Attention Utility: Evidence From Individual Investors

Edika Quispe–Torreblanca* John Gathergood† George Loewenstein‡ Neil Stewart§

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Abstract

We study attention utility, the hedonic pleasure or pain derived purely from paying attention to information, which differs from the news utility that arises from gaining new information. The main, field, study examines brokerage account login data to show that investors pay disproportionate attention to already-known positive information on their stocks. Through its effect on logins, this selective attention affects their trading activity. Three experimental studies then show that (1) investors are more likely to engage in a paid task that will involve attention to a prior investment if that investment has gained value; (2) paying attention to a winning stock is more motivating than a doubling of monetary incentives; and that (3) attention has value independent of information acquisition.

Keywords: information utility, attention, login, investor behavior

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* Leeds University Business School. Email: E.Quispe-Torreblanca@leeds.ac.uk.

† School of Economics, University of Nottingham; Network for Integrated Behavioural Science. Email: john.gathergood@nottingham.ac.uk.

‡ Social and Decision Sciences, Carnegie Mellon University. Email: gl20@andrew.cmu.edu.

§ Warwick Business School, University of Warwick. Email: neil.stewart@wbs.ac.uk.

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"I know this is a time to be buying stocks based on rules I've developed over decades of investing. But in order to do that, I have to log on to my brokerage account. When I do, the first number I'll see is the current market value of my portfolio. I haven't looked in days. I don't want to look now."

James B. Stewart, The New York Times

Contrary to the assumption of traditional economic models of information, beginning with Stigler (1961), as well as later models of asymmetric information (e.g., Akerlof, 1978, Spence, 1978, Stiglitz, 1975), people often avoid information even when it would be beneficial for decision making, is known to be available, and is free to access or even costly to avoid (Golman et al., 2017). Examples of information avoidance include patients who avoid getting, or viewing, the results of medical tests when they fear bad news (Ganguly and Tasoff, 2016, Kőszegi, 2003, Oster et al., 2013, Schwardmann, 2019), investors who avoid looking at financial portfolios when the stock market declines (Karlsson et al., 2009, Sicherman et al., 2015), individuals who avoid checking their financial accounts when they are very indebted, have low cash holdings or have spent a lot (Olafsson and Pagel, 2017),[1] and managers who avoid hearing arguments that conflict with their preliminary decisions (Deshpande and Kohli, 1989 Schulz-Hardt et al., 2000, Zaltman, 1983). The common feature of these examples is that potentially useful information is actively avoided because it might confer bad news about the state of the world.

In economics, the by-now standard approach to dealing with these phenomena involves "belief-based utility" (Brunnermeier and Parker, 2005, Caplin and Leahy, 2001, Geanakoplos et al., 1989, Loewenstein, 1987) – the idea that people derive utility not (only) from objective reality, but from their beliefs about that reality.[2] Models of belief-based utility can predict information avoidance for different reasons. One is that people can be risk-averse over beliefs in the same way that they are risk-averse over material outcomes; they may, thus, avoid information because the expected disutility of getting bad news exceeds the expected utility of getting good news (see, e.g., Kőszegi, 2010, and Pagel, 2018, in the context of investor decisions). The second is that people may form motivatedly optimistic beliefs (Brunnermeier and Parker, 2005), and may be reluctant to risk having their 'optimism bubble' burst by realistic information they cannot ignore (Oster et al., 2013).[3]

[1] Moreover, using data from financial aggregation and service app from Iceland, Olafsson and Pagel (2017) and Carlin et al. (2017) show that individuals could avoid substantial financial penalty payments if they were to check their accounts more often.

[2] The models of "news utility" proposed by Koszegi and Rabin (2006, 2007, 2009) likewise assume that people derive utility not from objective circumstances, but from news – i.e., new information – they obtain about those circumstances. Pagel (2018) draws out implications of their model for information avoidance.

[3] Another line of work on rational inattention (e.g., Caplin and Dean, 2015; Sallee, 2014; Sims, 2003) is also focused on allocation of attention, but on efficient allocation of attention for purposes of decision making given limitations on overall attention, rather than, as in the work on information avoidance, on avoidance of information despite a *loss* of efficiency in decision making. Yet, a third line of economic research on attention examines the consequences of the observation that different types of information are more or less likely to attract attention (Bordalo et al., 2012; Bushong et al., 2015; Kőszegi and Szeidl, 2012). Some research also draws attention to irrationality in attention allocation and examines consequences for phenomena such as response to taxes (Chetty et al., 2009; Taubinsky

Yet, beyond the utility of obtaining good or bad news, the act of attending to information, even when it is already known – i.e., not 'news' – may directly confer utility to individuals.

In this paper, we present four studies – a main study examining the portfolio look-up behavior of retail investors and three experimental studies examining investors' decisions to make money by answering questions about a stock. All four studies show that individuals devote disproportionate attention to already-known positive as opposed to negative information about stocks, and that this pattern of behavior has significant economic consequences.

The retail investor study uses detailed data on investor portfolio performance, together with login records, to examine the relationship between stock returns and investor attention. This study shows that investors are more likely to pay attention – i.e., log in – to their portfolios when recently-purchased stocks exhibit gains, even though the investor would already have to know this information to behave in this fashion. The excess logins devoted to positively performing stocks, therefore, reflects attention devoted to positive information which is already known to the investor, consistent with attention-, as opposed to news- or belief-based, utility.

The study of retail investors also shows that attention utility has implications for consequential behavior on the part of investors. Specifically, it shows that decreased attention to bad information – losses on recently acquired stocks – leads to decreased trading activity, on both the buy and sell dimensions. Further, the effect of losses on trading is wholly mediated by reduced attention. By reducing attention to their brokerage accounts to avoid the disutility of paying attention to their losses, investors reduce their trading activity (because trading necessitates logging-in to their brokerage account). In this way, considerations of attention utility decrease all types of trading when logging in exposes the investor to known negative information.

We draw on data from Barclays Stockbroking, one of the UK's largest execution-only trading platforms for individual investors. The data cover a large sample of investors over a multi-year panel, with detailed information on investor characteristics and records of daily login behaviour. A key advantage of our data is that we can observe the exact portfolio holdings of investors on a daily basis. The data also provide daily flags for whether the investor made a login to their account.[4]

The main innovation in the retail investor study is its reliance upon detailed daily-level information on the value of positions within investor portfolios. This allows us to distinguish investor behavior consistent with attention utility from that consistent with information avoidance. Recent studies of information avoidance by investors document decreased login activity when market indices decline, as in Gherzi et al. (2014), Karlsson et al. (2009) and

and Rees-Jones, 2018) or highway tolls (Finkelstein, 2009).

[4] We use these login data to measure investors' attention to their accounts. Gabaix (2019) suggests different measures of attention including inferring inattention from sub-optimal behaviour (i.e., implied inattention), survey measures of time spent paying attention and proxy measures of attention, such as logins. Our use of logins as a proxy measure of attention is facilitated by the rise of online-only trading platforms and is a reliable measure by virtue of the automated, machine-driven collection of the login records.

Sicherman et al. (2015). The behavior shown in those studies is investors' reluctance to see how declines in the market index translate into declines in the value of their portfolios, an example of information avoidance.[5]

In contrast, our research design isolates attention utility by examining the relationship between account logins and the performance of individual stocks within the investor's portfolio. This eliminates the information-gap between the market index and an individual investor's stock performance, and allows us to isolate a purely attention-based response to movements in stock prices. In this way, we can detect excess logins arising purely from the desire to *look* at portfolios as distinct from the desire to *discover* how movements in the market index translate into changes in the value of the individual's imperfectly correlated portfolio.

Our research design uses an event study of login activity in the days following the purchase of a new stock. We show that recently acquired stocks which make gains lead to increased account logins on subsequent days compared to stocks that make losses. This effect is observed when controlling for movements in the market index and other covariates, indicating that investors' attention is a function of returns on their own stocks, apart from broader market movements. This pattern can only arise if investor login choices are determined, at least in part, by the known performance of individual stocks. The pattern we observe occurs from the first day following purchase and persists over the following month, exists across different types of stock purchases, such as the top-up of an existing stock and purchase of a new stock, and occurs in both thin and thick portfolios.

Furthermore, and similar to Sicherman et al. (2015),[6] we find evidence that stock gains drive attention even through periods of market closure. Our estimates show that investors who have made a gain on a recently acquired stock are more likely to login to their accounts on successive subsequent market closure days, such as through the weekend and through public holidays, even though there is no new information to be gained on market closure days. For example, among the sample of investors who log in to their accounts on a Saturday, investors are more likely to log in to their account again on a Sunday if they made a gain on their recently purchased stock on the preceding Friday.

We further find that selective attention on the part of investors affects their trading activity. Specifically, investors who experience losses on a recently purchased stock are less likely to make either buy or sell trades on *other* stocks. Estimates show that this effect can be completely explained by the impact of gains and losses in recently purchased stocks on login activity. Once

[5] Previous studies have focused on the relationship between movements in some proxies of the investor expectations about their portfolio returns, such as VIX index, Dow index and the FTSE100 index, and investor login behaviour. However, there is much evidence in the previous literature showing that most investors hold only a few stocks (Barber and Odean, 2013; Barberis and Huang, 2001; Barberis, 2018; Goetzmann and Kumar, 2008). As such, these proxies, which typically cover hundreds of stocks, might not closely coincide with the real investors' portfolio return movements. Unlike those studies, ours examines how investors respond to movements in the prices of the stocks in their own portfolios, and also examines the dynamics of attention around the time of investors' trading activity.

[6] Sicherman et al. (2015) find that when the stock market index is in gain, investors are more likely to log in multiple times on weekends, even though logins beyond the first login do not reveal new information.

we have conditioned on login activity, losses on a recently purchased stock have no effects, or only very small effects, on trades of other stocks. By reducing login activity so as not to look at losses on one stock, investors neglect to use the trading platform and, as a result, reduce trading activity on other stocks. This effect is also present when markets reopen (e.g., on Mondays) with the legacy of a loss on the last market closure day (e.g, the preceding Friday) leading to reduced trading activity at market reopening. Once we have conditioned on login activity, this effect attenuates, again indicating that attention is the channel through which gains and losses influence subsequent trading activity.

All of these results from the investor sample are consistent with the idea that investor logins and trades are influenced by the desire to avoid paying attention to already known bad news. However, observational studies are inevitably vulnerable to endogenity issues and to potential alternative explanations. For these reasons, to provide more direct evidence of the role of attention utility in decision-making and economic outcomes, we conducted three online pre-registered[7] experiments designed to directly test whether investors will incur financial sacrifices to avoid attending to bad news about their stocks. In the first experiment, we recruited investors who had been holding at least one stock for at least six months. In an initial survey (Survey 1), we asked them to name the stock with the highest current total valuation out of all shares they were holding. Then, we sent them an email giving them information about their stock's performance over the past 6 months, as well as its performance relative to the FTSE100. That email included an invitation to a second survey (Survey 2), which, they were told, would ask them questions about the stock in question and about their investment behavior in general. The survey was optional, but participants were informed that they would receive an additional flat payment if they completed it. We predicted that participants would be more likely to respond to Survey 2 when their stock performance increased either in absolute terms or relative to the FTSE100.

As predicted, we find that the gains increase the likelihood of responding to Survey 2. The effect was economically sizable: Participants were 20.8% more likely to respond to Survey 2 when their stocks showed gains in comparison to losses; and 23.5% more likely to respond to Survey 2 when their stocks showed gains relative to the FTSE100. Because they made extra money by completing the survey, these results provide additional evidence that the reluctance to think about their stock performance has economic consequences that go beyond the allocation of attention.

