# Visual Saliency and Investment Decisions

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**Abstract**

Despite regulatory efforts to improve fee transparency, investors persistently underweight fees and overweight past performance. 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 screen 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.

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# 1 Introduction

The Efficient Markets Hypothesis 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).

Although U.S. regulators are fully aware of investors' under-sensitivity to fees, it is fair to say they have not yet effectively tackled the problem. Thus far, the SEC has focused on mandated disclosure documents—namely, the statutory and summary prospectuses—which unfortunately undermines their efficacy. The fundamental issue is that investors do not necessarily read, or even browse through, prospectuses (Palmiter 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),[1] must present standardized fee and expense data whenever performance information is disclosed.

We formulate the hypothesis that past performance chasing and failure to minimize fees are *in part* motivated by the relative bottom-up saliency of the information pertaining to past performance versus fund fees on brokerage providers' websites or apps. 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). A burgeoning literature highlights that bottom-up saliency can distort choices, as economic agents tend to overweight salient attributes while underweighting non-salient ones (Bordalo et al., 2012, 2013, 2022). Information on past performance is almost invariably presented using highly salient graphs (Bose et al., 2022), and human attention is naturally drawn to images (Sanchez and Wiley, 2006). In contrast, information about fees is often presented as small numbers hidden in obscure parts of the website.

We test this hypothesis by conducting a large-scale online experiment ($N = 2000$) using webcam-based eye-tracking technology. Respondents are asked to make three investment decisions, allocating \$100 each time between three pairs of funds. Following best practices in the literature (Heeb et al., 2023), the investment choices are incentivized and consequential: after one year, we pay out the full value of the investment to ten randomly selected respondents. For each pair of funds, one fund has lower fees but worse past performance, while the other has higher fees

[1] 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.

but better past performance. Since this experiment aims to precisely capture the mechanism, respondents are shown information only about past performance and fees when making their investment decisions. In the treatments, we manipulate the visual saliency of the information by changing *only* the relative size and/or screen position of the fees and performance information. Because our treatments do not alter the information set, they should have no effect on fully rational investors. However, our hypothesis predicts that increasing the relative saliency of fund fees would lead respondents to allocate a larger portion of their budget to funds with lower fees and worse past performance.

A crucial advantage of relying on webcam-based eye tracking is that it allows us to measure the visual saliency of the information at the individual level. 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 area of interest (AOI). TTFF is the most direct measure of visual saliency, as defined in Bordalo et al. (2022). *Dwell Time Fixation* (in milliseconds) represents the total duration that respondents spend 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.

Our results suggest that bottom-up saliency is a key determinant of investing behavior. First, we observe that past performance attracts significantly more visual attention than fees, which, according to the literature on bottom-up saliency, implies that investors may overweight past performance and underweight fees (Bordalo et al., 2012, 2013, 2022). Second, we find that respondents in the treatment conditions paid relatively 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 graph. Third, we find that respondents allocated significantly more assets to funds with lower fees in the treatment conditions.

The magnitude of these effects is striking. On average, in our three treatments the TTFF for the graph is more than three times higher than in the control, and it is 5.9 times higher in the most effective treatment. Meanwhile, the treatments more than halve the TTFF for fees compared to the control, with the most effective treatment reducing it by 75%. These results suggest that our treatments effectively reduced the bottom-up saliency of the graph while increasing the bottom-up saliency of the fees.

Moreover, simply by altering the relative bottom-up saliency of fees and graphs, our three treatments lead respondents to allocate 11.2% more ($33.6 out of $300) to funds with low fees and worse past performance compared to the control group. The most effective treatment prompts an even greater shift, increasing allocations to funds with low fees and worse past performance by 16.9% compared to the control group. These findings indicate that bottom-up saliency of fees and graphs can have a substantial impact on investment choices.

Two additional observations suggest that our study allowed us to precisely pinpoint the mechanism and connect bottom-up saliency to investment decisions. First, the treatments that have a larger effect on bottom-up saliency also have the largest impact on investment decisions. Second, the effect of the treatments is greater for fund pairs in which the wedge in fund fees is larger, suggesting that a stronger emphasis on fees is driving these results.

Our results demonstrate that, by influencing bottom-up saliency through interface design choices—such as prioritizing fee visibility over performance graphics—biases in investor decision-making can be meaningfully reduced. Building on these insights, we are currently working on a follow-up study that will provide concrete guidance to policymakers. Still relying on webcam-based eye-tracking technology, we will ask participants to make consequential investment decisions in a more realistic setting. In the control condition, a new set of respondents will make an investment choice similar to those in the first experiment; however, this time, they will be presented with a webpage resembling an actual investment platform. In the treatment conditions, we will implement interventions to reduce the bottom-up saliency of the graph and increase the bottom-up saliency of the fees. Our hypothesis is that these interventions will once again redirect visual attention from past performance to fees, even in this more realistic setting.

