popular “Robinhood” trading platform’s interface design.

and Morgenstern (2007)). Their findings align with the results of numerous empirical studies. For instance, Chetty et al. (2009) demonstrate that individuals underreact to taxes when they are not visually salient. Similarly, Finkelstein (2009) provide evidence that drivers underweighted changes in highway tolls when paying electronically, as the change is less visually salient. More broadly, the literature shows that consumers tend to underweight attributes that are hidden or lack visual saliency (Gabaix and Laibson, 2006).

Saliency also plays an important role in finance. While most models of investor behavior assume that the manner in which information is presented has little impact on portfolio choice, evidence suggests that saliency can significantly influence investment decisions. For instance, Frydman et al. (2020) show that the visual salience of a stock's capital gain influences the investment decisions of Chinese investors. In a field experiment, Choi et al. (2017) observe that cues that make high savings rates salient increased 401(k) contribution rates by almost 3%. Similarly, Badoer, et al. (2020) demonstrate that a more salient disclosure of the indirect fees earned by 401(k) service providers results in a reduction in the total fees paid by smaller plans.

These studies adopt a broad definition of saliency, with a driving assumption that non-salient information is effectively hidden or “shrouded.” For instance, in Frydman et al. (2020), the treatment condition includes information that, in the control condition, requires three mouse clicks to access. Choi et al. (2017) increase the saliency of the treatment by adding sentences highlighting the advantages of a given investment option. Finally, Badoer et al. (2020) exploit a regulatory change requiring the disclosure of information about indirect fees that funds were previously not required to disclose.

Moreover, saliency is generally *assumed* and examined as a treatment condition. For example, consider the seminal paper by Chetty et al. (2009). In their main experiment, the authors increase the saliency of the sales tax for treated products by posting tax-inclusive prices, while for control products, the price tags on the shelves display only pretax prices. The authors observe that the treatment reduces product sales by 8%. However, as they note, the design of their main study does not allow for isolating the precise mechanism at play (2009). The consumers might have been uninformed about the tax price,<sup>8</sup> or the effect may relate with a bounded-rationality model in which consumers face a cognitive cost to calculate tax-inclusive prices. Furthermore, the authors cannot directly measure whether their treatment truly increases the salience of the information; they can only infer it from the results.

---

<sup>8</sup>To be sure, the authors design clever complementary tests to reduce the likelihood that this is the mechanism at play.

However, webcam-based eye-tracking allows us to directly test what Chetty and coauthors describe as an “entirely different theory of attention,” where the allocation of attention is driven by visual cues rather than economic optimization. This approach enables us to precisely identify the underlying mechanism.<sup>9</sup> Furthermore, webcam-based eye-tracking enables us to measure the visual saliency of information at the individual level.

Precisely identifying the mechanism where saliency condition conditions is crucial, as it helps design more effective information strategies. To illustrate, assume that the intervention implemented by [Chetty et al. \(2009\)](#) had not actually led to a decrease in consumption. This assumption is not far-fetched, as most information designs appear to be ineffective in inducing behavioral changes ([Ben-Shahar and Schneider, 2011](#)). In that case, it would have been impossible to distinguish whether the absence of a treatment effect could be attributable to the tax not being sufficiently salient in their treatment or because consumers were already optimally accounting for it when only pretax prices were displayed. Should policymakers, then, respond by making the tax even more salient or by preserving the status quo, understanding that regulatory costs are associated with mandatory rules of disclosure? A better understanding of the mechanism behind the effect (or lack thereof) of a given information design choice can help answer such questions.

Against this background, we contribute to the literature on salience by providing novel evidence on an important facet of salience: the role played by the visual prominence of an attribute ([Bordalo et al., 2022](#)). Unlike the studies cited above, our respondents are exposed to the exact same information in both control and treatment conditions, with only the visual prominence of key attributes being manipulated. Furthermore, eye-tracking technology enables us to measure, at the individual level, the extent to which the treatment increased or decreased the visual saliency of information relative to an attribute.

## 3 Methodology

### 3.1 Webcam-based Eye Tracking

Recent advancements in computer vision have made it possible to implement scalable eye tracking using participants’ webcams, commonly referred to as “webcam-based eye tracking” ([Hutt et al., 2024](#)). Webcam-based eye tracking has two primary advantages over traditional eye-tracking

---

<sup>9</sup>As acknowledged by the Chetty et. al., their experiment does not allow them to distinguish between the competing explanations.

studies carried out in laboratories. On the one hand, it enables scholars to recruit larger samples at lower cost. On the other hand, it allows participants to complete studies on their own laptops, wherever they prefer. Because many relevant decisions, including investment decisions, are made on laptops, webcam-based eye tracking further enhances ecological validity.

An expanding body of research demonstrates that webcam-based eye tracking is sufficiently accurate for addressing a wide range of research questions (Xu et al., 2015; Papoutsaki et al., 2017; Semmelmann and Weigelt, 2018; Valliappan et al., 2020; Yang and Krajbich, 2021; Hutt et al., 2024), provided that the design does not require extreme precision. For instance, if we were interested in pinpointing the exact spot on a stock price that attracts the most visual attention, a laboratory-based study would be necessary. However, in our study, we focus on the relative visual saliency of larger areas, such as the entire graph portraying a fund's past performance and the entire area in which the fund's exchange ratio is reported. Consequently, webcam-based eye tracking is suitable for our purposes.<sup>10</sup>

### 3.2 Fund Selection

In line with the approach of Choi et al. (2010), we established specific criteria for selecting three fund-pairs (six funds in total) for our study. Our initial sample comprised all funds in the CRSP Mutual Fund Database reporting fees (i.e., expense ratios) in 2023.<sup>11</sup> Because we sought to offer funds with a wide range of total fees and some variation in historical returns, we restricted our sample to equity-only funds and excluded those containing any fixed-income components. Given our focus on expense ratios rather than front or back-end loads, in contrast to Choi et al. (2010), we further removed all funds that charged either front or back loads.

From this refined universe, we generated what we term a “fund-pair” universe, comprising all possible combinations of funds.<sup>12</sup> We then followed Choi et al. (2010) in preserving only those fund-pairs in which fees were positively correlated with historical returns. In other words, in each retained pair, the fund with higher returns also exhibited higher fees, preventing a strictly dominant choice for any investor inclined toward returns-chasing behavior.<sup>13</sup>

---

<sup>10</sup>We include further information on webcam-based eye tracking in the Appendix.

<sup>11</sup>Throughout this article, we use “fees” and “expense ratios” interchangeably.

<sup>12</sup>For instance, in a universe with funds A, B, and C, we create the fund-pair universe: A-B, A-C, and B-C. Combinations are considered only, and order does not matter. More generally, for a universe with  $n$  funds, the total number of unique fund-pairs is given by the combination formula:  $\binom{n}{2} = \frac{n(n-1)}{2}$ . This formula accounts for all possible pairs where order is irrelevant.

<sup>13</sup>Our rationale for including this condition parallels that of Choi et al. (2010), who adopted a similar requirement to distinguish returns-chasing behavior from rational fee-avoidance.

Finally, in view of prior research underscoring how the magnitude of fee differentials can influence investment decisions ([Sirri and Tufano \(1998\)](#); [Barber et al. \(2005\)](#); [Gil-Bazo and Ruiz-Verdú \(2009\)](#)), we sought a broad range of fee variations within our selected pairs. To that end, we computed a “fee-wedge” for every fund-pair—defined as the absolute difference in fees—and sorted all pairs accordingly. We then chose our final three pairs at the 25th, 50th (median), and 75th percentiles of the fee-wedge distribution, labeling them fund-pairs “A–B”, “C–D”, and “E–F”, respectively.

### 3.3 The Experiment

We recruited a sample of  $N = 2000$  U.S. residents on Prolific.co. All participants were pre-screened for investment experience. Participants were paid about \$8.00 per hour for taking part in the experiment, and the median time to complete the survey was 11 minutes and 29 seconds. The full protocol of the study is included in the appendix. This study involved remote eye tracking carried out through i-Motions. The flow of Study I is illustrated in Figure 1.

At the beginning of the survey, we explained the investment task to participants. They had to make three investment decisions, each requiring an allocation of \$100 between two funds. We informed respondents that for three randomly selected individuals, after one year, we would pay out the real value of their investments. Therefore, these investment decisions were incentivized with relatively high stakes.

Afterwards, respondents were automatically redirected to the i-Motions platform, where they were *randomly* allocated to one of four conditions and underwent calibration to ensure proper eye-tracking. The four conditions were: (i) Control; (ii) Bigger fees; (iii) Bigger fees on the top; and (iv) Bigger fees on the left. We illustrate an example of these conditions in Figure 2, where they are depicted for Fund E–F.