Our experimental results are difficult to reconcile with competing explanations which contend that participants' attention choices are motivated by the desire to acquire new information regarding their stocks to aid in future trading decisions. In particular, news utility explanations, such as those described in Kőszegi and Rabin (2009), Olafsson and Pagel (2017), and Andries and Haddad (2020), fail to match key features of our field and experimental data. They cannot

[7] The pre-registrations can be accessed at `https://aspredicted.org/kg5yf.pdf` and `https://aspredicted.org/ZRF_K52`.

explain why investors return to view winning stocks when no new information is available (e.g., on weekends or public holidays), or why subjects are willing to forego earnings to avoid looking at already known bad news. Attention utility, in contrast, explains why individuals desire to keep engaging with good news and avoid bad news, because an ongoing flow of (dis)utility is derived by the act of paying attention.

Experiments 2 and 3 replicate and extend the findings from Experiment 1. Experiment 2 seeks to calibrate the magnitude of the effect observed in Experiment 1 by examining the impact of doubling the payment for participating in the second survey. Doing so does increase willingness to complete the second survey, but the impact on participation rates is smaller than the effect of the investor's stock being in gains versus losses. Experiment 3 introduces a condition in which investors will receive additional information about their stock if they complete the second survey (as opposed to simply being made to pay attention to information they already had). This informational intervention has little impact on participation rates compared to the baseline attentional manipulation, suggesting that our effect is mainly due to attention-avoidance and not information-avoidance.

In combination, the findings of the field, and three experimental, studies contribute to the recent literature on financial attention. Some studies examine the role of attention in enabling high fees on mutual funds, even index funds for which management costs are low. Barber et al. (2005) document the drop in mutual funds carrying loads, and the commensurate increase in annual fees, and argue that this transition is resulted from the greater attention attracted by loads, while "operating expenses ... are smaller, and are easily masked by the volatility of equity returns." Choi et al. (2010) test different explanations for insensitivity to fees, and show that providing subjects with an attention-grabbing fee schedule increases the impact of fees on decisions.

Other papers show that factors related to attention influence buying and selling behavior as well as prices. DellaVigna and Pollet (2009) compare responses to company earnings announcements on Fridays relative to other days, and find that Friday announcements produce a 15% lower immediate price response (but a 70% higher delayed response), and have an 8% smaller impact on volume. They conclude that "these findings support explanations of post-earnings announcement drift based on under-reaction to information caused by limited attention." Hirshleifer et al. (2009) find, consistent with a limited attention account, that the market reacts more slowly to a given announcement when more firms announce on the same day. Barber and Odean (2008) show that individual (but not institutional) investors are net buyers of attention-grabbing stocks (with high levels of news, unusual trading volume, or extreme returns), and argue that such "Attention-driven buying results from the difficulty that investors have searching the thousands of stocks they can potentially buy." Da et al. (2011) find that internet search volume predicts short-term gains and long-term losses.

Most relevant to the current research, some recent models focus specifically on preference-based explanations for information (or attention) aversion. Pagel (2018) develops a news-utility theory for inattention in which investors have a preference to ignore their portfolios due to the desire to avoid potential news about losses. Andries and Haddad (2020) develop a life-cycle model in which preference-based utility costs of information can lead to under-diversification because investors choose only a few stocks in order to reduce the likelihood of receiving disappointing information. Hence, they show that information aversion has implications for real activity (for reviews of the literature on information avoidance see Golman et al., 2017; and Sweeny et al., 2010). Falk and Zimmermann (2022) study the factors that determine preferences for sooner or later information. They show, experimentally, that while subjects generally prefer sooner information, later information becomes more appealing when the environment permits them to avoid focusing on (negative) consumption events. To our knowledge, with the recent exceptions of Golman and Loewenstein (2015) and Bolte and Raymond (2022), the literature has yet to see the development of models of attention utility.

Our specific hypothesis, in both the field study of individual investors and the three experiments, is that people will be more likely to take actions (logging in to their account, for individual investors and completing a stock-related survey in the experiments) that will predictably draw their attention to a stock when they know if has performed well relative to when they know that it has performed poorly. This hypothesis results from two component assumptions, for which we derive inspiration from psychology, while not providing a formal economic theory. The first is that looking at the information will naturally attract attention to it, and that people will be able to anticipate this. This mechanism, which can explain why people display trophies or photographs of happy occasions from their life – often on their phone or computer, where they are likely to be the only person seeing them – is so self-apparent that it has not received much attention in research on attention. In these types of situations, people are undoubtedly aware of the outcomes that led them to win a trophy, and they likely recall happy family vacations. The fact that they position these items where they themselves are likely to encounter them more often, undoubtedly serves, in part, an attentional function.

The second part of our proposed mechanism is that people derive direct positive utility from paying attention to positive (utility-conferring) events and situations. These would include memories of enjoyable past experiences, favorable current stimuli (e.g., a compliment in a conversation) and facts that support positive expectations about the future. Perhaps the most important positive stimuli, however, are those that involve ego – memories and facts that reflect positively on oneself.

Combining these two components, we predict that people who have a salient winning stock – a stock that has gained value over some relevant period of time, and which is salient either because it was the last stock they purchased or because their attention is drawn to it in the experiments – will be more likely to take actions that draw further attention to it. In the field study, this action is logging in to their brokerage account; in the experiment, it is completing a survey about their stock (e.g., how they came to buy it). For stocks that gain value, such information will be positive for investors not only because it is positive (they made money) but also because they did so as a result of a decision they made – bringing ego into play.

Our results have implications for economic models dealing with the allocation of attention. While the canonical model of optimal inattention of Sims (2003) assumes that individuals allocate attention rationally, our results show a strong role for hedonic utility in the allocation of attention, just as prior work has shown the importance of hedonics for the acquisition of information. People naturally focus their attention on things that are more salient (Bordalo et al., 2012; Chetty et al., 2009; Finkelstein, 2009). The current research shows, consistent with Golman et al. (2017) and Bolte and Raymond (2022), that people also tend to focus their attention on things that make them feel good. As Bolte and Raymond (2022) show, such a motivated focus on the positive can potentially help to explain phenomena such as overconfidence and loss aversion; people may be especially averse to losses not only because they don't like experiencing them, but also because they don't like having their attention focused on them.

Our study also contributes to the broader literature on the behaviour of individual investors. The prior literature shows that, although the optimal portfolio diversification strategy is long-established (Markowitz, 1952), many investors hold only a few stocks in their portfolio (Barber and Odean, 2013; Goetzmann and Kumar, 2008). Investors also exhibit biases in their trading behaviour, such as over-trading and rank effects (Barber and Odean, 2000, 2001; Hartzmark, 2015). Our work suggests that, in addition to being averse to *realising* losses in their trading activity (the disposition effect), investors are also averse to *seeing* losses on their accounts, also with consequences for trading behavior. Understanding how individuals allocate attention in practice is important for understanding individual financial behaviour and developing realistic models of financial market interaction (cf. Barberis, 2018).

The idea that attention is an important determinant of utility – attention-based utility – has consequences that go well beyond investor behavior. In health psychology, forcing individuals who regularly participate in risky health behaviors (e.g. smoking) to repeatedly pay attention to the likely health consequences (e.g. via labelling cigarette packets with cancer warnings, and gruesome images) is an example of exploiting attention disutilty to achieve behavioral change. Caplin (2003) "Fear as a Policy Instrument" presents a model in which forcing attention can be used as a policy tool.[8] More generally, it is quite likely that people choose friends and romantic partners who help them focus their attention on aspects of themselves and of life that make them feel good about themselves and good about life in general (Loewenstein and Moene, 2006). The same goes for choices involving work and education, geographic location, consumption, and a wide range of other choices; people like to be in locations and contexts that draw their attention to things they like thinking about.

The paper proceeds as follows. In Section 1, we describe the first study based on retail investor data. The first three subsections provide an overview of the individual investor data,

[8] Also see Fisher et al. (1995) and Caplin and Leahy (2004). More generally, Becker and Mulligan (1997) model time preference as malleable and influenced by economic and psychological factors.

sample selection, and summary statistics. Section 1.4 presents our main results on attention utility and login behavior. Section 1.5 presents results on the relationship between stock gains, attention and trading activity. Section 2, presents the methods and results of our three experiments on investor attention. Section 3 concludes the paper.

1 Study 1: Portfolio Look-Up Behaviour of Retail Investors

1.1 Data

Data were provided by Barclays Stockbroking, an execution-online brokerage service operating in the United Kingdom. The data cover the period April 2012 to March 2016 and include daily-level records of trades and quarterly-level records of portfolio positions. Combining the account-level data with daily stock price data allows us to calculate the value of each stock position in an investor's portfolio on each day of the sample period. The data also includes a daily-level dummy variable indicating whether the investor logged into their account each day.[9] The daily-level login dummy variable covers all days, including days on which the market is closed, such as Sundays and public holidays, which we use later in our analysis.

1.2 Sample Selection

Our starting sample, provided by Barclays, contains approximately 155,000 accounts which are open at some point during the sample period. The focus of our analysis is on the relationship between the performance of individual stocks and investor attention, measured using login activity data. We therefore make sample restrictions, for example, removing dormant accounts with no trading or login activity during the sample period. We make the following sample restrictions:

First, we remove inactive years, defined as those years in which the investor makes fewer than two logins or two transactions. This restriction enables us to calculate the frequency of attention and trading using the time period between logins or trades. Second, we remove accounts which have no securities with prices available at a daily level from Datastream.[10] Finally, we trim the data by removing the top and bottom 1% of the accounts by the average value of the total portfolio over the whole data period, in order to remove extreme outlier values.[11]

From the starting sample of approximately 155,300 accounts, the largest drop of accounts is due to the removal of approximately 41,000 inactive accounts, with a further approximately 14,900 accounts dropped due to having securities for which we could not match prices. The resulting sample, which we refer to as the baseline sample, retains approximately 97,400

[9] During the data period, the online brokerage operated only through a browser-based interface. Barclays has subsequently introduced a mobile phone trading app.

[10] This sample restriction is necessary to ensure completeness in our calculation of portfolio values.

[11] Results are not sensitive to this sample restriction.

accounts (62.7%). Our sample restrictions tend to drop accounts with below-average logins and trades (in particular the drop of inactive accounts), hence the baseline sample retains 80.1% of login-days, 83.3% of transaction-days and 82.9% of buy-days from the starting sample.[12]

1.3 Summary Statistics on Investor Attention

We provide first summary statistics for investors in our sample, and then summarize patterns in investor attention.

1.3.1 Investor Summary Statistics

Summary statistics for the baseline sample are provided in Table 1. Account holder characteristics in Panel A show that more than three-quarters of account holders are male[13]. The average age of an account holder is 54 years (median 57 years).[14] Account holders have held their accounts for, on average, 5 years (median 4 years). Twenty-five percent of account holders had held their accounts for more than six years. This profile of account holders is similar to that seen in US data (see Barber and Odean, 2001).[15]

Summary statistics for account characteristics in Panel B show that the average portfolio value is approximately £65,000 (median £16,400), of which the majority of the holdings are common stocks. Only 7% of holdings by value are held in mutual funds (median 0%). On average, investors hold just five stocks (median 3). The small number of stocks held in the sample is consistent with evidence from previous studies that individual investors tend to hold under-diversified portfolios (Barber and Odean, 2013, Goetzmann and Kumar, 2008).

1.3.2 Summarizing Investor Attention and Trading

We summarize the relationship between attention and trading by comparing login activity to trading activity. For each account, we calculate the frequency of login-days and the frequency of transaction-days (defining a transaction-day as a day on which at least one buy or sell transaction is made).[16] Because our account data contain account openings and closings, the panel is unbalanced. We calculate the frequency of logins as the account-level average duration (in days) between login-days and the frequency of transactions as the account-level average duration (in days) between transaction-days. The data show a clear positive relationship

[12] Calculations showing the effects of sample selection on accounts, login-days, transaction-says and buy-days are available from the authors on request.

[13] Gender information is missing from approximately 9.4% of the accounts.