If confirmed, the policy implications of such a result would be straightforward: policymakers should regulate the bottom-up saliency of fund fees on investment platforms and brokerage providers' websites or apps. Specifically, we will discuss how such a policy could be implemented by building on Saliency Attentive Models (SAMs) (Cornia et al., 2018; Bose et al., 2022).

# 2 Background Literature

## 2.1 Chasing Past Performance and Inattention to Fees

According to the Efficient Markets Hypothesis (EMH), asset prices rapidly reflect all publicly available information, suggesting that past performance should not reliably predict future returns

(Fama, 1970; Jensen, 1978; Beechey et al., 2000). However, behavioral finance research reveals a persistent disconnect between theory and empirical evidence: many investors chase past performance and overlook fee minimization,[2] despite substantial evidence that these behaviors erode long-term returns (Barber et al., 2005; Fisch and Wilkinson-Ryan, 2014). For instance, in the index fund market—where funds tracking the same index offer nearly identical portfolios prior to fees—price dispersion rivals that of actively managed funds (Hortaçsu and Syverson, 2004). More recently, DeHaan et al. (2021) demonstrate that S&P 500 index funds, despite homogeneous returns and risks, continue to charge varying fees. At the same time, empirical studies consistently document "performance-chasing" behavior, with investors favoring funds boasting strong recent returns, even in the face of regulatory disclaimers emphasizing 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).[3] To make sense of the latter, one 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

[2] Throughout this article, we use "fees" and "expense ratios" interchangeably.

[3] We turn to a more thorough discussion of salience in Section 2.3.

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 Efficient Markets Hypothesis predictions, highlighting how behavioral and psychological factors can shape both fund selection and fee minimization.

## 2.2 Regulatory Framework

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,[4] containing 13 Items prescribed by the SEC. They may also prepare a "summary prospectus",[5] 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)."[6] 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.[7]

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' understanding in this area" (SEC, 2020). Such reforms were never adopted.

[4] SEC rules require the use of this form for securities of open-end management investment companies: 17 C.F.R. § 239.15A (2024).

[5] 17 C.F.R. § 230.49 (2024).

[6] Securities and Exchange Commission, Form N-1A (11 December 2023), 2–3.

[7] 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).

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 (Palmiter 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),[8] 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.[9]

## 2.3 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. 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).

[8] Supra note 1.

[9] The lack of fee prominence is exemplified by the popular "Robinhood" trading platform's interface design.

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 and Wang (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 employ a broad interpretation of saliency, often treating non-salient information as effectively hidden or "shrouded." For example, in Frydman and Wang (2020), the treatment condition reveals information that, in the control condition, is buried behind three mouse clicks, making it effectively inaccessible without deliberate effort. Similarly, Choi et al. (2017) enhance saliency by explicitly highlighting the benefits of an investment option, which would otherwise remain obscured. Badoer et al. (2020) leverage a regulatory change to disclose previously hidden indirect fees, further illustrating how treatments often involve making concealed information visible rather than merely increasing its prominence. Thus, these interventions go beyond simple saliency adjustments, as they address the deliberate concealment of critical information.

Moreover, saliency is often assumed and examined as a treatment condition without directly identifying the underlying mechanisms. For instance, consider the seminal work 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 (Chetty et al., 2009). The consumers might have been uninformed about the tax price,[10] 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.

However, webcam-based eye-tracking allows us to directly test what Chetty et al. (2009) 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

[10] To be sure, the authors design clever complementary tests to reduce the likelihood that this is the mechanism at play.

underlying mechanism.[11] 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 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,

[11] As acknowledged by Chetty et al. (2009), their experiment does not allow them to distinguish between the competing explanations.

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.[12]

## 3.2 Fund Selection

Our initial sample comprised all funds in the CRSP Mutual Fund Database reporting fees (i.e., expense ratios) in 2023. 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.[13] 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.[14]

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

[12] We include further information on webcam-based eye tracking in the Appendix.

[13] 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.

[14] 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.

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 prescreened 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 conditions paid relatively 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. The effect on investment choices is larger for treatments that increase divert more visual attention from the graph to the fees and for fund pairs for which the wedge between the fund fees is greater. 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, further supporting the hypothesis that the increased bottom up saliency is leading participants to assign more weight to the fund fees.

## 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).[15] 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).

[15] In our setting, participants might simultaneously examine both the graphs and fees while making their investment decisions.

# 5 Conclusion

Our study demonstrates that the visual saliency of information plays a crucial role in shaping investment decisions. By manipulating the prominence of fund fees—through larger font sizes or strategic screen placement—we found that investors allocate significantly more attention to fees and less to past performance graphs. This shift in attention led to an 11.2% greater allocation to lower-fee funds in treatment groups, with the most effective treatment increasing this allocation by 16.9%. These results highlight how interface design can influence investor behavior, reducing biases that lead to suboptimal decision-making.

