Less Attention is Better: The Effect of Portfolio Disclosure on Retail Investors' Trading

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Abstract

This paper studies the effect of attention on trading behavior by utilizing browsing activities of retail investors on a mutual fund trading APP. Exploiting a quasi-experiment of a sudden change in portfolio disclosure frequency for a certain type of mutual funds, we show that after the adoption of the policy, investors browse affected funds (treated) more frequently than unaffected funds (control). The effect holds for both holding and non-holding funds and during both trading and non-trading hours. Investors, nevertheless, shorten their attention span on treated relative to control funds when not holding these assets or when browsing them during non-trading hours. We further show that after the new policy, investors hold less treated funds and are subject to a greater disposition effect. Investors' trading performance on treated funds is worsened compared to control funds following the new policy. The heterogeneity in the effect of the disclosure policy on trading parallels that on attention across investors with varying financial literacy and attention capacity. Finally, an instrumented difference-in-differences estimation supports a causal interpretation of the effect of attention on trading. Overall, our results suggest the role of attention in shaping beliefs and causing myopic loss aversion.

Keywords: Retail investors, information disclosure, attention, trading, myopic loss aversion, disposition effect, belief

JEL Classification: G4, G11, G14, G53

1. Introduction

Researchers have increasingly come to recognize the important role of attention played in individuals' investment decisions and its relation to the macroeconomic phenomenon. For example, there has been considerable effort across economics and finance to explain the equity premium puzzle. Benartzi and Thaler (1995) augment the standard model by leveraging two general features of human cognition—attention myopia and loss aversion—to provide an intriguing explanation for the puzzle. Also, survey evidence by Giglio et al. (2021) suggest that attention is an important factor in determining the sensitivity of portfolio allocation to beliefs.

There is growing micro-level evidence on the effect of attention on retail investors' trading behavior based on experimental designs. As these designs may not adequately represent real-life investment-decision processes, investigating the effect of attention in a non-experimental environment is important but also challenging. First, unlike experimental subjects whose attention is exposed to the arrival of information by design, it is unclear whether investors' attention would attend to it in an uncontrolled environment, and if so, how. Second, it is not a trivial task to observe and measure investors' attention. A proper account for investors' attention should capture not only their total attention but also the more subtle dimensions, such attention frequency and depth. Third, parsing market data to isolate mediators and moderators consonant with attention is difficult, and attention decisions could be endogenous to investor trading decisions. For example, the two decisions could simply reflect an investor's interest in a well-performing asset.

In this paper, we utilize a novel dataset of 8,157 mutual fund investors and their product-level browsing activities on a trading APP. We measure total attention and attention frequency at the product level by tracing the total time and the number of times that an investor browses a fund's page on the APP each month. We also look at the frequency that an investor browses a fund's constituent funds. To further capture attention span or depth, we examine the time that an investor devotes to each product per view.

We exploit a quasi-experimental setting of a sudden change in the frequency of portfolio disclosure policy for a certain type of funds, which introduces a plausibly exogenous shock that makes investors' attention devoted to these products more frequent. Disclosure frequency, e.g., mutual fund portfolio disclosure, has been, in its own right, the focus of a longstanding debate among practitioners, regulators, and academics. While some share a belief that frequent disclosure benefits investors through increased transparency, others are concerned about speculative activities that it might spur among investors. We employ a difference-in-differences design to compare changes in attention devoted to treated funds relative to that devoted to control funds before and after the adoption of the new disclosure policy, while controlling for investor, product, and time fixed effects and time-varying fund characteristics. We also examine investors' trading behavior between the treated and control funds following the adoption of the new disclosure policy.

We first document several interesting patterns of attention that points to the existence of attention limits among retail investors. First, the maximum level of total view time does not vary with the number of products held by an investor, and average browsing time per view and browsing frequency for a product decreases with the number of products held by an investor. Second, attention span per view and view frequency are negatively correlated, and, more interestingly, exhibits a convex shape. These patterns suggest that investors' attention capacity is subject to a limit.

Leveraging the diff-in-diff design, we first investigate how investors' attention responds to the more frequent arrival of portfolio information. We find that more frequent information disclosure results in an increase in attention paid to treated funds relative to control funds. By increased attention, it means a greater amount of total time (14.114 seconds, or a 25% increase from the mean) and, more importantly, frequency (0.454 times, or a 31.17% from the mean) spent on browsing a fund. At the constituent fund level, we also find an increase in view frequency for the constituent funds of treated funds relative to those of control funds (0.052 times, or a 38.8% increase from the mean). Conditional on paying attention to a fund, we find that attention devoted to treated funds and their constituent funds becomes more frequent than to control funds after the adoption of the new disclosure policy but exhibits no significant difference in total time devoted to treated and control funds. This finding suggests that the increase in total attention, not conditional on paying attention, is driven by increased browsing frequency at the extensive margin.

When looking at more refined attention patterns, we show that more frequent information disclosure results in attention fragmentation (i.e., shorter attention span per view) devoted to treated funds than to control funds. For example, investors reduce their median attention span allocated to treated funds by 2.776 seconds relative to control funds following the new disclosure policy, translating into an 18.9% reduction from the mean.

When differentiating attention over time and across products, we find robust evidence for an increase in attention frequency and strong heterogeneity in total attention and attention span. The new disclosure policy induces investors to make more frequent visits to the pages of treated funds relative to those of control funds both during and off working/trading hours and for both holding and non-holding assets. In other words, this finding suggests a positive effect of information disclosure frequency on attention frequency. In contrast, only for views made inside working/trading hours and for holding assets do we observe an increase in total attention; and only outside working/trading hours and for non-holding assets do we observe more fragmented attention. These behaviors could be consistent with rational inattention for investors who have limited attention capacity. They may choose to devote deeper attention (i.e., longer attention span) during working/trading hours and for holding assets, because information acquisition could be more relevant to trading performance in these scenarios.

Next, we examine investors' trading behavior. We first examine the effect of disclosure in relation to myopic loss aversion. There has been considerable effort across economics and finance to understand the equity premium puzzle. More recently, Benartzi and Thaler (1995) have augmented the standard model by leveraging two general features of human cognition—myopia and loss aversion—to provide an intriguing explanation for the puzzle. Myopic loss aversion (MLA) is a situation characterized by loss-averse investors (Kahneman and Tversky, 1979) paying too much attention to the short-term performance of their asset portfolios and becoming overly averse to risky assets. We find that more frequent information disclosure increases transaction frequency of treated funds relative to control funds. The effect is mostly driven by sell trades and consequently results in less holding of the treated funds relative to control funds. Our results could be consistent with MLA whereby more frequent information disclosure exacerbates attention myopia and causes investors to cut back on risky investment.

We next examine how disclosure affects trading behavior in relation to investors' beliefs. As an illustration, we revisit the classic disposition effect (Odean, 1998). Investors are more reluctant to sell losing investments than wining stock either because of prospect theory (Kahneman and Tversky, 1979) or because of a belief in mean reversion (Andreessen, 1988). When investors' attention receives an exogenous shock, we believe that the shock is less likely to alter the curvature of investors' utility function. Therefore, we conjecture that attention can exacerbate the disposition effect through reinforcing the mean reversion expectation. We find that more frequent disclosure leads to more attention paid to treated funds than control funds following both gains and losses. Meanwhile, the treated funds are subject to an amplified disposition effect after the adoption of the disclosure policy, i.e., more sells following gains and less sells following losses. Our findings is consistent with greater attention reinforcing investors' mean reversion expectation: more frequent views of negative (positive) performance reinforce investors' belief that asset return will bounce back (drop) in future.

Consistently, we find that investors' performance on the treated funds experiences a decline of 41.9 basis points or 147.1 basis points after adjusting for the average return of funds in the same category, relative to that on the control funds. Thus, contrary to the belief that more information disclosure could improve investors' decision-making, we find that investment performance worsens following more frequent portfolio disclosure.

Next, we explore the effect of more frequent information disclosure across investors with different levels of financial literacy and attention capacity. To examine the heterogeneity across financial literacy, we separate investors based on: (1) whether working in the financial sector, and (2) whether holding a graduate degree. We find evidence of increased attention at the constituent fund level across all groups of investors. Increased attention in terms of total view time and view frequency, however, exists mainly among less sophisticated investors, i.e., non-financial professionals and those with an education degree lower than graduate. In addition, we show that less sophisticated investors' performance on the treated funds worsens relative to that on the control funds, and their sell trades of treated funds increase relative to that of the control funds. But we do not find similar effects for the more sophisticated investors. To examine the heterogeneity across attention capacity, we use the number of funds held by an investor in each month to measure the bindingness of attention capacity. We find that the effects of the new disclosure policy on investors' attention and trading are mitigated as the number of funds held increases.

The variations of the effect of the disclosure policy on trading behavior across subsamples parallel those on attention. In particular, the disclosure policy has no effects on trading for investors where it has no effects on attention. This suggests that the disclosure effect on trading is caused by the changes in attention. We then use this to construct instrumental variables (IV) estimates of the effect of attention on trading. Specifically, we employ an instrumented difference-in-differences approach (Duflo, 2001). In the first stage, we instrument browsing frequency of each product with the interaction term used in the DiD baseline specification, that is, the interaction of an indicator for a treated fund and an indicator for time after the adoption of the disclosure policy. In the second stage, we regress trading behaviors on the predicted value of browsing frequency while controlling for other covariates. We find that all our results on trading behaviors are robust to the IV estimation and that the magnitudes are consistent with the reduced-form DID estimation.

Our paper contributes to budding empirical literature that studies financial attention empirically. Since its inception, this literature has faced significant challenges in measuring attention itself, leading researchers to resort to attention proxies such as trading volume (Gervais, Kaniel, and Mingelgrin 2001), price limits (Li and Yu 2012; Seasholes and Wu 2007), and news (Yuan 2015; Barber and Odean 2007), and making the implicit assumption that investors are likely to pay attention to stocks that are mentioned in the news or that have been heavily traded on a given day. More recently, Da, Engelberg, and Gao (2011) propose the use of Google searches as a direct measure of aggregate attention and—using Google searches—Vlastakis and Markellos (2012) and Andrei and Hasler (2015) show that aggregate attention varies as a function of stock market volatility. The only studies that obtain direct measures of individual investor attention at the individual level—and are therefore closest to ours—are Karlsson, Loewenstein, and Seppi (2009), Sicherman et al.

(2016), Gargano and Rossi (2018) and Arnold, Pelster, and Subrahmanyam (2022). Karlsson, Loewenstein, and Seppi (2009) and Sicherman et al. (2016) use a large panel of investors' logins to 401K accounts as a measure of attention. Gargano and Rossi (2018) have information on brokerage accounts and construct measures of attention, such as what information investors browse and how much time they spend doing it. Arnold, Pelster, and Subrahmanyam (2022) obtain push message sent to brokerage accounts. Our data consists of mutual investors and allows us to construct attention not only at the individual level but also the product level across investors' holding and searching assets.

Second, our paper informs the theoretical literature that studies the cross-sectional dimension of how attention-constrained investors allocate their attention across a number of assets (Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2009, 2010). It also contributes to the literature that looks at the time-series dimension of investor attention. It shows that, if information acquisition is costly, it is optimal to alternate long periods of inaction to brief spurs of attention, where information is acquired and investment decisions are made (see Gabaix and Laibson 2002; Abel, Eberly, and Panageas 2007, 2013; Huang and Liu 2007; and Alvarez, Guiso, and Lippi 2012). We contribute to this literature by showing that attention-constrained investors may pay greater attention to financial assets with more frequent information disclosure, especially holding assets and assets with losses. In addition, under the stimulant of more frequent information disclosure, investors adjust attention pattern from long to short attention span.

