CENTRE FOR DECISION RESEARCH & EXPERIMENTAL ECONOMICS

Discussion Paper No. 2022-19

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September 2022

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CeDEx Discussion Paper Series
ISSN 1749 - 3293

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Attention Utility: Evidence From Individual Investors

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September 10, 2022

Abstract

We introduce attention utility, the hedonic pleasure or pain derived purely from paying attention to information, and differs from the news utility that arises from gaining new information. Two studies document selective attention to good news. The first 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. A second experimental study shows that investors are more likely to engage in a paid task that will involve attention to a prior investment if that investment has gained value.

Keywords: information utility, attention, login, investor behavior

JEL Codes: G40, G41, D14

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This paper is an extension of the results presented in Quispe-Torreblanca's PhD Thesis Chapter 4: Selective Attention Among Individual Investors. This work was supported by Economic and Social Research Council grants ES/K002201/1, ES/N018192/1, ES/P008976/1, and Leverhulme grant RP2012-V-022.

"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. We introduce the concept of *attention utility*. Attention utility is the hedonic pleasure, or displeasure, derived purely from looking at, or thinking about – i.e., paying attention to – known information. Casual observation suggests that individuals enjoy spending time looking at, or thinking about, positive information even when this information is already known, with examples including exam scores, sports results and large retirement porfolios. What distinguishes attention utility from models of beliefs-based utility, and from most prior analyses of information avoidance, is that the information is already known to the individual, yet a stream of utility is conferred from the act of paying attention to – savouring – the information. Attention-based utility is not entirely separable from belief-based utility – one's beliefs constrain what one can think about, and what one thinks about and pays attention to affects one's beliefs – but what one pays attention to at a particular moment is very different from the overall set of beliefs that one has cumulatively developed.

In this paper, we present two studies – a main study examining the portfolio look-up behavior of retail investors and a second, experimental, study examining investor's decisions to make money by answering questions about a stock – both showing 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 already knows this information. 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

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

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 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,[6] 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 performance of individual stocks. The pattern we observe occurs from the first day following purchase, persists over the following month since purchase, exists across different types of stock purchases, such as top-up of an existing stock and purchase of a new stock, and

[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.

[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) point to the existence of a pure attention-utility effect by examining login behavior on Sundays. They 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 (because the market is closed on weekends).

occurs in both thin and thick portfolios.

Furthermore, 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 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 affect again 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 an online pre-registered[7] experiment designed to test whether investors are reluctant to pay attention to bad news about their stocks. 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), in 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

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

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 combination, the findings of these two 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 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). Applied to investors, 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. It is quite likely that people choose friends and romantic partners who help them to focus attention on aspects of themselves and of life that make them feel good about themselves and good about life in general. 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, 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. In Section 2, we present our second study, an experiment on investors' attention. An overview of the experimental design is presented in Section 2.1, followed by a discussion of the main results in Section 2.2. 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 in to their account each day.[8] 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.[9] Third, we remove accounts for which basic demographic data is missing (including age, gender and account tenure). 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.[10]

Table A1 reports the effects of these steps in sample selection. The table reports the number of accounts dropped due to each step in the sample restrictions, together with the number of login-days, transaction-days and buy-days dropped at each step. From the starting sample of approximately 155,000 accounts, the largest drop of accounts is due to the removal of approximately 41,000 inactive accounts (26.4%). The resulting sample, which we refer to as the baseline sample, retains approximately 87,000 accounts (56.1%). 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 69.5% of login-days, 71.9% of transaction-days and

[8] During the data period the brokerage operated only through an online interface. Barclays has subsequently introduced a mobile phone trading app.

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

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

71.8% of buy-days from the starting sample.

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 Stastistics

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. The average age of an account holder is 54 years (median 57 years).[11] 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-and-a-half years. This profile of account holders is similar to that seen in US data (see Barber and Odean, 2001).[12]

Summary statistics for account characteristics in Panel B show that the average portfolio value is approximately £60,000 (median £15,000), 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).[13] 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.

Figure A1 Panel A 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

[11] Age is top coded at 77 years to account for potential recording errors in age (3% of accounts have a recorded age over 87 years).

[12] 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).

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

observations.[14] The plot shows a clear positive relationship between login frequency and trading frequency. The plot also reveals that logins are much more frequent than trades across the full distribution of login and trading frequency. 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 (located in the bottom-left quadrant of the plot) and, to a lesser extent, for accounts that are less active in trading (located in the top-right quadrant of the plot).[15] Panels B and C of Figure A1 illustrate the distributions of login frequency and trading frequency, independently.[16] Table A6 provides summary statistics for the frequency of logins and frequency of trades. The account-level average number of days between logins (including non-market days) is 18.4 (median 8.6) whereas the average number of days between transactions is 115.9 (median 71). The ratio of login days to transaction days is on average 20.7 (median 9.8), with an inter-quartile range of 5 to 21. 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.

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 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.[17] In this way, we can detect excess logins arising purely

[14] In the plots in Figure A1, we restrict the data to the bottom 95% of accounts, which excludes those who log in at intervals greater than 70 days.

[15] In Panel A, 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.

[16] These two marginal distributions have similar shapes. Approximately 4.9% of accounts log in every day, with 45.1% 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 3.6% of accounts trade on average at least once per week.

[17] 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.

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.

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. We first restrict the baseline sample to the sub-sample of accounts in which investors made at least one buy-trade in the sample period. We define a buy-day as a day on which an investor makes a stock purchase, either purchasing a new stock or adding to an existing position. For purposes of this analysis only (when we examine trades, we use a different restriction), we first examine six-day periods during which an individual makes a stock purchase and then, over the next five days, does not make a subsequent stock purchase or sale (so that the purchased stock remains, during the period, the most recently purchased stock). This restriction allows us to focus on login activity over the five-day period that is for non-trading purposes, or that at least *ex post* does not result in a trade. Login activity spikes around buy-days, as illustrated in Figure A2 in the Online Appendix.[18] In subsequent analysis of investor attention, we extend the length of the window beyond five days. This sample restriction retains 61,842 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.[19] 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[20], with days 1-5 being the five days in the period following the buy transaction. The blue line illustrates observations (days) for which the return on the previous day is a gain, with the red line illustrating observations for which the return on the previous day is a loss (including a loss of zero). 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

[18] Figure A2 shows that the probability of login increases in the day before a trade, then decreases gradually over the following days.

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

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

returns and the probability of login, with evidence of a jump in the probability of login when the stock return becomes positive.

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

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).[21] Results are shown in Table 2. Column 1 includes only this dummy variable. The coefficient value of 0.039 implies that a gain on the most recently purchased stock increases the likelihood of login by approximately 3.9 percentage points, an increase of 9% 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 login 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. 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 3.4% on the baseline probability calculated from the constant term in Column 1.

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.[22] These estimates

[21] 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.

[22] Regressions in this main analysis and in the robustness and sensitivity tests exclude account × day outliers in

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.[23]

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 in to their accounts in order *to discover* stock returns, we would see an equal likelihood of login for stocks that have gained or lost value, as, at the point of login, 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, next we present robustness and sensitivity tests.

1.4.2 Robustness and Sensitivity Tests

Functional Form

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 continuously 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. The coefficient on the dummy variable indicating gain/loss on the most recent 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 3% on the baseline

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returns, removing observations below or above percentiles 1 and 99.

[23] 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 A2 for estimates).

probability calculated from the constant term in Column 1 of Table 2.

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.[24] 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).

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 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. Figures are presented in Figure A3 to Figure A6. Regression estimates are reported in Table 5. 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 compared with 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

[24] 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 53,110 accounts from the baseline sample.

purchase price.[25] 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. We therefore substitute the measure of returns in the sample used in our main results. In the main sample, the correlation between the two measures of returns is 0.495. The results presented in the Online Appendix reveal very similar patterns when this alternative measure of returns is used in the analysis. Figure A7 reproduces the same patterns as those seen in Figure 1 using returns since purchase. Table A3 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 A5 shows similar results to Table 5 in a specification in which returns since the previous day are replaced by returns since purchase.

1.4.3 Attention over Sequences of Market Closure Days

As an additional test, we analyse login behaviour on sequential market closure days.[26] The rationale for examining logins on sequential market closure days is as follows. Markets are often closed over a sequence of days, such as at weekends and on public holidays; hence the value of an individual's stock holdings on sequential market closure days is unchanged from the day before closure (such as a Friday) until the market opens again (such as a Monday). We can therefore treat login events 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. 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. 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). Hence, 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

[25] 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).

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

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 purchase of the stock. 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 0.0116 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 1.2 percentage points, or 2.6%, 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.

1.4.4 Further Extensions

Attention to Most Recent vs. Earlier Stocks

Our main result is that investors are more likely to login 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. We specifically focus on the effect of returns on the most recently purchased stock compared with the second most recently purchased stock. 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. This allows us to test whether the coefficient on the most recent stock converges to the coefficient on the second most recent stock over time.

Table A7 presents results from this test. 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 80.47%.

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.

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. 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. Equally, the interaction term with the size of the portfolio shows a negative coefficient, although not statistically significantly different from zero. Table A8 replicates these results using returns since purchase.

1.5 From Attention to Action in Trading Behavior

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. Investors' willingness to look at gains and losses on their most recent purchase could affect their trading decisions because, in order to trade, investors have to log in to their accounts. Once they do, 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.

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 purchase 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.[27]

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 on which 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 downwards when the magnitude of the loss is omitted. The coefficient value of 0.0063 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 0.6 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 behaviour 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 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 buying 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 9. 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

[27] 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.

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. As a sensitivity test, in Table A10 and Table A11 we replicate the analysis from Table 8 and Table 9 but shorten the time period of analysis to two weeks. When we do so, results are unchanged.[28]

This analysis is extended to the sample of sequential market closure days, with results shown in Table 10. In this analysis, the dependent variable of interest across Columns 4 - 6 is a dummy indicating that at least one trade took place on the day after the last market closed day in the sequence (e.g., a trade on a Monday following the Sunday). For clarity, in Columns 1 - 3 we replicate our main findings from Table 6 but with a larger set of observations (contrary to Table 6, transactions could occur during the 30 days subsequent to the purchase of the target stocks). The dependent variable in Columns 1 - 3 is a dummy indicating whether the account made a login on the day subsequent to the first login day in each series of sequential market closure days (usually, but not necessarily, a login on a Sunday following a login on a Saturday). The coefficient in Column 3 on the gain dummy on the most recent stocks shows that investors are 0.086 percentage points more likely to log in after a recent stock gain.

In Columns 4 to 6, the dependent variable is a dummy for a transaction on the subsequent Monday (or the first business day following the sequence of market closure days). Across all columns, the return of the target stock corresponds to the latest market open day (usually, but not necessarily, to Friday returns). The sample is restricted to observations following the first login day in each series of sequential market closure days. During weekends, it is restricted to logins on the first market closure day, $Login_{i,t+1} = 1$.

Columns 4 shows that, in line with the results from the main sample, individuals are more likely to make a trade on another stock on the next market open day if the stock made a gain on the previous market open day prior to the sequence of market closure days. However, consistent with the main analysis, this effect attenuates and loses precision with the inclusion of login dummies (Columns 5 and 6), either for a login on the last market closure day in the sequence (e.g., Sunday) or the next market open day (e.g., Monday). Hence this effect of gains on trading behavior diminishes when one controls for investor attention behavior, consistent with the main analysis.

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

[28] As a further sensitivity test, we replace returns since the previous day in this specification with returns since purchase. Results are shown in Table A9 and Table A12. 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.

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.

2 Study 2: The Experiment

To provide more direct evidence of the role of attention utility in decision-making and economic outcomes, we conducted an online experiment[29] designed to rule out the possibility that participants' attention choices are motivated by the desire to acquire new information regarding their stocks. Although the previous section demonstrated that there is 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).[30]

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 ran an online experiment that we describe next.