[14] Age is top coded at 77 years to account for potential recording errors in age (3% of accounts with available age information report ages exceeding 77 years). Moreover, age information is missing from approximately 2.6% of the accounts.

[15] In the Barber and Odean trading data set, 79% of account holders are male, with an average age of 50 years, see Table 1 in Barber and Odean (2001).

[16] Our definition of transaction-days excludes automatic transactions, such as automatic dividend re-investments. Hence, we define a transaction-day as a day on which the investor logged-in to their trading account and placed a manual instruction.

between login frequency and trading frequency. Logins are much more frequent than trades, and this is seen across the full distribution of login and trading frequency.[17]

The account-level average number of days between logins (including non-market days) is 18.1 (median 8.4) whereas the average number of days between transactions is 114.6 (median 69.8). The ratio of login days to transaction days is on average 21.2 (median 9.9), with an inter-quartile range of 5 to 21.5 Although it cannot be ruled out that many of the logins on days without trades were nevertheless done with some consideration of trading, the much higher frequency of logins than trades is consistent with the proposition that many logins are only oriented toward monitoring stocks rather than gathering information for trading decisions – i.e., that they are purely attentional.[18]

1.4 Results

In this section, we present our first main result that investors are more likely to pay attention to winning stocks compared to losing stocks. Our research design focuses on login activity in the days following the purchase of a new stock. We show that investors are more likely to pay attention to their accounts when their recently-purchased stocks have made gains, compared with recently-purchased stocks which made losses. Importantly, this result does not arise due to the returns on individual stocks acting as a proxy for market returns, as this result is robust to controlling for movements in the market index and other covariates. This pattern can only arise if investor login choices are determined, at least in part, by already-known information about the performance of individual stocks.[19] In this way, we can detect excess logins arising purely from the desire to *look* at portfolios as distinct from the desire to *discover* how movement in the market index translate into changes in the value of the individual's imperfectly correlated portfolio.

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[17] Figure A1 Panel A in the Online Appendix shows the correlation between frequency of logins (shown on the y-axis, on a scale of 0–40 days) and frequency of trades (shown, on the x-axis on a scale of 0–400 days) in a binscatter plot. Each point in the graph encompasses an equal number of observations. In the plots, we restrict the data to the bottom 95% of accounts, which excludes those who log in at intervals greater than 70 days. A quadratic line of best fit approximates the data, indicating that login frequency is much higher than trading frequency for accounts that are very active in logging in and trading and, to a lesser extent, for accounts that are less active in trading. The data bins fit closely to the quadratic line, apart from one notable data bin at zero on the x-axis. This bin contains accounts that see a cluster of trades in quick succession but for the majority of the period show a long period between logins. Panels B and C illustrate the distributions of login frequency and trading frequency, independently. These two marginal distributions have similar shapes. Approximately 5.4% of accounts log in every day, with 45.3% of accounts making a login on average at least once per week. Panel B illustrates the frequency of trades. Notably, the density of high-frequency trade accounts is far lower than that of high-frequency login accounts. Only 3.4% of accounts trade on average at least once per week.

[18] Additional summary statistics are available from the authors on request.

[19] Our analysis therefore differs from previous studies of investor attention that examine the relationship between movements in the market index and investor login behavior. The relationship between movements in the market index and investor attention might be driven by investors paying attention to their accounts to see market index movements translated into gains and losses in their imperfectly correlated portfolios. A reduced propensity to look when the market declines might therefore be attributable to information aversion. In our testing context, we directly estimate the propensity of investors to pay attention to stocks in their portfolios, thereby isolating the pure attention-utility effect of winning and losing stocks.

1.4.1 *Excess Attention to Winning Stocks*

We examine the focus of investor attention, as proxied by logins, in the days following a stock purchase. Initially, we narrow our baseline sample to days when investors made a buy-trade followed by no other trades during the subsequent six-day period. We define a buy-day as a day on which an investor either purchases a new stock or adds to an existing position.[20] This restriction allows us to focus on login activity over the next five days that is for non-trading purposes, or that at least *ex post* does not result in a trade. Login activity spikes around buy-days.[21] In subsequent analysis of investor attention, we extend the length of the window beyond five days. This sample restriction retains 69,100 accounts, or 70.9% of accounts from the baseline sample.

Our focus is on whether logins in the period following purchase are more common when the most recently purchased stock makes a gain compared to a loss. Figure 1 illustrates the relationship between returns on the stock purchased on the buy-day and the probability of login. Our baseline measure of returns is returns since the previous day.[22] In Panel A, the y-axis shows the probability of login and the x-axis shows the number of days from the buy transaction. The buy-day is day zero[23], with days 1-5 being the five days in the period following the buy transaction. The upper line corresponds to days when the stock experienced a gain the previous day, while the lower line corresponds to days when it experienced a loss or no change. The figure shows a clear difference in the probability of login: days on which the recently bought stock has made a gain relative to the previous day's price exhibit a higher login propensity compared with days on which the recently bought stock has made a loss. The increase in probability of login for observations in gain is approximately five percentage points on each day, an increase of more than 10% in the average login probability among observations in loss.

Figure 1 Panel B pools together all account × days from Panel A and illustrates a binned scatterplot showing the probability of an account login on the y-axis and the returns on the stock since the previous day on the x-axis. The plot illustrates a positive relationship between returns and the probability of login, with evidence of a jump in the probability of login when the stock return becomes positive. This discrete change in behavior between situations involving gains and losses is common in behavioral data. Homonoff (2018), for example, proposes that a value function with a level discontinuity – a discrete jump between losses and gains – is necessary to explain the hugely different reactions of shoppers to small taxes on the use of disposable bags as compared to the negligible impact on rewards for the use of resusable bags.

We use regression models to estimate the relationship seen in Figure 1, conditioning on

[20] We exclude days where multiple stocks were purchased, which account for 15% of all purchase days.

[21] This is illustrated in Figure A2 in the Online Appendix, which shows that the probability of login increases in the day before a trade, then decreases gradually over the following days.

[22] In additional analysis we replace this measure with returns since purchase.

[23] Day zero is omitted, the probability of login on the purchase day is one.

movements in the market index and other covariates, including returns on the other stocks held in the investor's portfolio concurrently with the stock purchased on the buy-day. Observations in our regression models are at the account × day level. If returns on the market index and on other stocks held by the investor are positively correlated with returns on the stock purchase on the buy-day, the unconditional effect we observe in Figure 1 could be attributable to this correlation, reflecting an information aversion effect measured, by proxy, through the returns on the stock purchased on the buy-day. Hence, the addition of these controls is important for distinguishing login behavior consistent with attention utility from login behavior consistent with information aversion.[24]

The regression models pool together all account × days in the buy-day periods (i.e. the observations in Figure 1 Panel B). The dependent variable is a dummy variable for login on the account × day and the independent variable of interest is a dummy indicator of whether the stock purchased on the buy-day exhibits a gain or loss compared to the price on the previous day (the x-axis variable in Figure 1 Panel B).[25] Results are shown in Table 2. Column 1 includes only this dummy variable. The coefficient value of 0.037 implies that a gain on the most recently purchased stock increases the likelihood of login by approximately 3.7 percentage points, an increase of 8.2% on the baseline probability calculated from the constant term in the model.

Columns 2-6 of Table 2 introduce additional controls. In Columns 2 and 3, separate terms for the positive and negative continuous return on the previous day (in percentages) are included. The positive coefficients imply that investors are more likely to log in when returns are higher, in addition to the "jump" in probability when returns become positive. Columns 4 and 5 add controls for daily returns on the FTSE100 index and on the value of all other stocks in the investor's portfolio.[26] Both coefficients are positive, implying that investors are more likely to log in when they make positive returns on the rest of their portfolio, or, consistent with the 'ostrich effect', when the market is higher. The coefficient on the most recently purchased stock remains positive and precisely defined. The coefficient value of 0.015 in Column 5 implies that a gain on the purchased stock increases the likelihood of login by approximately 1.5 percentage points, an increase of 3.3% on the baseline probability calculated from the constant term in Column 1.

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[24] An alternative account of information aversion consistent with Andries and Haddad (2020) would posit that people who receive adverse information about the performance of their most recent stock become more information-averse, and hence reluctant to log in to their account, as a result of a negative wealth effect (shifting them to a more risk averse portion of their utility function). We think this account is unlikely for several reasons. First, any utility function that exhibited such a dramatic increase in concavity as a result of a loss in a single stock would have untenable predictions in other situations (c.f., Rabin, 2000). Second, we observe an obvious discontinuity at zero, which is again inconsistent with such an account. Moreover, the main theory that has introduced a gain/loss discontinuing (Prospect Theory) into economics predicts that people are risk-seeking for losses, which would imply that people should be information-seeking and not avoidant when the stock they are tracking loses value.

[25] The dummy indicating a gain/loss in the stock as well as other control variables showing the size of the gain/loss refer to observations for account i on day t, however we omit these subscripts for ease of exposition.

[26] These models adjust for cardholder age and gender, including dummy variables for instances where this information is missing, and employ quartile-based dummies to capture account characteristics such as trade frequency, portfolio value, and stock count.

We also add individual fixed effects in Column 6. This specification controls for individual differences in attention, identifying the model from within-person changes in stock returns and in the probability of a login. The coefficients on the regressors retain the same signs and approximate precision as those in the models without individual fixed effects.[27] These estimates show that recently purchased stocks that gain value generate excess logins compared with those that have lost value, consistent with login behavior being driven by attention utility.[28]

Note that our econometric specification makes it possible to rule out several alternative explanations, other than attention-based utility. First, it is unlikely that investors are logging in to learn how their most recently purchased stock is performing. If investors were logging into their accounts in order *to discover* stock returns, we would see an equal likelihood of logging in for stocks that have gained or lost value, as, at the point of logging in, investors would not know how the stock had performed. Second, the effect we observe for most recently purchased stock does not proxy for an effect of returns on the market index, or returns on other stocks, as results are robust to the inclusion of controls for those variables. The effect we observe is robust to controlling for the return on the FTSE100, hence we control for the effect on login activity of observing movements in the market index (i.e., the effect explored by Sicherman et al., 2015, which we replicate). Third, the effect is not driven by the intention to buy or sell the recently purchased stocks, since during the period under observation no other transactions take place. Fourth, given the robustness of the result to the inclusion of individual fixed effects, the effect does not pick up individual-level differences in stock-picking ability or attention across investors. Before turning to the implications of this result, we next present robustness and sensitivity tests.

1.4.2 Robustness and Sensitivity Tests

Functional Form and Estimator

Our baseline estimates in Table 2 control for the daily return on the FTSE100 and for the daily return on the other stocks in the portfolio. In Table 3, we expand the specification such that daily returns on the FTSE100 and the remaining stocks in the portfolio enter with the same functional form as that used for the most recent stock: separate continuous linear controls for returns either side of zero, plus a dummy variable indicating gain/loss. This allows us to control thoughtfully for returns across the most recent stock, FTSE100 and remaining stocks, which might be highly correlated.

Table 3 shows that the inclusion of these additional terms leaves the main result unchanged.[29] The coefficient on the dummy variable indicating gain/loss on the most recent

[27] Regressions in this main analysis and in the robustness and sensitivity tests exclude account $\times$ day outliers in returns, removing observations below or above percentiles 1 and 99.

[28] Replacing the dependent variable with the number of logins occurring on the day, we find the same pattern in results as in the main analysis (see Table A1 for estimates).

[29] The results remain consistent when using the count of logins as the dependent variable instead of the login

stock remains positive and precisely defined. The coefficients on the gain/loss dummy for the FTSE100 and for the remaining stocks are also positive, indicating an increased likelihood of login when the index is in gain, or the remainder of the investor's portfolio is in gain. The coefficient value on the most recent stock dummy is 0.013, implying that a gain on the purchase stock increases the likelihood of login by approximately 1.3 percentage points, an increase of 2.9% on the baseline probability calculated from the constant term in Column 1 of Table 2.