Third, our paper also contributes to the literature on retail trading in financial markets. A longstanding view is that behavioral biases drive retail trading. Indeed, several studies highlight that retail investors trade for speculative reasons, such as overconfidence (Barber and Odean, 2001), sensation seeking (Grinblatt and Keloharju, 2009), or lottery preferences (Kumar, 2009). Benartzi and Thaler (1995) argue that as investor focus too much on the short-term fluctuations of assets, they will be more averse to asset volatility. On top of this, Larson, List and Metcalfe (2022) conduct a field experiment controlling for variables and concluded that investors who receive information infrequently invest 30%-80% more in risky assets than those who receive information frequently and gain higher returns. Iqbal et al (2021) find similar evidence. Our analysis adds to this discussion by showing that investors in a real investing environment also displays MLA based on within-investor analysis by utilizing cross-product variations. More importantly, we are the first to study attention patterns associated with MLA and the heterogeneity across investors with different demographic characteristics and attention capacity.

Fourth, our paper is also related to the literature that studies the performance of individual investors. For the most part, the literature has documented the mistakes of individual investors. For example, Odean (1999) and Barber and Odean (2000) show that—on average—individual investors trade too frequently and that trading is detrimental to their wealth. Behavioral biases can induce investors to undertake speculative trades that reduce their own welfare (Odean, 1998; Gervais et al., 2001). Superior trading performance has been linked to investors' IQ (Grinblatt, Keloharju, and Linnainmaa 2012; Korniotis and Kumar 2013), education (Von Gaudecker 2015), wealth (Calvet, Campbell, and Sodini 2007), experience (Korniotis and Kumar 2011; Nicolosi, Peng, and Zhu 2009), and portfolio concentration (Ivkovic, Sialm, and Weisbenner 2008). More recently, Frydman, Hartzmark, and Solomon (2017) document that investors make better investment decisions when they sell one asset and quickly buy another one. Our results provide novel empirical evidence on the relation between attention myopia and trading performance. The fact that we find a negative relation between attention and performance, even in the presence of investor and product fixed effects, is an indication that more frequent information disclosure may exacerbate MLA and result in worse performance.

Finally, it complements the literature that studies fund portfolio disclosures. Aragon et al. (2014) and Parida and Teo (2018) find that confidential positions earn positive and significant abnormal returns over the post-filing confidential period. Agarwal et al. (2013) find that the fear of being front-run thus motivates filers to seek confidentiality until the desired transactions are complete. While this literature focuses mostly on the performance of mutual funds, our paper focuses on the effect of the frequency of fund portfolio disclosures on retail investors.

2. Institutional Background and Methodology

2.1. Institutional Background

In October 2019, the Chinese Securities Regulatory Commission (CSRC) issued the Circular of the Pilot Program for Investment Advisory Service Business for Public Securities Investment Funds (the "Pilot Program Circular"), unveiling the pilot program of so-called "buy-side mode" fund investment advisory services, as opposed to the existing "sell-side mode" fund distribution business services. Until the end of 2022, 60 institutions have been granted a pilot qualification, including 26 fund management companies or their subsidiaries, 28 securities companies, three commercial banks, and three third-party distribution agencies or their joint venture subsidiaries. Pursuant to the Pilot Program Circular, institutions providing fund investment advisory services ("pilot institutions") may provide clients with fund investment portfolio strategies upon their entrustment and in accordance with the terms of their agreements and seek direct or indirect economic benefits by doing so. The Pilot Program Circular further clarifies that the target investments proposed by the fund investment portfolio strategies must be public funds or similar products approved by the CSRC.[2]

Similar to Fund of Funds (FOFs), investment advisory products are also portfolios of funds. There are, however, major differences in product designs, service and investment scopes, and fee-charging approaches. First, FOFs are essentially standardized fund products. Thus, the ownership of the investment fund belongs to the fund, and the management right of the investments belongs to the FOF fund manager. In contrast, investment advisory products provide personalized account management services according to the customer's risk preference and liquidity needs. The ownership of the account and invested funds belongs to the customer, but the management right of investments is designated to the professional investment advisory team. Second, investment advisory products can only invest in funds, while up to 20% of Assets under Management of FOF products can be directly allocated to assets such as stocks and bonds. Third, FOF funds charge subscription and redemption fees, fixed management custody fees,

[2] More details can be found at http://www.junhe.com/law-reviews/1613.

etc., while the investment advisory business charges investment advisory service fees.[3] Finally, FOF products follow a black-box strategy by disclosing positions quarterly, whereas investment advisory products follow a more transparent policy with disclosure frequency no less than quarterly.

2.2. Methodology

We exploit a quasi-natural experiment that introduces a plausibly exogenous shock to investors' attention. Starting from September of 2022, the disclosure policy of investment advisory products sold on the platform was changed. Specifically, the weights of asset allocation of investment advisory funds are disclosed from quarterly to daily (so called "white box"). The implementation of the new policy was not consulted with their clients and thus unexpected to investors.

We adopt a difference-in-differences strategy that compares investors' attention and investment behavior of the funds that are affected by the disclosure policy (treated funds) to those that are not (control funds) before and after the policy shock. We estimate the following specification:

$$(1)\ V_{ijt} = \alpha + \beta\ After_t \times High\ frequency_j + \text{Control} + \gamma_i + \delta_j + \lambda_t + \varepsilon_{ijt}$$

where V_{ijt} is the outcome variable, including the monthly browsing and trading behavior of an investor i on a product j in month t. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. Control variables include investor i's holding of the product j and the product j's return and volatility in month $t-1$. We also control the time-invariant differences across investors and products by including investor (γ_i) and product (δ_j) fixed effects, and add month fixed effects (λ_t) to account for any influences of macroeconomic conditions on investor behavior. We clustered standard error at the investor level. We are interested in the coefficient β, which represents the changes in investor

[3] The highest investment advisory fee charged by the pilot institutions has been even lower than fees charged by FOF products.

attention between white-boxed and non-white-boxed products after the increase in the information disclosure frequency.

3. Data and Sample Construction

Our data is from a professional third-party financial institution in China that has obtained an independent fund sales license. It provides transactions of public funds, private funds, private equity funds, fixed-income securities, FOFs, and other products. Retail services of financial products are also provided. The advantages of our data lie in its high frequency and granularity of browsing and transaction behavior of individual customers. The data records investors' product-level browsing information on the company's trading APP, including the start and end time of an investor browsing a financial product' page each time and information regarding whether the investor browses the fund's constituent fund through an embedded link. The data also contains investors' asset holding information and transaction records (i.e., the transaction time, trade type, and price). Finally, we also observe investors' personal characteristics, including gender, age, education, and profession.

To capture investors' total attention paid to a fund product, we construct three main dependent variables: *Views*, *Constituent views*, and *View time_ttl*. *Views* is defined as the number of times that the customer view the page of a fund product each month. *Constituent views* measures the number of times that the customer browses a fund's constituent fund through an embedded link on the fund's page each month. *View time_ttl* represents the total time duration (as measured in seconds) that a customer spends browsing a fund product each month. To further capture more refined browsing behavior, we examine the average time paid to each product per view by examining three additional measures: *View time_mean, View time_med,* and *View time_min.* They are defined as the mean, median and minimum time duration that an investor spends browsing a fund product each month. To capture investors' trading behavior, we examine their transaction frequency per month and numbers of buy and sell trades. We also look at their asset holding and performance in each month. We aggregate our data at the investor×product×month level and winsorize our variables at the 0.5% and 99.5% percentile.

Our original data contains investors who have held or purchased at least one financial product that was white-boxed and at least one other financial product from December 1, 2021 to October 31, 2022. We utilize a sample period that spans from July 1, 2022 to October 31, 2022, i.e., two months before and after the adoption of the new disclosure policy. Our final sample consists of 8,157 investors. In total, 23 investment advisory funds were white-boxed. Our sample investors have browsed 11,775 funds and invested in 7,793 funds over the sample period. An average (median) investor views 59 (27) funds, trades eight (three) funds, and hold or held 82 (12) funds per month.

Table 1 reports the summary statistics of the variables used in our analysis. Panel A shows that an average investor is between 40-50 years old and holds an undergraduate degree and that 42.6% of investors are female. In Panel B, unconditional on paying attention, investors, on average, view a product 1.5 times and spend 56.6 seconds in total on the product per month. The minimum time spent on the product per view is ten seconds on average. Conditional on paying attention, an average investor views a product 4.1 times and spends a total of 177.5 seconds on the product per month and a minimum of 28 seconds per view; a median investor views a product two times and spends a total of 29 seconds on the product per month and a minimum of four seconds per view. When constructing the sample in Panel C, we include assets that investors hold or once held during our sample period. Panel C shows that, unconditional on trading, an average investor makes 0.5 transactions for one product per month, with 0.25 buy trades and 0.22 sell trades. Conditional on trading, an average investor makes 4.2 transactions on one product per month, with 2.1 buy trades and 1.75 sell trades; a median investor makes two transactions for one product per month, with one buy trade and zero sell trade. An average investor holds 18.9 thousands RMB per product and earns a monthly return of -2.7% on the product and -4.9% after adjusting for the average performance of funds with the same type.

In Figure 1, we provide a heat-map to show total attention across investors and over time. For each investor, we generate a time series at the daily level for our sample period, and then compute, for each investor, the daily numbers of views (Panel A) and browsing seconds (Panel B) across all products. To ease the visualization, we sort the accounts by the total number of views and seconds over the full sample based on their behavior at the sample beginning date, so that the more active accounts are at the top of the figure. Both panels uncover considerable heterogeneity in behavior across accounts. At the top, we find the more attentive investors that check funds 20 times per day and spend about one to two minutes per day on their account. At the very bottom, on the other hand, we find those individuals rarely check. The figure also highlights some heterogeneity in individual accounts' behavior over time. For example, the horizontal lines of "warmer" colors—that appear in multiple parts of the figure—identify periods when a given investor pays more attention than usual to his or her investment portfolio. The opposite holds true for the horizontal lines of "colder" colors. We also find that during weekends, investors pay much less attention, as indicated by vertical stripes with "colder" colors.

In Figure 2, we plot a heat-map to show attention behavior across number of products held. X-axis represents the logarithm of number of products held by an investor each month, and Y-axis the logarithm of total view time aggregated across all products held by an investor each month. Heat from dark to light represents the logarithm of average view time per view and average browsing frequency spent on a product per month from low to high. We find that for a given level of the total view time for a product in a month, the average time per view and browsing frequency spent on each product decreases as the number of products increases. Also, the variability of average view time and frequency decreases with the number of products, as indicated by the narrowed spectrum of heat colors. In particular, the maximum level of average view time decreases with the number of products. While the minimum level of total view time for a product in a month increases with the number of products, the maximum level of total view time does not vary with it as much. These patterns suggest the existence of attention limit. A back-of-the-envelope calculation implies attention limit for sample investors at the product level is around 6 (i.e., exp(10)/3600) hours per month.