2.1 Experimental Setting

We explore attention allocation in a quasi-experimental setting. This 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. In an initial survey (Survey 1), we asked them for the name of the stock that had the highest total valuation of shares they had owned for at least 6 months.[31] Then we

[29] Strictly, the 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.*

[30] 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.

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

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 investing behaviour more generally. An example of this email can be found in Figure A11. This survey included checks that verified that they understood the information they received by email.[32] The survey was optional. 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 second survey) or had increased relative to the FTSE100. We pre-registered the experimental design and outcomes.[33]

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.[34] 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. Detailed sample selection steps are presented in Table A13. Our baseline sample excludes 21 participants who failed to pass the checks verifying that they understood the information they received (e.g., when their stocks' performance actually declined, they reported it as having increased). Sample summary statistics across respondents and non-respondents of Survey 2 are given in Table A14. Except for gender (male investors were more likely to respond to the survey), observable characteristics are quite similar between these two groups.

2.2 Experimental 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 11 reports our baseline regressions. Columns 1 and 2 examine the effect of absolute gains. Columns 1 and 2 demonstrate that participants were 5.38 percentage points more likely

[32] Survey questions can be found in Figure A12 and Figure A13.

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

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

to respond to Survey 2 when their stock was in gain (with a baseline of 25.82% when the stock was in loss, given by the constant; this change represents a relative increase of 20.8% 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 6.05 percentage points (against a baseline of 25.72% when the stock is in loss, represented by the constant; this change represents a relative increase of 23.5% in the probability of responding to the survey).

2.2.1 Robustness Tests

In the Online Appendix, we perform additional robustness checks. Table A15 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 think about their 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.

2.2.2 Participants Trading Habits

Survey 2 asked participants about their trading habits. While we did not make hypotheses regarding participants' responses, the results of this survey, displayed in Figure A8, reveal that stock gains increased the probability of making a sale (a phenomenon known as the disposition effect); however, they have the opposite effect on the probability of making a purchase. The similarity of these trading behaviors to those observed in the literature is indicative that our sample is representative of average retail investors. We found no significant differences between participants who experienced gains in relation to the frequency with which they monitor their portfolios, the levels of confidence in their investments (Figure A9), and the reasons they bought their shares (Figure A10).

3 Conclusion

We contribute to the literature on information and attention by introducing the concept of attention utility: the hedonic pleasure derived purely from looking at information. We use detailed daily-level data on individual investor stock portfolios, combined with daily-level information on login activity, to examine how stock performance affects attention and trading. We show that individuals devote excess attention to already-known positive information about the performance of individual stocks in their portfolios. Hence, 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.

In addition, our results demonstrate 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 login to 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.

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, however, such as the current study, 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".[35] 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 – e.g., "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."[36] Consistent with the latter strategy, the current

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

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

research identifies selective attention as one strategy that investors use to maximize positive and minimize negative emotions associated with investing, with potential benefits for their investing behavior.

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 (Koszegi et al., 2019). In the domain of healthcare, people may not take medications in part because doing so forces a focus of attention on health conditions that people would prefer not to think about (Schwardmann, 2019). In the financial realm, someone who finds it painful to think about a parking ticket that 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 it (Olafsson and Pagel, 2017). And, 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."

In general, attention utility has implications for the allocation of time. Individuals will prefer tasks and activities that confer positive attention utility and will avoid tasks and activities that involve negative attention utility. Individuals 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.

In addition, 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). When it comes down to it, we suspect, for many actions and activities that have been interpreted as conveying information, the direction of attention may also play an important role (cf. Schwartzstein and Sunderam, 2019).

Our results provide a new dimension to the literature on information and attention, suggesting a purely attentional motivation for experiencing looking at information. The concept of attention utility has hitherto not been considered by economists, and is an area we see as fruitful for future research and theorizing, including models that might contribute to the theoretical underpinnings of utility derived from paying attention.

References

Akerlof, G. A. (1978). The market for "lemons": Quality uncertainty and the market mechanism. In *Uncertainty in Economics*, pp. 235–251. Elsevier.

Andries, M. and V. Haddad (2020). Information aversion. *Journal of Political Economy 128*, 1901–1939.

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

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

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

Barber, B. M. and T. Odean (2013). The behavior of individual investors. *Handbook of the Economics of Finance; Volume 2A* (1), 1533–1570.

Barber, B. M., T. Odean, and L. Zheng (2005). Out of sight, out of mind: The effects of expenses on mutual fund flows. *The Journal of Business 78*(6), 2095–2120.

Barberis, N. (2018). Psychology-based models of asset prices and trading volume. In *Handbook of Behavioral Economics: Foundations and Applications 1*, pp. 79–175. Elsevier.

Barberis, N. and M. Huang (2001). Mental accounting, loss aversion and individual stock returns. *Journal of Finance 56*, 1247–1292.

Bolte, L. and C. Raymond (2022, February). Emotional inattention.

Bordalo, P., N. Gennaioli, and A. Shleifer (2012). Salience theory of choice under risk. *Quarterly Journal of Economics 127*, 1243–1285.

Brunnermeier, M. K. and J. A. Parker (2005). Optimal expectations. *American Economic Review 95*, 1092–1118.

Bushong, B., M. Rabin, and J. Schwartzstein (2015). A model of relative thinking. *Unpublished manuscript, Harvard University, Cambridge, MA.*

Caplin, A. and M. Dean (2015). Revealed preference, rational inattention, and costly information acquisition. *American Economic Review 105*, 2183–2203.

Caplin, A. and J. Leahy (2001). Psychological expected utility theory and anticipatory feelings. *Quarterly Journal of Economics 116*, 55–79.

Carlin, B., A. Olafsson, and M. Pagel (2017). Fintech adoption across generations: Financial fitness in the information age. Technical report, National Bureau of Economic Research.

Chang, T. Y., D. H. Solomon, and M. M. Westerfield (2016). Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect. *Journal of Finance 71*, 267–302.

Chetty, R., A. Looney, and K. Kroft (2009). Salience and taxation: Theory and evidence. *American Economic Review 99*, 1145–77.

Choi, J. J., D. Laibson, and B. C. Madrian (2010). Why does the law of one price fail? an experiment on index mutual funds. *The Review of Financial Studies 23*(4), 1405–1432.

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

DellaVigna, S. and J. M. Pollet (2009). Investor inattention and friday earnings announcements. *Journal of Finance 64*, 709–749.

Deshpande, R. and A. K. Kohli (1989). Knowledge disavowal: structural determinants of information-processing breakdown in organizations. *Knowledge 11*, 155–169.

Falk, A. and F. Zimmermann (2022). Information demand: Experimental evidence on preferences for information.

Feng, L. and M. S. Seasholes (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance 9*, 305–351.

Finkelstein, A. (2009). E-ztax: Tax salience and tax rates. *Quarterly Journal of Economics 124*, 969–1010.

Gabaix, X. (2019). Behavioral inattention. In *Handbook of Behavioral Economics: Foundations and Applications 2*, pp. 261–343. Elsevier.

Ganguly, A. and J. Tasoff (2016). Fantasy and dread: The demand for information and the consumption utility of the future. *Management Science 63*, 4037–4060.

Geanakoplos, J., D. Pearce, and E. Stacchetti (1989). Psychological games and sequential rationality. *Games and Economic Behavior 1*, 60–79.

Gherzi, S., D. Egan, N. Stewart, E. Haisley, and P. Ayton (2014). The meerkat effect: Personality and market returns affect investors' portfolio monitoring behaviour. *Journal of Economic Behavior & Organization 107*, 512–526.

Goetzmann, W. N. and A. Kumar (2008). Equity portfolio diversification. *Review of Finance 12*, 433–463.

Golman, R., D. Hagmann, and G. Loewenstein (2017). Information avoidance. *Journal of Economic Literature 55*, 96–135.

Golman, R. and G. Loewenstein (2015). Curiosity, information gaps, and the utility of knowledge. *Information Gaps, and the Utility of Knowledge (April 16, 2015).*

Hartzmark, S. M. (2015). The worst, the best, ignoring all the rest: The rank effect and trading behavior. *Review of Financial Studies 28*, 1024–1059.

Hirshleifer, D., S. S. Lim, and S. H. Teoh (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance 64*(5), 2289–2325.

Karlsson, N., G. Loewenstein, and D. Seppi (2009). The ostrich effect: Selective attention to information. *Journal of Risk and Uncertainty 38*, 95–115.

Kőszegi, B. (2003). Health anxiety and patient behavior. *Journal of Health Economics 22*, 1073–1084.

Kőszegi, B. (2010). Utility from anticipation and personal equilibrium. *Economic Theory 44*, 415–444.

Koszegi, B., G. Loewenstein, and T. Murooka (2019). Fragile self-esteem. *Available at SSRN 3412006.*

Kőszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *Quarterly Journal of Economics 121*, 1133–1165.

Kőszegi, B. and M. Rabin (2007). Reference-dependent risk attitudes. *American Economic Review 97*, 1047–1073.

Kőszegi, B. and M. Rabin (2009). Reference-dependent consumption plans. *American Economic Review 99*, 909–36.

Kőszegi, B. and A. Szeidl (2012). A model of focusing in economic choice. *Quarterly Journal of Economics 128*, 53–104.

Loewenstein, G. (1987). Anticipation and the valuation of delayed consumption. *Economic Journal 97*, 666–684.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance 7*, 77–91.

Marshall, G. (2015). *Don't even think about it: Why our brains are wired to ignore climate change.* Bloomsbury Publishing USA.

Olafsson, A. and M. Pagel (2017). The ostrich in us: Selective attention to financial accounts, income, spending, and liquidity. Technical report, National Bureau of Economic Research.

Oster, E., I. Shoulson, and E. Dorsey (2013). Optimal expectations and limited medical testing: evidence from huntington disease. *American Economic Review 103*, 804–30.

Pagel, M. (2018). A News-Utility Theory for Inattention and Delegation in Portfolio Choice. *Econometrica 86*, 491–522.

Sallee, J. M. (2014). Rational inattention and energy efficiency. *The Journal of Law and Economics 57*, 781–820.

Schulz-Hardt, S., D. Frey, C. Lüthgens, and S. Moscovici (2000). Biased information search in group decision making. *Journal of Personality and Social Psychology 78*, 655.

Schwardmann, P. (2019). Motivated health risk denial and preventative health care investments. *Journal of Health Economics 65*, 78–92.

Schwartzstein, J. and A. Sunderam (2019). Using models to persuade. Technical report, National Bureau of Economic Research.

Shapira, Z. and I. Venezia (2001). Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance 25*, 1573–1587.

Sharot, T. and C. R. Sunstein (2020). How people decide what they want to know. *Nature Human Behaviour 4*, 14 – 19.

Shefrin, H. and M. Statman (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance 40*, 777–790.

Sicherman, N., G. Loewenstein, D. J. Seppi, and S. P. Utkus (2015). Financial attention. *Review of Financial Studies 29*, 863–897.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics 50*, 665–690.

Spence, M. (1978). Job market signaling. In *Uncertainty in Economics*, pp. 281–306. Elsevier.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy 69*, 213–225.