After calibration, participants made their investment decisions while we tracked their eye movements. In all conditions, the same information was displayed: each fund’s expense ratio and a graph depicting the previous year’s performance. At the top of the screen, a slider allowed participants to decide how much to invest in each fund.

The only difference across conditions was the relative visual saliency of the expense ratio and the graph. In the “Bigger fees” condition, we increased the font size used to present the expense ratio. In the “Bigger fees on the top” condition, we applied the same larger font size and placed it at the top of the screen. In the “Bigger fees on the left” condition, we kept the larger font size and

positioned it on the left. All the treatments aimed to increase the visibility of the expense ratio relative to that of the graph.

After completing the investment task, participants underwent an additional calibration to improve the accuracy of eye-tracking. We then interrupted eye-tracking, and participants were automatically transferred to Qualtrics, where they answered additional questions on: (i) their beliefs about their investment (Table 1); (ii) their financial literacy (Table 2); (iii) their investing behavior and risk attitudes (Table 3); and (iv) standard demographic information. Table 9 presents summary statistics on participants' characteristics and confirms that the treatment and control groups are balanced, with no covariates differing significantly at the 10% level.

## 4 Results

We present the results of Study I. First, we demonstrate that respondents in the treatment condition paid less visual attention to the graph and more visual attention to fund fees, indicating that our treatments effectively increased the visual saliency of fees relative to the graphs. Second, we find that respondents allocated significantly more assets to funds with lower fees in the treatment conditions. These findings support the hypothesis that increasing the bottom-up saliency of an attribute enhances the weight respondents assign to that attribute when making decisions (Taylor and Thompson, 1982; Bordalo et al., 2022).

### 4.1 Visual Saliency

Table 4 reports the summary statistics for eye-tracking measures, whereas Tables 5 and 6 illustrate how the treatments influenced the visual saliency of the two primary AOIs: graphs and fees. The variable TTFF (time-to-first-fixation) represents the time elapsed between the onset of the stimulus and the respondent's first fixation within the AOI. TTFF is the most direct measure of visual saliency, as defined in Bordalo et al. (2022). Dwell Time Fixation (in ms) represents the total duration that respondents spent fixating on an AOI (i.e., the sum of all fixation durations within that AOI), whereas Dwell Time Fixation (%) indicates the proportion of participants' total viewing time spent fixating on an AOI. Although dwell-time metrics correlate with saliency, they also reflect whether the stimulus retains the respondent's attention, making them a less direct measure of bottom-up saliency.

All metrics suggest that the treatments effectively redirected visual attention from the graphs to

the fees. The effects are substantial and statistically significant at the 1% level. On average, the TTFF for the graph AOI is more than three times higher in the treatments than in the control. In the Bigger fees on the top condition, the TTFF for the graph is 5.9 times higher than in the control; in Bigger fees on the left, it is 4.8 times higher; and in Bigger fees, it is 2.7 times higher. Meanwhile, the treatments more than halve the TTFF for the fee AOI compared to the control. Specifically, Bigger fees reduces it by 47%, Bigger fees on the left by 66%, and Bigger fees on the top by 75%.

Turning to the dwell time measures, Figure 3 displays the distribution of dwell time for the fund-pair E-F. These heatmaps reveal two key findings. First, as anticipated, the majority of visual attention is directed toward the slider used to make the investment decision. Second, in both the control and treatment conditions, the graph attracts substantially more visual attention than the fund fees. This result aligns with the hypothesis that the visual saliency of graphs may lead investors to overweight past performance while underweighting fund fees.

As shown in Tables 5, and 6, respondents in the treatment conditions spent 27.6% less time fixating on the graph AOI and 3% more time fixating on the fees AOI overall. Comparing treatments, Bigger fees on the top and Bigger fees on the left divert a larger portion of dwell time from the graph AOI than Bigger fees does. For instance, Dwell Time Fixation (%) on the graph is 31.7% lower than in the control condition when participants are in the Bigger fees on the left condition, whereas it is only 24.5% lower in the Bigger fees condition. These results for TTFF and dwell time measures align with the observation that the treatments “Bigger fees on the top” and “Bigger fees on the left” not only reduce the relative size of the graph, but also position it in a less visually salient area of the screen.

To reinforce our findings, Figure 4 illustrates the distribution of TTFFs for the fee and graph AOIs, while Figure 5 presents the distribution of dwell-time fixations for these AOIs, clearly demonstrating how the treatments shift visual attention from the graphs to the fees.

## 4.2 Investment Decisions

We now turn to analyzing the effect of the treatments on investment decisions. Table 7 indicates that, on average, respondents in the treatment conditions invest 11.2% less in funds with better past performance and higher fees compared to those in the control condition, with the difference statistically significant at the 1% level. Put differently, respondents in the treatment groups allocate \$33.6 more out of \$300 to funds with lower fees and worse past performance than those in

the control. This suggests that, on average, the treatment groups assign greater weight to fees and less to graphs.

All treatments increase the percentage of assets that respondents allocate to funds with lower fees and worse past performance compared to the control group. However, the effect of Bigger fees is smaller and less robust, achieving significance only with certain combinations of controls. This aligns with the finding that Bigger fees diverts the least visual attention from graphs, suggesting the presence of a threshold effect—specifically, a change in visual saliency may significantly influence choices only when the change is sufficiently large. Figure 5 further shows that respondents in the treatments allocate a larger share of their assets to funds with lower fees.

We then analyze the treatments' effects across different fund pairs (Table 8). The effect is weakest for pair A-B and strongest for pair E-F. This pattern reflects the smallest fee wedge for A-B and the largest for E-F, aligning with our earlier hypothesis in Section 3.2 that a larger fee wedge may be correlated with stronger saliency.

### 4.3 Causal Mediation

Causal mediation analysis aims to disentangle how much of a treatment's effect operates through a specific mediator. In our setting, this mediator could be related to eye-tracking measures influencing investment allocation. However, the assumptions required for causal mediation are strong and may not fully hold here—for example, it typically requires a clear temporal ordering in which participants are exposed to the mediator before the outcome (VanderWeele, 2015).<sup>14</sup> Despite these limitations, cross-sectional mediation analyses remain common in practice, especially in psychology (Maxwell and Cole, 2007).

As an extension of our primary findings, we present the results of a causal mediation analysis using TTFF as the mediator in Table 10. Our results suggest that approximately 16.9% to 20.8% of the treatment effect on investment is mediated by the TTFF on Graphs, with these coefficients being statistically significant at the 5% level. By contrast, we find that 16.5% to 20.8% of the treatment effect on investment is mediated by the TTFF on Fees; however, these coefficients do not reach significance at the 10% level, potentially because participants spend considerably different amounts of dwell time on Graphs versus Fees (see Table 4).

---

<sup>14</sup>In our setting, participants might simultaneously examine both the graphs and fees while making their investment decisions.