In Figure 3, we show attention behavior over time, also measured at the investor×product×month level. X-axis represents an investors' average view time spent on a product per month, and Y-axis the view frequency. Heat represents the four months in our sample (i.e., from July to October). We find that, across all months, average view time and view frequency are negatively correlated. In addition, the relation at the frontier exhibits a convex shape, suggesting the existence of attention limit at the product level as also indicated by Figure 2.[4]

4. Effects on Attention

4.1. Baseline Results on Total Attention

Panel A, Table 2 presents baseline regression results for investors' total attention, as measured by *Views*, *Constituent views*, and *View time_ttl*. In column (1), (3), and (5), we employ a DiD specification where we include *After* × *High frequency* and investor, month, and product fixed effects in the regression without adding other control variables. In column (2), (4), and (6), we further include the control variables as described in Section 2.2. We find that the coefficient estimates on *After* × *High Frequency* are positive and significant. Specifically, as indicated by columns (2), (4) and (6), investors increase view frequency of white-boxed funds 0.454 times and its constituent funds 0.052 times, and total view time 14.114 seconds relative to funds that are not white-boxed after the adoption of the new disclosure policy. To put these magnitudes into perspective, high frequent disclosure policy leads to an increase in view frequency by 31.17% (0.454/1.459), constituent funds view frequency by 38.8% (0.052/0.134), and total view time by 25% (=14.114/56.586) from respective sample means.

In Panel B, we restrict our analysis conditional on paying attention to the fund and repeat the analysis as in Panel A. We find that the coefficient estimates on *After* × *Treat* for dependent variables *Views* and *Constituent views* are positive and significant, with greater magnitudes than those in Panel A. The coefficient for *View time_ttl* is positive but insignificant at conventional levels. This result suggests that the increase in total attention unconditional on paying attention in Panel A is by the extensive margin of increased browsing activities.

Overall, our baseline regressions suggest a positive effect of high-frequency disclosure policy on investor attention at both the fund and constituent fund levels for

[4] For example, the product of average view time and view frequency could be capped at a certain level.

treated funds. While the new disclosure policy increases total view time, it also induces investors to pay attention more frequently to treated funds.

4.2. Validation

The DiD coefficient of interest, β, can be interpreted as causal as long as the dependent variable for attention paid by investors to the treated and control funds would follow parallel trends in the absence of the merger. This assumption is not directly testable, but we can find evidence in its favor by adding the lead dummy variables of the treatment variable and showing that the parallel trends hold before the treatment occurred. In particular, we estimate the following regression:

$$(2)\ V_{ijt} = \alpha + \sum_{j=-3}^{-1} \beta_j\ Before\_j \times High\ frequency_j + \sum_{j=1}^{4} \gamma_j\ After\_j \times \text{High frequency}_j + \text{Control} + \gamma_i + \delta_j + \lambda_t + \varepsilon_{ijt}$$

Specifically, we aggregate the data at the weekly level and construct seven lead and lag indicator variables. *Before_3–Before_1* are pre-treatment dummy variables that equal one if the current week t is three weeks or more, two weeks, and one week before September 1, 2022, and zero otherwise. *After_1−After_4* are post-treatment dummy variables that equal one if the current week t is one, two, three, and four weeks or more after September 1, 2022, and zero otherwise. We take the week before September 1, 2022 as the base for comparison, and thus the coefficients of these lead and lag variables should be interpreted as changes in attention relative to that week.

We present the results that investigate the pre-trend between the treated and control groups in Figure 4. We plot the coefficients of lead and lag variables on the y-axis, and the x-axis shows the week relative to September 1, 2022. The vertical solid lines in the figure correspond to the 95% confidence intervals of the coefficient estimates. We find that the coefficients on all the lead variables are small in magnitude and not statistically significant, suggesting parallel trends leading up to the treatment. Also, we find persistent and significant increases in attention paid to treated funds relative to those in the control group after the implementation of the daily disclosure policy.

One may also argue that the disclosure policy may have an impact on the performance of the treated funds, which causes investors to pay more attention to them. To alleviate this concern, we control time-varying fund characteristics as shown in Equation (1). Furthermore, in Panels D and E of Figure 4, we investigate dynamic changes in the fund's performance following Equation (3):

$$(3)\ U_{jt} = \alpha + \sum_{j=-3}^{-1} \beta_j\ Before\_j \times High\ frequency_j + \sum_{j=1}^{4} \gamma_j\ After\_j \times \text{High frequency}_j + \delta_j + \lambda_t + \varepsilon_{jt}$$

where U_{jt} is the outcome variable, including the product j's return and volatility in week t. As shown in Panels D and E, neither the treated funds' return nor their volatility experience significant changes following the adoption of the new disclosure policy, lending further support to our DiD design.

4.3. More Refined Attention Behavior

In this section, we examine more refined attention behavior. We first examine the effect of increasing disclosure policy on investors' attention span. We then examine changes in investors' attention at different time of the day and across different assets.

4.3.1. Attention Span

To measure attention span, we examine investors' average time (*View time_mean*) spent on per view of a fund in a month. We examine the median time (*View time_med*) and minimum time (*View time_min*) spent per view as supplementary measures. Table 3 reports the results. In column (1), (3), and (5), we employ a DiD specification where we include *After* × *High Frequency* and investor, month, and product fixed effects in the regression without adding other control variables. In column (2), (4), and (6), we further include the control variables as described in Section 2.2.

We find that the coefficient estimates on *After* × *High Frequency* are consistently negative in all columns and significant in most columns. Specifically, as indicated by columns (2), (4) and (6), investors reduce their average attention span by 1.970 seconds, median attention span by 2.776 seconds, and minimum attention span by 3.176 seconds relative to funds that are not white-boxed after the adoption of the new disclosure policy.

To put these magnitudes into perspective, high frequent disclosure policy leads to a decrease in average attention span by 10.86% (1.970 /18.14), median attention span by 18.9% (2.776/14.689), and minimum attention span by 31.58% (=3.176/10.057) from respective sample means. Our findings, therefore, suggest that while more frequent information disclosure leads to more total attention paid to the treated fund, it reduces investors' attention span and thus results in attention fragmentation. This result is consistent with Figures 2 and 3 which indicate that investors are subject to attention limit.

4.3.2. Attention During and Off Working/Trading Hours

In this subsection, we investigate changes in investors' attention at different time of the day.

In Table 4, we examine total attention (from columns (1)−(3)) and attention span (from columns (4)−(6)) during and off working hours. We define working hours as from 9am to 12am and from 1pm to 6pm on Monday to Friday, and other time as non-working hours. We examine attention changes during working hours in Panel A and off working hours in Panel B. In all columns, we employ a DiD specification in Equation (1) where we include *After* × *High Frequency* and investor, month, and product fixed effects and add the control variables.

In Panel A, we find that investors significantly increase view frequency of white-boxed funds 0.366 times and its constituent funds 0.034 times, and total view time 13.338 seconds during working hours relative to funds that are not white-boxed after the adoption of the new disclosure policy. When looking at attention span, we do not find a significant reduction for any of the measures. In Panel B, while we also find that investors increase total attention paid to treated funds, the magnitudes of coefficients are smaller than in Panel A. When looking at attention span, investors significantly reduce their average attention span by 1.682 seconds, median attention span by 2.022 seconds, and minimum attention span by 2.126 seconds relative to funds not white-boxed after the adoption of the new disclosure policy.

In Appendix Table A.1, we examine total attention (from columns (1)−(3)) and attention span (from columns (4)−(6)) during and off trading hours. Fund trading hours in

China are from 9:30am to 11:30am and from 1pm to 3pm on Monday to Friday. While one can place orders outside these periods, the transaction price will be determined by the next-day closing price. We examine attention changes during trading hours in Panel A and off trading hours in Panel B. We find similar results as in Table 4. That is, increases in total attention for treated funds relative to that for control funds hold for views made both during and off trading hours. Attention fragmentation for treated funds relative to that for control funds, however, occurs only off trading hours.

As investors face limited attention, they may choose to spend deeper attention (or longer attention span) during working/trading hours when information acquisition is more relevant to trading. Outside working/trading hours, while increasing information disclosure frequency encourages total and more frequent attention, it also induces more fragmented attention.

4.3.3. Attention to Holding Assets

In this subsection, we investigate changes in investors' attention for holding assets. When constructing the sample, we include assets that investors hold or once held during our sample period. In Table 5, examine total attention (from columns (1)−(3)) and attention span (from columns (4)−(6)) for holding assets. In all columns, we employ a DiD specification in Equation (1) where we include *After* × *High Frequency* and investor, month, and product fixed effects and add the control variables.

We find that investors significantly increase view frequency of white-boxed funds that they hold 0.312 times and its constituent funds 0.015 times, and total view time 10.652 seconds relative to funds that are not white-boxed after the adoption of the new disclosure policy. When looking at attention span, we do not find a significant reduction for any of the measures. In light of the results in Table 3, the negative effect of high frequency disclosure policy seems to impact only non-holding assets.

Consistent with the findings in Section 4.3.2, limited attention may choose to spend deeper attention to assets for which information acquisition is more relevant to trading, i.e., holding assets. For assets that they do not hold, the new disclosure policy induces more frequent but fragmented attention.

5. Effects on Trading

In this subsection, we examine if increasing disclosure frequency also affects investors' trading behavior and performance. When constructing the sample, we include assets that investors hold or once held during our sample period following Table 5.

5.1. Reduced-form DID Results

We apply the same identification strategy as in Section 4 to estimate the effect of the disclosure policy on trading.

5.1.1. Attention and Loss Aversion: Myopia

We first examine investors' trading frequency and asset holding. There has been considerable effort across economics and finance to understand the equity premium puzzle. A general equilibrium framework with additively separable utility functions requires an implausibly large coefficient of relative risk aversion to explain the underlying data (Mehra and Prescott, 1985). More recently, Benartzi and Thaler (1995) have augmented the standard model by leveraging two general features of human cognition—myopia and loss aversion—to provide an intriguing explanation for the puzzle. Myopic loss aversion (MLA) is a situation characterized by loss-averse investors (Kahneman and Tversky, 1979) paying too much attention to the short-term performance of their asset portfolios and becoming overly averse to risky assets.

There is growing micro-level evidence based on experimental designs for MLA (e.g., Larson, List and Metcalfe, 2022). As these designs may not adequately represent real-life investment-decision processes, testing the theory in a non-experimental environment is important but also challenging. We take a fresh look at the question by utilizing the browsing data and quasi-experiment design. To measure investors' trading frequency, we examine investors' total number of transactions (*Transactions*), total number of buy trades (*Buys*), and total number of sell trades (*Sells*) made on the product per month in columns (1)-(6). In columns (7) and (8), we examine the holding value of the asset in that month. Table 6 reports the results. In column (1), (3), (5) and (7), we employ a DiD specification where we include *After* × *High Frequency* and investor, month, and product fixed effects in the regression without adding other control variables. In column (2), (4), (6) and (8), we further include the control variables as described in Section 2.2.

For total frequency of trades, we find that the coefficient estimates on *After* × *High Frequency* are positive and significant. For example, as indicated by column (2), investors increase total trades by 0.021 times for white-boxed funds relative to funds that are not white-boxed after the adoption of the new disclosure policy. When taking a closer look at the types of trades, we find that sell trades mostly drive the effect. The coefficient estimate in column (4) for buy trade frequency is small in magnitude (0.005) and significant at conventional levels. In contrast, the coefficient estimate in column (6) for sell trade frequency is 0.011 and significant at the 1% level. When looking at fund holding in columns (7) and (8), we find a significant contraction for treated funds relative to control funds after the adoption of the new disclosure policy. For example, as indicated by column (8), investors downsize holding of white-boxed funds relative to funds that are not white-boxed by 807.809 RMB after the adoption of the new disclosure policy, which is 4.263% (0.807/18.931) reduction of the sample mean.