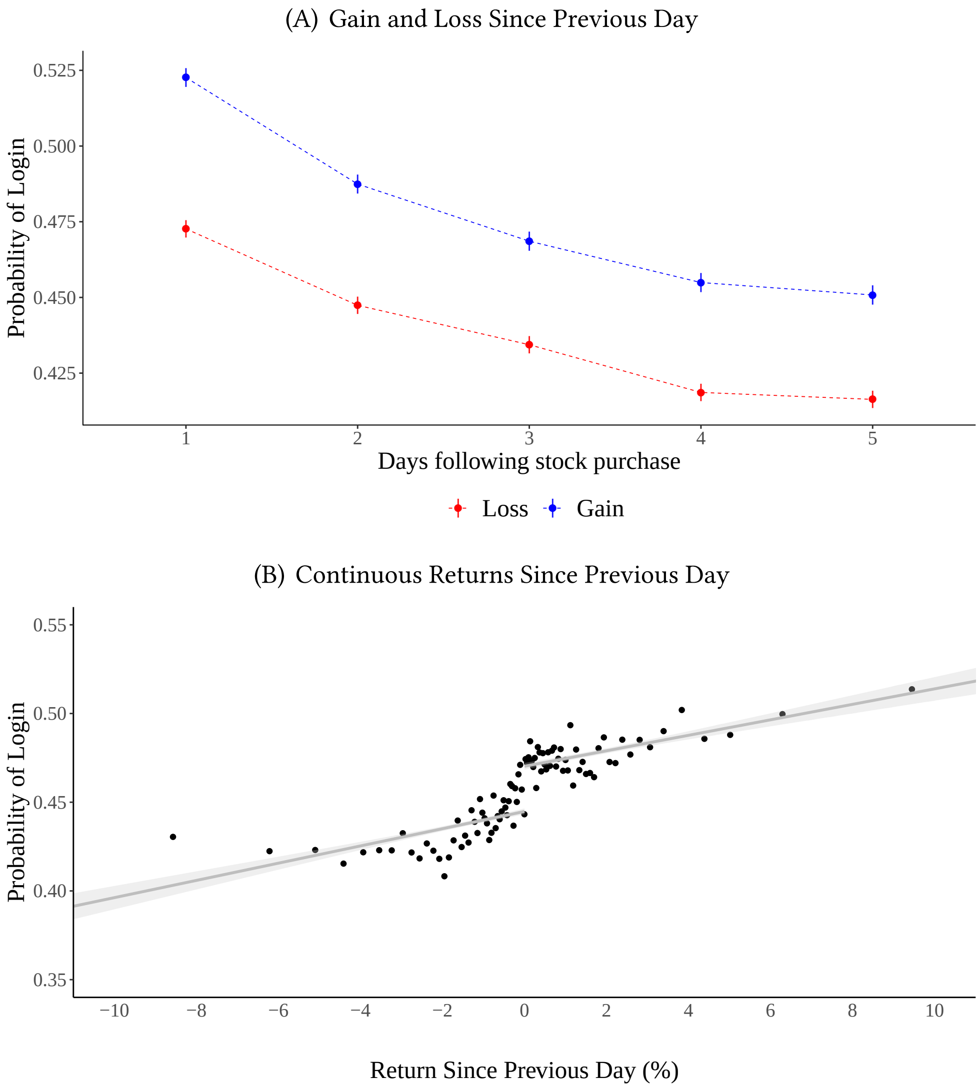
Stiglitz, J. E. (1975). The theory of "screening," education, and the distribution of income. *American Economic Review 65*, 283–300.

Sweeny, K., D. Melnyk, W. Miller, and J. A. Shepperd (2010). Information avoidance: Who, what, when, and why. *Review of General Psychology 14*, 340–353.

Taubinsky, D. and A. Rees-Jones (2018). Attention variation and welfare: Theory and evidence from a tax salience experiment. *Review of Economic Studies 85*, 2462–2496.

Zaltman, G. (1983). Knowledge disavowal in organizations. *Producing Useful Knowledge for Organizations*, 173–87.

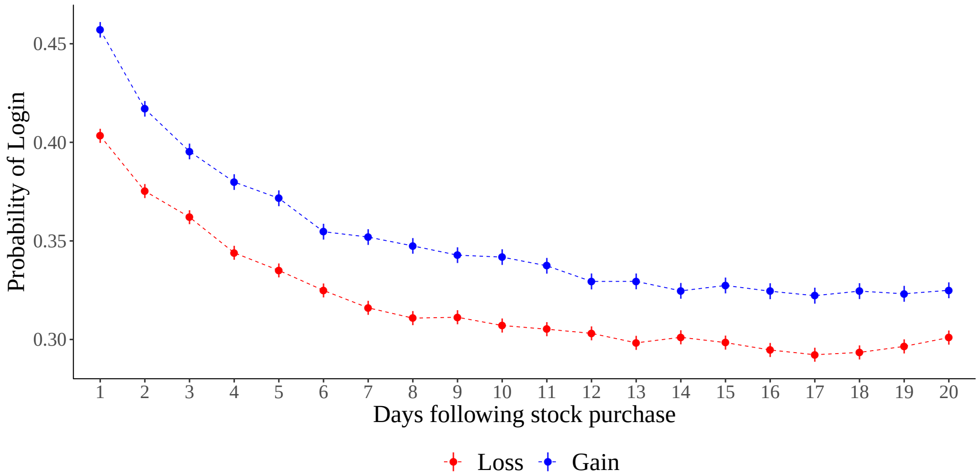
Figure 1: Probability of Login by Stock Returns



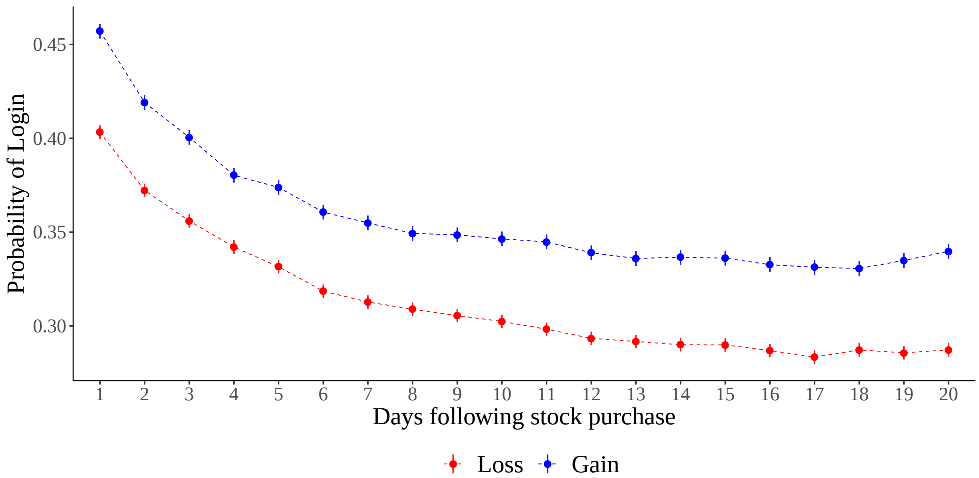
Note: Figure illustrates the relationship between returns on a recently purchased stock, and the probability of an account login, over the following five market open days after the purchase day. Panel A shows the probability of a login on each of the five market open days following the purchase of a 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 216,164 five-day periods from 61,842 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 123,555 twenty-day periods from 53,110 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	0.22						
Age (years)	53.76	14.17	17.00	47.00	57.00	67.00	77.00
Account Tenure (years)	4.97	3.40	0.03	2.73	3.99	6.53	16.99
B. Account Characteristics							
Portfolio Value (£1000)	60.00	173.69	0.04	4.59	15.34	45.27	3058.87
Investment in Mutual Funds (%)	7.04	20.64	0.00	0.00	0.00	0.00	100.00
Number of Stocks	5.07	6.60	0.02	1.55	3.19	6.36	772.75
Login days (% all days)	20.00	20.97	0.27	4.16	11.04	29.65	98.95
Transaction days (% all market open days)	2.72	4.81	0.19	0.61	1.27	2.82	93.01
N Accounts	87152						

Note: Statistics for the baseline sample of accounts defined in Table A1. 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 64% 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	0.0395***	0.0255***	0.0264***	0.0178***	0.0149***	0.0107***
	(0.0011)	(0.0015)	(0.0014)	(0.0015)	(0.0016)	(0.0012)
Most Recent Stock, %Δ +		0.0044***	0.0057***	0.0051***	0.0035***	0.0072***
		(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0004)
Most Recent Stock, %Δ -		0.0049***	0.0027***	0.0028***	0.0029***	-0.0008**
		(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0004)
FTSE100, %Δ				0.0110***	0.0063***	0.0082***
				(0.0005)	(0.0007)	(0.0006)
Remaing Stocks, %Δ					0.0091***	0.0079***
					(0.0005)	(0.0004)
Constant	0.4379***	0.4448***	0.1808***	0.1846***	0.2233***	
	(0.0019)	(0.0021)	(0.0143)	(0.0144)	(0.0167)	
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	1,057,409	1,057,409	1,057,409	1,050,761	870,827	870,827
R^2	0.0016	0.0018	0.0707	0.0713	0.0654	0.4617
Adjusted R^2	0.0016	0.0018	0.0706	0.0713	0.0654	0.4273

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 61,842 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	0.0130***
	(0.0016)
Most Recent Stock, %Δ +	0.0048***
	(0.0006)
Most Recent Stock, %Δ -	0.0019***
	(0.0006)
FTSE100, %Δ + = 1	0.0094***
	(0.0015)
FTSE100, %Δ +	-0.0061***
	(0.0015)
FTSE100, %Δ -	0.0092***
	(0.0015)
Remaing Stocks, %Δ + = 1	0.0150***
	(0.0016)
Remaing Stocks, %Δ +	-0.0019*
	(0.0011)
Remaing Stocks, %Δ -	0.0125***
	(0.0011)
Constant	0.2246***
	(0.0168)
Customer Controls	YES
Account Controls	YES
Observations	870,827
R^2	0.0659
Adjusted R^2	0.0659

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	0.0147***	0.0149***	0.0119***	0.0128***
	(0.0021)	(0.0021)	(0.0020)	(0.0020)
Most Recent Stock, %Δ +	0.0030***	-0.0018**	-0.0020**	-0.0037***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Most Recent Stock, %Δ -	0.0047***	0.0059***	0.0052***	0.0068***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Remaing Stocks, %Δ	0.0076***	0.0093***	0.0089***	0.0072***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
FTSE100, %Δ	0.0068***	0.0050***	0.0035***	0.0044***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Constant	0.2228***	0.1515***	0.1152***	0.1059***
	(0.0173)	(0.0168)	(0.0165)	(0.0163)
Customer Controls	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES
Observations	473,853	472,348	469,461	465,803
R^2	0.0510	0.0578	0.0607	0.0640
Adjusted R^2	0.0509	0.0577	0.0607	0.0640

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 43,563 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	0.0304***	0.0163***	0.0131***
	(0.0050)	(0.0021)	(0.0022)
Most Recent Stock, %Δ +	0.0126***	0.0033***	0.0039***
	(0.0014)	(0.0007)	(0.0008)
Most Recent Stock, %Δ -	-0.0003	0.0033***	0.0021***
	(0.0013)	(0.0007)	(0.0008)
FTSE100, %Δ	0.0013	0.0061***	0.0066***
	(0.0016)	(0.0009)	(0.0010)
Remaing Stocks, %Δ		0.0092***	0.0088***
		(0.0006)	(0.0007)
Constant	0.0871***	0.1704***	0.2545***
	(0.0311)	(0.0221)	(0.0180)
Customer Controls	YES	YES	YES
Account Controls	YES	YES	YES
Observations	96,946	482,755	388,072
R^2	0.0442	0.0696	0.0595
Adjusted R^2	0.0438	0.0695	0.0594

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	0.0116***	0.0231***
	(0.0040)	(0.0077)
Most Recent Stock, %Δ +	-0.0060***	-0.0091***
	(0.0013)	(0.0026)
Most Recent Stock, %Δ -	0.0057***	0.0063**
	(0.0015)	(0.0030)
Remaing Stocks, %Δ + = 1	0.0089**	0.0236***
	(0.0042)	(0.0075)
Remaing Stocks, %Δ +	-0.0132***	-0.0232***
	(0.0028)	(0.0050)
Remaing Stocks, %Δ -	0.0145***	0.0213***
	(0.0035)	(0.0065)
FTSE100, %Δ + = 1	-0.0011	0.0012
	(0.0041)	(0.0078)
FTSE100, %Δ +	0.0072**	0.0069
	(0.0036)	(0.0066)
FTSE100, %Δ -	-0.0053	-0.0012
	(0.0040)	(0.0075)
Single-Stock Portfolio = 1	-0.0025	0.0204
	(0.0084)	(0.0153)
Constant	0.1974***	0.2741***
	(0.0261)	(0.0522)
Customer Controls	YES	YES
Account Controls	YES	YES
Observations	94,098	94,098
R^2	0.0155	0.0155
Adjusted R^2	0.0151	0.0151