## **5 Conclusion**

## 6 Tables and Figures

Figure 1: A Flow Chart of the Experiment

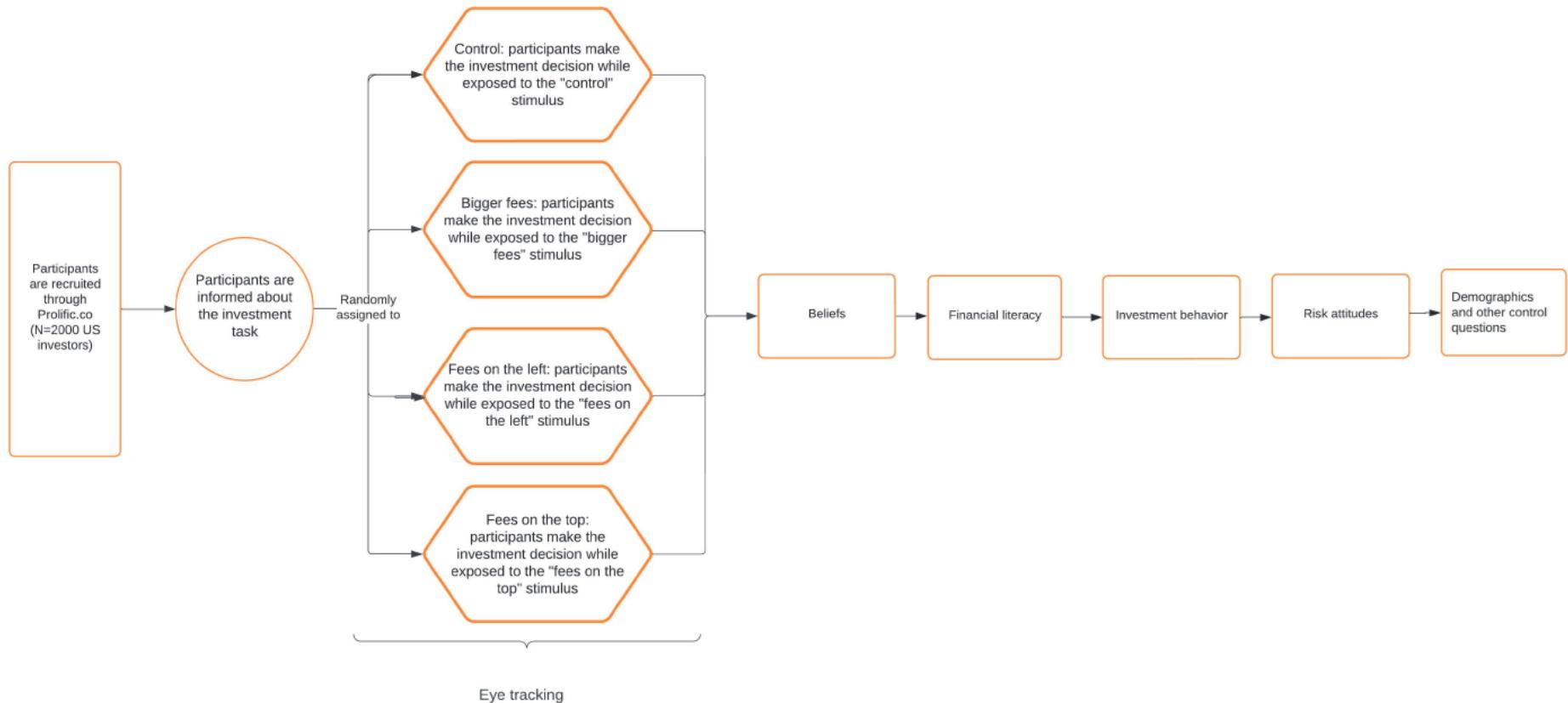
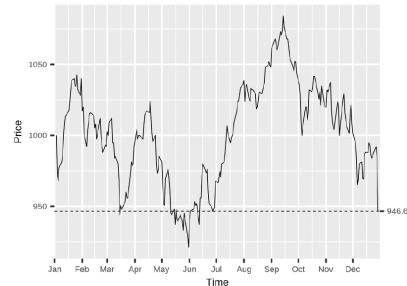


Figure 2: Saliency Treatment Conditions



14

Expense ratio: 1.92%



Expense ratio: 1.27%



Expense ratio: 1.92%



Expense ratio: 1.27%



Note: This Figure displays four treatment conditions affecting visual saliency: the control group (top-left), bigger fees (top-right), bigger fees on the top (bottom-left), and bigger fees on the left (bottom-right).

Table 1: Questions aimed at measuring respondents' beliefs regarding their investment

<b>Question</b>	<b>Answers (range)</b>
In the previous task, you were asked to allocate \$300 among different mutual funds. How important were the following factors in shaping your final investment decision? i) Expense ratio; ii) Fund performance over the past year; iii) Desire to diversify across funds.	From "Not at all important" to "Extremely important"
How confident are you that the decision you made is the right one for you?	From "Not at all confident" to "Very confident"
What percentage return do you expect the following asset types to earn annually, on average, over the next five years?	Percentage points on a slider

Table 2: Questions aimed at measuring respondents' financial literacy. From ??

<b>Question</b>	<b>Answers (range)</b>
Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?	"More than \$102", "Exactly \$102", "Less than \$102", "Do not know", "Refuse to answer"
Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?	"More than today", "Exactly the same as today", "Less than today", "Do not know", "Refuse to answer"
Please tell me whether this statement is true or false: "Buying a single company's stock usually provides a safer return than a stock mutual fund."	"True", "False", "Do not know", "Refuse to answer"

Table 3: Questions aimed at learning respondents' investing behavior (From ??) and risk attitudes (From ??).

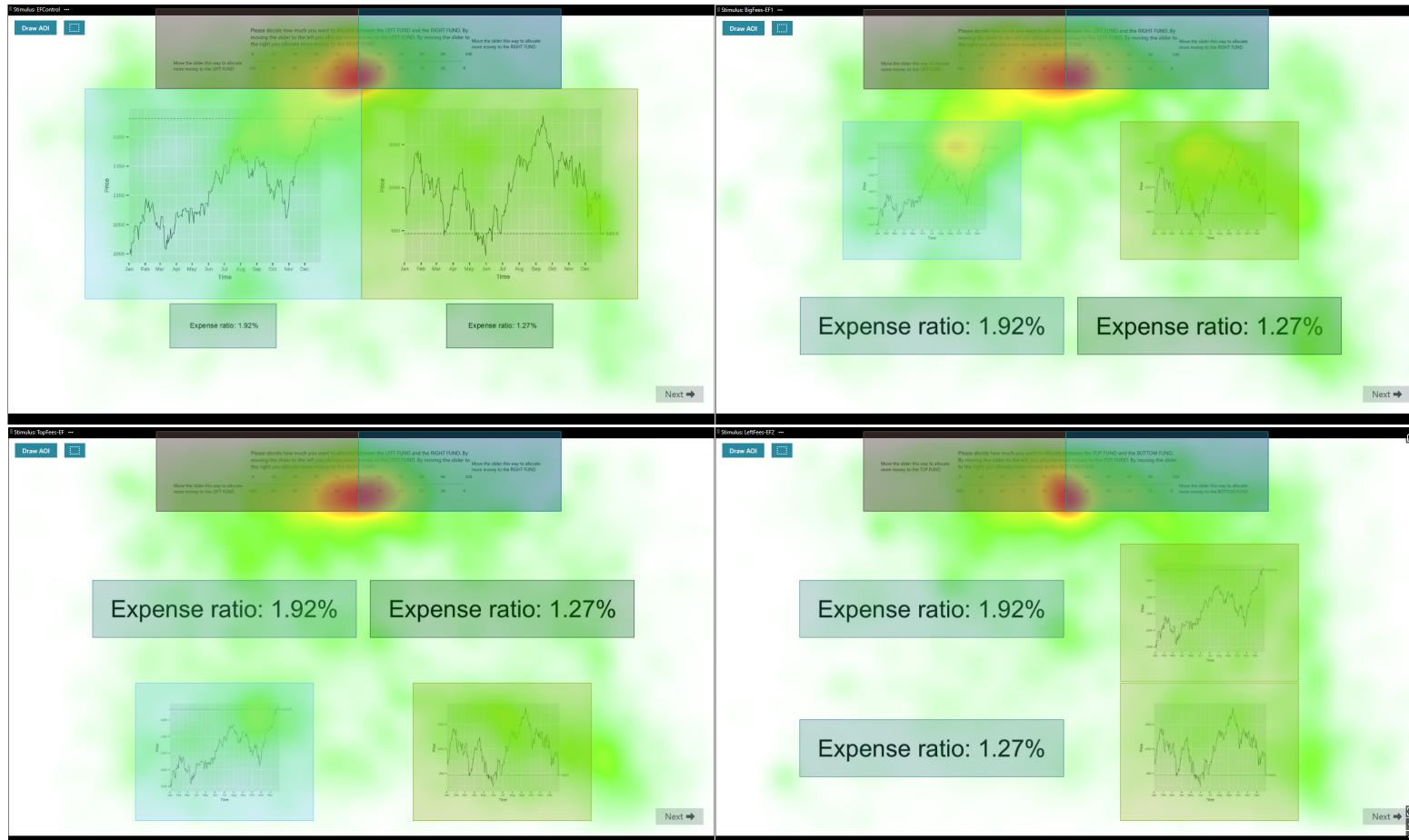
<b>Question</b>	<b>Answers (range)</b>
<b>Investing behavior</b>	
How many years have you been investing in the stock market?	"Less than 1 year", "Between 1 year and 3 years", "Between 3 years and 5 years", "Between 5 years and 10 years", "More than 10 years"
What percentage of your assets is currently invested in the stock market?	Percentage points on a slider
What percentages of your investments are in the following categories of assets?	Percentage points on a slider for: Individual stocks, Individual bonds, Mutual funds (other than exchange-traded funds), Exchange-traded funds, Cryptocurrencies
<b>Risk attitudes</b>	
For each of the following statements, please indicate the likelihood of engaging in each activity: "Betting a day's income at the horse races", "Co-signing a new car loan for a friend", "Investing 10% of your annual income in a blue chip stock", "Investing 10% of your annual income in a very speculative stock", "Investing 10% of your annual income in government bonds (treasury bills)", "Investing in a business that has a good chance of failing", "Lending a friend an amount of money equivalent to one month's income", "Spending money impulsively without thinking about the consequences", "Taking a day's income to play the slot-machines at a casino", "Taking a job where you get paid exclusively on a commission basis"	"Extremely unlikely", "Unlikely", "Not sure", "Likely", "Very likely"