These findings show that more frequent information disclosure increases transaction frequency of treated funds, especially sell trades, and, consequently, results in less holding of the treated funds relative to control funds. Combined with findings in previous sections, our results suggest that as investors pay more frequent attention to treated funds, high-frequency information disclosure makes investors more risk averse to investments in these funds. Thus, our results could be consistent with myopic loss aversion whereby more frequent information disclosure exacerbates loss aversion and causes investors to cut back on risky investment.

5.1.2. Attention and Disposition Effect: Belief

We next examine how attention affects trading by affecting investors' beliefs. A growing literature aims to link retail investors' equity market participation and equity shares to expected stock returns. Recent research by Giglio et al. (2021) shows that despite the small response of equity shares to beliefs about stock returns, investors are heterogeneous in their sensitivity along several economically interesting dimensions. One of these dimensions is investors' attention to their portfolios.

To explore the role of attention in reinforcing the effect of belief on trading, we revisit the classic disposition effect (Odean, 1998). Investors are more reluctant to sell losing investments than wining stock either because of prospect theory (Kahneman and Tversky, 1979) or because of a belief in mean reversion (Andreessen, 1988). The former channel claims that diminishing sensitivity makes investors more risk averse in the gain region than in the loss region. The latter channel posits that investors are unwilling (willing) to sell a losing (winning) stock when believing the result is likely to bounce back (drop). When investors' attention receives an exogenous shock, we believe that the shock is less likely to alter the curvature of investors' utility function than influence investors' belief in mean reversion. Therefore, we conjecture that attention can exacerbate the disposition effect through reinforcing the mean reversion expectation. Table 7 test this idea.

In Table 7, we define a dummy variable *Loss* that equals one if a product's monthly performance is negative and zero if non-negative. Our results are robust when using cumulative performance to define the loss dummy. We then interact the loss dummy with *After* × *High Frequency*. In columns (1) and (2), we look at the frequency of sell trades (*Transactions_sells*) in each month as the dependent variable. In columns (2) and (8), we examine the six attention variables. In column (1), we employ a triple DiD specification where we include other interaction term to complete the triple DiD specification and investor, month, and product fixed effects in the regression. In all other columns, we further include the time-varying control variables as described in Section 2.2.

In columns (1) and (2), we first show that investors make fewer sell trades when the product loses, confirming the disposition effect. More importantly, we find that the coefficient estimate on *After* × *High Frequency* are significantly positive, suggesting an intensified disposition effect following gains. For example, as shown in column (2), investors increase sell trades by 0.087 times more for white-boxed funds than for non-white-boxed funds following gains after the adoption of the new disclosure policy. Equally importantly, we find that the coefficient on *After* × *High Frequency* × *Loss* are significantly negative, suggesting an intensified disposition effect following losses. For example, column (2) shows that investors reduce sell trades by 0.071 times more for white-boxed funds than for non-white-boxed funds following losses after the adoption of the new disclosure policy.

When taking a closer look at the attention behavior, we find that the coefficient estimates on *After* × *High Frequency* and *After* × *High Frequency* × *Loss* are mostly positive and significant in columns (2)-(5), suggesting the browsing frequency and total browsing time increases for treated funds relative to control funds following both gains and losses. For example, as indicated by columns (2), investors increase total view frequency by 0.251 times more for white-boxed funds than non-white-boxed funds following gains and, additionally, 0.112 times more following losses after the adoption of the new disclosure policy. When looking at browsing duration per view in columns (6)-(8), the high-frequency disclosure policy leads investors to pay more fragmented attention to treated funds relative to control funds following gains, but more concentrated attention following losses.

Overall, our findings in this section show that more frequent disclosure leads to more attention paid to treated funds than control funds following both gains and losses. Meanwhile, the treated funds are subject to an amplified disposition effect. Our findings is consistent with greater attention reinforcing investors' mean reversion expectation. That is, more frequent views of negative (positive) performance reinforce investors' belief that asset return will bounce back (drop) in future, inducing them more reluctant (willing) to sell.

5.1.3. Trading Performance

In this subsection, we examine the effect of high-frequency disclosure on investors' trading performance.

We construct three performance measures. *Return (%)* is the monthly return on the product as defined by *Investment profit* divided by the average holding of the fund each month. *Adjusted return (%)* is measured by subtracting from *Return (%)* the average return of funds in the same fund type. *Profit* measures changes in accumulated profit of the holding fund over months. Table 8 reports the results. In column (1), (3) and (5), we employ a DiD specification where we include *After* × *High Frequency* and investor, month, and product fixed effects in the regression without adding other control variables. In column (2), (4), and (6), we further include the control variables as described in Section 2.2.

We find that the coefficient estimates on *After* × *High Frequency* are all negative and significant. For example, as shown by columns (2) and (4), performance on white-boxed funds experiences a decline relative to that on non-white-boxed ones by 41.9 basis points for *Return (%)* and 147.1 basis points for *Adjusted Return (%)* after the adoption of the new disclosure policy. The relative decline in returns translates to RMB 664.1, as indicated by column (6). Thus, contrary to the belief that more information disclosure could improve investors' decision-making, we find that investment performance worsens for the treated funds, lending additional support to a behavioral interpretation.

Our findings in this section suggest that paying frequent attention may exacerbate myopic loss aversion and lead to worse performance.

5.2. Heterogeneity

In this subsection, we explore the effect of more frequent information disclosure on attention and trading across investors subject to different levels of financial literacy and attention capacity. For the analysis of attention, we employ the sample of holding assets, as used in analyzing trading activities.

5.2.1. Job Profession

We first separate our sample by professions. In Table 9, we examine attention behavior and trading performance for investors who are financial professionals in Panel A and those of other professions in Panel B. In all columns, we employ a DiD specification in Equation (1) where we include *After* × *High Frequency* and investor, month, and product fixed effects and add the control variables as described in Section 2.2.

Financial professionals do not increase view frequency or total view time of white-boxed funds significantly more than non-white-boxed ones after the new disclosure policy. Neither do we find attention fragmentation among financial professionals. We do not find financial professionals make more sell trades nor experience worse performance on treated funds than control funds. In contrast, non-financial-professional investors significantly increase view frequency of the treated fund and its constituent funds by 0.328 and 0.014

times, and total view time by 10.835 seconds more relative to funds that are not white-boxed after the adoption of the new disclosure policy. We also find non-financial professionals make more sell trades and experience worse performance on treated funds than control funds. Also, both types of investors view more often the constituent funds of the treated funds but do not exhibit attention fragmentation for holding assets.

5.5.2. Education

In this subsection, we separate our sample by education. In Table 10, we examine attention behavior and trading performance for investors who obtained a graduate degree in Panel A and those with a lower degree in Panel B. In all columns, we employ a DiD specification in Equation (1) where we include *After* × *High Frequency* and investor, month, and product fixed effects and add the control variables as described in Section 2.2.

We find that while both types of investors increase view frequency and total view time of the treated funds relative to the control funds after the new disclosure policy, the effect is more pronounced for investors who are less educated. Consistently, the effect of information disclosure policy on sell trades and investment returns are also stronger for investors who are less educated. That is, compared to more educated investors, less-educated investors make more sell trades and experience worse performance on treated funds relative to control funds.

5.5.3. Sensitivity to Attention Capacity

In this subsection, we examine how the effects of disclosure policy on attention and trading vary with attention capacity. We use, *Num of Funds*, the number of unique funds held by an investor in each month, divided by 100, (i.e.,) to measure the bindingness of attention capacity. As shown by Figure 2, attention paid to a product decreases with the number of funds held. In Table 11, we employ a triple-difference specification where we include *After* × *High Frequency* × *Num of Funds* and other interactions to complete the specification. We also add investor, month, and product fixed effects and the control variables as described in Section 2.2.

We find that the main effect of *After* × *High frequency* are consistent with our previous findings. The triple-interaction shows that attention constraint mitigates the effect of the new disclosure policy on investors' attention and trading. As the attention capacity becomes more constrained, the increases in view frequency and sell trades and the reduction in return performance decline for treated funds relative to control funds after the adoption of the new disclosure policy.

Taken together, the findings in cross-sectional analyses suggest that changes in information disclosure frequency are more likely to affect the attention allocation of less sophisticated and more attention-constrained investors. The variations of the effect of the disclosure policy on trading behavior across investors parallel those on attention. In particular, the disclosure policy has no (smaller) effects on trading for investors where it has no (smaller) effects on attention. This suggests that the disclosure effect on trading is caused by the changes in attention. In the next subsection, we use this to construct instrumental variables (IV) estimates of the effect of attention on trading.

5.3. An Instrumented Difference-in-difference Estimation

Ordinary least-squares (OLS) estimates may lead to biased estimates if there is a correlation between attention and trading activities. If we assume the disclosure policy has no effect on trading other than by increasing browsing frequency, one can use this policy to construct instrumental variable estimates of the impact of additional browsing frequency on trading. We find strong support for this approach in the subsample analysis. Another concern, for this interpretation, is that the new disclosure policy might have affected not just the browsing frequency but also total browsing time and duration per view, and that changes in trading could reflect all these effects. We believe that this is also not a concern in our context. First, Table 2 shows that the increase the total view time is driven by the browsing frequency at the extensive margin. Second, Table 5 shows that for holding assets, investors' attention to the treated funds does not become more fragmented than that to the control funds. Thus, we believe that the interactions between $After_t$ and $High\ frequency_j$ is available as an instrument. This instrument been shown to have good explanatory power in the first stage in Section 3.

Estimates of Equation (1) for attention are of intrinsic interest because they provide an assessment of the impact of the disclosure policy on attention. But they also represent the first stage of a two-stage least-squares (2SLS) estimation of the impact of disclosure policy on attention. In the first stage, we instrument browsing frequency of each product with the interaction term used in the DiD baseline specification (1), i.e., $After_t \times High\ frequency_j$ the interaction of an indicator for a treated fund ($High\ frequency_j$) and an indicator for time after the adoption of the disclosure policy ($After_t$). The first stage estimates are already reported in Panel A, Table 5. In the second stage as shown in Equation (4) below, we regress trading behaviors on the predicted value of view frequency ($Predicted\ view\ frequency_{ijt}$) while controlling for other covariates.

(4) $V_{ijt} = \alpha + \beta\ Predicted\ view\ frequency_{ijt}$ + Control+ $\gamma_i + \delta_j + \lambda_t + \varepsilon_{ijt}$

In Appendix Table A.2, we present the results. We find that all our results on trading behaviors are robust to the IV estimation. When comparing magnitudes across reduced-form DID estimates and instrumented DID estimates, the magnitudes are consistent. For example, the instrumented DID estimate for sell trades is 0.035 (column (3), Panel A Table A.2), which is aligned with ratio of reduced-form DID estimates for sell trades and view frequency 0.011/0.312 (column (6) Table 6 and column (1) Panel A Table 5, respectively).

6. Conclusion

Our research provides new evidence on how investors allocate attention in response to more frequent information disclosure in a real investment environment. We utilize product-level browsing activities of mutual fund investors on a trading APP. We examine how investors' attention responds to a sudden change in the disclosure frequency of a certain type of mutual funds. Leveraging a diff-in-diff design, we find that investors visit the product's page more frequently following the new disclosure policy. The increase in total attention is driven by the extensive margin of increased browsing frequency rather than longer browsing time per view. At the constituent fund level, we also find an increase in view frequency for treated funds relative to control funds. When looking at more refined attention pattern, we find that more frequent information disclosure results in attention fragmentation. When differentiating attention over time and across products, we find robust evidence for an increase in attention frequency and strong heterogeneity in total attention and attention span during and off working/trading hours and for both holding and non-holding assets.