Our baseline estimates use OLS models. We also estimate logistic regression models.[30] Estimates from the logistic regression model return positive, statistically significant, coefficients which are of similar magnitude to those from the OLS models. We also estimate our main model using the regression discontinuity estimator for discrete outcome variables developed by Xu (2017). Results show a positive and statistically significant estimated treatment effect, consistent with our main models.[31]

Extending the Time Horizon

We test whether our main result that stocks in gain attract higher logins compared with stocks in loss persists over longer time periods. To test this, we extend the sample period to up to 20 days since the buy-day.[32] In Figure 2 we observe the same pattern over this longer time horizon as that seen in the main results. Table 4 shows regression estimates. In these estimates, the post-purchase sample is broken down into weekly periods for the four weeks since purchase. Results show that the coefficient on the gain/loss dummy for the most recent stock is again positive and precisely defined in each sample, with the coefficient magnitude stable across the four weekly period subsamples. Figure 2 presents the same pattern as Figure 1, with the probability of login for accounts for which the recently purchased stock is in gain persistently higher over the 20 day period compared with the probability of login for accounts for which the recently purchased stock is in loss. The pattern is consistent when we analyse the returns since the previous day (Panel A) or when we replace this measure with returns since purchase (Panel B).

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dummy. See Online Appendix Table A3.

[30] See Online Appendix Table A9.

[31] Standard RD estimators calculate average treatment effects for continuous outcomes. However, our dependent variable is a binary variable indicating whether an investor logged into their account on a specific day. Therefore, we opt for an RD specification designed for discrete outcomes using the 'rd.mnl' estimator developed by Xu (2017). The findings suggest an average treatment effect of approximately 0.9 percentage points, with a robust 95% CI of (0.005, 0.012), and an optimal bandwidth of 1.25%. Additional estimates are available from the authors on request.

[32] As in our main analysis, we continue to apply the additional sample restriction that the account has no other trades during the period of analysis. This sample restriction retains 59,158 accounts from the baseline sample. We further narrow the sample to portfolios containing at least two stocks to consider the performance of remaining stocks, resulting in 48,925 accounts. The results are not sensitive to these restrictions

Buy-Day Purchase Types

Our baseline sample contains buy trades of different types, such as purchases of a new stock that are additions to an existing portfolio of stocks, or purchases that top-up an existing position with additional shares. As a third robustness check, we explore the sensitivity of our main estimates to subsamples of purchase types. It is possible, for example, that top-up stock purchases do not attract the same pattern of attention as new purchases. The specific subsamples we examine are: i) top-ups of an existing stock held in the portfolio, with no other stocks present in the portfolio, ii) top-ups of an existing stock held in the portfolio, with other stocks present in the portfolio, and iii) purchases of a new stock.

Our main result is seen in all these subsamples, over both the five-day and twenty-day time horizons. Regression estimates are reported in Table 5.[33] Once again, the coefficient on the gain dummy for the most recently purchased stock is positive and precisely defined. In Columns 2 and 3, where the sample is restricted to multiple-stock portfolios, the coefficient magnitude is approximately half that of Column 1, which restricts the sample to single-stock portfolios only. This suggests that the attention effect arising from the performance of a single stock is reduced in larger portfolios.

Returns Since Purchase

In our main empirical specification, stock returns are measured as returns since the previous day. Investors may instead evaluate gains and losses against other reference prices, such as the purchase price.[34] Over short time horizons post-purchase, returns since purchase and returns since the previous day will be highly correlated. In order to explore the sensitivity of our results to the measure of returns, we replace daily returns with returns since purchase. In the main sample, the correlation between the two measures of returns is 0.497. The results reveal very similar patterns when this alternative measure of returns is used in the analysis.[35]

1.4.3 Attention over Sequences of Market Closure Days

As an additional test, we analyse login behavior on sequential market closure days.[36] The rationale for examining logins on sequential market closure days is as follows. Markets are often closed over a sequence of days, such as on weekends and on public holidays; hence the value of an individual's stock holdings on sequential market closure days is unchanged from the

[33] Figures are presented in Figure A3 to Figure A6 in the Online Appendix.

[34] A large literature documents the disposition effect, which is the propensity of investors to be more likely to sell stocks that have made a gain, compared with those that have made a loss, since purchase (Shefrin and Statman, 1985; Barber and Odean, 2000; Shapira and Venezia, 2001; Feng and Seasholes, 2005; Chang et al., 2016).

[35] Figure A7 in the Online Appendix reproduces the same patterns as those seen in Figure 1 using returns since purchase. Table A2 reports regression results based upon Table 2 in which the measure of daily returns is replaced with returns since purchase, again with very similar results. Finally, Table A4 shows similar results to Table 5 in a specification in which returns since the previous day are replaced by returns since purchase.

[36] This analysis is inspired by the analysis of logins on Sundays in Sicherman et al. (2015).

day before closure (such as a Friday) until the market opens again (such as a Monday). We can therefore treat login events not resulting in a trade on the day subsequent to the first login day in each sequence of market closure days as a test of attention to the investor's account purely for the pleasure of looking. We restrict the sample to observations where a trade does not occur on the next market-open day to rule-out the possibility that subsequent logins on market closure days were made in order to place trades.[37] Although this analysis restricts the sample to only a subsample of days, the available sample includes all Sundays, together with many Monday public holidays and some mid-week public holidays (e.g. Easter and Christmas). Using this approach, our data allows us to isolate the increased attention motivated by observing higher returns in the most recent stocks purchased from that motivated by observing changes in aggregate market performance.

Table 6 Column 1 presents estimates of our main econometric specification but in which the dependent variable is whether the investor made a login on the day subsequent to the first login in the sequence of market closure days (such as a login on Sunday following a login on Saturday). The sample draws on all sequences of market closure days in the first month after the purchase of the stock.[38] Results show that investors who made a gain on the most recent stock between the last two market-open days prior to the sequence of market closure days are more likely to log in on a the second, or subsequent, market closure days. The coefficient of 0.0104 on the gain dummy on the most recent stock implies that investors who make a gain, compared to a loss, on their most recent stock are 1.04 percentage points, or 4.9%, more likely to log in on the second, or subsequent, market closure day even though stock prices are unchanged over the sequence of intervening days.

Column 2 presents additional estimates in which the dependent variable is the count of logins made by the investor of the day. As in the main analysis, the coefficient on the gain dummy on the most recent stock implies that investors who make a gain, compared to a loss, on their most recent stock are more likely to login more times on the market closure day. Results from logistic regression models are consistent with results from OLS models.[39]

[37] The logic for this test is that an investor who makes a login to the account on any day in the sequence of market closure days cannot receive any new information by making a login to the account on a subsequent day until the market opens, due to the market being closed over the whole interval. Therefore, any effect of stock price returns during the days prior to the sequence of market closure days (e.g., such as between Thursday and Friday) on the probability of a login on the second or subsequent day in the sequence of market closure (e.g., a Sunday) conditional on having made a login on the preceding day in the sequence (e.g., a Saturday) represents a pure effect of attention-utility preferences for looking at gains compared with looking at losses.

[38] No transactions, such as buying or selling, occur during these periods, except for the initial purchase that defines the target stock. If the investor buys another stock, this new purchase becomes the target stock, resetting the observation period. Additionally, the analysis excludes any weekend or bank holiday directly followed by a trading day to eliminate instances where login activity could be motivated by trading intentions.

[39] Results from a logistic regression model are shown in Online Appendix Table A10. The coefficient on the gain dummy for the most recent stock purchased is positive and statistically significant, as in the OLS model estimates.

1.4.4 Further Extensions

Attention to Most Recent vs. Earlier Stocks vs Stocks in Highest Value Position

Our main result is that investors are more likely to log in to their accounts to look at winning stocks compared with losing stocks, based on analyses that focus on login behavior in the days following the purchase of a stock. In this extension, we test whether the sensitivity to the returns of the most recently purchased stocks differs from the sensitivity to returns to stocks purchased previously, or to the stock in the highest value position in the investor's portfolio. We implement this test by estimating our main econometric specification on separate subsamples by week since purchase of the stock, over one to four weeks. We then compare the coefficient on the dummy variable indicating gain on the previous day for the most recently purchased stock with the equivalent dummy variable for the second most recently purchased stock, or for the highest value position stock. This allows us to test whether the coefficient on the most recent stock converges to the coefficient on the other stocks over time.

Results for the second most recently purchased stock are shown in Table A5 in the Online Appendix. In the first column, which uses the subsample of days in the first week since purchase, the coefficient on the gain dummy for the most recent stock is positive and precisely defined. The coefficient on the most recently purchased stock gain dummy is larger than that on the second most recently purchased stock gain dummy, though a Wald test cannot reject the null hypotheses of equality of coefficients, or at least it cannot reject it at any significance level below 95.83%. In the subsequent columns, the coefficient estimates for the weeks two-to-four subsamples fail to reject the null hypothesis of equality at lower significance levels. This evidence suggests that attention is not exclusively directed towards the most recent stock, but indicates that people attend relatively more to their most recent stock in the period immediately after purchase.

Results for the highest value stock are shown in Table A6 in the Online Appendix. The coefficient on the gain dummy for the most recent stock is again positive and precisely defined, and also larger than the coefficient on the gain dummy for the highest value stock (though again a Wald test cannot reject equality). If the highest value stock happens to be the same as the most recent stock, then the combined effect of these coefficients would imply a 2 percentage point increase in the likelihood of logging in.

Interaction Terms

As a further extension to our main analysis, we test whether our main result that stocks in gain generate excess logins compared with those in loss varies with investor characteristics. To do so, we add interaction terms (and main effects) in separate models to our main econometric specification. The interaction terms we add are i) investor gender, ii) number of stocks held, and iii) portfolio value.

Estimates are presented in Table 7. The interaction term on investor gender, captured by the female dummy, is negative and statistically significant at the 5% level.[40] The coefficient on the interaction term is half the size of the main effect of the gain dummy for females. This indicates that the excess logins generated by stocks in gain is an effect attributable largely to male investors. The interaction term with the number of stocks suggests that investors with diversified portfolios pay less attention to the most recent stock than investors with fewer stocks. The portfolio size interaction term has a near-zero, non-significant coefficient.[41]

Post-Sale Login Behavior

As a final extension, we examine the relationship between the performance of stocks and logins following stock sales. In cases where individuals fully liquidate their position in a stock, the stock is no longer visible in an investor's portfolio account. Consequently, when an investor completely liquidates their position in a stock, eliminating it from their portfolio, they no longer have a reason to log in for either informational or hedonic purposes. In contrast, if an investor sells only part of their shares, they are likely to log in to monitor the performance of their remaining investment.

We therefore conducted additional analysis of logins following partial sales. We have no specific hypothesis regarding this relationship: such scenarios could potentially lead to feelings of regret should the stock's price increase post-sale (or a feeling of relief that they didn't sell it all), or, if the stock fell a feeling of relief that they sold part of it (or feeling of regret that they didn't sell all of it). This complexity does not arise in the context of stock purchases. Our findings reveal that after partial sales, investors seem to interact with their remaining stock holdings in a manner akin to how they engage with recently acquired stocks.[42]

1.5 From Attention to Action in Trading Behavior

1.5.1 Spillover Effects of Target Stock Attention on Other Stock Trades

We now move to explore whether the sensitivity of investors' attention to their trading accounts in response to gains and losses on their most recently purchased stock in the month – attention utility – affects investor trading behavior. This could occur for mechanistic reasons – because in order to trade, investors have to log into their accounts, and for both cost-based and information-based reasons. We have already seen, in Section Section 1.4, that good performance drives attention to recently purchased stocks. Once the investor is logged in, however, the cost of trading declines, which can be predicted to increase the likelihood of trading.[43] And, finally,

[40] Gender is represented by dummy variables, including an additional dummy for missing information. In the regression, male serves as the reference category, and coefficients for missing data interactions are omitted.