Table 4: Summary Statistics (Eye Tracking)

	Control	Big Fees	Top Fees	Left Fees	Total
Total Duration (Ms)	24106.27 (19411.62)	19726.26 (14068.99)	20704.67 (17056.79)	24199.33 (19773.78)	22128.36 (17761.04)
Prop of Sample Observed Graph (%)	99.69	96.79	86.95	96.00	94.87
Dwell Time (Fixation, Ms) (Graph AOI)	12385.24 (12752.79)	5,310.97 (5,934.34)	3,960.30 (5,249.60)	5,969.82 (8,028.13)	6,948.38 (9,144.74)
Dwell Time (Cond Fixation, Ms) (Graph AOI)	12423.47 (12753.85)	5,487.16 (5,951.32)	4,554.70 (5,384.22)	6,218.56 (8,098.86)	7,324.05 (9,241.04)
Dwell Time (Fixation, %) (Graph AOI)	48.99 (19.30)	24.96 (15.84)	16.92 (14.05)	22.75 (16.04)	28.63 (20.57)
Dwell Time (Cond Fixation, %) (Graph AOI)	49.15 (19.14)	25.79 (15.42)	19.46 (13.32)	23.70 (15.67)	30.18 (19.99)
Prop of Sample Observed Fees (%)	50.00	81.35	90.25	80.52	75.31
Dwell Time (Fixation, Ms) (Fee AOI)	451.58 (718.48)	941.64 (979.37)	1,062.88 (1,021.86)	845.79 (1,006.79)	820.18 (963.69)
Dwell Time (Cond Fixation, Ms) (Fee AOI)	910.22 (789.53)	1,162.56 (962.96)	1,185.37 (1,009.61)	1,060.60 (1,021.43)	1,100.19 (968.34)
Dwell Time (Fixation, %) (Fee AOI)	1.97 (3.22)	5.12 (4.80)	5.80 (4.62)	3.87 (4.12)	4.16 (4.48)
Dwell Time (Cond Fixation, %) (Fee AOI)	3.94 (3.60)	6.33 (4.56)	6.47 (4.41)	4.84 (4.06)	5.59 (4.35)
TTFF (Graph AOI)	854.06 (1215.22)	2310.88 (2873.70)	5003.68 (5453.70)	4080.20 (4835.46)	2948.67 (4177.33)
TTFF (Fee AOI)	10957.27 (12040.43)	5808.01 (7937.88)	2693.12 (4578.17)	3755.45 (6039.80)	5245.83 (8120.56)

We report mean values for each eye-tracking variable listed in the Table, while standard deviations are reported in parentheses.

Figure 3: Heatmaps of the Dwell Time (Fixation, Ms) for Different Treatment Conditions



Note: This figure displays heatmaps of the dwell time (fixation, in milliseconds) for four treatment conditions affecting visual saliency: the control group (top-left), bigger fees (top-right), bigger fees on the top (bottom-left), and bigger fees on the left (bottom-right).

Table 5: Comparison of TTFF + Dwell Time (ms and %) for Graphs across Treatment and Control Groups

	<b>Bigger fees</b>	<b>Bigger fees on the top</b>	<b>Bigger fees on the left</b>	<b>Average treatment</b>
Average % of no fixation in “graph”				
<b>TTFF</b>	1484.501*** (0.000)	4099.722*** (0.000)	3202.854*** (0.000)	2846.653*** (0.000)
<b>Dwell Time (ms)</b>				
Conditional on fixation detected	-9866.246*** (0.000)	-9214.436*** (0.000)	-11337.751*** (0.000)	-10047.954*** (0.000)
Unconditional	-7212.369*** (0.000)	-6615.453*** (0.000)	-8316.934*** (0.000)	-7381.834 (0.000)
<b>Dwell Time (%)</b>				
Conditional on fixation detected	-23.881*** (0.000)	-25.423*** (0.000)	-31.777*** (0.000)	-27.221*** (0.000)
Unconditional	-24.459*** (0.000)	-26.241*** (0.000)	-31.834*** (0.000)	-27.589*** (0.000)
N				

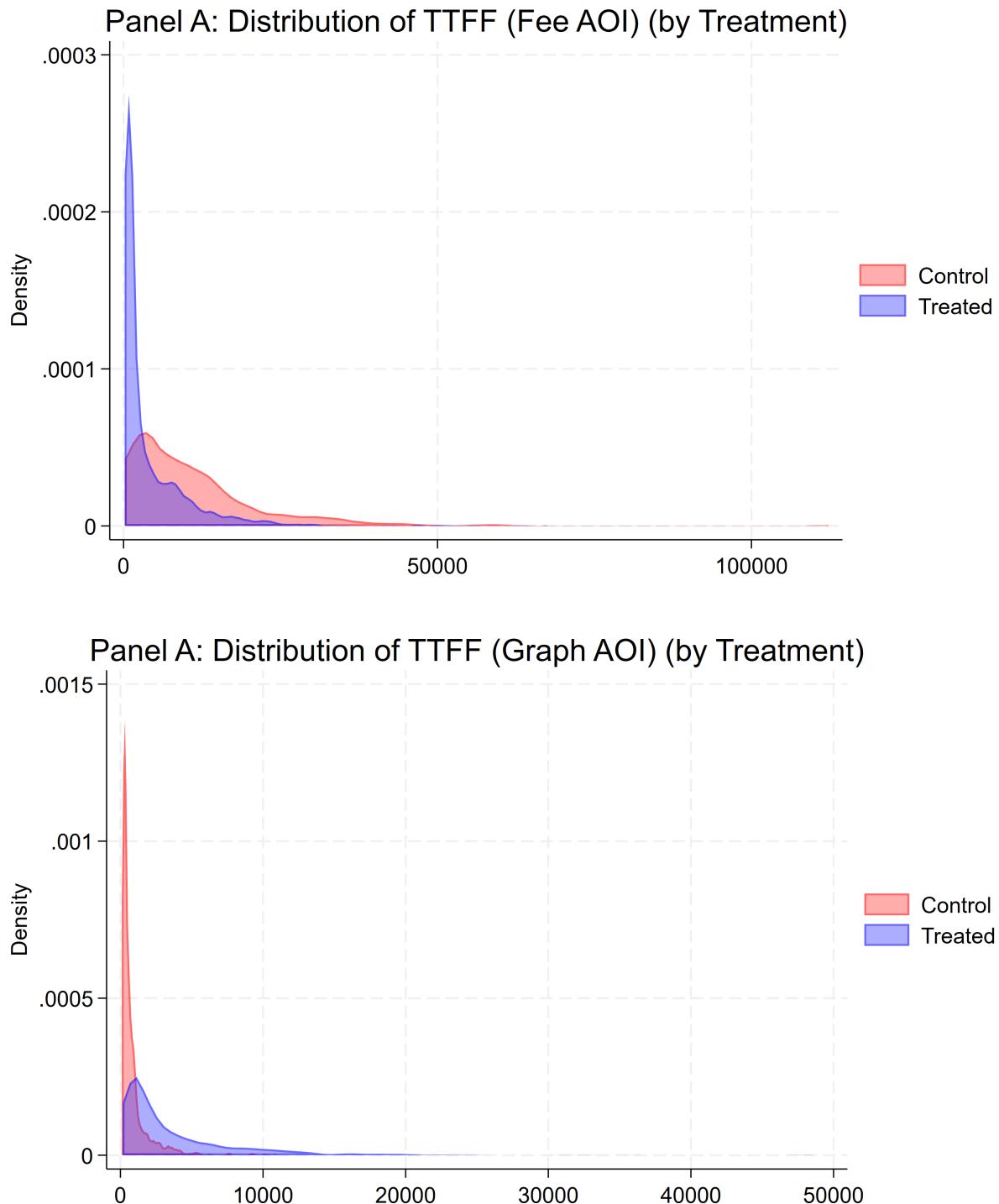
**Note.** The no-fixation value is the mean of the percentages of no fixation individuals for each item. The number of data points is indicated for both cases.