Note: Table reports ordinary least squares regression estimates. The sample is restricted to market closure days, following the first login day in each series of sequential market closure days. The dependent variable in Column 1 is a dummy variable indicating whether the account made a login on the day subsequent to the first login in the series (such as a login on Sunday following a login on Saturday). In Column 2, the dependent variable is the count of logins on that day. The sample includes market closure days occurring during the month following the day in which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock. Periods could be shorter of a month if the investor buys/top up an stock in between, in which case the new stock becomes the most recent stock. In most cases, the dependent variable corresponds to logins on the second day of the series $t + 2$ (e.g., on a Sunday), conditional on login events on the first day $t + 1$ (e.g., on a Saturday). However, in cases of three-day or four-day holiday periods, the sample could include observations with logins in the second or third day. In those cases, the dependent variable corresponds to logins in the third or fourth day, respectively. *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	0.0142***	0.0166***	0.0100***
	(0.0018)	(0.0021)	(0.0031)
Female = 1	-0.0176***		
	(0.0053)		
Most Recent Stock, %Δ + = 1 × Female = 1	-0.0082***		
	(0.0029)		
Number of Stocks (10 Stocks)		0.0913***	
		(0.0033)	
Most Recent Stock, %Δ + = 1 × Number of Stocks (10 Stocks)		-0.0050***	
		(0.0016)	
Log Portfolio Value (£1000)			0.0311***
			(0.0012)
Most Recent Stock, %Δ + = 1 × Log Portfolio Value (£1000)			0.0000
			(0.0008)
Most Recent Stock, %Δ +	0.0037***	0.0052***	0.0067***
	(0.0006)	(0.0006)	(0.0006)
Most Recent Stock, %Δ -	0.0034***	0.0013**	0.0004
	(0.0006)	(0.0006)	(0.0006)
FTSE100, %Δ	0.0052***	0.0064***	0.0062***
	(0.0007)	(0.0007)	(0.0007)
Remaing Stocks, %Δ	0.0097***	0.0088***	0.0089***
	(0.0005)	(0.0005)	(0.0005)
Constant	0.4818***	0.4028***	0.3674***
	(0.0026)	(0.0032)	(0.0044)
Observations	870,827	870,827	870,827
R^2	0.0025	0.0206	0.0119
Adjusted R^2	0.0025	0.0206	0.0118

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	0.0032***	0.0056***	0.0063***	-0.0028***	-0.0005	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Target Stock, %Δ +		0.0011***	0.0011***		-0.0001	-0.0001
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Target Stock, %Δ -		-0.0035***	-0.0038***		-0.0017***	-0.0020***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Login = 1				0.1522***	0.1521***	0.1518***
				(0.0010)	(0.0010)	(0.0010)
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	4,058,647	4,058,647	4,058,647	4,058,647	4,058,647	4,058,647
R^2	0.1221	0.1223	0.1257	0.1760	0.1761	0.1789
Adjusted R^2	0.1090	0.1093	0.1116	0.1638	0.1639	0.1657

Note: The table shows the effect of a gain in a target stock on trades on others stocks in the days following the purchase of the target stock. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes the 30 days subsequent to the purchase of the target stocks. 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: Logins and Spillovers:
Trades of Other Stocks and Returns Since Previous Day

	Sell Other Stock$_{it}$ = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0026***	0.0032***	0.0037***	0.0003	0.0008***	0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Target Stock, %Δ +		0.0007***	0.0007***		0.0003***	0.0002**
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Target Stock, %Δ -		-0.0014***	-0.0015***		-0.0007***	-0.0008***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
A Login = 1				0.0602***	0.0602***	0.0600***
				(0.0006)	(0.0006)	(0.0006)
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	4,058,647	4,058,647	4,058,647	4,058,647	4,058,647	4,058,647
R^2	0.0950	0.0951	0.0981	0.1138	0.1139	0.1166
Adjusted R^2	0.0816	0.0817	0.0836	0.1007	0.1007	0.1024

	Buy Other Stock$_{it}$ = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0013***	0.0037***	0.0042***	-0.0031***	-0.0009***	-0.0005*
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Target Stock, %Δ +		0.0005***	0.0005***		-0.0004***	-0.0004***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Target Stock, %Δ -		-0.0026***	-0.0029***		-0.0012***	-0.0015***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
A Login = 1				0.1131***	0.1130***	0.1128***
				(0.0008)	(0.0008)	(0.0008)
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	4,058,647	4,058,647	4,058,647	4,058,647	4,058,647	4,058,647
R^2	0.0942	0.0944	0.0975	0.1337	0.1337	0.1365
Adjusted R^2	0.0808	0.0809	0.0830	0.1208	0.1209	0.1226

Note: The table shows the effect of a gain in a target stock on trades on others stocks in the days following the purchase of the target stock. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes the 30 days subsequent to the purchase of the target stocks. 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 10: Logins and Spillovers:
Trades of Other Stocks Following Sequential Market Closure Days

	$Login_{i,t+2} = 1$ (Market Closed, Sunday)			$Trade\ Other\ Stock_{i,t+3} = 1$ (Market Open, Monday)		
	(1)	(2)	(3)	(4)	(5)	(6)
Friday Returns:						
Target Stock, %Δ + = 1	0.0131***	0.0079**	0.0086**	0.0040*	0.0003	0.0008
	(0.0025)	(0.0033)	(0.0034)	(0.0021)	(0.0026)	(0.0027)
Target Stock, %Δ +		0.0013	0.0006		0.0001	-0.0002
		(0.0010)	(0.0010)		(0.0008)	(0.0008)
Target Stock, %Δ -		0.0028**	0.0034**		0.0010	0.0012
		(0.0014)	(0.0015)		(0.0012)	(0.0012)
Mediators:						
A $Login_{i,t+2} = 1$ (Sunday)					0.0686***	0.0685***
					(0.0030)	(0.0029)
A $Login_{i,t+3} = 1$ (Monday)					0.1787***	0.1779***
					(0.0028)	(0.0028)
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	133,356	133,356	133,356	133,356	133,356	133,356
R^2	0.3441	0.3441	0.3710	0.2809	0.3119	0.3398
Adjusted R^2	0.1525	0.1526	0.1580	0.0709	0.1110	0.1162

Note: The table shows the effect of a gain in a target stock on the weekends and bank holidays logins; and on the trades in the subsequent first business day. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes sequential market closure days during the 30 days subsequent to the purchase of the target stocks (contrary to Table 6, transactions could occur during this period). The dependent variable in Column 1 to 3 is a dummy indicating whether the account made a login on the day subsequent to the first login day in each series of sequential market closure days (most often, a login on a Sunday following a login on a Saturday). In Columns 4 to 6, the dependent variable is a dummy for a transaction on the subsequent Monday (or the first business day following the sequence of market closure days). Across all columns, the return of the target stock correspond to the latest market open day (most often a Friday). The sample is restricted to observations following the first login day in each series of sequential market closure days. During weekends, it is restricted to logins on the first market closure day, $Login_{i,t+1} = 1$. In cases of three-day or four-day holiday periods, the sample could include observations with logins in the second day $t + 2$ or third day $t + 3$. In those cases, the dependent variable in Columns 1 to 3 corresponds to logins in the third day $t + 3$ or fourth day $t + 4$, respectively. 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.

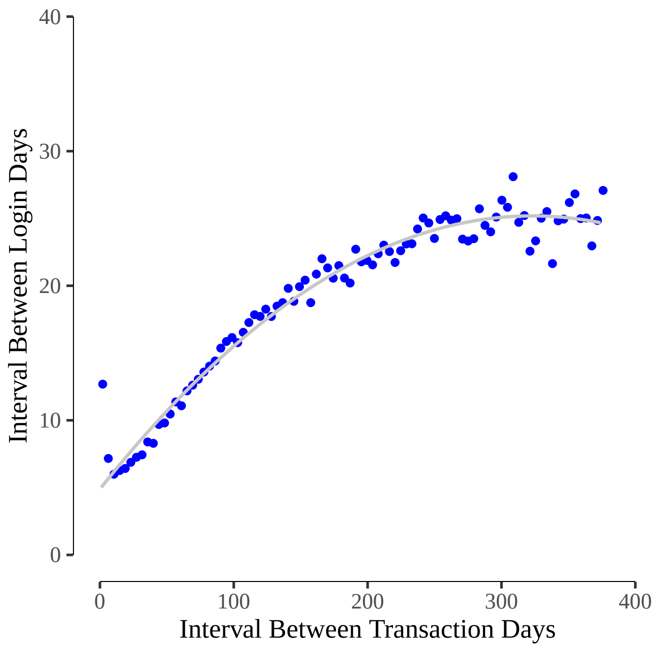
Table 11: Effect of Gains on Participation on Survey 2

	Effects of Absolute Gains		Effects of Gains Relative to the FTSE100	
	(1)	(2)	(3)	(4)
Gain = 1	0.0538**	0.0528**		
	(0.0248)	(0.0247)		
Gain Relative to $FTSE100$ = 1			0.0605**	0.0597**
			(0.0251)	(0.0250)
Gender (Ref: Male)				
Female		-0.0933***		-0.0934***
		(0.0220)		(0.0220)
Other/Unreported		-0.1001		-0.1016
		(0.1800)		(0.1800)
Ethnicity (Ref: White)				
Asian		0.0787*		0.0787*
		(0.0409)		(0.0408)
Black		0.0893		0.0913
		(0.0601)		(0.0601)
Mixed		0.0126		0.0120
		(0.0624)		(0.0624)
Other/Unreported		0.0443		0.0443
		(0.1068)		(0.1067)
Education (Ref: Secondary school)				
A-levels		-0.0726		-0.0716
		(0.0534)		(0.0534)
University		-0.0600		-0.0595
		(0.0496)		(0.0496)
Post-graduate degree		-0.0368		-0.0363
		(0.0518)		(0.0518)
Unreported		-0.2948		-0.2922
		(0.2399)		(0.2398)
Constant	0.2582***	0.3381***	0.2572***	0.3364***
	(0.0122)	(0.0478)	(0.0121)	(0.0478)
Observations	1,759	1,759	1,759	1,759
R^2	0.0027	0.0185	0.0033	0.0191

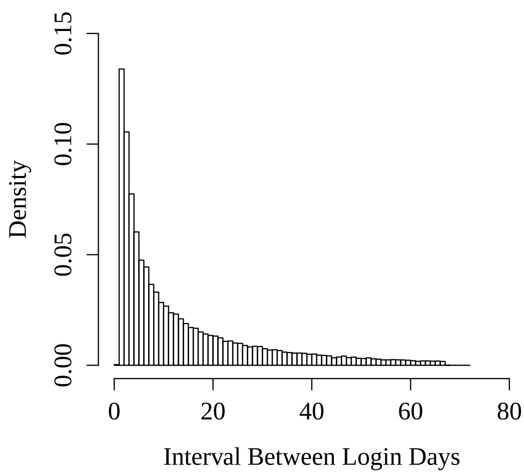
Note: The table displays ordinary least squares regression estimates for the effect of stock gains on the participation in Survey 2. The dependent variable is a dummy that takes the value of 1 if the participant replied to Survey 2. Columns 2 and 4 add demographic controls. *p<0.1; **p<0.05; ***p<0.01