[41] Table A7 in the Online Appendix replicates these results using returns since purchase.

[42] Additional analysis available from the authors on request.

[43] Investors might, for instance, not have to go through multiple authentication steps again, or navigate from the homepage to their portfolio.

logging in (disproportionately when the value of their last stock has increased) could also affect trading for informational reasons.

Once investors have logged in, they are more likely to look at their portfolio positions and further observe the selection of stocks available to trade. This is, to some extent, a feature of stockbroking account dashboards, which collate information on multiple securities on a single screen. While this is an efficient way to purvey a portfolio, it also means that it is difficult for investors who log in to escape looking at their positions in multiple stocks, and it is possible that the new information gained leads to occasional decisions to trade.

To test whether lookup behavior driven by attention utility affects trading, we modify our main econometric model by using, as dependent variables in different specifications, dummy variables to indicate whether the investor made a trade on the day and, in separate models, whether the investor made either a buy-trade or a sell-trade on any stock in their portfolio (other than their most recently purchased stock in the month). Hence, we relate gains and losses on a recently purchased stock, which we call the target stock, to investor trading decisions on other stocks held within the portfolio. We first estimate how gains and losses on the target stock affect trades on other stocks in the 30 days following the purchase of a target stock. Then, we incorporate into this specification the login dummy variable to test whether the estimated effect of gains and losses on the most recent stock on trading activity is explained through login activity.[44]

Results for trading activity are shown in Table 8. In this table, the dependent variable is a dummy indicating at least one trade took place on the account on the day. We refer to the recently-purchased stock as the "target" stock in these regressions and the dependent variable as trade in "others" stocks. Columns 1, 2 and 3 show estimates of the likelihood of the investor trading (buying or selling) a different stock. Columns 1 and 2 include account fixed effects and Column 3 adds stock fixed effects and day of the week fixed effects, which capture day-level and stock-level variation in the probability of trades. The coefficient on the gain / loss dummy for the target stock is positive in each model, indicating that on days when the investor makes a gain on the target stock, the likelihood of trading any other stock in the portfolio is increased. The coefficient changes in Columns 2 and 3 because of the inclusion of the magnitude of the loss on the target stock, suggesting the coefficient on the target stock in gain dummy is biased downward when the magnitude of the loss is omitted. The coefficient value of 0.0055 in Column 3 implies that when the target stock is in gain, there is an increase in the probability of a trade on other stocks of approximately 0.5 of a percent, an increase of approximately 10% on the baseline probability in the sample.

Our hypothesis is that the relationship between gains on the target stock and trading behavior on other stocks is mediated by whether the investor pays attention to the account, measured through account logins. For example, if the target stock is doing badly, the investor

[44] For these analyses, we no longer select periods based on a stock having been purchased and no other stock being purchased for some interval (e.g., 5 days, in our original analysis) as we did in our analyses of logins.

will not log in and thus will not trade in other stocks. But if the target stock is doing well, the investor will log in and, possibly, make a trade on another stock. Columns 4, 5, and 6 include a login dummy indicating whether investors logged in on the day. Again, including the magnitude of the loss on the target stock alters the coefficient on the target stock in gain dummy. In Columns 5 and 6, the coefficient on the target stock in gain dummy is a precise zero. That is, once we control for whether an investor logs in on day t, there is no effect of the previous day's target stock return on their decision to buy other stocks—the effect of the target stock returns on trading activity of other stocks is entirely mediated by the login effect (i.e., by attention utility). In other words, this effect of including the login dummy on the coefficient on the gain dummy for the target stock suggests that returns on the target stock influence trading via its influence on attention to the trading account.

Results from models estimated separately for selling and buying activity are shown in the two panels of Table A8 in the Online Appendix. In this specification, the dependent variable is a dummy indicating that at least one sell-trade (top panel) or buy-trade (bottom panel) took place on the account on the day. The coefficient on the gain / loss dummy for the target stock is positive in Columns 1, 2, and 3 in both the top and bottom panels, indicating that on days on which the investor makes a gain on the target stock, the likelihood of selling, or buying, a different stock is higher. The inclusion of the login dummy in the specifications in Columns 4, 5, and 6 attenuates the coefficient on the target stock by at least two-thirds in the top panel results for selling stocks, and yields a negative coefficient in the bottom panel results for buying stocks. Hence, it is again through the mechanism of attention to the trading account (captured by the login dummy) that losses on the target stock affect trades on other stocks.[45]

We interpret these results as showing that, by not making logins to their account when a recently purchased stock has fallen in value, investors reduce their overall trading activity. This demonstrates that the aversion to looking at losses on the recent stock effectively closes-down trading behavior on other stocks, because trading those stocks (or buying a new stock) would necessarily involve making a login to the account, which in turn would make it difficult to not pay attention to the stock that lost value.

[45] As a sensitivity test, we replicate the analysis from Table 8 and Table A8 but shorten the time period of analysis to two weeks. When we do so, results are unchanged. As a further sensitivity test, we replace returns since the previous day in this specification with returns since purchase. In these specifications, as in our main results, the positive effect of returns on the target stock upon the probability of trade in other stocks disappears when conditioning upon the login (on the day) dummy variable. In these specifications, gain on the target stock reduces the likelihood of trades on other stocks once the login dummy is incorporated into the model. Finally, we also extend the analysis to the sample of sequential market closure days. Consistent with our main results, individuals are more likely to trade another stock on the next market open day if the target stock had gained on the previous open market day before the closures. However, this effect dissipates when login dummies are included. All these results are available from the authors upon request.

1.5.2 Attention and the Disposition Effect

The tendency of investors to pay attention to winning stocks compared to losing stocks may be related to the disposition effect, which is the tendency of investors to sell winning stocks more so than losing stocks. To investigate this, we estimate the disposition effect using stock sales data, replicating this well-documented effect (see Barber and Odean, 2013 for a review of the literature on the disposition effect). We then split our sample into high-ostrich type and low-ostrich type investors (using a regression-based measure of ostricity obtained by computing individual estimates of the ostrich effect).[46] In Table A11, we observe that high ostrich-type investors have larger disposition effect coefficients, with the coefficients for the gain dummies being at least three times larger across all specifications, suggesting that these two phenomena may be linked. However, controlling for whether the account holder made a login on the day only slightly reduces the magnitude of the disposition effect. In combination, these results suggest that attention utility may contribute to, but is unlikely to fully account for the existence of the disposition effect.

2 Study 2: Experiments to Test for Attention Utility

To provide more direct evidence of the role of attention utility in decision-making and economic outcomes, crudely quantify the magnitude of the effect, and isolate the effect of attention relative to information, we conducted three online experiments.[47] Although the previous section demonstrated that there are a disproportionate number of logins following gains in the most recently purchased stock, our identification strategy assumes that investors are aware of these gains before they log in. It is difficult, however, to confidently assume that investors' decisions to log in are based on complete, rather than partial, knowledge regarding the value of their stocks (except for our weekends and bank holidays estimations, where we examine whether investors repeatedly log in when the market has been closed).[48]

[46] To do so, we restrict the sample to investors who have at least ten recorded logins to their account in the sample period and estimate individual-level regressions using observations at the individual × day level. The dependent variable is whether the individual made a login to their account on the day, with the coefficient measuring investor ostricity being a gain/loss dummy that considers daily returns for their most recently purchased stock. See Online Appendix Table A11.

[47] Strictly, the first study is a quasi-experiment, since participants were not randomly assigned to conditions, but were assigned based on whether their stock gained or lost value over the last 6 months. Given the randomness in stock returns, however, it seems unlikely that differences between investors which led them to invest in winning or losing stocks over that specific period were responsible for differences in decisions to complete the survey. Note also, that if their behavior was driven by wealth effects – i.e., those who realized their stock had lost money felt poorer– we would expect to observe the opposite effect: those with losing stocks should have been *more rather than less likely to complete the paid survey.*

[48] Models of information aversion may explain (qualitatively) the disproportionate number of logins following increases in the market price of the assets. For instance, Andries and Haddad's (2020) model of dynamic disappointment aversion predicts that partial positive information would be more likely to be followed by a full observation decision than partial negative information. In their model, disappointment aversion determines both information aversion and risk aversion.

If investors have imprecise signals of their stock gains before logging in, logging in may convey news. As a result, investors may be seeking information rather than simply enjoying information they already have (e.g., an investor may recall seeing that his stock appreciated, but he may not recall the new price or how many shares he owns; if he owns several assets, he may not know their prices as well). To convincingly show empirical evidence of 1) attention effects absent of any information effects and 2) economic outcomes that are entirely determined by the attention decisions, we conducted three online experiments. All three experiments were run on the website Prolific Academic, the first two using a UK sample, and the third with a US sample. In all experiments, participants were given information about whether a particular stock they owned was in gains or losses relative to an arbitrary reference point – the stock's value six months prior – and then were given the opportunity to complete a second survey in exchange for pay that would require them to pay attention to their winning or losing stock.[49]

2.1 Experiment 1: Stock Performance and Attention

The first (main) experiment was designed to determine whether investors are reluctant to think about or pay attention to bad news about their stocks. We recruited individuals who had been investing in at least one individual stock for at least six months.[50] In an initial survey (Survey 1), we asked them for the name of the stock that had the highest total valuation of shares that they had owned for at least 6 months.[51] Then, we sent them an email with information about the stock's absolute performance and performance relative to the FTSE100 during that period. The email included an invitation to a second paid survey (Survey 2), which, they were told, would ask them questions about their stock as well as about their investment behavior more generally[52] This survey included checks that verified that they understood the information they had received by email.[53] The survey was optional, and the decision to complete it was the dependent variable. Participants were informed that they would receive a flat payment of £1 if they chose to complete it. We predicted that they would be more likely to click on the link to Survey 2, and complete it, if their stock had gained value either in absolute terms over the past 6 months (the interval we provided information about in their invitation to complete the

[49] In this second survey, participants' trading habits were assessed to ensure comparability with the field study investors. Experimental participants, like the field study investors, demonstrated increased sales with stock gains—a known disposition effect—but were less likely to make purchases. This underscores the validity of our sample as representative of typical retail investors. Additionally, we observed no significant differences in portfolio monitoring, investment confidence, or share purchase reasons when comparing participants with gains to those with losses.

[50] We chose the six month minimum holding period as a compromise between including a period short enough to recruit a maximum number of potential participants, and long enough so that stock valuations would have changed substantially. We also wanted to use an interval long enough so that investors would find it emotionally meaningful – i.e., that they would feel good if their stock had performed well over a six month period and bad if it had performed poorly.

[51] Survey 1 also collected participants' demographic information.

[52] An example of this email can be found in Figure A8 in the Online Appendix.

[53] Survey questions are available from the authors on request.

second survey) or had increased relative to the FTSE100. We pre-registered the experimental design and outcomes.[54]

During Survey 1, we screened 2080 participants recruited through Prolific, and only sent a follow-up email to those who reported that they had held individual stocks for at least six months.[55] Our experiment involved 1780 retail traders from this sample, who were contacted via email with information about their most valuable stock and were invited to respond to Survey 2. Our baseline sample excludes 27 participants who failed to pass the checks verifying that they understood the information they received (e.g., reporting gains when their stocks declined or incorrectly stating their stocks outperformed the FTSE when they underperformed). Except for gender (male investors were more likely to respond to the survey), observable characteristics are quite similar between these two groups.[56]

2.1.1 Results

We analyse the experimental results at the individual level. We ran OLS regressions with a dummy that indicated a response to Survey 2 as the dependent variable. We included demographic controls from our first survey, including gender, education, and ethnicity. As in our earlier analysis, our independent variables are a gain dummy that equals one if the price of the stock has increased in the past six months and zero otherwise, and a second gain dummy that equals one if the return of the stock increased more than the FTSE100 in the same period, and zero otherwise. Since these two gain dummies are correlated (with a 0.974 correlation coefficient), we included them separately in our models. As small retail investors have little effect on the performance of their assets, we can interpret the coefficients of these variables as the causal effect of positive returns on the allocation of attention.