Table 6: Comparison of TTFF + Dwell Time (ms and %) for Fees across Treatment and Control Groups

	<b>Bigger fees on the top</b>	<b>Bigger fees on the left</b>	<b>Average treatment</b>	
Average % of no fixation in “fees”				
<b>TTFF</b>	-5362.359*** (0.000)	-8296.189*** (0.000)	-7124.899*** (0.000)	-6990.003*** (0.000)
<b>Dwell Time (ms)</b>				
Conditional on fixation detected	253.563*** (0.000)	132.591* (0.058)	234.408*** (0.000)	216.716*** (0.000)
Unconditional	495.254*** (0.000)	399.445*** (0.000)	592.069*** (0.000)	506.231*** (0.000)
<b>Dwell Time (%)</b>				
Conditional on fixation detected	2.566*** (0.000)	0.884*** (0.003)	2.387*** (0.000)	2.005*** (0.000)
Unconditional	3.205*** (0.000)	1.924*** (0.000)	3.749*** (0.000)	3.009*** (0.000)
N				

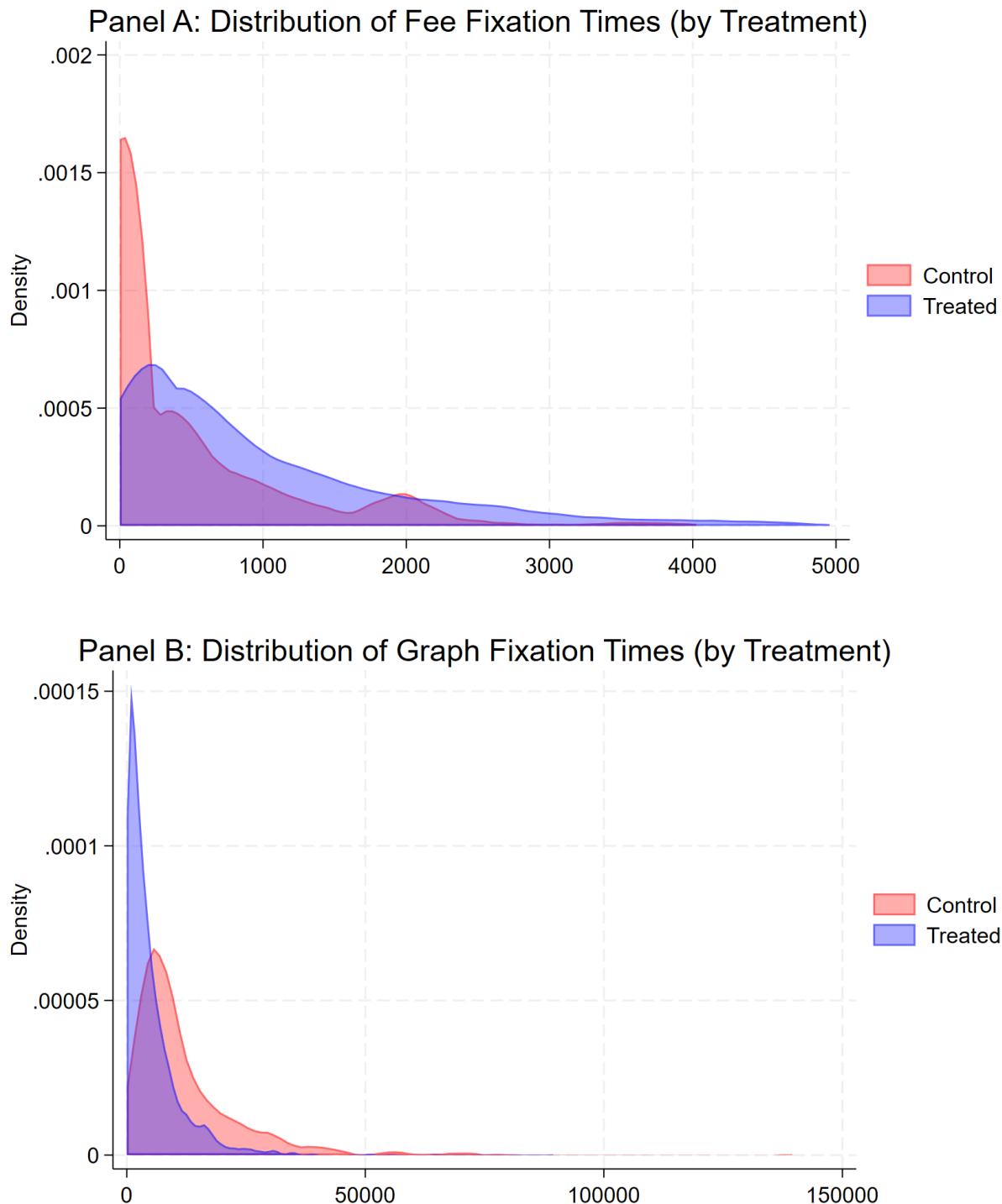
**Note.** The no-fixation value is the mean of the percentages of no-fixation individuals for each item. The number of data points is indicated for both cases.

Figure 4: Time to First Fixation (Ms) on Fees vs Graphs



Note: This figure illustrates differences in the time to first fixation (in milliseconds) spent on fees vis-a-vis graphs. In Panel A, we depict the densities of fixation times spent on Fee-related area of interests. In Panel B, we depict the densities of fixation times spent on Graph-related area of interests. The treated group is shown in blue, the control group in red, and overlapping regions are depicted in purple.

Figure 5: Dwell Time (Fixation, Ms) on Fees vs Graphs



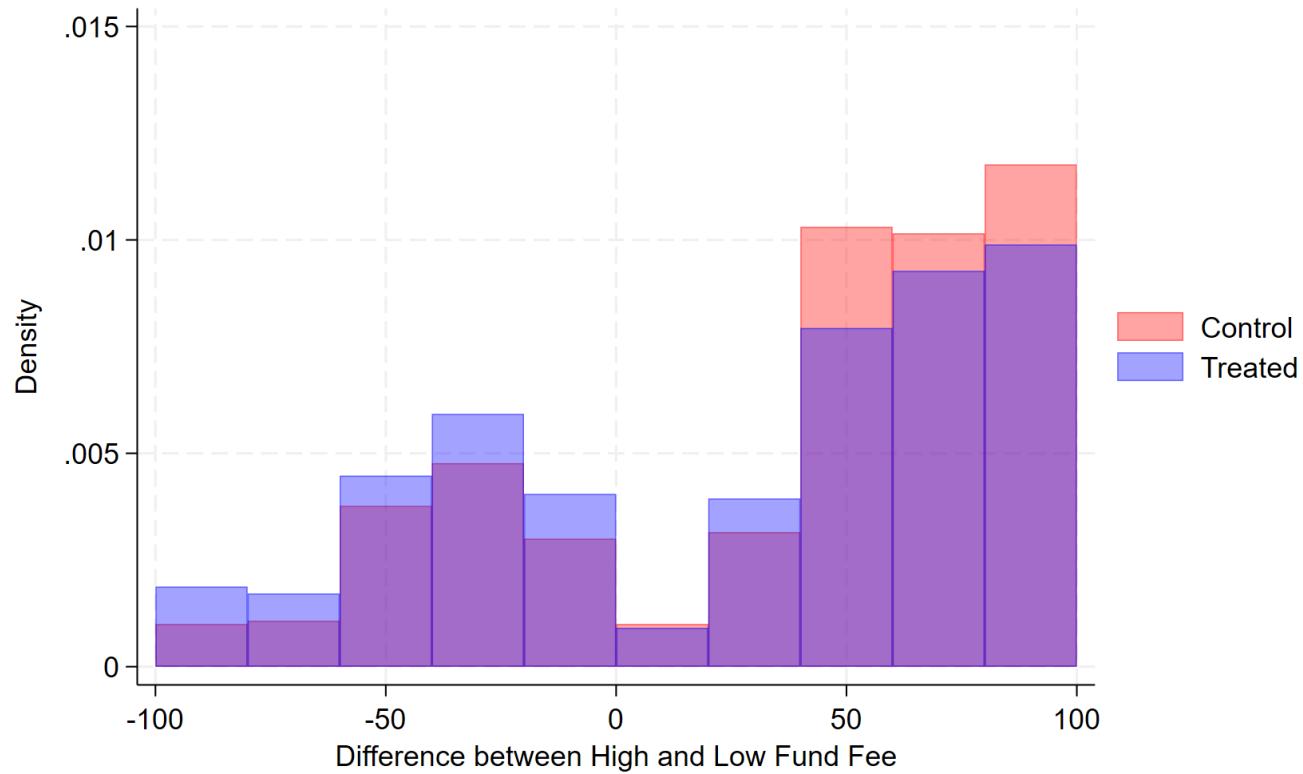
Note: This figure illustrates differences in the fixation time (in milliseconds) spent on fees vis-a-vis graphs. In Panel A, we depict the densities of fixation times spent on Fee-related area of interests. In Panel B, we depict the densities of fixation times spent on Graph-related area of interests. The treated group is shown in blue, the control group in red, and overlapping regions are depicted in purple.