Figure A1: Frequency of Logins vs. Frequency of Trades

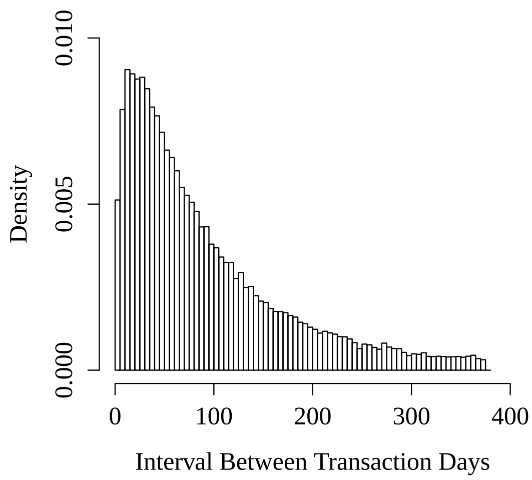
(A) Login Frequency vs. Trading Frequency



(B) Login Frequency

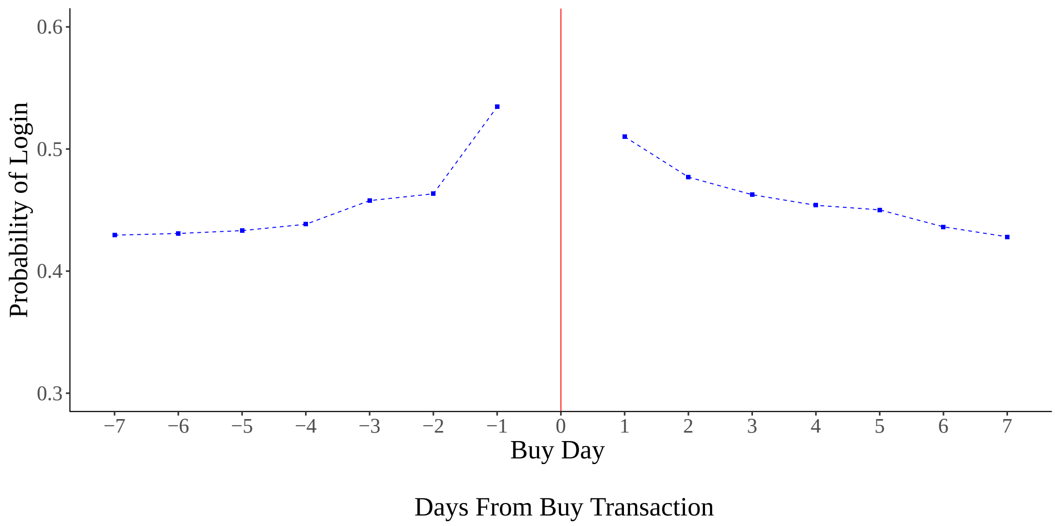


(C) Trading Frequency



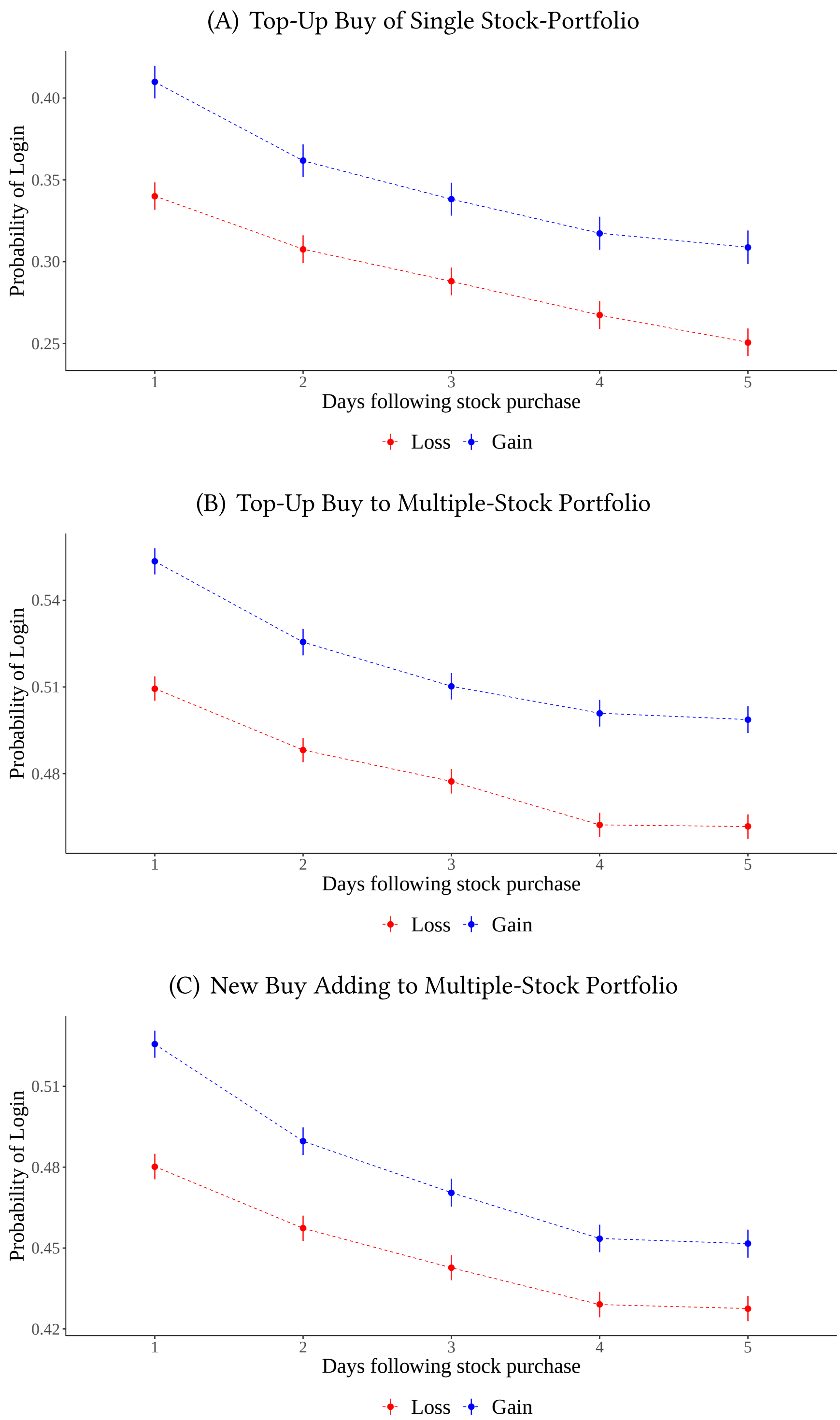
Note: Panel A shows shows a binned scatter plot (100 bins) of the account-level average distance between days with a login (y-axis) and the account-level average distance between days with a trade (x-axis). Panels B and C show histograms of the x- and y-axis variables. In Panels B and C the baseline sample is further restricted to the bottom 95% of observations.

Figure A2: Logins Around Buy-Days



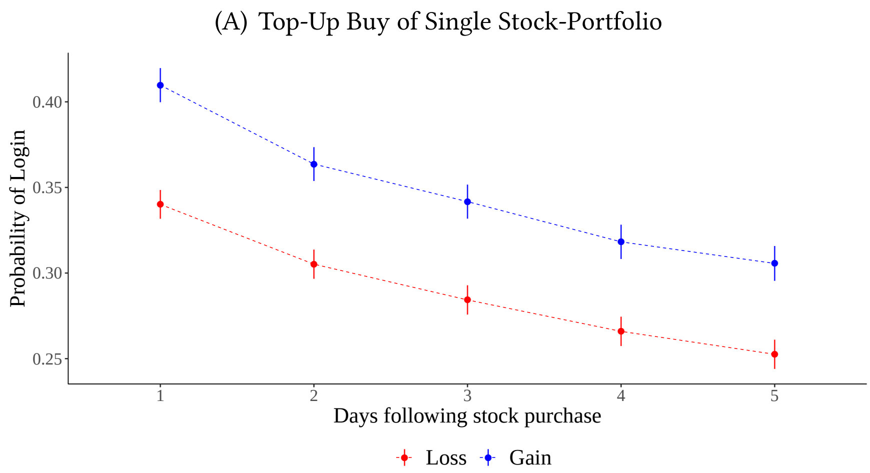
Note: Figure shows the probability of logging in the seven days before and after a buy transaction, conditional on no transaction the week before and after. Weekends are excluded. The figures includes 6,434,283 account × days.

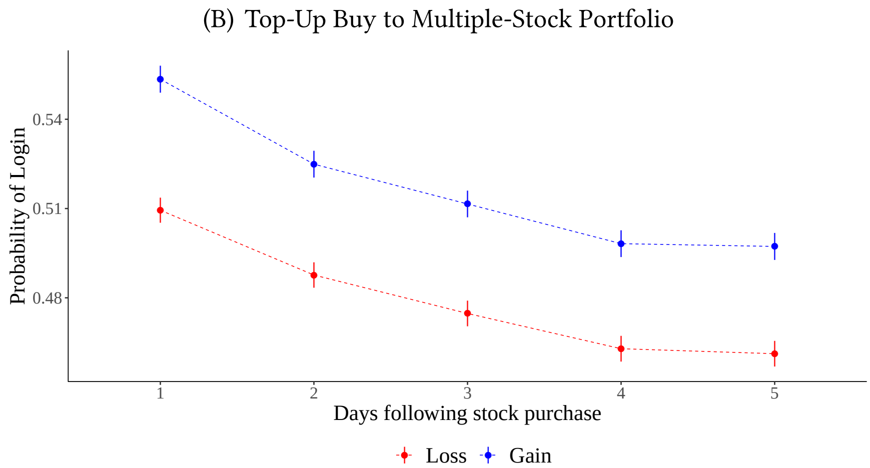
Figure A3: Daily Stock Returns and Logins for Top-Up Buys

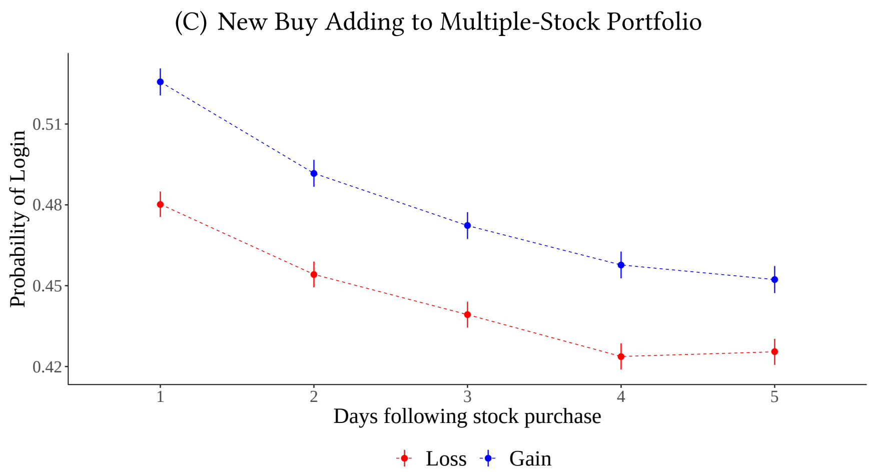


Note: The panels shows the probability of login during the 5 business days following the purchase of an stock, excluding bank holidays, by the daily return of that stock. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (20,129 weeks from 10,030 accounts), (B) has one or more stocks in his portfolio and increases his position in one of these stocks (101,451 weeks from 35,118 accounts), and (C) has a portfolio of stocks and buys a new stock (80,966 weeks from 40,586 accounts). In all weeks, no other transaction has taken place. Lines span 95% confidence intervals.