When looking at investors' trading behavior, we find that more frequent information disclosure increases transaction frequency of treated funds relative to control funds, especially sell trades. Investors consequently hold less of the treated funds relative to control funds. We also find that more frequent information disclosure leads to fewer sell trades of the treated funds following losses than following gains relative to the control funds, suggesting a stronger disposition effect for treated funds. Consistently, investors pay more frequent and concentrated attention to sell trades of treated funds after the increase in disclosure frequency compared to the control funds. Importantly, investors' performance on treated funds worsens relative to that on the control funds.

Exploring the effect of more frequent information disclosure across investors with different levels of financial literacy and attention capacity, we show that variations in the effect of information disclosure frequency on investors' attention allocation are consistent with those on investors' trading. Using an instrumented diff-in-diff estimation, we confirm the effect of attention myopia on trading. Our findings suggest the role of attention myopia in reinforcing investors' belief formation and exacerbating cognition limit of loss aversion. More broadly, our paper sheds light on understanding the role of attention in influencing asset prices.

Reference

Abel, A.B., Eberly, J.C. and Panageas, S., 2007. Optimal inattention to the stock market. *American Economic Review*, *97*(2), pp.244-249.

Abel, A.B., Eberly, J.C. and Panageas, S., 2013. Optimal inattention to the stock market with information costs and transactions costs. *Econometrica*, *81*(4), pp.1455-1481.

Agarwal, V., Jiang, W., Tang, Y. and Yang, B., 2013. Uncovering hedge fund skill from the portfolio holdings they hide. *The Journal of Finance*, *68*(2), pp.739-783.

Alvarez, F., Guiso, L. and Lippi, F., 2012. Durable consumption and asset management with transaction and observation costs. *American Economic Review*, *102*(5), pp.2272-2300.

Andrei, D. and Hasler, M., 2015. Investor attention and stock market volatility. *The Review of Financial Studies*, *28*(1), pp.33-72.

Aragon, G.O., Hertzel, M. and Shi, Z., 2013. Why do hedge funds avoid disclosure? Evidence from confidential 13F filings. *Journal of Financial and Quantitative Analysis*, *48*(5), pp.1499-1518.

Arnold, M., Pelster, M. and Subrahmanyam, M.G., 2022. Attention triggers and investors' risk-taking. *Journal of Financial Economics*, *143*(2), pp.846-875.

Barber, B.M. and Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, *55*(2), pp.773-806.

Barber, B.M. and Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, *116*(1), pp.261-292.

Barber, B.M. and Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, *21*(2), pp.785-818.

Benartzi, S. and Thaler, R.H., 1995. Myopic loss aversion and the equity premium puzzle. *The quarterly journal of Economics*, *110*(1), pp.73-92.

Calvet, L.E., Campbell, J.Y. and Sodini, P., 2007. Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy*, *115*(5), pp.707-747.

Da, Z., Engelberg, J. and Gao, P., 2011. In search of attention. *The Journal of Finance*, *66*(5), pp.1461-1499.

Duflo, E., 2001. Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. *American Economic Review*, 91(4), pp.795-813.

Frydman, C., Hartzmark, S.M. and Solomon, D.H., 2018. Rolling mental accounts. *The Review of Financial Studies*, *31*(1), pp.362-397.

Gabaix, X. and Laibson, D., 2001. The 6D bias and the equity-premium puzzle. *NBER macroeconomics annual*, *16*, pp.257-312.

Gargano, A. and Rossi, A.G., 2018. Does it pay to pay attention?. *The Review of Financial Studies*, *31*(12), pp.4595-4649.

Gaudecker, H.M.V., 2015. How does household portfolio diversification vary with financial literacy and financial advice?. *The Journal of Finance*, *70*(2), pp.489-507.

Gervais, S., Kaniel, R. and Mingelgrin, D.H., 2001. The high-volume return premium. *The Journal of Finance*, *56*(3), pp.877-919.

Grinblatt, M. and Keloharju, M., 2009. Sensation seeking, overconfidence, and trading activity. *The Journal of Finance*, *64*(2), pp.549-578.

Grinblatt, M., Keloharju, M. and Linnainmaa, J.T., 2012. IQ, trading behavior, and performance. *Journal of Financial Economics*, *104*(2), pp.339-362.

Huang, L. and Liu, H., 2007. Rational inattention and portfolio selection. *The Journal of Finance*, *62*(4), pp.1999-2040.

Iqbal, K., Islam, A., List, J.A. and Nguyen, V., 2021. Myopic loss aversion and investment decisions: from the laboratory to the field (No. w28730). National Bureau of Economic Research.

Ivković, Z., Sialm, C. and Weisbenner, S., 2008. Portfolio concentration and the performance of individual investors. *Journal of Financial and Quantitative Analysis*, *43*(3), pp.613-655.

Kahneman, D. and Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), pp.363-391.

Karlsson, N., Loewenstein, G. and Seppi, D., 2009. The ostrich effect: Selective attention to information. *Journal of Risk and uncertainty*, *38*, pp.95-115.

Korniotis, G.M. and Kumar, A., 2011. Do older investors make better investment decisions?. *The Review of Economics and Statistics*, *93*(1), pp.244-265.

Korniotis, G.M. and Kumar, A., 2013. Do portfolio distortions reflect superior information or psychological biases?. *Journal of Financial and Quantitative Analysis*, *48*(1), pp.1-45.

Kumar, A., 2009. Who gambles in the stock market?. *The Journal of Finance*, *64*(4), pp.1889-1933.

Larson, F., List, J.A. and Metcalfe, R.D., 2016. *Can myopic loss aversion explain the equity premium puzzle? Evidence from a natural field experiment with professional traders* (No. w22605). National Bureau of Economic Research.

Li, J. and Yu, J., 2012. Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics*, *104*(2), pp.401-419.

Mehra, R. and Prescott, E.C., 1985. The equity premium: A puzzle. *Journal of monetary Economics*, *15*(2), pp.145-161.

Nicolosi, G., Peng, L. and Zhu, N., 2009. Do individual investors learn from their trading experience?. *Journal of Financial Markets*, *12*(2), pp.317-336.

Odean, T., 1999. Do investors trade too much?. *American Economic Review*, *89*(5), pp.1279-1298.

Parida, S. and Teo, T., 2018. The impact of more frequent portfolio disclosure on mutual fund performance. *Journal of Banking and Finance*, *87*, pp.427-445.

Peng, L. and Xiong, W., 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), pp.563-602.

Seasholes, M.S. and Wu, G., 2007. Predictable behavior, profits, and attention. *Journal of Empirical Finance*, *14*(5), pp.590-610.

Sicherman, N., Loewenstein, G., Seppi, D.J. and Utkus, S.P., 2016. Financial attention. *The Review of Financial Studies*, *29*(4), pp.863-897.

Van Nieuwerburgh, S. and Veldkamp, L., 2009. Information immobility and the home bias puzzle. *The Journal of Finance*, *64*(3), pp.1187-1215.

Van Nieuwerburgh, S. and Veldkamp, L., 2010. Information acquisition and under-diversification. *The Review of Economic Studies*, *77*(2), pp.779-805.

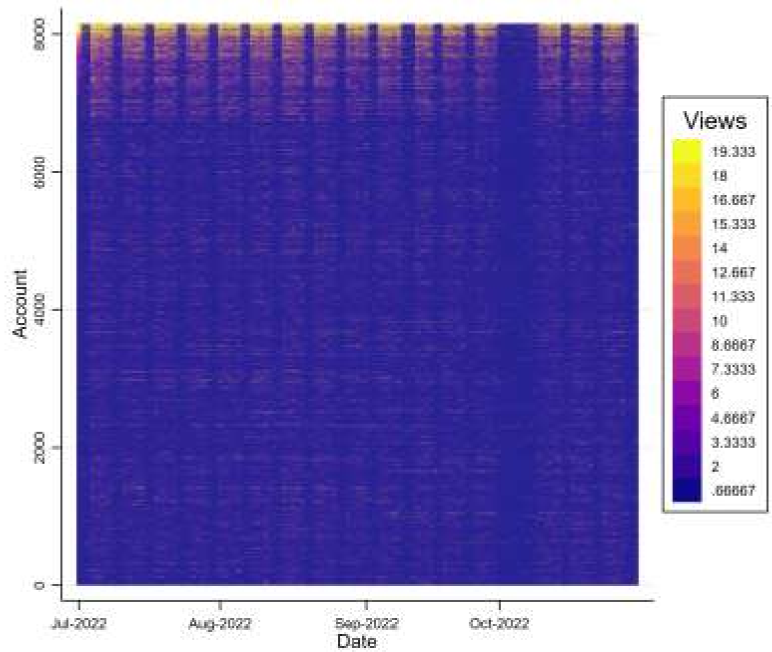
Vlastakis, N. and Markellos, R.N., 2012. Information demand and stock market volatility. *Journal of Banking & Finance*, *36*(6), pp.1808-1821.

Yuan, Y., 2015. Market-wide attention, trading, and stock returns. *Journal of Financial Economics*, *116*(3), pp.548-564.

Figure 1: Heat Map of Investor Total Attention across All Products

In this figure, we show heat-maps to show total attention across investors and over time. For each investor, we generate a time series at the daily level for our sample period, and then compute, for each investor, the daily numbers of views (Panel A) and browsing seconds (Panel B) across all products. We sort the accounts by the total number of views and seconds over the full sample based on their behavior at the sample beginning date.

Panel A: Views



Panel B: Total view time

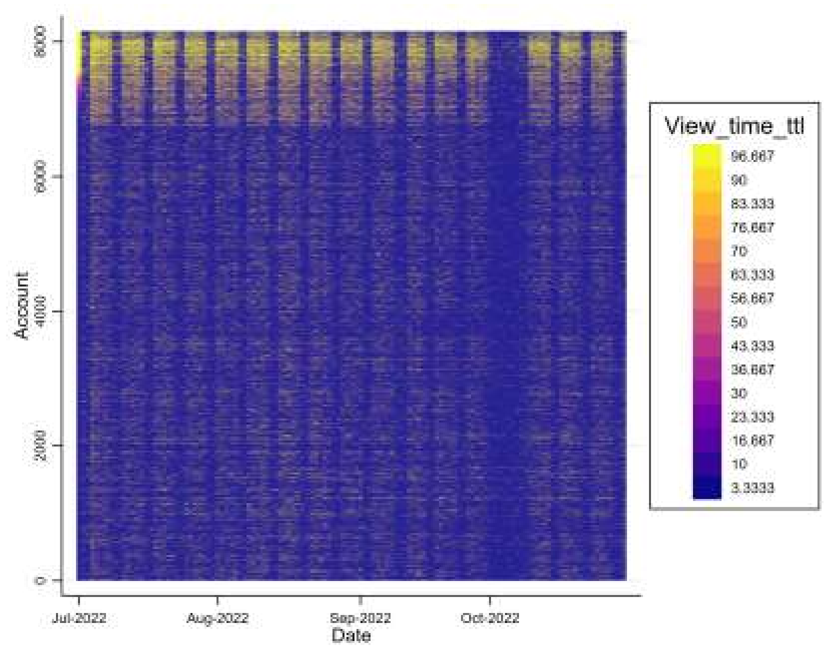
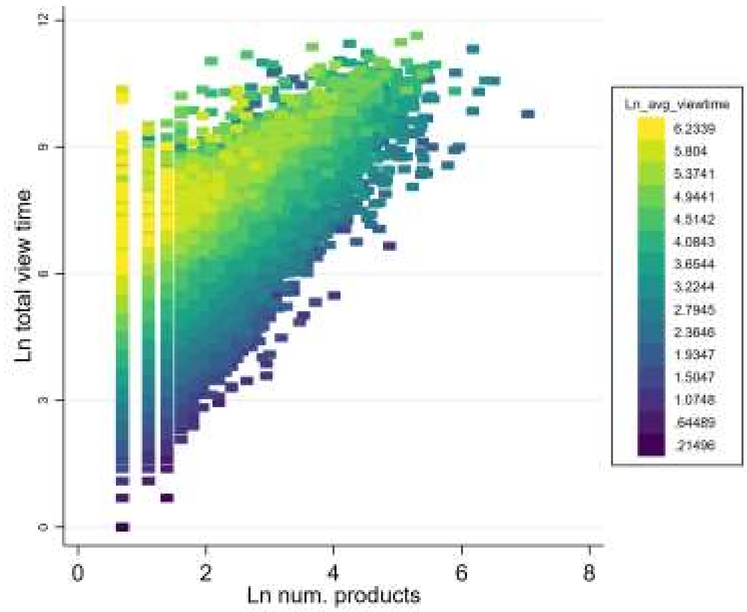


Figure 2: Heat Map of Attention and Number of Products

In this figure, we plot a heat-map to show attention behavior across number of products held. X-axis represents the logarithm of number of products held by an investor each month, and Y-axis the logarithm of total view time aggregated across all products held by an investor each month. Heat from dark to light represents the logarithm of average view time per view and average browsing frequency spent on a product per month from low to high.