Table 7: Average Treatment Effects by Saliency Features (with Controls)

	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Full
Treatment	-16.854*** (0.000)	-12.718*** (0.000)	-5.277* (0.085)	-11.237*** (0.000)
Observations	1225	1286	1304	2515
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.045	0.030	0.013	0.021
F Statistic	3.893	3.003	1.839	3.719

Note: \*\*\*  $p \leq 0.01$ , \*\*  $p \leq 0.05$ , \*  $p \leq 0.10$ . P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each saliency feature, while Specification (4) reports the average treatment effects for the entire pooled sample. In these regressions, the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. For each saliency feature, the treatment effects are pooled across all three fund-pairs AB, CD, and EF (note that in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Difference,” represents the allocation to the first fund minus the allocation to the second fund within a given saliency feature. A negative value indicates a relatively larger allocation to the second fund, which always has the lower fund fee. For instance, allocating the full \$100 to Fund B yields a dependent variable value of -100. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Figure 6: Allocation of Investments to Fund-Pairs by Treatment and Control Groups



Note: This figure illustrates differences in the allocation of investments between high-fee and low-fee funds in our experiments. The “difference between high and low fund fee” represents the allocation to the high-fee fund minus the allocation to the low-fee fund. Negative values indicate a larger allocation to the low-fee fund, while positive values indicate a larger allocation to the high-fee fund. The treated group is shown in blue, the control group in red, and overlapping regions are depicted in purple.

Table 8: Average Treatment Effects by Fund-Pairs (with Controls)

	(1) Fund-Pair A-B	(2) Fund-Pair C-D	(3) Fund-Pair E-F
Treatment	-8.062* (0.063)	-10.593** (0.018)	-15.083*** (0.001)
Observations	836	831	848
Controls	Yes	Yes	Yes
Adjusted R-Sq	0.025	0.007	0.013
F Statistic	2.091	1.296	1.572

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each fund-pair. In these regressions, the treated group is exposed to adjustments in the saliency features of the information provided to participants. The treatment effects are pooled across saliency features for each fund-pair (e.g., in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Difference,” represents the allocation to the first fund minus the allocation to the second fund within a given fund-pair. A negative value indicates a larger allocation to the second fund, which always has the lower fund fee. For instance, allocating the full \$100 to Fund B yields a dependent variable value of -100. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

## 7 Appendix

Table 9: Covariate Balance and Descriptive Statistics

	Control 650 (25.8%)	Treatment 1,865 (74.2%)	Total 2,515 (100.0%)	P-value
Age	40.42 (12.22)	39.63 (11.91)	39.84 (11.99)	0.149
Income	89,868.85 (44,962.24)	89,806.58 (44,727.36)	89,822.67 (44,779.24)	0.976
Gender				
Female	308 (47.4%)	828 (44.4%)	1,136 (45.2%)	0.349
Male	336 (51.7%)	1,013 (54.3%)	1,349 (53.6%)	
Others	6 (0.9%)	24 (1.3%)	30 (1.2%)	
Educational Level				
Associate college degree (2-year)	48 (7.4%)	145 (7.8%)	193 (7.7%)	0.602
Bachelor college degree (4-year)	301 (46.3%)	828 (44.4%)	1,129 (44.9%)	
Doctoral degree	29 (4.5%)	66 (3.5%)	95 (3.8%)	
High school graduate	29 (4.5%)	122 (6.5%)	151 (6.0%)	
Less than high school degree	3 (0.5%)	6 (0.3%)	9 (0.4%)	
Master's degree	120 (18.5%)	358 (19.2%)	478 (19.0%)	
Professional degree (JD, MD)	14 (2.2%)	41 (2.2%)	55 (2.2%)	
Some college but no degree	106 (16.3%)	299 (16.0%)	405 (16.1%)	
Race				
Asian	81 (12.5%)	252 (13.5%)	333 (13.2%)	0.463
Black	62 (9.5%)	211 (11.3%)	273 (10.9%)	
Others	29 (4.5%)	89 (4.8%)	118 (4.7%)	
White	478 (73.5%)	1,313 (70.4%)	1,791 (71.2%)	
Employment Status				
Others	125 (19.2%)	364 (19.5%)	489 (19.4%)	0.040
Working full-time	447 (68.8%)	1,203 (64.5%)	1,650 (65.6%)	
Working part-time	78 (12.0%)	298 (16.0%)	376 (15.0%)	
Political Ideology				
Democrat	341 (52.5%)	963 (51.6%)	1,304 (51.8%)	0.217
Republican	161 (24.8%)	419 (22.5%)	580 (23.1%)	
Something else	148 (22.8%)	483 (25.9%)	631 (25.1%)	
Equity Risk Premium	3.51 (16.95)	4.69 (16.10)	4.38 (16.33)	0.114

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. This table reflects covariate balance between the treatment and control groups. P-values greater than 0.1 indicate that the corresponding variable is not statistically different between the treatment and control groups at the 10% level. Mean values for continuous variables are presented with their standard deviations in parentheses. For categorical variables, frequencies are presented along with percentages in parentheses.

Table 10: Causal Mediation Analysis

	TTFF (Graph AOI)		TTFF (Fee AOI)	
	(1) with Controls	(2) w/o Controls	(3) with Controls	(4) w/o Controls
<b>NIE</b>				
Treat (1 vs 0)	-1.714** (0.048)	-2.124** (0.015)	-2.330 (0.108)	-1.888 (0.193)
<b>NDE</b>				
Treat (1 vs 0)	-8.444*** (0.002)	-8.101*** (0.002)	-8.895** (0.012)	-9.565*** (0.007)
<b>TE</b>				
Treat (1 vs 0)	-10.158*** (0.000)	-10.225*** (0.000)	-11.226*** (0.001)	-11.452*** (0.000)
Observations	2386	2386	1894	1894

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (2) present our causal mediation results, where time to first fixation (TTFF) serves as a mediator. The TE (“total effect”) captures the effect of treatment on investment allocation decisions. The NIE (“natural indirect effect”) represents the portion of the treatment effect mediated by TTFF, whereas the NDE (“natural direct effect”) reflects the treatment’s influence through other pathways. Control variables include age, income, gender, education, race, employment status, political orientation, and subjective risk premiums, calculated as the difference between participants’ expected valuation of future stock returns and their expected valuation of the future risk-free rate.

Table 11: Average Treatment Effects by Saliency Features (without Controls)

	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Full
Treatment	-16.800*** (0.000)	-13.059*** (0.000)	-4.891 (0.107)	-11.348*** (0.000)
Observations	1225	1286	1304	2515
Controls	No	No	No	No
Adjusted R-Sq	0.021	0.013	0.001	0.007
F Statistic	26.630	17.652	2.609	19.306

Note: \*\*\*  $p \leq 0.01$ , \*\*  $p \leq 0.05$ , \*  $p \leq 0.10$ . P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each saliency feature, while Specification (4) reports the average treatment effects for the entire pooled sample. In these regressions, the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. For each saliency feature, the treatment effects are pooled across all three fund-pairs AB, CD, and EF (note that in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Difference,” represents the allocation to the first fund minus the allocation to the second fund within a given saliency feature. A negative value indicates a relatively larger allocation to the second fund, which always has the lower fund fee. For instance, allocating the full \$100 to Fund B yields a dependent variable value of -100. The treatment effects are estimated without the inclusion of any additional control variables.

Table 12: Average Treatment Effects by Fund Pairs (without Controls)

	(1) Fund-Pair A-B	(2) Fund-Pair C-D	(3) Fund-Pair E-F
Treatment	-8.063* (0.064)	-11.091** (0.013)	-14.873*** (0.001)
Observations	836	831	848
Adjusted R-Sq	0.003	0.006	0.011
F Statistic	3.427	6.190	10.808

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each fund-pair. In these regressions, the treated group is exposed to adjustments in the saliency features of the information provided to participants. The treatment effects are pooled across saliency features for each fund-pair (e.g., in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Difference,” represents the allocation to the first fund minus the allocation to the second fund within a given fund-pair. A negative value indicates a larger allocation to the second fund, which always has the lower fund fee. For instance, allocating the full \$100 to Fund B yields a dependent variable value of -100. The treatment effects are estimated without the inclusion of any additional control variables.