Figure A4: Returns Since Purchase and Logins for Top-Up Buys

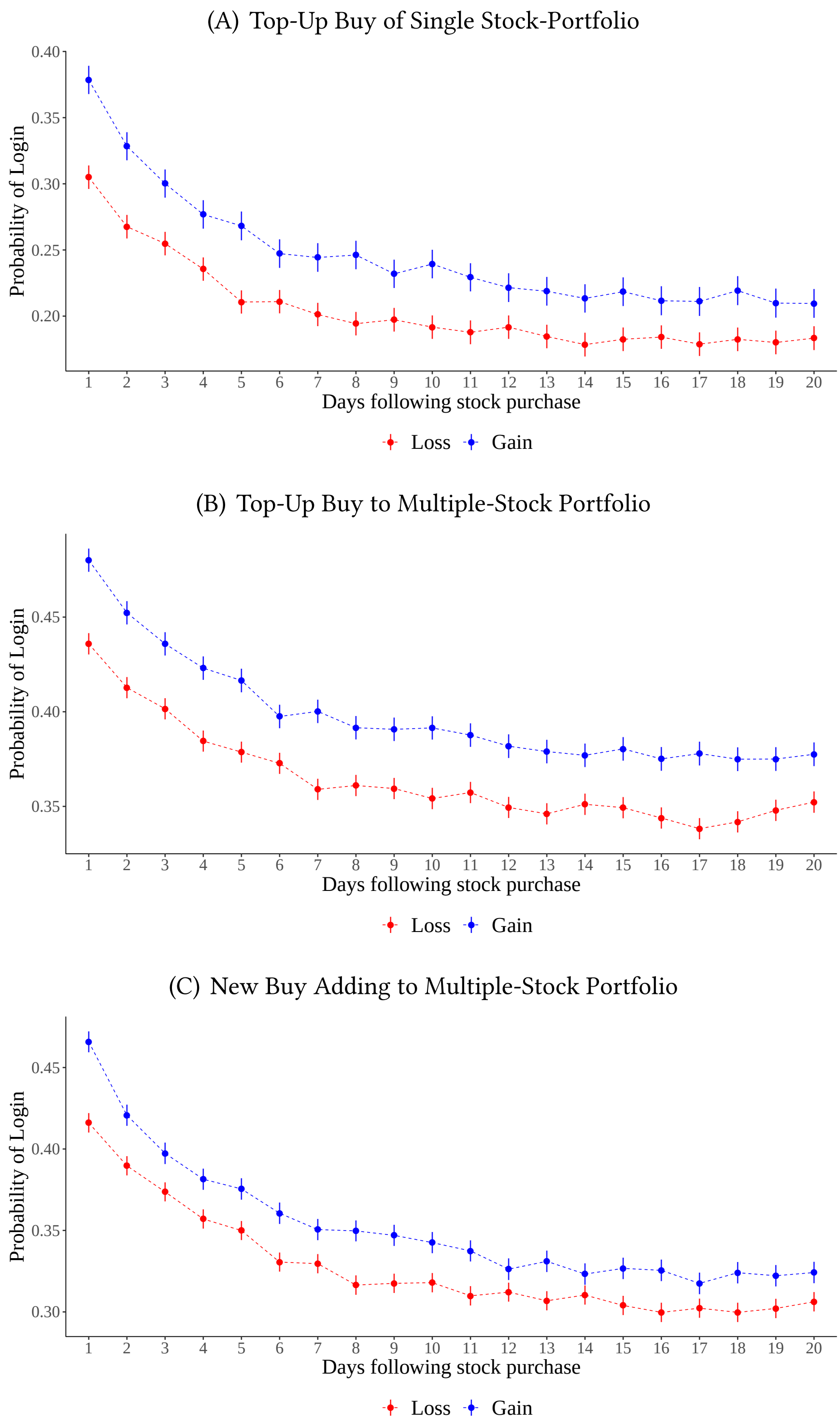






Note: The panels shows the probability of login during the 5 business days following the purchase of an stock, excluding bank holidays, by return of the stock since the purchase day. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (20,129 weeks from 10,030 accounts), (B) has one or more stocks in his portfolio and increases his position in one of these stocks (101,451 weeks from 35,118 accounts), and (C) has a portfolio of stocks and buys a new stock (80,966 weeks from 40,586 accounts). In all weeks, no other transaction has taken place. Lines span 95% confidence intervals.

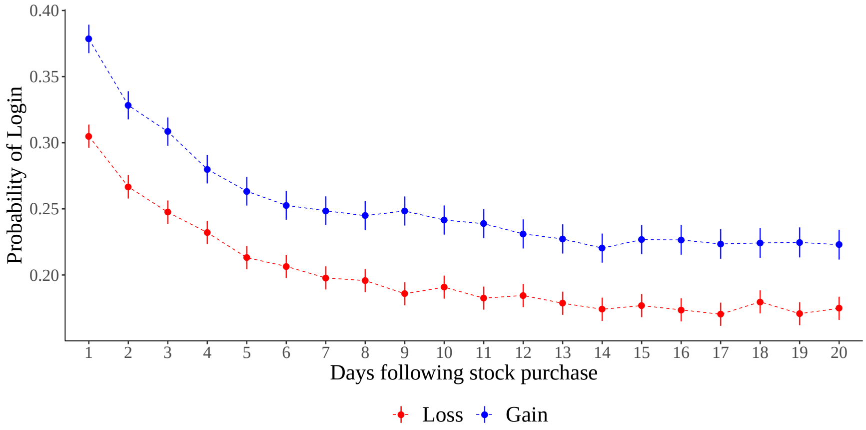
Figure A5: Daily Stock Returns and Logins for Top-Up Buys Over 20 Days



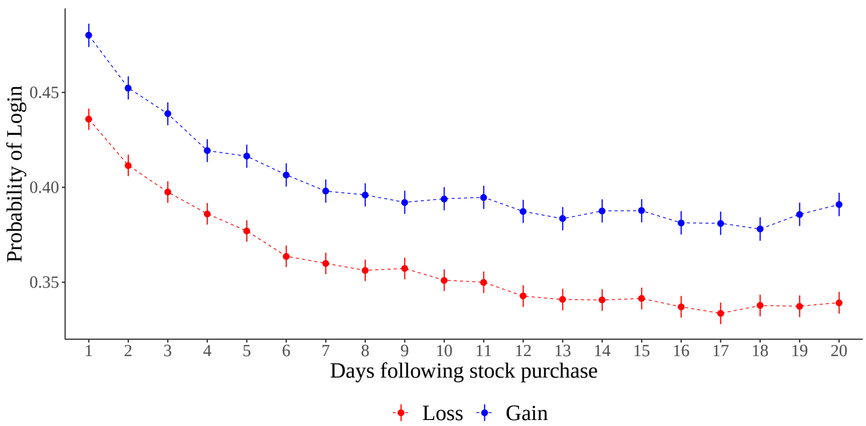
Note: The panels shows the probability of login during the 20 business days following the purchase of an stock, excluding bank holidays, by the daily return of that stock. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (14,543 months from 8,569 accounts), (B) has a portfolio of stocks and buys a new stock (53,587 months from 26,872 accounts), and (C) has one or more stocks in his portfolio and increases his position in one of these stocks (45,611 months from 30,216 accounts). In all months, no other transaction has taken place. Lines span 95% confidence intervals.

Figure A6: Returns Since Purchase and Logins for Top-Up Buys Over 20 Days

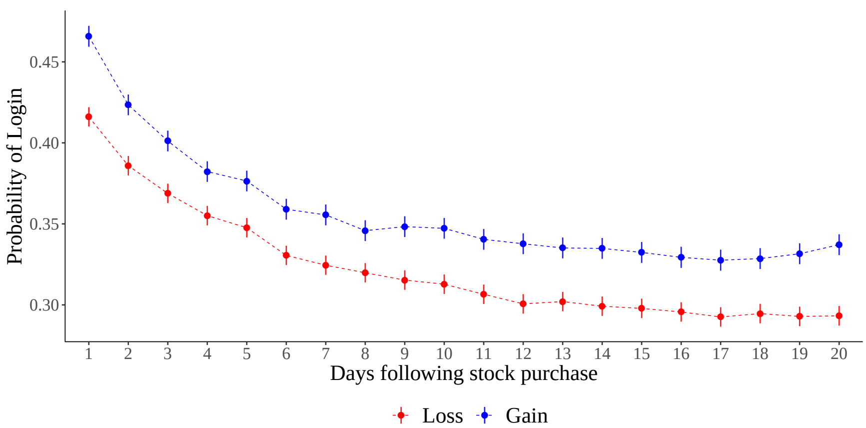
(A) Top-Up Buy of Single Stock-Portfolio



(B) Top-Up Buy to Multiple-Stock Portfolio

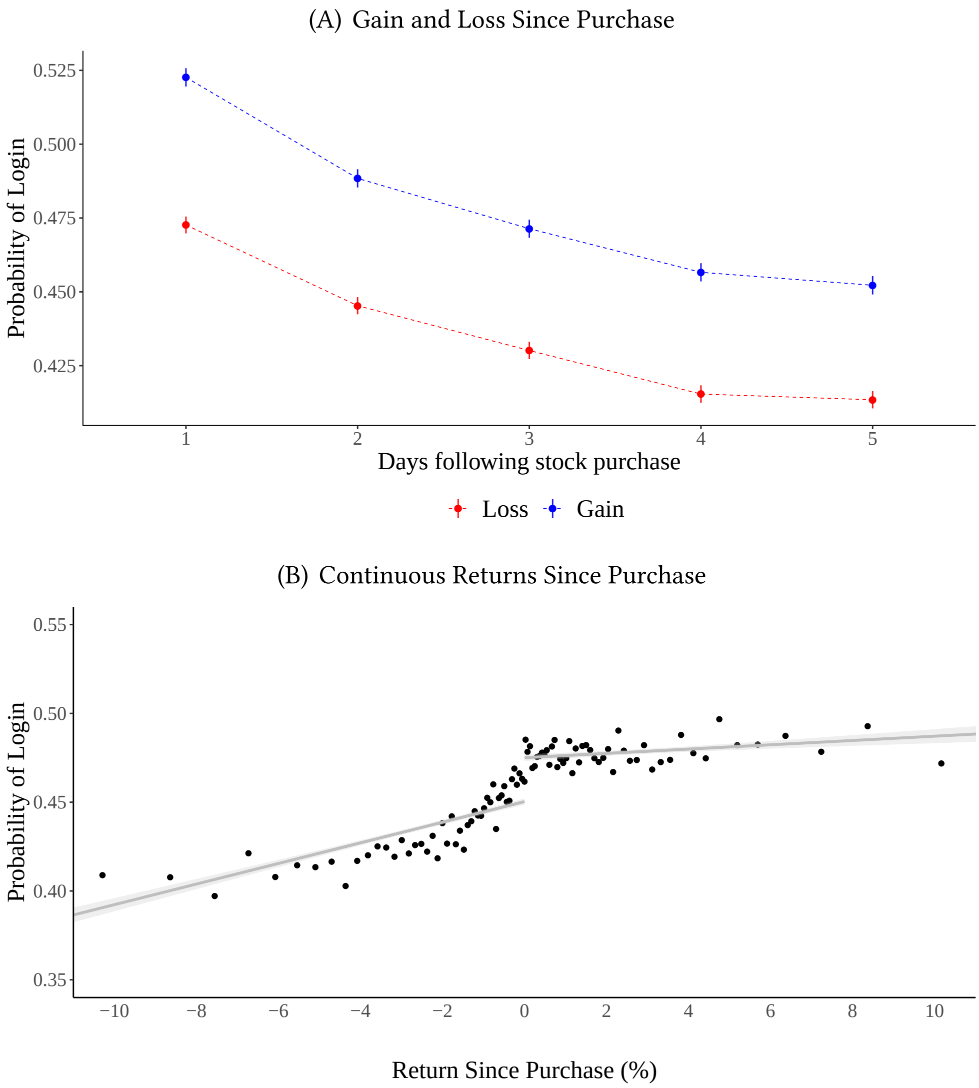


(C) New Buy Adding to Multiple-Stock Portfolio



Note: The panels shows the probability of login during the 20 business days following the purchase of an stock, excluding bank holidays, by the return of the stock since the purchase day. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (14,543 months from 8,569 accounts), (B) has a portfolio of stocks and buys a new stock (53,587 months from 26,872 accounts), and (C) has one or more stocks in his portfolio and increases his position in one of these stocks (45,611 months from 30,216 accounts). In all months, no other transaction has taken place. Lines span 95% confidence intervals.