Our findings have important implications for both investment platforms and regulators. By prioritizing the visibility of fees over performance graphics, platforms can help investors make more informed choices, ultimately improving long-term financial outcomes. For regulators, these results suggest that mandating the visual saliency of critical information, such as fees, could be an effective strategy to enhance transparency and protect investors. Future research should investigate how these findings apply in real-world investment scenarios and explore whether regulatory frameworks could require investment platforms to enhance the visual saliency of key information–such as fees and historical performance data–to promote more informed decision-making.

# 6 Tables and Figures

Figure 1: A Flow Chart of the Experiment

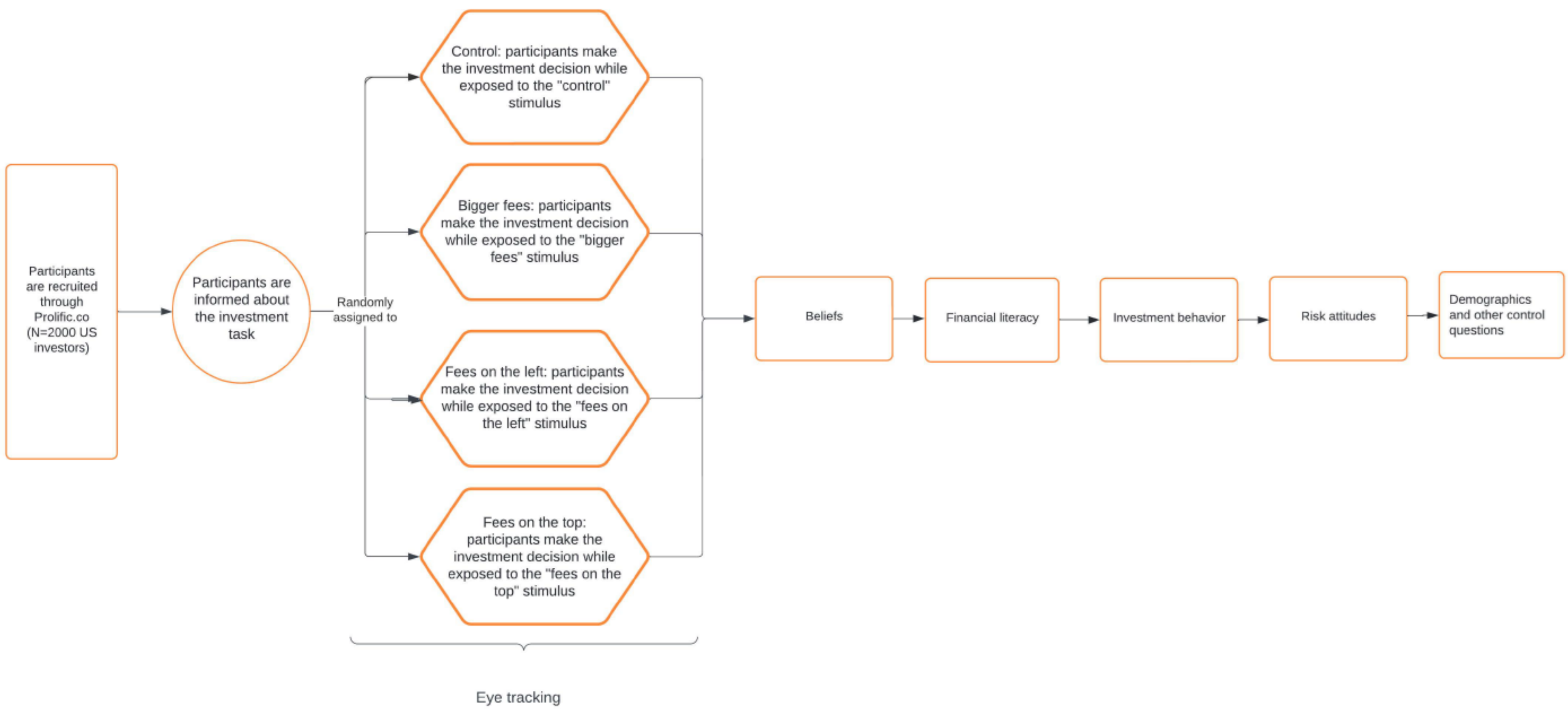
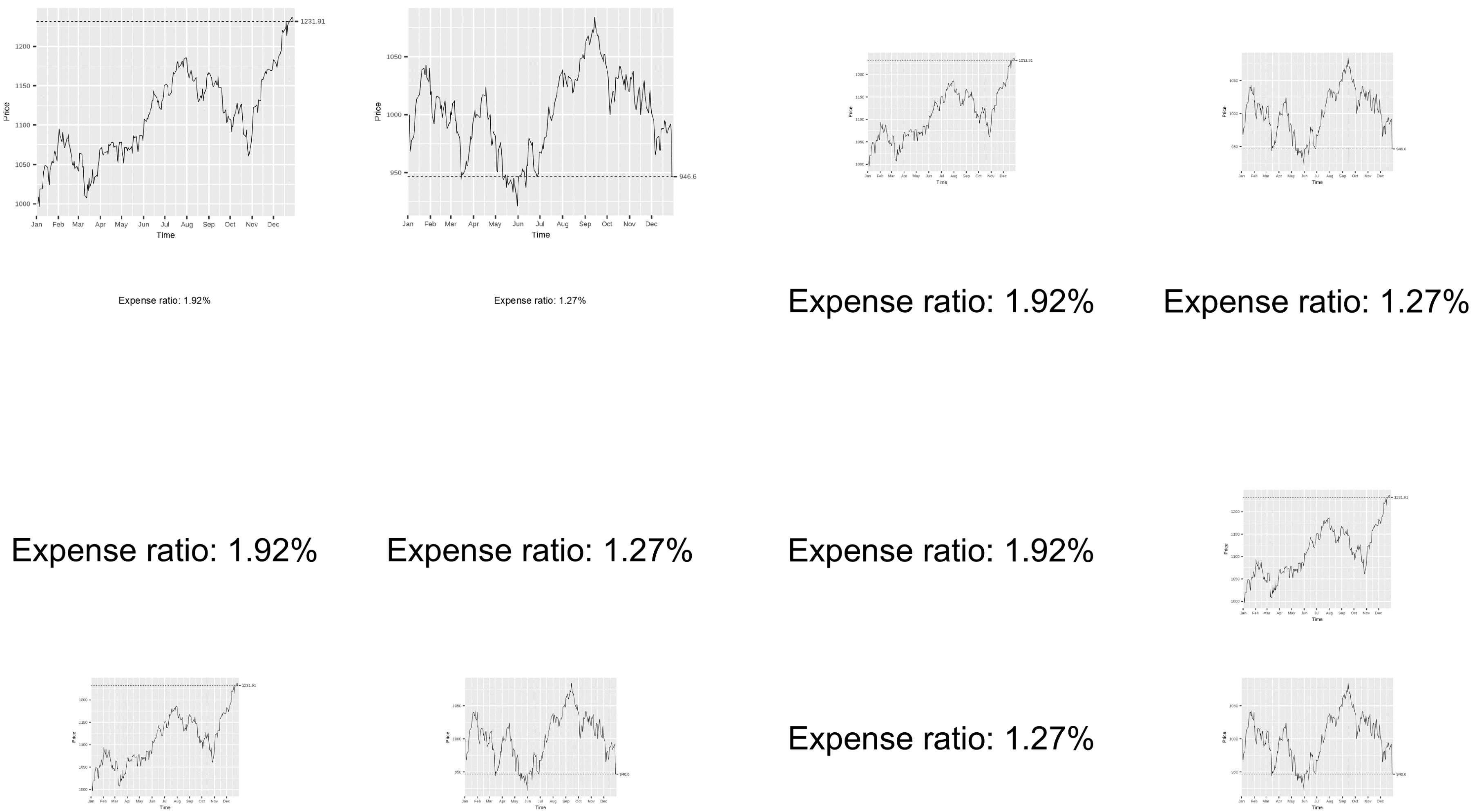