Panel A: Average view time



Panel B: Average view frequency

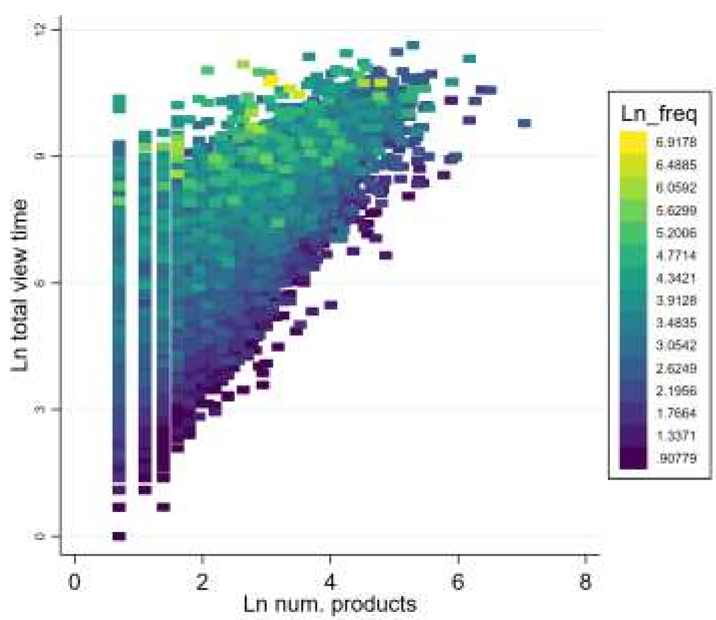


Figure 3: Product-level Attention by Month

In this figure, we show attention behavior over time, measured at the investor×product×month level. X-axis represents an investors' average view time spent on a product per month, and Y-axis the view frequency. Heat represents the four months in our sample (i.e., from July to October).

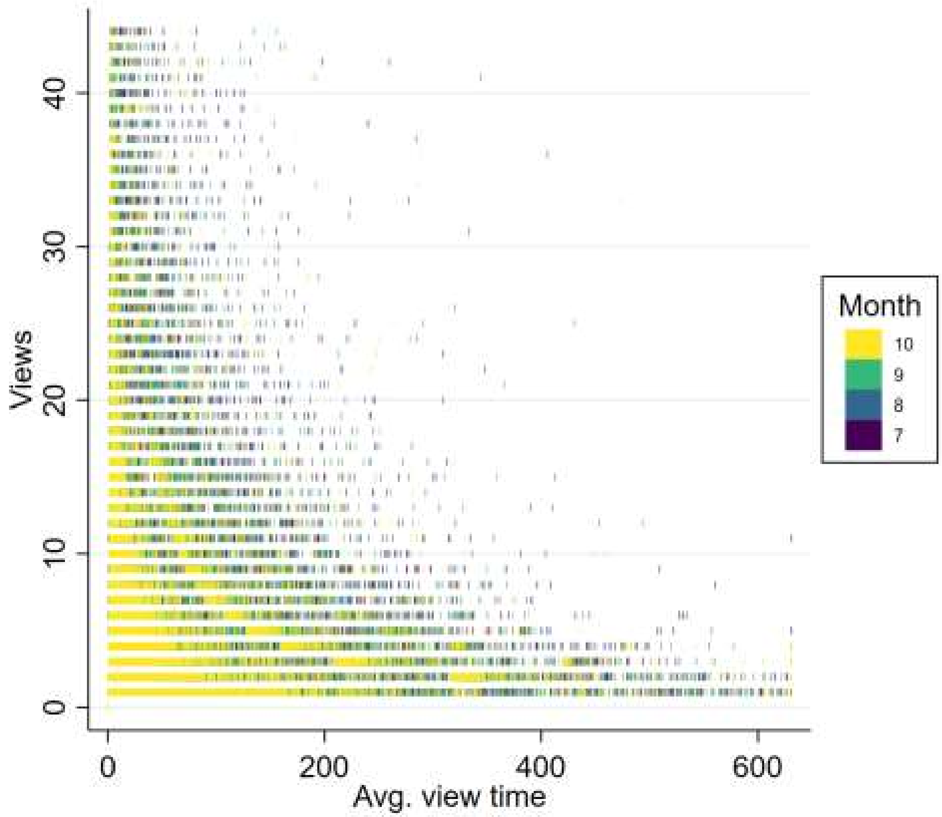
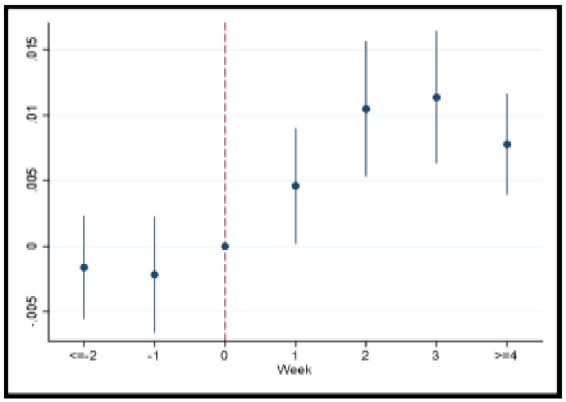


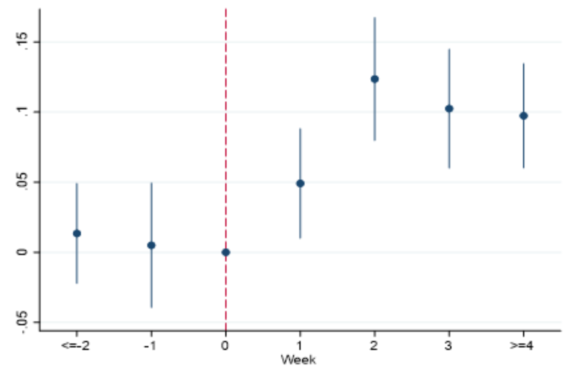
Figure 4: Validation: Dynamic Trends

In this figure, we present dynamic impacts of more frequent information disclosure on attention behavior following Equation (2) in Panels A–C, and on product performance following Equation (3) in Panels D and E. We plot the coefficients of lead and lag variables on y-axis, and the week relative to September 1, 2022 on x-axis. The vertical solid lines in the figure correspond to the 95% confidence intervals of the coefficient estimates.

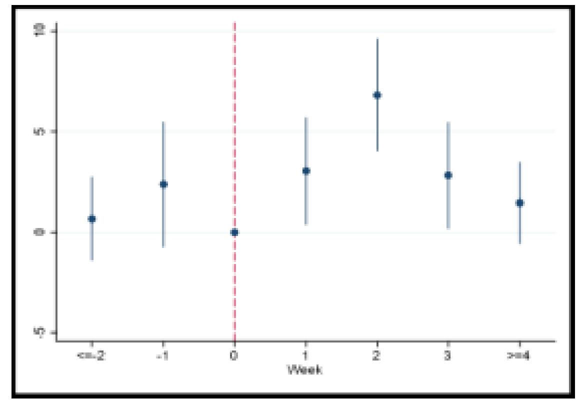
Panel A: Views



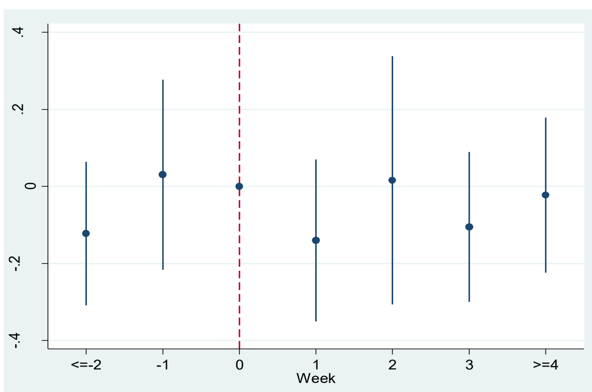
Panel B: Constituent views



Panel C: Total view time



Panel D: Product Return



Panel E: Product volatility

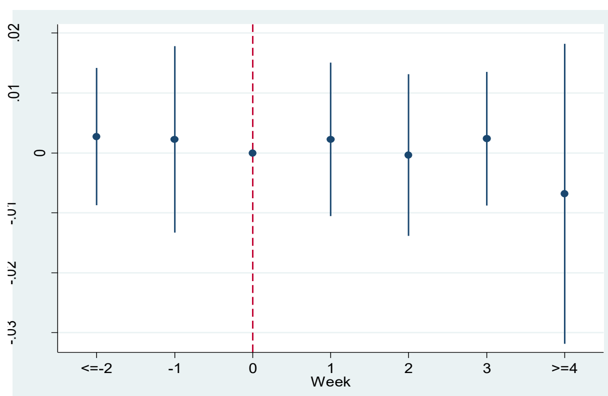


Table 1. Summary Statistics

The table presents the summary statistics of the variables used in our analysis. Panel A shows the summary statistics of investor characteristics. Panel B shows the summary statistics of attention patterns unconditional on paying attention. Panel C shows the summary statistics of trading behavior and performance by including assets that investors hold or once held during our sample period.