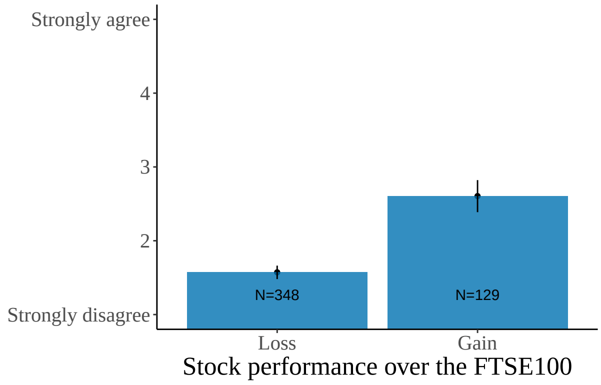
Figure A7: Returns Since Purchase and Logins



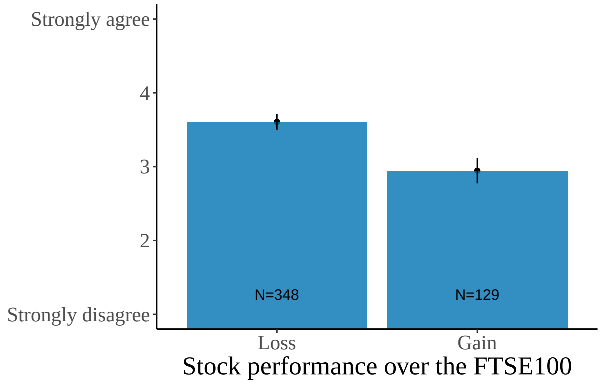
Note: Figure illustrates the relationship between returns on a recently purchased stock, and the probability of an account login, over the following five market open days after the purchase day. Panel A shows the probability of a login on each of the five market open days following the purchase of a stock, by the return since purchase of that stock. Panel B pools together account × day observations from the sample in Panel A and shows the probability of a login against stock return since purchase. 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 216,164 five-day periods from 61,842 accounts. In all weeks, no other transaction has taken place. Lines span 95% confidence intervals.

Figure A8: Trading Behaviour and Market Sentiment

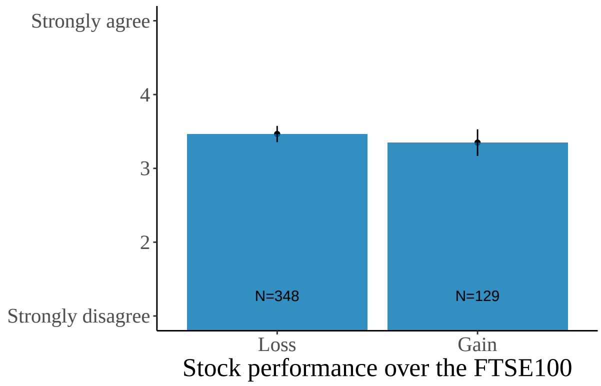
(A) Now is a good time to sell some or all of your stock



(B) Now is a good time to buy more shares of your stock



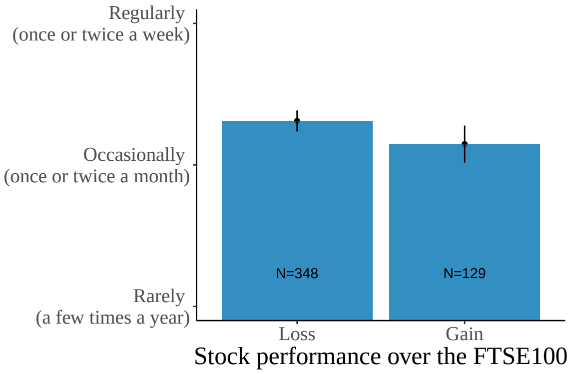
(C) Now is a good time to invest in the stock market



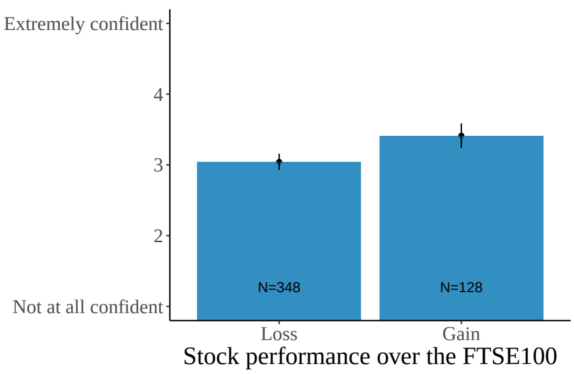
Note: The figure shows the participants market sentiment. As part of Survey 2, respondents were asked to evaluate whether they consider it a good idea to sell (or buy more) shares of their stock or to invest in the stock market. Those who skipped the related questions of the survey were excluded from the calculation of proportions. Vertical lines display 95% confidence intervals.

Figure A9: Frequency at which Portfolios Are Monitored and Confidence in Investment Choices

(A) Portfolio Monitoring Frequency



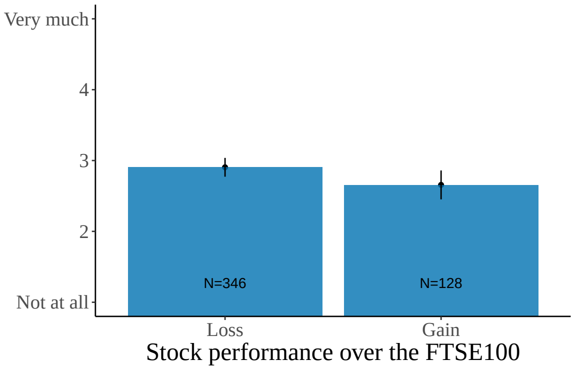
(B) Confidence in Investments



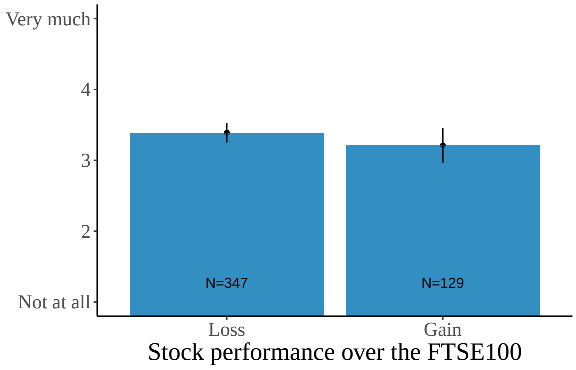
Note: The figure shows the frequency with which participants monitor their portfolios and their levels of confidence in their investments. Participants who skipped the related questions in Survey 2 were excluded from the calculation of proportions. Vertical lines display 95% confidence intervals.

Figure A10: Reason for the Acquisition of Shares

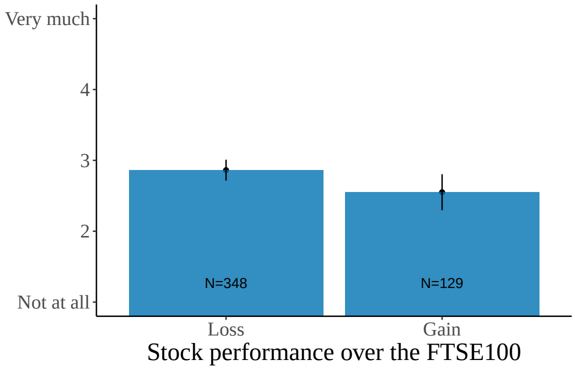
(A) Stock price trajectory



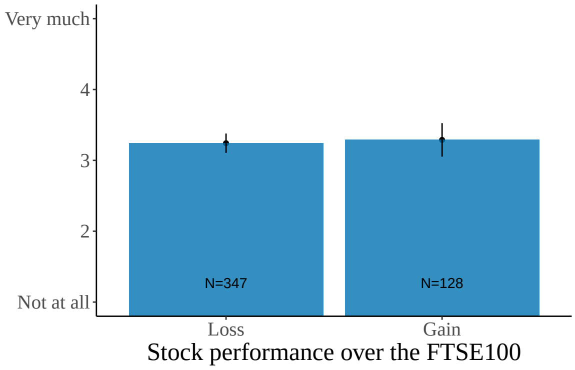
(B) Story of the company



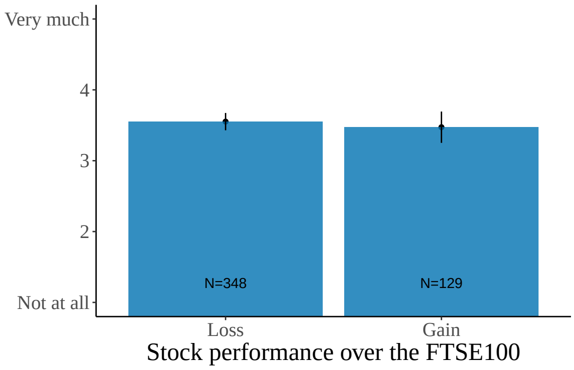
(C) Recommendations of another person



(D) Personal knowledge of the company



(E) Feelings about the company's products



Note: The figure shows the reason for the acquisition of shares. As part of Survey 2, respondents were asked to evaluate the reasons for buying their shares. Those who skipped the related questions of the survey were excluded from the calculation of proportions. Vertical lines display 95% confidence intervals.

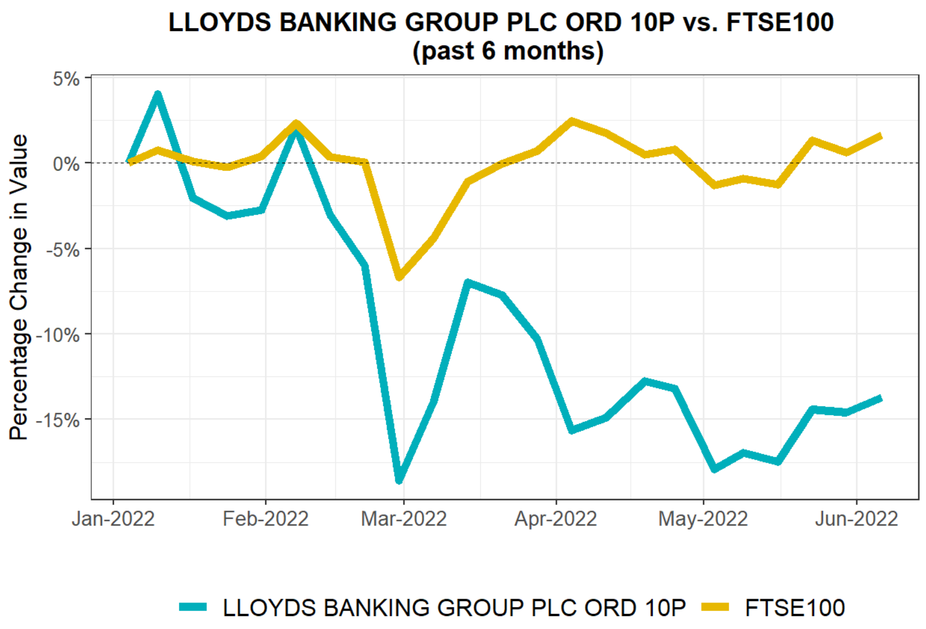
Figure A11: Example of Email Sent to Participants

Stock Performance

Hello,

This email is about the stock that you identified in the brief Qualtrics survey you received a few days ago (the most valuable individual stock you have owned for at least 6 months). Your stock **decreased below** its original price over the 6 months and **underperformed** the FTSE100. Its current price is £**45.595** as of month 6.