Figure 2: Saliency Treatment Conditions




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

| Question | Answers (range) |
|---|---|
| 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

| Question | Answers (range) |
|---|---|
| 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

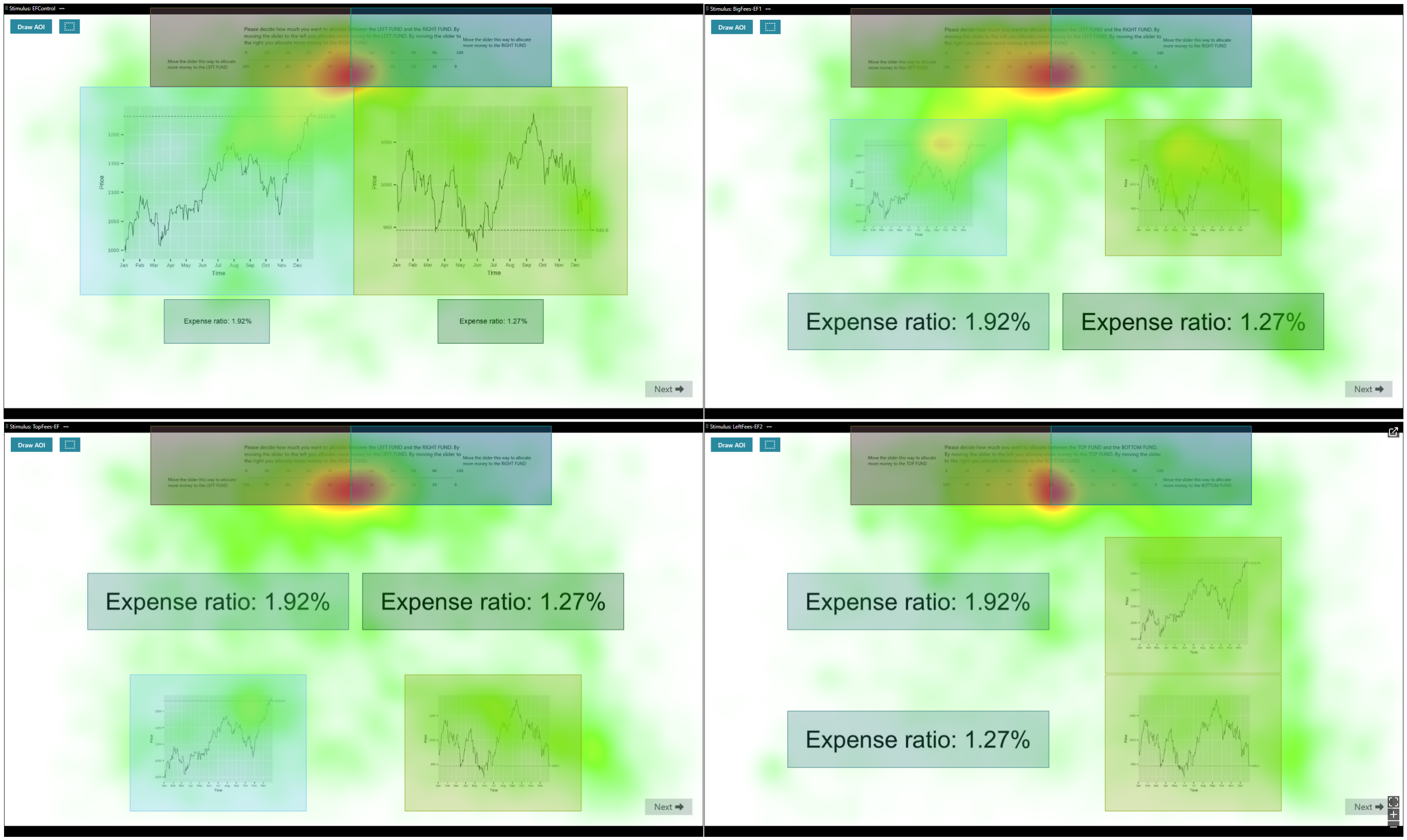
| Question | Answers (range) |
|---|---|
| **Investing behavior** | |
| How many years have you been investing in the stock market? | "Less than 1 year", "Between 1 year and 3 years", "Between 3 years and 5 years", "Between 5 years and 10 years", "More than 10 years" |
| What percentage of your assets 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 |
| **Risk attitudes** | |
| 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