Variable	N	mean	sd	p25	p50	p75
Panel A: Investor characteristics						
Age	8,157	46.641	12.719	40.000	40.000	50.000
Gender (F)	8,157	0.426	0.495	0.000	0.000	1.000
Education	8,157	3.388	1.148	3.000	4.000	4.000
Panel B: Investor attention						
High frequency	529,658	0.054	0.226	0.000	0.000	0.000
Views	529,658	1.459	4.154	0.000	0.000	1.000
Constituent views	529,658	0.134	0.588	0.000	0.000	0.000
View time_ttl	529,658	56.586	202.610	0.000	0.000	13.000
View time_mean	529,658	18.140	71.738	0.000	0.000	6.615
View time_med	529,658	14.689	69.502	0.000	0.000	5.000
View time_min	529,658	10.057	61.180	0.000	0.000	2.000
Holding (in 000s)	529,658	3.066	13.204	0.000	0.000	0.000
Product return	529,658	-0.006	0.076	-0.049	-0.008	0.016
Product volatility	529,658	0.063	0.109	0.011	0.032	0.064
Panel C: Trading and performance						
High frequency	515,011	0.201	0.400	0.000	0.000	0.000
Transactions	515,011	0.520	2.135	0.000	0.000	0.000
Transactions_sell	515,011	0.217	1.144	0.000	0.000	0.000
Transactions_buy	515,011	0.254	0.993	0.000	0.000	0.000
Holding (in 000s)	515,011	18.931	91.257	0.059	2.033	11.509
Return (%)	515,011	-2.689	4.756	-5.535	-1.107	0.000
Adjusted return (%)	515,011	-4.884	15.343	-16.092	0.000	4.277
Profit	515,011	-466.156	1,547.868	-229.828	-8.540	0.000
Product growth	515,011	-0.002	0.186	-0.052	-0.009	0.019
Product volatility	515,011	0.157	0.324	0.016	0.042	0.111

Table 2. Baseline Result: Total Attention

This table presents baseline regression results for investors' attention, as measured by *Views*, *Constituent views*, and *View time_ttl*. In Panel A, we use the full sample unconditional on paying attention to the fund. In Panel B, we restrict our analysis conditional on paying attention to the fund. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Views		Constituent views		View time_ttl	
			Panel A: Full sample			
After × High frequency	0.291***	0.454***	0.039***	0.052***	6.863*	14.114***
	(0.049)	(0.062)	(0.006)	(0.008)	(4.065)	(4.315)
Holding_t-1 (in 000s)		0.046***		0.002***		2.019***
		(0.004)		(0.000)		(0.263)
Product return_t-1		1.268***		0.088***		56.320***
		(0.179)		(0.023)		(8.853)
Product volatility_t-1		-0.328*		-0.102***		1.235
		(0.180)		(0.030)		(12.763)
Observations	529,658	529,658	529,658	529,658	529,658	529,658
R-squared	0.215	0.229	0.166	0.167	0.137	0.142
			Panel B: Conditional on paying attention			
After × High frequency	0.469***	0.613***	0.054***	0.068***	8.080	20.117
	(0.113)	(0.137)	(0.017)	(0.019)	(11.740)	(12.408)
Holding_t-1 (in 000s)		0.000***		0.000**		0.003***
		(0.000)		(0.000)		(0.000)
Product return_t-1		0.783**		0.088*		72.899***
		(0.348)		(0.046)		(22.047)
Product volatility_t-1		-1.040**		-0.125*		12.010

		(0.426)		(0.068)		(33.854)
Observations	190,251	190,251	190,251	190,251	190,251	190,251
R-squared	0.341	0.355	0.343	0.343	0.238	0.242
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Table 3: Attention Span

This table presents baseline regression results for investors' attention span, as measured by average time (*View time_mean*), the median time (*View time_med*) and minimum time (*View time_min*) spent on per view of a fund in a month. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	View time_mean		View time_med		View time_min	
After × High frequency	-2.898**	-1.970	-3.482***	-2.776**	-3.660***	-3.176***
	(1.212)	(1.270)	(1.171)	(1.222)	(1.052)	(1.091)
Holding_t-1 (in 000s)		0.077***		0.025**		0.000
		(0.011)		(0.010)		(0.009)
Product return_t-1		6.534***		4.842**		3.253*
		(2.129)		(1.998)		(1.773)
Product volatility_t-1		0.188		0.291		-0.515
		(3.295)		(3.105)		(2.696)
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Observations	529,658	529,658	529,658	529,658	529,658	529,658
R-squared	0.073	0.073	0.065	0.065	0.056	0.056

Table 4: Attention: During versus off Work

This table presents regression results for investors' attention during work in Panel A and off work in Panel B. We examine total attention (*Views*, *Constituent views*, and *View time_ttl*) from columns (1)−(3) and attention span (*View time_mean*, *View time_med*, and *View time_min*) from columns (4)−(6). We define working hours as from 9am to 12am and from 1pm to 6pm on Monday to Friday, and other time as non-working hours. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Views	Constituent views	View time_ttl	View time_mean	View time_med	View time_min
			Panel A: During work			
After × High frequency	0.366***	0.034***	13.338***	-0.484	-1.175	-1.434
	(0.051)	(0.006)	(3.454)	(1.080)	(1.037)	(0.928)
Holding_t-1 (in 000s)	0.033***	0.000***	1.562***	0.068***	0.026***	0.007
	(0.003)	(0.000)	(0.228)	(0.011)	(0.010)	(0.008)
Product return_t-1	1.003***	0.063***	41.410***	5.641***	4.543**	3.811**
	(0.150)	(0.018)	(7.566)	(1.889)	(1.798)	(1.577)
Product volatility_t-1	-0.274*	-0.065***	-0.943	0.832	1.203	0.574
	(0.140)	(0.022)	(11.162)	(3.079)	(2.908)	(2.504)
Observations	529,658	529,658	529,658	529,658	529,658	529,658
R-squared	0.235	0.145	0.145	0.072	0.062	0.053
			Panel B: Off work			
After × High frequency	0.088***	0.015***	0.776	-1.682**	-2.022**	-2.126***
	(0.021)	(0.003)	(1.690)	(0.853)	(0.836)	(0.782)
Holding_t-1 (in 000s)	0.013***	0.000***	0.457***	0.076***	0.047***	0.026***
	(0.001)	(0.000)	(0.059)	(0.009)	(0.008)	(0.007)
Product return_t-1	0.264***	0.025***	14.910***	2.830**	1.936	0.836

	(0.056)	(0.009)	(3.023)	(1.441)	(1.404)	(1.287)
Product volatility_t-1	-0.054	-0.034***	2.178	0.238	-0.050	0.071
	(0.078)	(0.013)	(4.736)	(1.972)	(1.888)	(1.699)
Observations	529,658	529,658	529,658	529,658	529,658	529,658
R-squared	0.160	0.132	0.078	0.059	0.055	0.051
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Table 5: Attention: Holding versus Non-holding Assets

This table presents regression results for investors' attention to holding assets in Panel A and to non-holding assets in Panel B. We examine total attention (*Views*, *Constituent views*, and *View time_ttl*) from columns (1)−(3) and attention span (*View time_mean*, *View time_med*, and *View time_min*) from columns (4)−(6). We define working hours as from 9am to 12am and from 1pm to 6pm on Monday to Friday, and other time as non-working hours. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Views	Constituent views	View time_ttl	View time_mean	View time_med	View time_min
			Panel A: Holding assets			
After × High frequency	0.312***	0.015***	10.652***	0.318	0.021	-0.291
	(0.037)	(0.002)	(1.560)	(0.275)	(0.263)	(0.238)
Holding_t-1 (in 000s)	0.004***	0.000***	0.296***	0.027***	0.021***	0.013***
	(0.001)	(0.000)	(0.045)	(0.003)	(0.002)	(0.002)
Product return_t-1	0.113***	0.007***	5.593***	0.266	0.233	0.043
	(0.024)	(0.001)	(1.384)	(0.334)	(0.329)	(0.304)
Product volatility_t-1	-0.545**	-0.030*	-3.094	-2.842	-2.313	-1.008
	(0.235)	(0.018)	(15.335)	(2.187)	(2.074)	(1.710)
Observations	515,011	515,011	515,011	515,011	515,011	515,011
R-squared	0.447	0.200	0.265	0.097	0.076	0.065
			Panel B: Non-holding assets			
After × High frequency	0.149***	0.031***	5.554	-2.203	-3.056**	-3.316**
	(0.046)	(0.008)	(4.179)	(1.546)	(1.511)	(1.342)
Product return_t-1	0.589***	0.059*	28.969***	9.215***	7.185***	5.792***
	(0.146)	(0.031)	(9.258)	(2.766)	(2.563)	(2.213)
Product volatility_t-1	-0.243*	-0.107***	-1.268	1.676	1.533	-0.092

	(0.141)	(0.030)	(11.937)	(3.622)	(3.417)	(2.958)
Observations	429,327	429,327	429,327	429,327	429,327	429,327
R-squared	0.140	0.175	0.096	0.077	0.068	0.060
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Table 6: Attention and Loss Aversion: Myopia

This table presents regression results for investors' trading behavior, as measured by *Transactions, Buys, Sells,* and *Holding*. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Transactions		Buys		Sells		Holding	
After × High frequency	0.047***	0.021***	0.022***	0.005	0.015***	0.011***	-498.835***	-807.809***
	(0.007)	(0.008)	(0.005)	(0.006)	(0.003)	(0.003)	(154.098)	(178.445)
Holding_t-1 (in 000s)		0.000***		0.001***		-0.000***		1,450.992***
		(0.000)		(0.000)		(0.000)		(42.540)
Product return_t-1		-0.062***		-0.041***		-0.011***		418.088**
		(0.008)		(0.006)		(0.004)		(164.439)
Product volatility_t-1		0.379***		0.245***		0.134***		115.414
		(0.061)		(0.043)		(0.023)		(1,595.715)
Product FE	Y	Y	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	515,011	515,011	515,011	515,011	515,011	515,011	515,011	515,011
R-squared	0.447	0.447	0.353	0.354	0.437	0.437	0.437	0.616

Table 7: Attention and Disposition Effect: Belief Reinforcement

This table presents regression results for investors' attention and disposition effect. In columns (1) and (2), we look at the frequency of sell trades (*Sells*) as the dependent variable. In columns (2) and (8), we examine the six attention variables (*Views*, *Constituent views*, *View time_ttl*, *View time_mean*, *View time_med*, and *View time_min*). $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We define a dummy variable *Loss* that equals one for a product whose monthly performance is negative and zero if non-negative, and interact it with *After* × *High Frequency*. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Sells		Views	Constituent views	View time_ttl	View time_mean	View time_med	View time_min
Loss	-0.009**	-0.007**	0.163***	-0.000	3.411	0.357**	0.390***	0.371***
	(0.004)	(0.004)	(0.033)	(0.002)	(2.188)	(0.161)	(0.146)	(0.118)
After × Loss	0.056***	0.058***	-0.063**	-0.004**	-4.900***	-0.438**	-0.355**	-0.135
	(0.007)	(0.007)	(0.031)	(0.002)	(1.803)	(0.170)	(0.153)	(0.123)
High frequency × Loss	-0.064***	-0.066***	-0.181***	-0.001	-5.153**	-1.056**	-0.940**	-0.691*
	(0.007)	(0.007)	(0.036)	(0.002)	(2.527)	(0.434)	(0.422)	(0.374)
After × High frequency	0.089***	0.087***	0.251***	0.010***	9.187**	-0.544	-0.844**	-1.430***
	(0.011)	(0.011)	(0.045)	(0.002)	(4.419)	(0.461)	(0.430)	(0.347)
After × High frequency × Loss	-0.077***	-0.071***	0.112**	0.007**	3.774	1.400**	1.334**	1.518***
	(0.012)	(0.012)	(0.046)	(0.003)	(4.756)	(0.557)	(0.533)	(0.451)
Holding_t-1 (in 000s)		-0.000***	0.004***	0.000***	0.296***	0.027***	0.021***	0.013***
		(0.000)	(0.001)	(0.000)	(0.044)	(0.003)	(0.002)	(0.002)
Product return_t-1		0.004	0.098***	0.006***	5.198***	0.322	0.270	0.067
		(0.004)	(0.024)	(0.001)	(1.472)	(0.342)	(0.337)	(0.311)
Product volatility_t-1		0.173***	-0.431*	-0.033*	-2.692	-2.674	-2.087	-0.700
		(0.023)	(0.236)	(0.018)	(15.696)	(2.188)	(2.074)	(1.712)
Product FE	Y	Y	Y	Y	Y	Y	Y	Y