Table 9 reports our baseline regressions. Columns 1 and 2 examine the effect of absolute gains. Columns 1 and 2 demonstrate that participants were 5.06 percentage points more likely to respond to Survey 2 when their stock was in gain (with a baseline of 25.66% when the stock was in loss, given by the constant; this change represents a relative increase of 19.7% in the probability of responding to the survey). Column 2 shows that adding demographic controls has no impact on these estimates. Columns 3 and 4 report the effect of experiencing a gain relative to the FTSE100. Point estimates resemble those found in Columns 1 and 2 and vary only slightly with the addition of demographic controls. Gains relative to the FTSE100 increased the probability of responding to Survey 2 by 5.94 percentage points (against a baseline of 25.5% when the stock is in loss, represented by the constant; this change represents a relative increase of 23.3% in the probability of responding to the survey).

[54] The pre-registration can be accessed at `https://aspredicted.org/kg5yf.pdf`.

[55] An existing Prolific filter pre-screened these participants to ensure that they had invested in the stock market in some fashion in the past.

[56] Additional summary statistics are available from the authors on request.

2.1.2 Robustness Tests

In the Online Appendix, we perform additional robustness checks. Table A12 reports the results for all participants, including those who did not pass the checks that verified that they understood the information they received by email. Columns 1 and 2 show the effect of our standard gain dummies. Columns 3 and 4 replace these gain dummies with dummies showing their perceived performance (i.e., a dummy equal to one when participants reported 'My stock increased in value'). Participants who reported that they did not remember the performance were excluded from the latter analysis. The results consistently suggest that stock gains increase response rates to Survey 2.

These findings are difficult to reconcile with competing explanations which contend that participants' attention choices are motivated by the desire to acquire new information regarding their stocks, perhaps for purposes of trading. In our experiment, the treatment of interest (whether the stock increased or decreased in value relative to FTSE100) was described to the participants in both text and graphical forms; therefore, no new information regarding their stocks was acquired by the participants when they responded to Survey 2. In addition, by incentivizing the survey, we show that losing subjects may be willing to forego receiving a payment to turn off a screen that will force them to pay attention to, and hence think about, their stock's performance. In both surveys, the average hourly wage was approximately 25 pounds; however, participants were not aware of this information prior to completing the surveys. What they did know was that the first survey paid a flat rate of £0.70, while the second survey paid a flat rate of £1. Hence, those who were deterred from responding to the second survey by the prospect of having to pay attention to unfavorable information, were turning down a larger absolute payment than had induced them to participate in the first survey.

2.2 Additional Experiments: Quantifying Aversion, Attention vs. Information Avoidance

We conducted two additional experiments, the first to quantify participants' aversion to attending to negative information, and the second to shed further light on the role of attention- versus information-avoidance.[57]

Experiment 2, the "additional incentive experiment," was identical to the first experiment, but randomly assigned participants to either a £1 or a £2 payment for completing survey 2.[58] Table 10 reports results, which mimic Table 9, but add a dummy indicating whether the individual was in the £2 treatment arm. Across the specifications, the coefficient on the £2 treatment dummy is approximately three-quarters that on the gain dummy, indicating that doubling the payment had a smaller measured impact on participation than did an individual's stock having lost money. A crude interpretation of this result is that individuals with stocks in

[57] The pre-registration can be accessed at `https://aspredicted.org/ZRF_K52`.

[58] See Figure A9 for the survey screen, additional summary statistics are available from the authors on request.

loss are willing to forego more than a doubling of the incentive to avoid participating in survey 2, which would force them to pay attention to their losses. Experiment 2 also replicates the main result of Experiment 1.

Experiment 3, using a sample of US instead of UK investors, compared the impact of the attention manipulation to one that, instead, altered the *information* that participants would receive.[59] This "information experiment" was again identical to the first experiment, but added an experimental manipulation in which participants were randomly assigned either to the original invitation to participate in the second survey, or to a treatment in which the information on stock performance in the invitation was held back to the second survey itself. Specifically, in this treatment, the percentage values for gain/loss on the y-axis of the graph showing stock performance were removed in the email communication, with the invitation stating that "By participating in our follow-up survey, you will also gain access to information on the specific prices and percentage changes for your stock".[60] If information on stock performance is of value, subjects in this treatment had an added incentive to participate in the second survey.

Table 11 reports regression estimates from a regression model that includes a dummy indicating whether the observation is from the information treatment arm. The coefficient on the gain dummy (and gain relative to S&P500 dummy) is again positive, showing the robustness of our primary effect in a new, completely different, population of investors. The coefficient on the information treatment dummy, in contrast, is negative, with a large standard error. This pattern persists when incorporating the interaction between the gain dummy and the information treatment dummy, as shown in Table 12. Hence, these results suggest that information acquisition does not play an important role beyond attention in the decision to participate in the second survey.[61]

3 Conclusion

We contribute to the literature on information and attention by exploring the concept of attention utility: the hedonic pleasure derived purely from looking at information. We use detailed day-level data on individual investor stock portfolios, combined with daily information on login activity, to examine how stock performance affects attention and trading. We show

[59] In this sample of US investors, the majority of respondents reported their largest stock holding was of a stock listed in the S&P500, whereas in the sample of UK investors the majority of respondents reported their largest stock holding was of a stock listed in the FTSE100.

[60] See Figure A10 and Figure A11 in the Online Appendix. Details on sample selection and summary statistics are available from the authors on request.

[61] Experiments 2 and 3 replicate the exclusion criteria of Experiment 1, excluding participants who did not pass comprehension checks regarding the information received via email. Nonetheless, the results are consistent even when including all participants (see Tables A14 and A18). In Experiment 1, survey invitations were sent through Prolific's text-only system, linked to participants' personal emails, without tracking link openings. This might have left some participants unaware of the survey opportunity. In Experiments 2 and 3, we introduced a link opening tracker to monitor who accessed the survey invitations. Limiting the sample to these individuals, we found that the results closely aligned with our main findings (see Tables A13 and A15 for Experiment 2 results, and Tables A16, A17, and A19 for Experiment 3 results).

that individuals devote excess attention to already-known positive information about the performance of individual stocks in their portfolios. Knowing that a stock has performed well, individuals choose to log in to their brokerage account to gain attention utility from looking at the good news about their investment choices, and for equivalent reasons, they stay off when the news is bad.

Our results demonstrate, further, that the flip side of attention utility—aversion to looking at bad news—has implications for real activity. In order to trade, investors have to log into their accounts, and aversion to looking at their portfolio when their most recent stock has declined in value discourages investors from looking, and, hence, trading.

We supplement our analysis of portfolio data with three online experiments. The first experiment shows that investors are more likely to engage in a paid task that will involve attention to a prior investment if the investment gained in value. The second experiment shows that paying attention to a gaining as opposed to a losing stock is more motivating than a doubling of monetary incentives. The third experiment tests whether the motivation to respond to the survey when one's stock has gained value is augmented by the prospect of acquiring specific information about the stock's performance. However, our findings indicate otherwise, suggesting that attention-based effects outweigh information-based effects.

At a higher level, the current work also presents a challenge to the general types of models used to make sense of the behavior of individual investors. Conventional models of investor behavior assume that retail investors' goals are to maximize return and minimize risk at the point when a portfolio is liquidated (typically at retirement), leading to a natural focus on tactics, such as diversification, to achieve these twin goals. Research on motivated direction of attention (such as the current study), however, supports a different perspective which recognizes that investors have to live with their portfolios during the intervening period, and that doing so can give rise to powerful emotions (Pagel, 2018). Investment advisors often report that, more than advising a particular investment strategy, their role is to hand-hold during rocky times, encouraging skittish investors to "stay the course".[62] Likewise, the widely espoused "set it and forget" it strategy encourages investors not only to invest in highly diversified low-cost index funds, but also not to monitor those funds. As Rick Ferri writes, in an article about how he and his wife successfully followed such a strategy, "The second thing we did was not open statements from the fund company for about three years. I didn't want to know what the monthly balance was, because my emotions and bad judgment had hurt us in the past and I wasn't going let it happen this time."[63] In contrast to not paying attention at all, the current research identifies selective attention to gains as a strategy that investors use to maximize positive and minimize negative emotions associated with investing, with potential benefits for their investing behavior.

[62] e.g., https://www.ft.com/content/045bf4d9-5c1c-4932-90ad-ab6c2daa2c65

[63] https://www.forbes.com/sites/rickferri/2015/06/11/set-it-and-forget-it-works/#56ffda306e61

Attention utility has economic consequences that go beyond the behaviour of investors. What people pay attention to affects the economic decisions they make, and the economic decisions they make have an impact on utility in part by affecting what they pay attention to. In the domain of education, for example, poorly performing students may drop out of school or fail to apply themselves to coursework in part because being in school and applying themselves to coursework focus their attention on aspects of themselves that they would prefer not to think about (Kőszegi et al., 2022). In the domain of healthcare, people may not take medications in part because doing so forces a focus of attention on health conditions that they would prefer not to think about (Schwardmann, 2019). In the financial realm, someone who finds it painful to think about a parking ticket they know they received, or a notification that they have not paid their rent or their mortgage or the minimum amount on their credit card bill, may simply avoid phone, email or snail mail communications, with the inevitable effect of exacerbating the problem by avoiding paying attention to it (Olafsson and Pagel, 2017). Finally, as argued in an eloquent book titled "Don't Even Think About It," about why humanity is failing to deal with the imminent and fateful problem of climate change, George Marshall (2015) writes that "The bottom line is that we do not accept climate change because we wish to avoid the anxiety it generates and the deep changes it requires."

Individuals will, in general, prefer tasks and activities that confer positive attention utility and avoid tasks and activities that involve negative attention utility. They may, therefore, seek to postpone necessary corrective tasks, such as reviewing their retirement under-saving, monitoring their high body mass index, or calculating their carbon footprint because these activities requiring engaging with information that confers negative utility.

Regulators and policymakers should become aware of the impact of information on attention utility when they formulate policy. By ignoring people's tendency to avoid negative information, they might overestimate the impact of information on people's actions. For example, they might overestimate the benefits of information disclosure regarding calorie labels, graphic health warnings on cigarette packs, genetically modified foods, etc., because consumers might decide not to read labels or even pay attention to warning messages and might prefer to remain ignorant if the information provided to them is likely to induce negative affective states (Sharot and Sunstein, 2020).

Our results provide a new dimension to the literature on information and attention, and suggest that some prior results that were interpreted as evidence of information seeking or avoidance may have instead, or in addition, involved attentional motivation. The concept of attention utility is an area we see as fruitful for future research and theorizing.

4 Data Availability Statement

The data underlying this article are proprietary and were provided to the authors under a restricted data-sharing agreement with Barclays Stockbroking. The replication package, available on Zenodo at `https://dx.doi.org/10.5281/zenodo.14692293`, provides instructions for researchers on how to request access to the data. It also includes the full experimental datasets used in all three experiments.