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

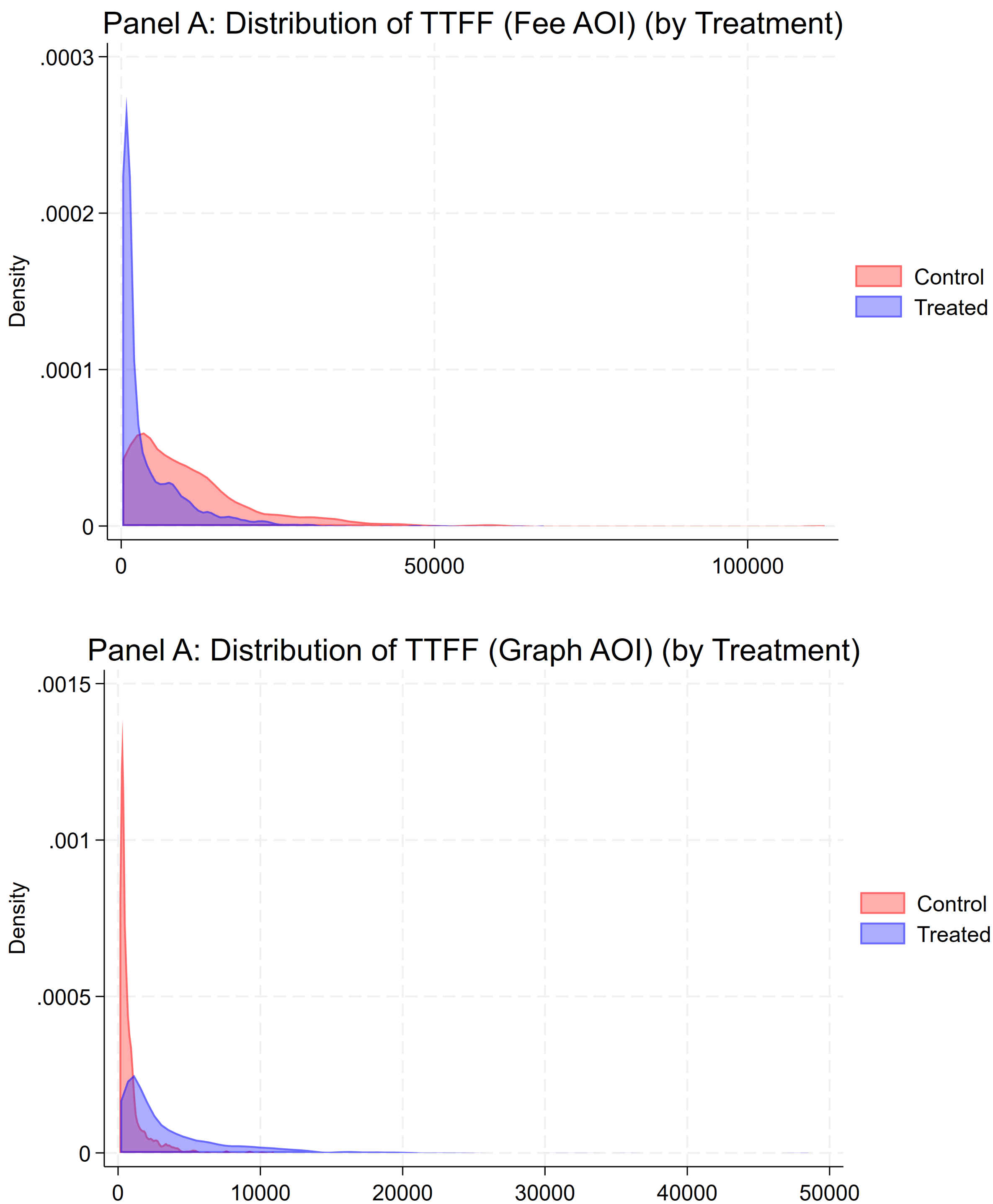
**Note.** The no-fixation value is the mean of the percentages of no fixation individuals for each item. The number of data points is indicated for both cases.

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

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

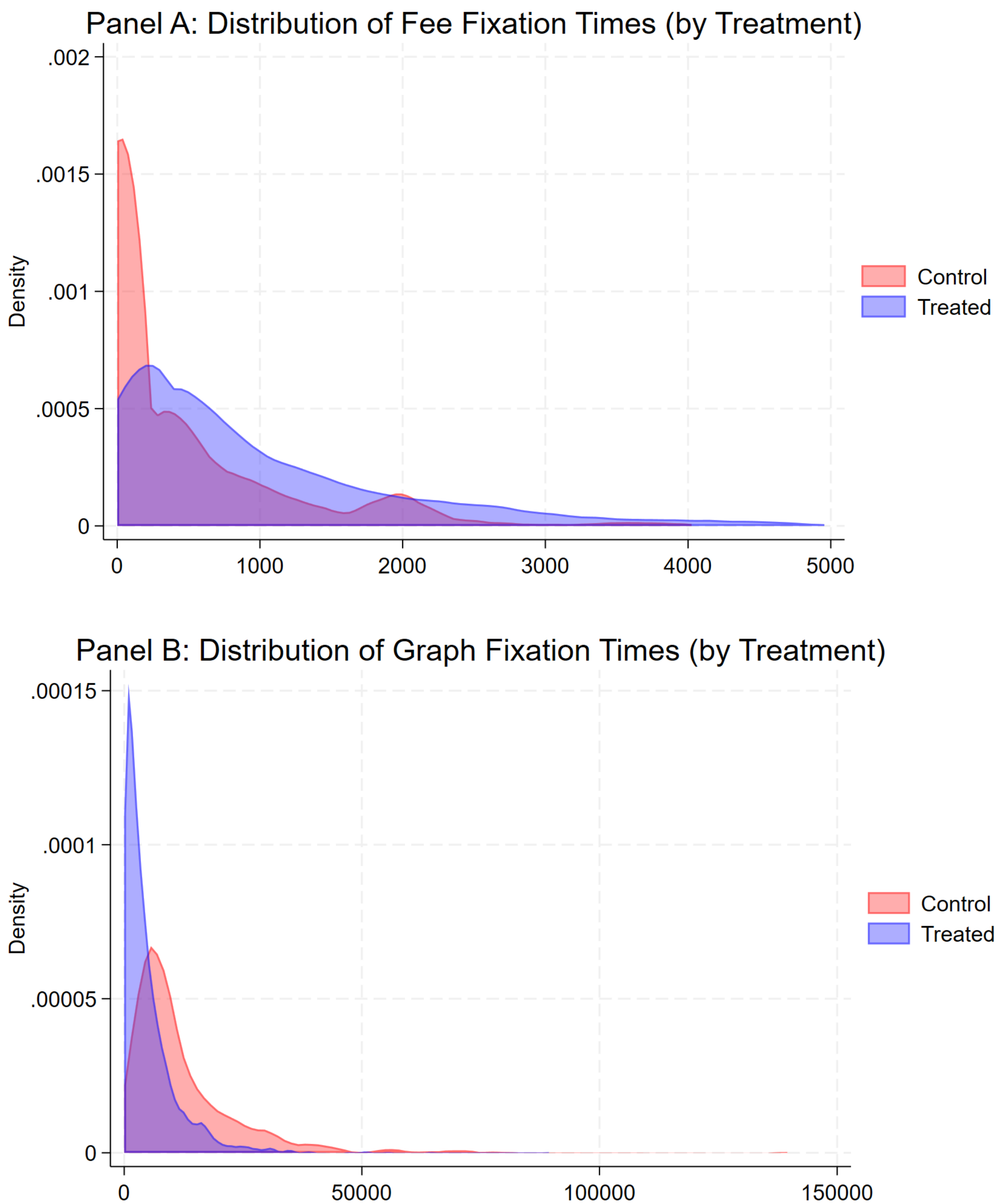
**Note.** The no-fixation value is the mean of the percentages of no-fixation individuals for each item. The number of data points is indicated for both cases.