Table 13: Average Treatment Effects by Experiment (with Controls)

	Fund Pair A-B			Fund Pair C-D			Fund Pair E-F		
	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Left Fees	(5) Top Fees	(6) Big Fees	(7) Left Fees	(8) Top Fees	(9) Big Fees
Treatment	-15.969*** (0.004)	-10.745** (0.042)	0.874 (0.865)	-12.041** (0.038)	-11.394** (0.040)	-9.019* (0.099)	-22.218*** (0.000)	-15.996*** (0.004)	-8.098 (0.125)
Observations	406	427	437	407	425	429	412	434	438
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.059	0.019	0.005	0.010	0.009	-0.009	0.030	0.012	0.005
F Statistic	2.267	1.415	1.103	1.210	1.196	0.807	1.646	1.272	1.109

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. This table presents the average treatment effects for each experiment, where the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. The dependent variable, "Difference," represents the amount a participant allocates to the first fund minus the amount allocated to the second fund within a given fund-pair (e.g., in fund-pair "AB," Fund A is the first fund, and Fund B is the second). A negative value indicates a larger allocation to the second fund, which always has the lower fund fee. For instance, allocating the entire \$100 to Fund B results in a dependent variable value of -100. All treatment effects are estimated with the inclusion of control variables such as participants' age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Table 14: Average Treatment Effects by Experiment (with Controls)

	Fund Pair A-B			Fund Pair C-D			Fund Pair E-F		
	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Left Fees	(5) Top Fees	(6) Big Fees	(7) Left Fees	(8) Top Fees	(9) Big Fees
Treatment	-15.341*** (0.005)	-11.023** (0.035)	1.016 (0.841)	-12.987** (0.023)	-11.422** (0.037)	-9.064* (0.090)	-21.909*** (0.000)	-16.701*** (0.002)	-6.875 (0.186)
Observations	406	427	437	407	425	429	412	434	438
Adjusted R-Sq	0.017	0.008	-0.002	0.010	0.008	0.004	0.032	0.019	0.002
F Statistic	7.859	4.466	0.040	5.247	4.366	2.896	14.712	9.596	1.757

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. This table presents the average treatment effects for each experiment, where the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. The dependent variable, "Difference," represents the amount a participant allocates to the first fund minus the amount allocated to the second fund within a given fund-pair (e.g., in fund-pair "AB," Fund A is the first fund, and Fund B is the second). A negative value indicates a larger allocation to the second fund, which always has the lower fund fee. For instance, allocating the entire \$100 to Fund B results in a dependent variable value of -100. The treatment effects are estimated without the inclusion of any additional control variables.

Table 15: Dwell Time (Fixation, Ms) (Fee AOI)

	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Full
Treatment	592.069*** (0.000)	399.445*** (0.000)	495.254*** (0.000)	506.231*** (0.000)
Observations	1245	1198	1287	2440
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.117	0.061	0.084	0.061
F Statistic	9.248	4.885	6.891	8.957
Treatment (Conditional on Fixation Detected)	234.408*** (0.000)	132.591* (0.058)	253.563*** (0.000)	216.716*** (0.000)
Observations	858	761	840	1819
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.049	0.023	0.032	0.025
F Statistic	3.304	1.955	2.376	3.315

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each saliency feature, while Specification (4) reports the average treatment effects for the entire pooled sample. In these regressions, the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. For each saliency feature, the treatment effects are pooled across all three fund-pairs AB, CD, and EF (note that in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Dwell Time (Fixation, Ms) (Fee AOI),” represents the Dwell Time to Fixation in milliseconds for all Area of Interests associated with fees. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Table 16: Dwell Time (Fixation, Ms) (Graph AOI)

	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Full
Treatment	-8316.934*** (0.000)	-6615.453*** (0.000)	-7212.369*** (0.000)	-7381.834*** (0.000)
Observations	1286	1225	1304	2515
Controls				
Adjusted R-Sq	0.179	0.106	0.128	0.139
F Statistic	15.034	8.245	10.589	21.247
Treatment (Conditional on Fixation Detected)	-11337.751*** (0.000)	-9214.436*** (0.000)	-9866.246*** (0.000)	-10047.954*** (0.000)
Observations	899	788	857	1894
Controls				
Adjusted R-Sq	0.255	0.147	0.186	0.168
F Statistic	17.145	8.111	10.778	20.059

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each saliency feature, while Specification (4) reports the average treatment effects for the entire pooled sample. In these regressions, the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. For each saliency feature, the treatment effects are pooled across all three fund-pairs AB, CD, and EF (note that in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Dwell Time (Fixation, Ms) (Graph AOI),” represents the Dwell Time to Fixation in milliseconds for all Area of Interests associated with graphs. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Table 17: Dwell Time (Fixation, %) (Fee AOI)

	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Full
Treatment	3.749*** (0.000)	1.924*** (0.000)	3.205*** (0.000)	3.009*** (0.000)
Observations	1249	1204	1283	2440
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.190	0.072	0.146	0.088
F Statistic	15.643	5.697	11.950	12.779
Treatment (Conditional on Fixation Detected)	2.387*** (0.000)	0.884*** (0.003)	2.566*** (0.000)	2.005*** (0.000)
Observations	862	767	836	1819
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.087	0.015	0.083	0.029
F Statistic	5.310	1.619	4.761	3.679

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each saliency feature, while Specification (4) reports the average treatment effects for the entire pooled sample. In these regressions, the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. For each saliency feature, the treatment effects are pooled across all three fund-pairs AB, CD, and EF (note that in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Dwell Time (Fixation, %) (Fee AOI),” represents the Dwell Time to Fixation for all Area of Interests associated with fees as a proportion of all Area of Interests. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Table 18: Dwell Time (Fixation, %) (Graph AOI)

	(1) Left Fees	(2) Top Fees	(3) Big Fees	(4) Full
Treatment	-31.834*** (0.000)	-26.241*** (0.000)	-24.459*** (0.000)	-27.589*** (0.000)
Observations	1286	1225	1304	2515
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.482	0.359	0.332	0.355
F Statistic	60.820	35.332	33.362	70.265
Treatment (Conditional on Fixation Detected)	-31.777*** (0.000)	-25.423*** (0.000)	-23.881*** (0.000)	-27.221*** (0.000)
Observations	899	788	857	1894
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.513	0.371	0.340	0.308
F Statistic	50.695	25.386	23.075	43.147

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each saliency feature, while Specification (4) reports the average treatment effects for the entire pooled sample. In these regressions, the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. For each saliency feature, the treatment effects are pooled across all three fund-pairs AB, CD, and EF (note that in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Dwell Time (Fixation, %) (Graph AOI),” represents the Dwell Time to Fixation for all Area of Interests associated with graphs as a proportion of all Area of Interests. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Table 19: Dwell Time (Fixation, Ms and %) (Individual AOIs)

	(1) Left Fee (Fixation, Ms)	(2) Right Fee (Fixation, Ms)	(3) Left Graph (Fixation, Ms)	(4) Right Graph (Fixation, Ms)	(5) Left Fee (Fixation, %)	(6) Right Fee (Fixation, %)	(7) Left Graph (Fixation, %)	(8) Right Graph (Fixation, %)
Treatment	252.774*** (0.000)	209.384*** (0.000)	-3877.105*** (0.000)	-3504.729*** (0.000)	1.486*** (0.000)	1.370*** (0.000)	-14.415*** (0.000)	-13.173*** (0.000)
Observations	2440	2440	2515	2515	2440	2440	2515	2515
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.039	0.044	0.111	0.128	0.064	0.063	0.241	0.257
F Statistic	5.939	6.644	16.740	19.393	9.367	9.174	40.991	44.372

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each saliency feature, while Specification (4) reports the average treatment effects for the entire pooled sample. In these regressions, the treated group is exposed to a specific adjustment in the saliency feature of the information provided to participants. For each saliency feature, the treatment effects are pooled across all three fund-pairs AB, CD, and EF (note that in fund-pair “AB,” Fund A is the first fund, and Fund B is the second). The dependent variable, “Dwell Time (Fixation, %) (Graph AOI),” represents the Dwell Time to Fixation for all Area of Interests associated with graphs as a proportion of all Area of Interests. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Table 20: Time to First Fixation (Ms) (Graph AOIs)

	(1) Top Fees	(2) Left Fees	(3) Big Fees	(4) Full
Treatment	4099.722*** (0.000)	3202.854*** (0.000)	1484.501*** (0.000)	2846.653*** (0.000)
Observations	1201	1200	1281	2386
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.235	0.188	0.105	0.100
F Statistic	19.470	14.843	8.482	14.220

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. The dependent variable, “TTFF”, represents the Time to First Fixation in milliseconds for Graph AOIs. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

Table 21: Time to First Fixation (Ms) (Fee AOIs)

	(1) Top Fees	(2) Left Fees	(3) Big Fees	(4) Full
Treatment	-8296.189*** (0.000)	-7124.899*** (0.000)	-5362.359*** (0.000)	-6990.003*** (0.000)
Observations	899	788	857	1894
Controls	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.201	0.142	0.067	0.106
F Statistic	12.924	7.838	4.053	12.217

Note: \*\*\* p≤0.01, \*\* p≤0.05, \* p≤0.10. P-values are reported in parentheses. The dependent variable, “TTFF”, represents the Time to First Fixation in milliseconds for Fee AOIs. All treatment effects are estimated with the inclusion of control variables such as participants’ age, income, gender, education, race, employment status, political orientation, and subjective risk premiums (calculated as the difference between their expected valuation of future stock returns and their expected valuation of the future risk-free rate).