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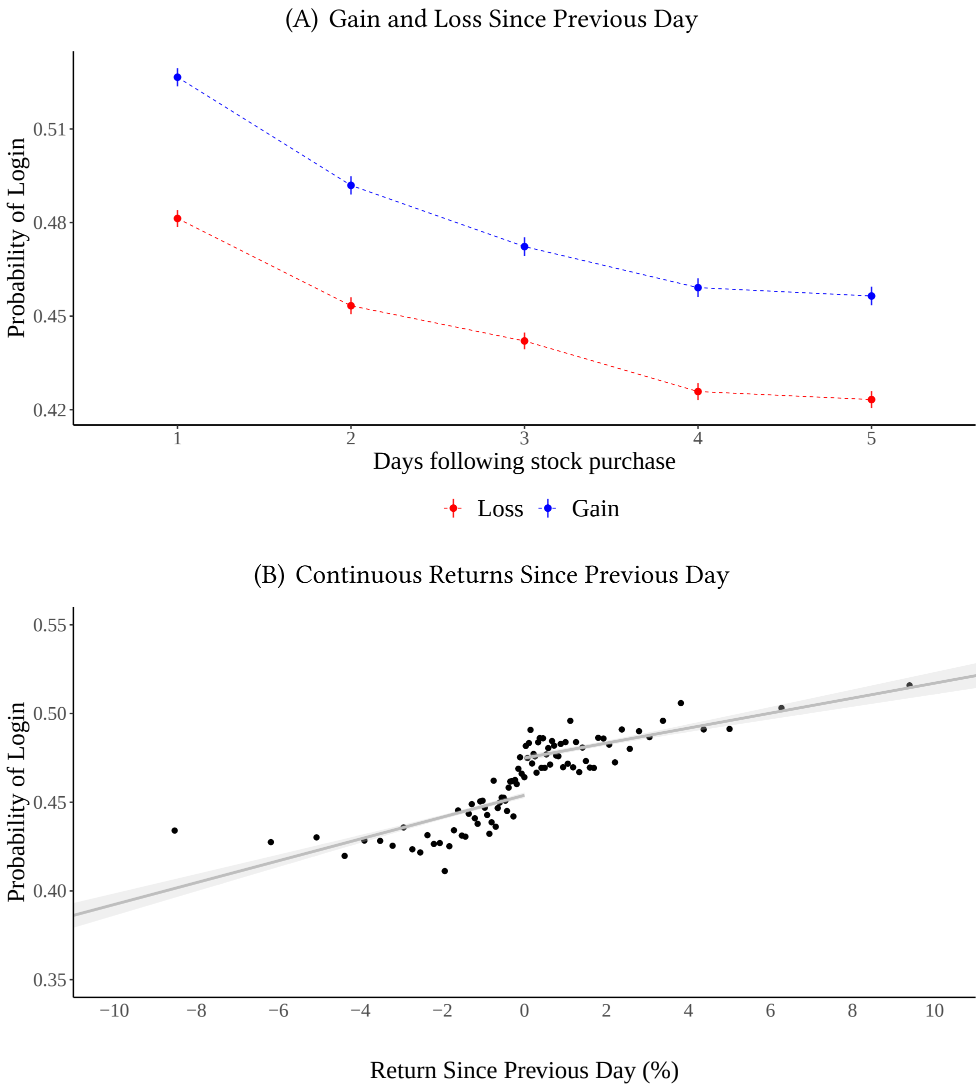
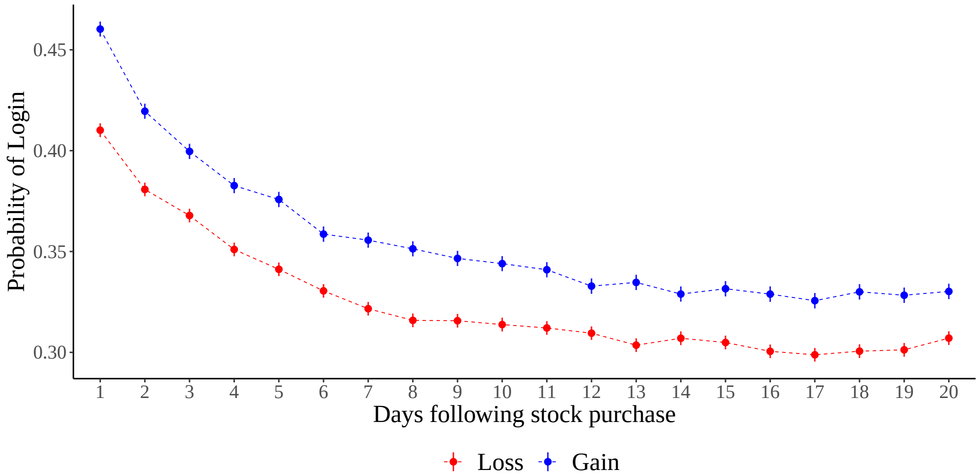
Figure 1: Probability of Login by Stock Returns



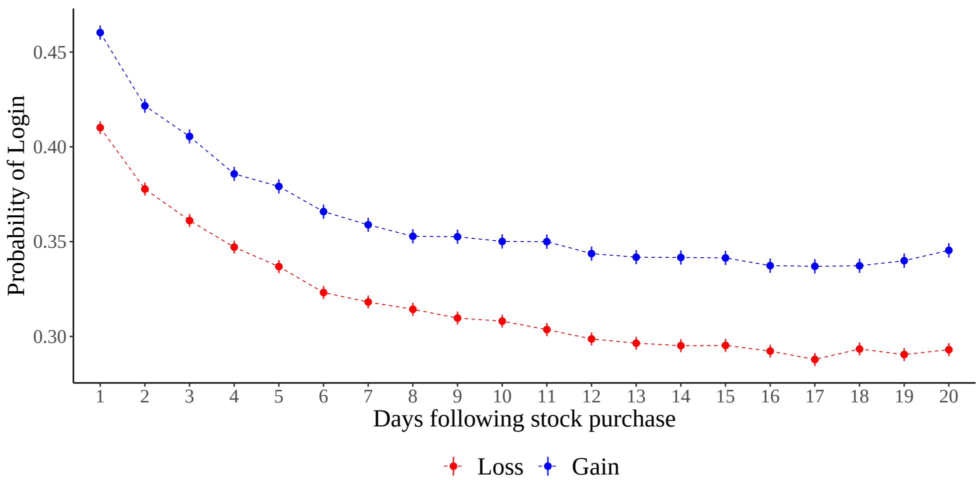
Note: Figure illustrates the relationship between returns on a recently purchased stock, and the probability of an account login, over the following five market open days after the purchase day. Panel A shows the probability of a login on each of the five market open days following the purchase of a stock, as a function of the return of that stock on the previous day. Panel B pools together account × day observations from the sample in Panel A and shows the probability of a login as a function of the return of that stock on the previous day. The sample is restricted to five-day periods following the day on which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock, and makes no other trades over the following five days. This sample restriction provides 243,386 five-day periods from 69,100 accounts. Lines span 95% confidence intervals.

Figure 2: Daily Stock Returns and Logins Over 20 Days

(A) Return Since Previous Day



(B) Return Since Purchase



Note: Figure illustrates the relationship between returns on a recently purchased stock, and the probability of an account login, over the following twenty market open days after the purchase day. Panel A shows the probability of a login on each of the twenty market open days following the purchase of a stock, by the return the previous day for that stock. Panel B shows the probability of a login on each of the twenty market open days following the purchase of a stock, by the return since purchase that stock. The sample is restricted to twenty-day periods following the day on which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock, and makes no other trades over the following five days This sample restriction provides 138,255 twenty-day periods from 59,158 accounts. In all periods, no other transaction has taken place. Lines span 95% confidence intervals.

Table 1: Baseline Sample Account-Level Summary Statistics

	Mean	SD	Min	Percentiles p25	p50	p75	Max
A. Account Holder Characteristics							
Female	0.19						
Age (years)	54.37	14.14	17.00	47.00	57.00	67.00	77.00
Account Tenure (years)	4.84	3.29	0.03	2.80	3.98	6.00	16.99
B. Account Characteristics							
Portfolio Value (£1000)	64.96	183.51	0.04	4.92	16.44	48.93	3058.88
Investment in Mutual Funds (%)	6.77	20.18	0.00	0.00	0.00	0.00	100.00
Number of Stocks	5.24	6.83	0.02	1.59	3.28	6.60	772.52
Login days (% all days)	20.38	21.16	0.27	4.24	11.36	30.55	99.79
Transaction days (% all market open days)	2.77	4.92	0.19	0.61	1.28	2.88	93.01
N Accounts	97385						

Note: Portfolio value, investment in mutual funds and number of stocks are account average measures. Account tenure is defined since the account open date (available for 57% of the accounts). For observations where the open date was unavailable, it is defined as the first login date of that account in the sample period.

Table 2: Logins and Returns Since Previous Day

	$Login_{it} = 1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Most Recent Stock, %Δ + = 1	0.0366***	0.0210***	0.0222***	0.0178***	0.0146***	0.0099***
	(0.0010)	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0011)
Most Recent Stock, %Δ +		0.0042***	0.0055***	0.0048***	0.0034***	0.0071***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Most Recent Stock, %Δ -		0.0062***	0.0040***	0.0030***	0.0031***	-0.0004
		(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
FTSE100, %Δ				0.0106***	0.0058***	0.0078***
				(0.0005)	(0.0007)	(0.0005)
Remaing Stocks, %Δ					0.0092***	0.0082***
					(0.0005)	(0.0004)
Constant	0.4452***	0.4539***	0.2260***	0.2274***	0.2630***	
	(0.0018)	(0.0020)	(0.0075)	(0.0075)	(0.0100)	
Customer Controls	NO	NO	YES	YES	YES	NO
Account Controls	NO	NO	YES	YES	YES	NO
Account FE	NO	NO	NO	NO	NO	YES
Observations	1,191,201	1,191,201	1,191,201	1,190,208	992,891	992,891
R^2	0.0013	0.0017	0.0703	0.0706	0.0648	0.4631

Note: Table reports ordinary least squares regression estimates. The dependent variable is a dummy variable indicating whether the account made a login on a given day. The sample is restricted to five-day periods following the day on which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock, and makes no other trades over the following five days. This sample restriction provides 69,100 accounts. Each five-day period provides five account × day observations for the regression sample. Regressions exclude account × day outliers in returns, returns below or above percentiles 1 and 99. Columns 5 and 6 are conditional on having a portfolio with at least 2 stocks. Standard errors clustered by account in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Logins and Returns Since Previous Day, Slopes Specification

	$Login_{it} = 1$
	(1)
Most Recent Stock, %Δ + = 1	0.0128***
	(0.0015)
Most Recent Stock, %Δ +	0.0046***
	(0.0005)
Most Recent Stock, %Δ -	0.0022***
	(0.0005)
FTSE100, %Δ + = 1	0.0082***
	(0.0014)
FTSE100, %Δ +	-0.0053***
	(0.0014)
FTSE100, %Δ -	0.0083***
	(0.0014)
Remaing Stocks, %Δ + = 1	0.0141***
	(0.0015)
Remaing Stocks, %Δ +	-0.0010
	(0.0011)
Remaing Stocks, %Δ -	0.0122***
	(0.0011)
Constant	0.2639***
	(0.0100)
Customer Controls	YES
Account Controls	YES
Observations	992,891
R^2	0.0652

Note: Table reports ordinary least squares regression estimates. The dependent variable is a dummy variable indicating whether the account made a login on a given day. The sample is restricted to five-day periods following the day on which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock, and makes no other trades over the following five days. Each five-day period provides five account × day observations for the regression sample. Sample is further conditional on having a portfolio with at least 2 stocks. Standard errors clustered by account in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Logins and Returns Since Previous Day Over Four Weeks

	$Login_{it} = 1$			
	(1)	(2)	(3)	(4)
	Week 1	Week 2	Week 3	Week 4
Most Recent Stock, %Δ + = 1	0.0136***	0.0150***	0.0115***	0.0133***
	(0.0020)	(0.0020)	(0.0019)	(0.0019)
Most Recent Stock, %Δ +	0.0033***	-0.0016**	-0.0019**	-0.0037***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Most Recent Stock, %Δ -	0.0046***	0.0056***	0.0053***	0.0063***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Remaing Stocks, %Δ	0.0077***	0.0092***	0.0088***	0.0075***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
FTSE100, %Δ	0.0066***	0.0055***	0.0040***	0.0040***
	(0.0009)	(0.0009)	(0.0008)	(0.0008)
Constant	0.2667***	0.1940***	0.1668***	0.1576***
	(0.0105)	(0.0102)	(0.0101)	(0.0101)
Customer Controls	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES
Observations	537,340	535,744	532,849	528,733
R^2	0.0503	0.0566	0.0595	0.0626