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



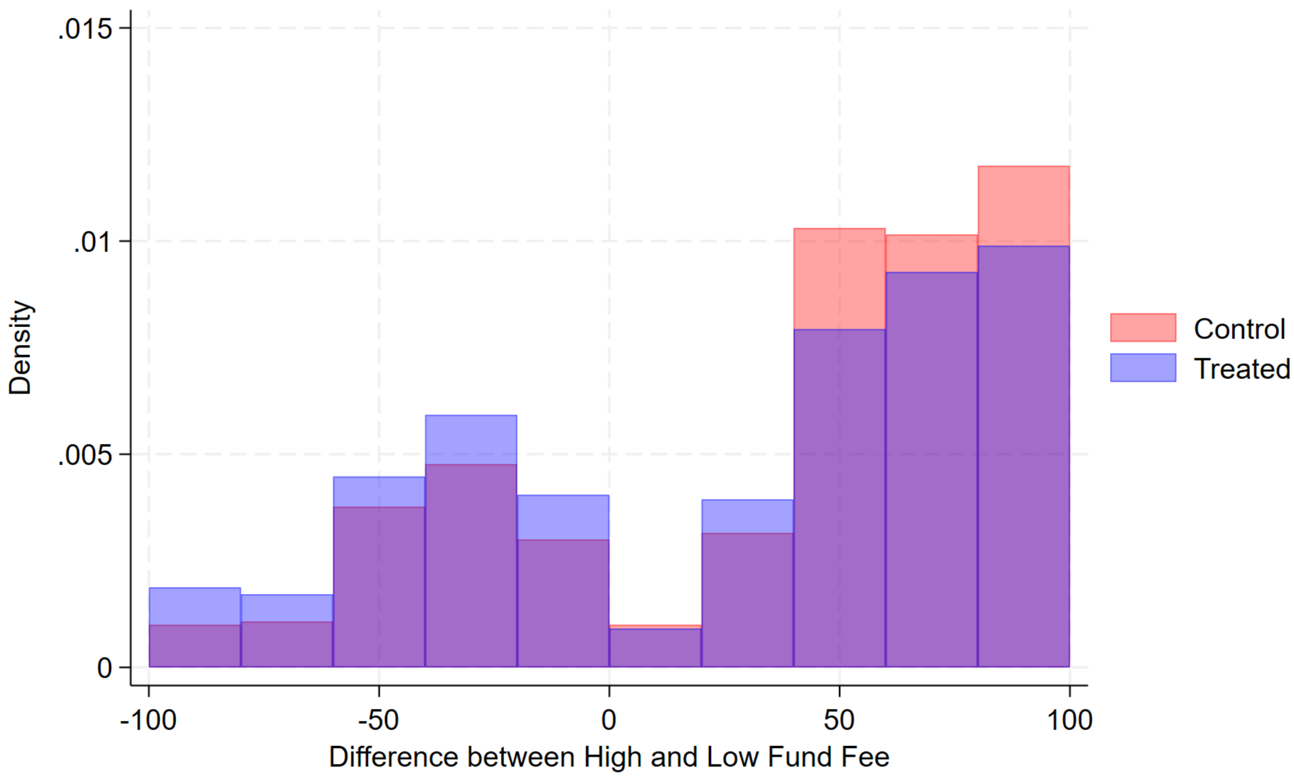

Note: This figure illustrates differences in the fixation time (in milliseconds) spent on fees vis-a-vis graphs. In Panel A, we depict the densities of fixation times spent on Fee-related area of interests. In Panel B, we depict the densities of fixation times spent on Graph-related area of interests. 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*** | -12.718*** | -5.277* | -11.237*** |
| | (0.000) | (0.000) | (0.085) | (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* | -10.593** | -15.083*** |
| | (0.063) | (0.018) | (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: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. P-values are reported in parentheses. Specifications (1) to (3) present the average treatment effects for each 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<br>650 (25.8%) | Treatment<br>1,865 (74.2%) | Total<br>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 |
| NIE | | | | |
| Treat (1 vs 0) | -1.714** | -2.124** | -2.330 | -1.888 |
| | (0.048) | (0.015) | (0.108) | (0.193) |
| NDE | | | | |
| Treat (1 vs 0) | -8.444*** | -8.101*** | -8.895** | -9.565*** |
| | (0.002) | (0.002) | (0.012) | (0.007) |
| TE | | | | |
| Treat (1 vs 0) | -10.158*** | -10.225*** | -11.226*** | -11.452*** |
| | (0.000) | (0.000) | (0.001) | (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)<br>Left Fees | (2)<br>Top Fees | (3)<br>Big Fees | (4)<br>Full |
|---|---|---|---|---|
| Treatment | -16.800*** | -13.059*** | -4.891 | -11.348*** |
| | (0.000) | (0.000) | (0.107) | (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≤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, "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)<br>Fund-Pair A-B | (2)<br>Fund-Pair C-D | (3)<br>Fund-Pair E-F |
|---|---|---|---|
| Treatment | -8.063* | -11.091** | -14.873*** |
| | (0.064) | (0.013) | (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*** | -10.745** | 0.874 | -12.041** | -11.394** | -9.019* | -22.218*** | -15.996*** | -8.098 |
| | (0.004) | (0.042) | (0.865) | (0.038) | (0.040) | (0.099) | (0.000) | (0.004) | (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: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. 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*** | -11.023** | 1.016 | -12.987** | -11.422** | -9.064* | -21.909*** | -16.701*** | -6.875 |
| | (0.005) | (0.035) | (0.841) | (0.023) | (0.037) | (0.090) | (0.000) | (0.002) | (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: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. 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*** | 399.445*** | 495.254*** | 506.231*** |