## 8 Bibliography

- Badoer, D. C., Costello, C. P., and James, C. M. (2020). I can see clearly now: The impact of disclosure requirements on 401 (k) fees. *Journal of Financial Economics*, 136(2):471–489. [5](#)
- Barber, B. M., Odean, T., and Zheng, L. (2005). Out of sight, out of mind: The effects of expenses on mutual fund flows. *The Journal of Business*, 78(6):2095–2120. [2](#), [8](#)
- Barberis, N., Shleifer, A., and Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics*, 49(3):307–343. [2](#)
- Beechey, M., Gruen, D. W., and Vickery, J. (2000). *The efficient market hypothesis: a survey*. Reserve Bank of Australia Sydney. [2](#)
- Ben-Shahar, O. and Schneider, C. E. (2011). The failure of mandated discourse. *University of Pennsylvania Law Review*, 159:647. [6](#)
- Bloomfield, R. and Hales, J. (2002). Predicting the next step of a random walk: experimental evidence of regime-shifting beliefs. *Journal of financial Economics*, 65(3):397–414. [2](#)
- Bordalo, P., Gennaioli, N., and Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly journal of economics*, 127(3):1243–1285. [4](#)
- Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Salience and consumer choice. *Journal of Political Economy*, 121(5):803–843. [4](#)
- Bordalo, P., Gennaioli, N., and Shleifer, A. (2020). Memory, attention, and choice. *The Quarterly journal of economics*, 135(3):1399–1442. [4](#)
- Bordalo, P., Gennaioli, N., and Shleifer, A. (2022). Salience. *Annual Review of Economics*, 14(1):521–544. [4](#), [6](#), [9](#)
- Chetty, R., Looney, A., and Kroft, K. (2009). Salience and taxation: Theory and evidence. *American economic review*, 99(4):1145–1177. [5](#), [6](#)
- Choi, J. J., Haisley, E., Kurkoski, J., and Massey, C. (2017). Small cues change savings choices. *Journal of economic behavior & organization*, 142:378–395. [5](#)
- Choi, J. J., Laibson, D., and Madrian, B. C. (2010). Why does the law of one price fail? an experiment on index mutual funds. *The Review of Financial Studies*, 23(4):1405–1432. [2](#), [3](#), [7](#)
- Collins, S. (2005). Are s&p 500 index mutual funds commodities? *Perspective*, 11(3):N3. [3](#)

- De Bondt, W. F. and Thaler, R. (1985). Does the stock market overreact? *The Journal of finance*, 40(3):793–805. [2](#)
- De Bondt, W. P. (1993). Betting on trends: Intuitive forecasts of financial risk and return. *International Journal of forecasting*, 9(3):355–371. [2](#)
- DeHaan, E., Song, Y., Xie, C., and Zhu, C. (2021). Obfuscation in mutual funds. *Journal of Accounting and Economics*, 72(2-3):101429. [2](#)
- Elton, E. J., Gruber, M. J., and Busse, J. A. (2004). Are investors rational? choices among index funds. *the Journal of Finance*, 59(1):261–288. [3](#)
- Fama, E. F. (1970). Efficient capital markets. *Journal of finance*, 25(2):383–417. [2](#)
- Finkelstein, A. (2009). E-ztax: Tax salience and tax rates. *The Quarterly Journal of Economics*, 124(3):969–1010. [5](#)
- Fisch, J. E. and Wilkinson-Ryan, T. (2014). Why do retail investors make costly mistakes? an experiment on mutual fund choice. *University of Pennsylvania Law Review*, 162(3):605–647. [2](#)
- Frydman, C. and Wang, B. (2020). The impact of salience on investor behavior: Evidence from a natural experiment. *The Journal of Finance*, 75(1):229–276. [5](#)
- Gabaix, X. and Laibson, D. (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics*, 121(2):505–540. [5](#)
- Gil-Bazo, J. and Ruiz-Verdú, P. (2009). The relation between price and performance in the mutual fund industry. *The Journal of Finance*, 64(5):2153–2183. [8](#)
- Hortaçsu, A. and Syverson, C. (2004). Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds. *The Quarterly journal of economics*, 119(2):403–456. [2](#)
- Hutt, S., Wong, A., Papoutsaki, A., Baker, R. S., Gold, J. I., and Mills, C. (2024). Webcam-based eye tracking to detect mind wandering and comprehension errors. *Behavior Research Methods*, 56(1):1–17. [6](#), [7](#)
- Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of financial economics*, 6(2/3):95–101. [2](#)
- Loewenstein, G. and Wojtowicz, Z. (2023). The economics of attention. Available at SSRN 4368304.

- Maxwell, S. E. and Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological methods*, 12(1):23. [11](#)
- Mercer, M., Palmeter, A. R., and Taha, A. E. (2010). Worthless warnings? testing the effectiveness of disclaimers in mutual fund advertisements. *Journal of Empirical Legal Studies*, 7(3):429–459. [2](#), [4](#)
- Offerman, T. and Sonnemans, J. (2004). What's causing overreaction? an experimental investigation of recency and the hot-hand effect. *The Scandinavian Journal of Economics*, 106(3):533–554. [2](#)
- Palmeter, A. R. and Taha, A. E. (2008). Mutual fund investors: divergent profiles. *Colum. Bus. L. Rev.*, page 934. [4](#)
- Papoutsaki, A., Laskey, J., and Huang, J. (2017). Searchgazer: Webcam eye tracking for remote studies of web search. In *Proceedings of the 2017 conference on conference human information interaction and retrieval*, pages 17–26. [7](#)
- SEC (2020). Tailored shareholder reports, treatment of annual prospectus updates for existing investors, and improved fee and risk disclosure for mutual funds and exchange-traded funds; fee information in investment company advertisements 262–309 (2020). Proposed Rule 33-10814. [3](#), [4](#)
- Semmelmann, K. and Weigelt, S. (2018). Online webcam-based eye tracking in cognitive science: A first look. *Behavior Research Methods*, 50:451–465. [7](#)
- Sirri, E. R. and Tufano, P. (1998). Costly search and mutual fund flows. *The journal of finance*, 53(5):1589–1622. [8](#)
- Taylor, S. E. and Thompson, S. C. (1982). Stalking the elusive “vividness” effect. *Psychological review*, 89(2):155. [9](#)
- Tversky, A. and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *science*, 211(4481):453–458. [4](#)
- Valliappan, N., Dai, N., Steinberg, E., He, J., Rogers, K., Ramachandran, V., Xu, P., Shojaeizadeh, M., Guo, L., Kohlhoff, K., et al. (2020). Accelerating eye movement research via accurate and affordable smartphone eye tracking. *Nature communications*, 11(1):4553. [7](#)
- VanderWeele, T. J. (2015). *Explanation in causal inference: methods for mediation and interaction*. Oxford University Press. [11](#)

Von Neumann, J. and Morgenstern, O. (2007). Theory of games and economic behavior: 60th anniversary commemorative edition. In *Theory of games and economic behavior*. Princeton university press. [4](#)

Weiss-Cohen, L., Newall, P. W., and Ayton, P. (2022). Persistence is futile: Chasing of past performance in repeated investment choices. *Journal of Experimental Psychology: Applied*, 28(2):341. [2](#)

Xu, P., Ehinger, K. A., Zhang, Y., Finkelstein, A., Kulkarni, S. R., and Xiao, J. (2015). Turkergaze: Crowdsourcing saliency with webcam based eye tracking. *arXiv preprint arXiv:1504.06755*. [7](#)

Yang, X. and Krajbich, I. (2021). Webcam-based online eye-tracking for behavioral research. *Judgment and Decision making*, 16(6):1485–1505. [7](#)