Account FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	515,011	515,011	515,011	515,011	515,011	515,011	515,011	515,011
R-squared	0.437	0.438	0.447	0.200	0.265	0.097	0.076	0.065

Table 8: Investment Return

This table presents regression results for investors' trading performance. *Return (%)* is the monthly return on the product as defined by *Investment profit* divided by the average holding of the fund each month. *Adjusted return (%)* is measured by subtracting from *Return (%)* the average return of funds in the same fund type. *Profit* measures changes in accumulated profit of the holding fund over months. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1, Product volatility_t-1* and *Product return_t*. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Return (%)		Adjusted return (%)		Profit	
After × High frequency	-0.776***	-0.419***	-1.898***	-1.471***	-662.162***	-664.097***
	(0.034)	(0.068)	(0.036)	(0.067)	(17.662)	(19.486)
Holding_t-1 (in 000s)		-0.004***		-0.003***		-22.814***
		(0.000)		(0.000)		(0.255)
Product return_t-1		0.378***		2.407***		-73.898***
		(0.083)		(0.112)		(13.221)
Product volatility_t-1		23.774***		29.904***		2,566.425***
		(0.463)		(1.218)		(109.729)
Product return_t		1.875***		-8.492***		212.633***
		(0.057)		(0.089)		(8.462)
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Observations	515,011	515,011	515,011	515,011	515,011	515,011
R-squared	0.397	0.410	0.565	0.592	0.373	0.529

Table 9: Heterogeneity: Profession

This table presents regression results for attention and trading performance for investors who work in the financial sector in Panel A and investors who do not work in the financial sector in Panel B. We examine total attention (*Views*, *Constituent views*, and *View time_ttl*) from columns (1)−(3), attention span (*View time_med*) in column (4), frequency of sell trades in column (5), and *Return (%)* in column (6). $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects in all specification. We also control *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* in columns (1)-(6), and *Product return_t* in addition in column (6). We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Views	Constituent views	View time_ttl	View time_med	Sells	Investment return (%)
			Panel A: Finance professional			
After × High frequency	0.101	0.016***	7.378	-0.390	0.006	-0.357
	(0.068)	(0.004)	(5.700)	(1.553)	(0.009)	(0.224)
Observations	38,400	38,400	38,400	38,400	38,400	38,400
R-squared	0.370	0.187	0.160	0.104	0.441	0.438
			Panel B: Others			
After × High frequency	0.328***	0.014***	10.835***	0.035	0.013***	-0.427***
	(0.040)	(0.002)	(1.624)	(0.264)	(0.003)	(0.072)
Observations	476,611	476,611	476,611	476,611	476,611	476,611
R-squared	0.452	0.206	0.284	0.077	0.438	0.409
Control	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Table 10: Heterogeneity: Education

This table presents regression results for attention and trading performance for investors who hold a graduate degree in Panel A and investors who do not hold a graduate degree in Panel B. We examine total attention (*Views*, *Constituent views*, and *View time_ttl*) from columns (1)−(3), attention span (*View time_med*) in column (4), frequency of sell trades in column (5), and *Return (%)* in column (6). $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects in all specification. We also control *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* in columns (1)–(6), and *Product return_t* in addition in column (6). We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Views	Constituent views	View time_ttl	View time_med	Sells	Investment return (%)
			Panel A: Graduate degree			
After × High frequency	0.164***	0.009**	6.561**	0.695	0.003	-0.230**
	(0.050)	(0.003)	(2.809)	(0.659)	(0.006)	(0.109)
Observations	121,465	121,465	121,465	121,465	121,465	121,465
R-squared	0.464	0.186	0.176	0.083	0.461	0.416
			Panel B: Below graduate degree			
After × High frequency	0.359***	0.016***	11.974***	-0.154	0.014***	-0.476***
	(0.046)	(0.002)	(1.863)	(0.285)	(0.003)	(0.083)
Observations	393,546	393,546	393,546	393,546	393,546	393,546
R-squared	0.453	0.218	0.296	0.080	0.432	0.411
Control	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Table 11: Heterogeneity: Attention Capacity

This table presents regression results for attention and trading performance across investors holding different numbers of funds. We examine total attention (*Views*, *Constituent views*, and *View time_ttl*) from columns (1)−(3), attention span (*View time_med*) in column (4), frequency of sell trades in column (5), and *Return (%)* in column (6). $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. *Num of Funds (/100)* denotes the number of unique funds held by investors in each month, divided by 100 to zoom in the magnitude. We control investor, product, and month fixed effects in all specification. We also control *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* in columns (1)–(6), and *Product return_t* in addition in column (6). We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Views	(2) Constituent views	(3) View time_ttl	(4) View time_med	(5) Sells	(6) Investment return (%)
After × High frequency	0.330***	0.015***	11.810***	0.133	0.013***	-1.416***
	(0.035)	(0.002)	(1.620)	(0.268)	(0.003)	(0.035)
After × Num of Funds (/100)	0.016*	0.001*	0.967***	0.073***	0.002***	-0.089***
	(0.010)	(0.000)	(0.187)	(0.018)	(0.001)	(0.015)
High frequency × Num of Funds (/100)	-0.002	-0.000	6.006**	0.407	-0.155**	-0.081***
	(0.048)	(0.002)	(2.651)	(0.333)	(0.072)	(0.020)
After × High frequency × Num of Funds (/100)	-0.034**	-0.001	-2.731*	-0.458	-0.010*	0.089*
	(0.014)	(0.001)	(1.620)	(0.344)	(0.006)	(0.046)
Control	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Observations	515,011	515,011	515,011	515,011	515,011	515,011
R-squared	0.447	0.200	0.265	0.076	0.438	0.404

Table A.1. Attention: During versus off Trading Hours

This table presents regression results for investors' attention during trading hours in Panel A and outside trading hours in Panel B. We examine total attention (*Views*, *Constituent views*, and *View time_ttl*) from columns (1)−(3) and attention span (*View time_mean*, *View time_med*, and *View time_min*) from columns (4)−(6). We define working hours as from 9am to 12am and from 1pm to 6pm on Monday to Friday, and other time as non-working hours. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. In column (2), (4), and (6), we further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Views	Constituent views	View time_ttl	View time_mean	View time_med	View time_min
Panel A: During trading hour						
After × High frequency	0.316***	0.028***	11.231***	-0.542	-1.161	-1.095
	(0.046)	(0.005)	(2.838)	(0.951)	(0.917)	(0.808)
Holding_t-1 (in 000s)	0.000***	0.000***	0.001***	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Product return_t-1	0.912***	0.054***	37.080***	4.329**	3.124*	2.338
	(0.140)	(0.015)	(6.790)	(1.709)	(1.644)	(1.431)
Product volatility_t-1	-0.252**	-0.056***	-7.684	-0.768	0.577	0.626
	(0.127)	(0.018)	(9.383)	(2.714)	(2.599)	(2.267)
Observations	529,658	529,658	529,658	529,658	529,658	529,658
R-squared	0.242	0.138	0.144	0.065	0.058	0.050
Panel B: Off trading hour						
After × High frequency	0.138***	0.021***	2.883	-1.264	-1.863*	-1.922**
	(0.026)	(0.004)	(2.249)	(1.000)	(0.972)	(0.886)
Holding_t-1 (in 000s)	0.000***	0.000***	0.001***	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Product return_t-1	0.356***	0.031**	19.240***	3.917**	2.922*	1.701
	(0.069)	(0.012)	(4.021)	(1.666)	(1.609)	(1.449)
Product volatility_t-1	-0.076	-0.041**	8.919	1.468	0.695	-0.237
	(0.096)	(0.017)	(6.466)	(2.525)	(2.405)	(2.139)
Observations	529,658	529,658	529,658	529,658	529,658	529,658
R-squared	0.161	0.138	0.085	0.062	0.057	0.052
Product FE	Y	Y	Y	Y	Y	Y
Account FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Table A.2. Instrumented Difference-in-difference Estimation

In this table, we estimate the effect of view frequency on trading behavior and investment outcomes based on instrumented difference-in-differences estimation following Equation (2). In the first stage of a two-stage least-squares (2SLS) estimation, we instrument browsing frequency of each product with the interaction term used in the DiD baseline specification (1), i.e., *Aftert* × *High frequency*$_j$. The first stage estimates are already reported in Panel A, Table 5. In the second stage as shown in Equation (4), we regress trading behaviors on the predicted value of view frequency while controlling for other covariates. Panels A, B and C report the second stage estimates of trading behavior as those in Tables 6, 7, and Panel C, Table 8. $After_t$ takes the value one from September 2022 onwards and zero otherwise. $High\ frequency_j$ is a dummy variable that equals one if the product's asset allocation disclosure frequency changes from quarterly to daily since September 2022 and zero otherwise. We control investor, product, and month fixed effects across all specifications. We further include the control variables *Holding_t-1 (in 000s), Product return_t-1,* and *Product volatility_t-1* as described in Section 2.2. We clustered standard error at the investor level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Trading Behavior

Second stage:	(1)	(2)	(3)	(4)
Dep. Var.:	Transactions	Buys	Sells	Holding
Predicted view frequency	0.068***	0.014	0.035***	-2,585.629***
	(0.025)	(0.020)	(0.009)	(571.167)
Holding_t-1 (in 000s)	0.000	0.000***	-0.000***	1.462***
	(0.000)	(0.000)	(0.000)	(0.043)
Product return_t-1	-0.070***	-0.042***	-0.015***	711.397***
	(0.007)	(0.005)	(0.003)	(133.246)
Product volatility_t-1	0.416***	0.253***	0.153***	-1,293.462
	(0.062)	(0.044)	(0.023)	(1,602.170)
Product FE	Y	Y	Y	Y
Account FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Observations	515,011	515,011	515,011	515,011
R-squared	0.447	0.354	0.437	0.616

Panel B: Myopic loss aversion

Second stage:	(1)
Dep. Var.:	Sells
Predicted view frequency	-0.635***
	(0.107)
Loss	0.096***
	(0.017)
After × Loss	0.018***
	(0.007)

High frequency × Loss	-0.181***
	(0.020)
After × High frequency	0.246***
	(0.038)
Holding_t-1 (in 000s)	0.000***
	(0.000)
Product return_t-1	0.067***
	(0.011)
Product volatility_t-1	-0.100*
	(0.052)
Product FE	Y
Account FE	Y
Month FE	Y
Observations	515,011
R-squared	0.438

Panel C: Investment return

Second stage:	(1)	(2)	(3)
Dep. Var.:	Return (%)	Adjusted return (%)	Investment profit
Predicted view frequency	-0.732***	-2.672***	-1,161.110***
	(0.120)	(0.097)	(34.070)
Holding_t-1 (in 000s)	0.004***	0.026***	-10.151***
	(0.001)	(0.001)	(0.463)
Product return_t-1	0.565***	2.696***	223.609***
	(0.056)	(0.074)	(12.051)
Product volatility_t-1	24.154***	32.113***	3,168.909***
	(0.447)	(1.201)	(105.037)
Product return_t	1.976***	-7.213***	373.354***
	(0.043)	(0.074)	(8.157)
Product FE	Y	Y	Y
Account FE	Y	Y	Y
Month FE	Y	Y	Y
Observations	515,011	515,011	515,011
R-squared	0.410	0.607	0.529