| | (0.000) | (0.000) | (0.000) | (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*** | 132.591* | 253.563*** | 216.716*** |
| | (0.000) | (0.058) | (0.000) | (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)<br>Left Fees | (2)<br>Top Fees | (3)<br>Big Fees | (4)<br>Full |
|---|---|---|---|---|
| Treatment | -8316.934*** | -6615.453*** | -7212.369*** | -7381.834*** |
| | (0.000) | (0.000) | (0.000) | (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*** | -9214.436*** | -9866.246*** | -10047.954*** |
| | (0.000) | (0.000) | (0.000) | (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*** | 1.924*** | 3.205*** | 3.009*** |
| | (0.000) | (0.000) | (0.000) | (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*** | 0.884*** | 2.566*** | 2.005*** |
| | (0.000) | (0.003) | (0.000) | (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: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. 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, "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)<br>Left Fees | (2)<br>Top Fees | (3)<br>Big Fees | (4)<br>Full |
|---|---|---|---|---|
| Treatment | -31.834*** | -26.241*** | -24.459*** | -27.589*** |
| | (0.000) | (0.000) | (0.000) | (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*** | -25.423*** | -23.881*** | -27.221*** |
| | (0.000) | (0.000) | (0.000) | (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)<br>Left Fee<br>(Fixation, Ms) | (2)<br>Right Fee<br>(Fixation, Ms) | (3)<br>Left Graph<br>(Fixation, Ms) | (4)<br>Right Graph<br>(Fixation, Ms) | (5)<br>Left Fee<br>(Fixation, %) | (6)<br>Right Fee<br>(Fixation, %) | (7)<br>Left Graph<br>(Fixation, %) | (8)<br>Right Graph<br>(Fixation, %) |
|---|---|---|---|---|---|---|---|---|
| Treatment | 252.774*** | 209.384*** | -3877.105*** | -3504.729*** | 1.486*** | 1.370*** | -14.415*** | -13.173*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (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)<br>Top Fees | (2)<br>Left Fees | (3)<br>Big Fees | (4)<br>Full |
|---|---|---|---|---|
| Treatment | 4099.722*** | 3202.854*** | 1484.501*** | 2846.653*** |
| | (0.000) | (0.000) | (0.000) | (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)<br>Top Fees | (2)<br>Left Fees | (3)<br>Big Fees | (4)<br>Full |
|---|---|---|---|---|
| Treatment | -8296.189*** | -7124.899*** | -5362.359*** | -6990.003*** |
| | (0.000) | (0.000) | (0.000) | (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).

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