Note: Table reports ordinary least squares regression estimates. The dependent variable is a dummy variable indicating whether the account made a login on a given day. The sample is restricted to portfolios with at least two stocks. The sample includes four weeks, four five-day periods following the day on which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock, and makes no other trades over the following twenty days. This sample restriction provides 48,925 accounts. Each five-day period provides five account × day observations for the regression sample. Outliers above or below the 99 and 1 percentiles of returns (both, since purchase and since the previous day) for the most recent stocks and remaining stocks are excluded. Standard errors clustered by account in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Logins and Returns Since Previous Day for Account Sub-Samples

	$Login_{it} = 1$		
	(1)	(2)	(3)
	Top-Up Buy Single-Stock Portfolio	Top-Up Buy Multiple-Stock Portfolio	New Buy Multiple-Stock Portfolio
Most Recent Stock, %Δ + = 1	0.0336***	0.0153***	0.0136***
	(0.0048)	(0.0020)	(0.0021)
Most Recent Stock, %Δ +	0.0117***	0.0032***	0.0038***
	(0.0014)	(0.0007)	(0.0007)
Most Recent Stock, %Δ -	0.0001	0.0036***	0.0022***
	(0.0013)	(0.0007)	(0.0007)
FTSE100, %Δ	0.0009	0.0056***	0.0060***
	(0.0016)	(0.0009)	(0.0010)
Remaing Stocks, %Δ		0.0094***	0.0088***
		(0.0006)	(0.0007)
Constant	0.1597***	0.2153***	0.2894***
	(0.0145)	(0.0145)	(0.0106)
Customer Controls	YES	YES	YES
Account Controls	YES	YES	YES
Observations	106,322	551,776	441,115
R^2	0.0430	0.0684	0.0588

Note: Table reports ordinary least squares regression estimates. The dependent variable is a dummy variable indicating whether the account made a login on a given day. The sample is restricted to five-day periods following the day on which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock, and makes no other trades over the following five days. Each five-day period provides five account × day observations for the regression sample. Sample split into mutually exclusive sub-samples in Columns 1 - 3. Standard errors clustered by account in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Logins on Sequential Market Closure Days

	$Login_{i,t+2} = 1$	$N\ Logins_{i,t+2}$
	(1)	(2)
Most Recent Stock, %Δ + = 1	0.0104***	0.0305**
	(0.0038)	(0.0144)
Most Recent Stock, %Δ +	-0.0053***	-0.0365
	(0.0013)	(0.0291)
Most Recent Stock, %Δ -	0.0054***	0.0371
	(0.0015)	(0.0301)
Remaing Stocks, %Δ + = 1	0.0083**	0.0616
	(0.0041)	(0.0415)
Remaing Stocks, %Δ +	-0.0119***	-0.0273***
	(0.0027)	(0.0085)
Remaing Stocks, %Δ -	0.0149***	0.0776
	(0.0034)	(0.0538)
FTSE100, %Δ + = 1	-0.0022	-0.0431
	(0.0040)	(0.0420)
FTSE100, %Δ +	0.0048	0.0041
	(0.0035)	(0.0069)
FTSE100, %Δ -	-0.0001	-0.0193
	(0.0039)	(0.0231)
Single-Stock Portfolio = 1	-0.0123	-0.0404
	(0.0084)	(0.0442)
Constant	0.1924***	0.4698**
	(0.0157)	(0.2338)
Customer Controls	YES	YES
Account Controls	YES	YES
Observations	97,734	97,734
R^2	0.0134	0.0037

Note: The table presents ordinary least squares regression estimates for market closure days. The analysis focuses on the day immediately following the first login in each sequence of consecutive market closure days. Column 1 assesses whether the account logged in the day after the initial login ($t + 2$), such as a Sunday login following Saturday. Column 2 considers the number of logins on this subsequent day. The sample includes market closure days within the month after an investor purchases or tops up a stock, excluding days when the investor trades on the first market-open day following the closures. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Logins and Returns Since Previous Day Interaction Terms

	$Login_{it}$ = 1		
	(1)	(2)	(3)
Most Recent Stock, %Δ + = 1	0.0138***	0.0159***	0.0086***
	(0.0017)	(0.0020)	(0.0030)
Female = 1	-0.0177***		
	(0.0053)		
Most Recent Stock, %Δ + = 1 × Female = 1	-0.0076***		
	(0.0029)		
Number of Stocks (10 Stocks)		0.0877***	
		(0.0029)	
Most Recent Stock, %Δ + = 1 × Number of Stocks (10 Stocks)		-0.0045***	
		(0.0014)	
Log Portfolio Value (£1000)			0.0318***
			(0.0011)
Most Recent Stock, %Δ + = 1 × Log Portfolio Value (£1000)			0.0003
			(0.0007)
Most Recent Stock, %Δ +	0.0038***	0.0052***	0.0067***
	(0.0006)	(0.0006)	(0.0006)
Most Recent Stock, %Δ -	0.0035***	0.0016***	0.0006
	(0.0006)	(0.0005)	(0.0005)
FTSE100, %Δ	0.0048***	0.0059***	0.0058***
	(0.0007)	(0.0007)	(0.0007)
Remaing Stocks, %Δ	0.0098***	0.0090***	0.0089***
	(0.0005)	(0.0005)	(0.0005)
Constant	0.4821***	0.4081***	0.3670***
	(0.0025)	(0.0030)	(0.0042)
Observations	992,891	992,891	992,891
R^2	0.0028	0.0199	0.0124

Note: The table tests whether the main results presented in Table 2, that stocks in gain induce excess logins compared with those in loss, vary by investor characteristics and account characteristics: gender (Column 1), the number of stocks held (Column 2), and the portfolio value (Column 3). Standard errors clustered by account in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Logins and Spillovers:
Trades of Other Stocks and Returns Since Previous Day

	$Trade\ Other\ Stock_{it} = 1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0030***	0.0048***	0.0055***	-0.0025***	-0.0005**	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Target Stock, %Δ +		0.0009***	0.0010***		-0.0003***	-0.0003***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Target Stock, %Δ -		-0.0027***	-0.0030***		-0.0013***	-0.0015***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
A Login = 1				0.1216***	0.1215***	0.1213***
				(0.0007)	(0.0007)	(0.0007)
Account FE	YES	YES	YES	YES	YES	YES
Stock FE	NO	NO	YES	NO	NO	YES
Day FE	NO	NO	YES	NO	NO	YES
Observations	8,966,204	8,966,204	8,966,204	8,966,204	8,966,204	8,966,204
R^2	0.1090	0.1092	0.1115	0.1534	0.1535	0.1554

Note: The table displays the effect of a gain in a target stock on the trading activity of other stocks in the days after the target stock is purchased. The target stock is defined as the first stock purchased in the month. Target stocks exclude those purchased on days when the investor traded multiple stocks. The sample includes the 30 days subsequent to the purchase of the target stocks, excluding weekends, during which transactions in other stocks may or may not have occurred. Outliers above or below the 99 and 1 percentile of returns are excluded. Standard errors clustered by account in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 9: Effect of Gains on Participation in Survey 2 - Baseline Experiment

	Effects of Absolute Gains		Effects of Gains Relative to the FTSE100	
	(1)	(2)	(3)	(4)
Gain = 1	0.0506**	0.0492**		
	(0.0248)	(0.0247)		
Gain Relative to $FTSE100$ = 1			0.0594**	0.0582**
			(0.0251)	(0.0250)
Constant	0.2566***	0.3147***	0.2550***	0.3125***
	(0.0121)	(0.0484)	(0.0121)	(0.0484)
Demographic Controls	NO	YES	NO	YES
Observations	1,753	1,753	1,753	1,753
R^2	0.0024	0.0188	0.0032	0.0196

Note: The table displays ordinary least squares regression estimates for the effect of stock gains on the participation in Survey 2. The dependent variable is a dummy that takes the value of 1 if the participant replied to Survey 2. Columns 2 and 4 add demographic controls. *p<0.1; **p<0.05; ***p<0.01

Table 10: Effect of Gains on Participation on Survey 2 - Additional Incentive Experiment

	Effects of Absolute Gains		Effects of Gains Relative to the FTSE100	
	(1)	(2)	(3)	(4)
Gain = 1	0.0461***	0.0399**		
	(0.0166)	(0.0167)		
Gain Relative to $FTSE100$ = 1			0.0432***	0.0372**
			(0.0165)	(0.0166)
£2 Treatment = 1	0.0293*	0.0285*	0.0297*	0.0288*
	(0.0165)	(0.0165)	(0.0165)	(0.0165)
Constant	0.3011***	0.3360***	0.2982***	0.3350***
	(0.0137)	(0.0436)	(0.0145)	(0.0438)
Demographic Controls	NO	YES	NO	YES
Observations	3,274	3,274	3,274	3,274
R^2	0.0034	0.0113	0.0031	0.0111

Note: The table displays ordinary least squares regression estimates for the effect of stock gains on the participation in Survey 2. The dependent variable is a dummy that takes the value of 1 if the participant replied to Survey 2. Columns 2 and 4 add demographic controls. *p<0.1; **p<0.05; ***p<0.01

Table 11: Effect of Gains on Participation on Survey 2 - Information Experiment

	Effects of Absolute Gains		Effects of Gains Relative to the S&P500	
	(1)	(2)	(3)	(4)
Gain = 1	0.0141	0.0144		
	(0.0149)	(0.0149)		
Gain Relative to *S&P*500 = 1			0.0741***	0.0734***
			(0.0139)	(0.0139)
Information Treatment = 1	-0.0097	-0.0104	-0.0083	-0.0090
	(0.0139)	(0.0139)	(0.0138)	(0.0139)
Constant	0.2498***	0.3014***	0.2245***	0.2756***
	(0.0141)	(0.0374)	(0.0118)	(0.0366)
Demographic Controls	NO	YES	NO	YES
Observations	3,945	3,945	3,945	3,945
R^2	0.0004	0.0033	0.0073	0.0101

Note: The table displays ordinary least squares regression estimates for the effect of stock gains on the participation in Survey 2. The dependent variable is a dummy that takes the value of 1 if the participant replied to Survey 2. Columns 2 and 4 add demographic controls. *p<0.1; **p<0.05; ***p<0.01

Table 12: Effect of Gains and Treatment Interaction on Survey 2 Participation - Information Experiment

	Effects of Gains Relative to the S&P500			
	(1)	(2)	(3)	(4)
Gain Relative to *S&P*500 = 1	0.0741***	0.0734***	0.0613***	0.0606***
	(0.0139)	(0.0139)	(0.0196)	(0.0197)
Information Treatment = 1	-0.0083	-0.0090	-0.0201	-0.0208
	(0.0138)	(0.0139)	(0.0188)	(0.0189)
Gain Relative to *S&P*500 = 1 × Information Treatment = 1			0.0256	0.0256
			(0.0277)	(0.0278)
Constant	0.2245***	0.2756***	0.2305***	0.2814***
	(0.0118)	(0.0366)	(0.0135)	(0.0372)
Demographic Controls	NO	YES	NO	YES
Observations	3,945	3,945	3,945	3,945
R^2	0.0073	0.0101	0.0075	0.0103

Note: The table displays ordinary least squares regression estimates for the effect of stock gains on the participation in Survey 2. The dependent variable is a dummy that takes the value of 1 if the participant replied to Survey 2. Columns 2 and 4 add demographic controls. *p<0.1; **p<0.05; ***p<0.01