The chart below shows your stock's performance in terms of percentage change in price, compared with the percentage change of the index value for the FTSE100. All values reflect prices relative to the original price six months ago.



Thank you for examining this information about the performance of your biggest stock holding. We would like to ask you some additional questions about your stock and your investing behavior more generally. If you are willing to complete another short survey (in exchange for a bonus payment of £1 on the prolific study you replied to a few days ago), please click on the link:
https://wbs.qualtrics.com/jfe/form/SV_3NVQYPyBYL3owzs

Note: The figure shows an example of the email sent to participants. Participants were shown the performance of their stocks with respect to the FTSE100 and invited to participate in a second survey in exchange for a reward of £1.

Figure A12: Survey 2 (part 1)

Stock Performance Questions

Now that you have received your stock performance update, please answer the following questions relating to its progress over the last 6 months. Please do not look at the information in the link you received.

How did your stock perform overall?

- My stock increased in value
- My stock decreased in value
- I don't remember

How did your stock's performance compare to that of the FTSE100's?

- My stock did better than the FTSE100
- The FTSE100 did better than my stock
- I don't remember

Investment Approach Questions

What made you buy this stock in the first place?

When you purchased this stock, were you influenced by:

	Not at all				Very much
The stock price trajectory	○	○	○	○	○
The 'story' of the company	○	○	○	○	○
The recommendations of another person or people	○	○	○	○	○
Personal knowledge you have of the company	○	○	○	○	○
Your feelings about the company's product	○	○	○	○	○

Figure A13: Survey 2 (part 2)

Are you confident in your investment choices?

- Extremely confident
- Quite confident
- Confident
- Slightly confident
- Not at all confident

Considering the recent performance of your stock:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Now is a good time to sell some or all of your stock	○	○	○	○	○
Now is a good time to buy more shares of your stock	○	○	○	○	○
Now is a good time to invest in the stock market	○	○	○	○	○

Finally, how often do you do look up the value of your portfolio?

- Rarely (a few times a year)
- Occasionally (once or twice a month)
- Regularly (once or twice a week)

Table A1: Sample Selection

	Accounts	Login-Days	Transaction-Days	Buy-Days
Unrestricted Sample	155300	30559730	2706498	1929235
Drop due to:				
Inactive Accounts	40985	2480802	22085	13864
Unmatched Prices	14855	3141480	379984	278983
Missing Demographic Data	10539	3359296	317056	222040
Trim Top and Bottom 1% by Portfolio Value	1769	345412	38696	27379
Baseline sample	87152	21232740	1948677	1386969

Note: The unrestricted sample is the starting sample as received from Barclays Stockbroking. See Section 1.2 for a detailed description of the steps in sample selection.

Table A2: Logins and Returns Since Previous Day (Frequency of Logins)

	$N\ Logins_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Most Recent Stock, %Δ + = 1	0.1216***	0.0626***	0.0677***	0.0348***	0.0296***	0.0327***
	(0.0046)	(0.0066)	(0.0064)	(0.0065)	(0.0071)	(0.0042)
Most Recent Stock, %Δ +		0.0371***	0.0395***	0.0367***	0.0335***	0.0295***
		(0.0027)	(0.0026)	(0.0026)	(0.0030)	(0.0016)
Most Recent Stock, %Δ -		-0.0009	-0.0058***	-0.0069***	-0.0083***	-0.0038**
		(0.0023)	(0.0022)	(0.0022)	(0.0026)	(0.0015)
FTSE100, %Δ				0.0501***	0.0306***	0.0330***
				(0.0022)	(0.0028)	(0.0021)
Remaing Stocks, %Δ					0.0380***	0.0361***
					(0.0021)	(0.0015)
Constant	1.0954***	1.0940***	0.2347***	0.2494***	0.3735***	
	(0.0091)	(0.0098)	(0.0699)	(0.0703)	(0.0803)	
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	1,057,409	1,057,409	1,057,409	1,050,761	870,827	870,827
R^2	0.0009	0.0015	0.0552	0.0558	0.0535	0.5883
Adjusted R^2	0.0009	0.0015	0.0552	0.0558	0.0534	0.5620

Note: Table reports ordinary least squares regression estimates. The dependent variable is the count of logins 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 61,842 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 A3: Regression Estimates: Logins and Returns Since Purchase

	$Login_{it} = 1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Most Recent Stock, %Δ + = 1	0.0425***	0.0247***	0.0254***	0.0212***	0.0175***	0.0133***
	(0.0015)	(0.0018)	(0.0017)	(0.0017)	(0.0019)	(0.0014)
Most Recent Stock, %Δ +		0.0012***	0.0017***	0.0013***	0.0003	0.0025***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Most Recent Stock, %Δ -		0.0058***	0.0047***	0.0046***	0.0041***	0.0030***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
FTSE100, %Δ				0.0055***	0.0016**	0.0035***
				(0.0005)	(0.0006)	(0.0005)
Remaing Stocks, %Δ					0.0068***	0.0064***
					(0.0004)	(0.0003)
Constant	0.4357***	0.4503***	0.1877***	0.1892***	0.2287***	
	(0.0020)	(0.0022)	(0.0143)	(0.0143)	(0.0167)	
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	1,057,409	1,057,409	1,057,409	1,049,986	866,879	866,879
R^2	0.0018	0.0024	0.0710	0.0718	0.0656	0.4620
Adjusted R^2	0.0018	0.0024	0.0710	0.0717	0.0656	0.4276

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 61,842 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. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A4: Logins and Returns Since Previous Day Slopes Specification (Frequency of Logins)

	N $Logins_{it}$ (1)
Most Recent Stock, %Δ + = 1	0.0218***
	(0.0072)
Most Recent Stock, %Δ +	0.0371***
	(0.0030)
Most Recent Stock, %Δ -	-0.0101***
	(0.0026)
FTSE100, %Δ + = 1	0.0490***
	(0.0063)
FTSE100, %Δ +	-0.0423***
	(0.0066)
FTSE100, %Δ -	0.0564***
	(0.0062)
Remaing Stocks, %Δ + = 1	0.0558***
	(0.0068)
Remaing Stocks, %Δ +	0.0319***
	(0.0054)
Remaing Stocks, %Δ -	0.0165***
	(0.0049)
Constant	0.3487***
	(0.0804)
Customer Controls	YES
Account Controls	YES
Observations	870,827
R^2	0.0539
Adjusted R^2	0.0538

Note: Table reports ordinary least squares regression estimates. The dependent variable is the count of logins 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 A5: Logins and Returns Since Purchase for Account Sub-Samples

	$Login_{it} = 1$		
	Top-Up Buy Single-Stock Portfolio	Top-Up Buy Multiple-Stock Portfolio	New Buy Multiple-Stock Portfolio
Most Recent Stock, %Δ + = 1	0.0271***	0.0188***	0.0157***
	(0.0057)	(0.0025)	(0.0027)
Most Recent Stock, %Δ +	0.0069***	0.0003	0.0006
	(0.0011)	(0.0006)	(0.0006)
Most Recent Stock, %Δ -	0.0045***	0.0040***	0.0041***
	(0.0009)	(0.0005)	(0.0006)
FTSE100, %Δ	-0.0006	0.0011	0.0022**
	(0.0014)	(0.0008)	(0.0010)
Remaing Stocks, %Δ		0.0067***	0.0070***
		(0.0006)	(0.0006)
Constant	0.0980***	0.1768***	0.2595***
	(0.0312)	(0.0222)	(0.0181)
Customer Controls	YES	YES	YES
Account Controls	YES	YES	YES
Observations	96,837	480,604	386,275
R^2	0.0449	0.0693	0.0601
Adjusted R^2	0.0445	0.0693	0.0600

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. *p<0.1; **p<0.05; ***p<0.01.

Table A6: Baseline Sample Login Summary Statistics

	Mean	SD	Min	Percentiles p25	p50	p75	Max
Interval Between Logins (days)	18.43	26.95	1.00	3.28	8.60	22.61	623.00
Interval Between Transactions (days)	115.94	138.85	1.00	32.49	71.00	144.20	1432.00
Ratio of Login Days to Transaction Days	20.73	36.26	1.00	5.00	9.81	21.20	650.50
N Accounts	87152						

Note: The intervals between login days, the intervals between transaction days, and the ratio of login to transaction days are account average measures.

Table A7: Logins and Returns Since Previous Day, Recent vs Earlier Stocks

	$Login_{it} = 1$			
	(1)	(2)	(3)	(4)
	Week 1	Week 2	Week 3	Week 4
Most Recent Stock, %Δ + = 1	0.0143***	0.0127***	0.0118***	0.0129***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Most Recent Stock, %Δ +	0.0028***	-0.0010	-0.0017*	-0.0037***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Most Recent Stock, %Δ -	0.0037***	0.0058***	0.0047***	0.0069***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Second Most Recent Stock, %Δ + = 1	0.0135***	0.0142***	0.0101***	0.0141***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Second Most Recent Stock, %Δ +	-0.0047***	-0.0040***	-0.0038***	-0.0042***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Second Most Recent Stock, %Δ -	0.0080***	0.0071***	0.0083***	0.0065***
	(0.0011)	(0.0011)	(0.0010)	(0.0010)
FTSE100, %Δ	0.0098***	0.0095***	0.0073***	0.0064***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Constant	0.2693***	0.1990***	0.1809***	0.1597***
	(0.0242)	(0.0235)	(0.0234)	(0.0234)
Wald test on equality of coefficients, $\chi 2$	0.0611	0.1819	0.272	0.1258
Wald test on equality of coefficients, p	0.8047	0.6698	0.602	0.7228
Customer Controls	YES	YES	YES	YES
Account Controls	YES	YES	YES	YES
Observations	347,832	346,971	344,992	342,276
R^2	0.0508	0.0559	0.0577	0.0610
Adjusted R^2	0.0507	0.0558	0.0576	0.0609

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 The sample is restricted to portfolios with at least three 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. 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 A8: Regression Estimates Interaction Terms, Returns Since Purchase

	$Login_{it} = 1$		
	(1)	(2)	(3)
Most Recent Stock, %Δ + = 1	0.0174***	0.0202***	0.0140***
	(0.0021)	(0.0027)	(0.0040)
Female = 1	-0.0177***		
	(0.0054)		
Most Recent Stock, %Δ + = 1 × Female = 1	-0.0090**		
	(0.0040)		
Number of Stocks (10 Stocks)		0.0911***	
		(0.0034)	
Most Recent Stock, %Δ + = 1 × Number of Stocks (10 Stocks)		-0.0067***	
		(0.0024)	
Log Portfolio Value (£1000)			0.0304***
			(0.0013)
Most Recent Stock, %Δ + = 1 × Log Portfolio Value (£1000)			-0.0001
			(0.0010)
Most Recent Stock, %Δ +	0.0008*	0.0014***	0.0023***
	(0.0005)	(0.0004)	(0.0004)
Most Recent Stock, %Δ -	0.0041***	0.0030***	0.0021***
	(0.0004)	(0.0004)	(0.0004)
FTSE100, %Δ	0.0004	0.0016**	0.0011*
	(0.0007)	(0.0007)	(0.0007)
Remaing Stocks, %Δ	0.0073***	0.0066***	0.0066***
	(0.0004)	(0.0004)	(0.0004)
Constant	0.4853***	0.4070***	0.3728***
	(0.0027)	(0.0033)	(0.0046)
Observations	866,879	866,879	866,879
R^2	0.0029	0.0206	0.0118
Adjusted R^2	0.0029	0.0206	0.0118

Note: The table tests whether the main results presented in Table A3, 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). *p<0.1; **p<0.05; ***p<0.01.

Table A9: Logins and Spillovers: Trades of Other Stocks and Returns Since Purchase

	$Trade\ Other\ Stock_{it} = 1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0037***	0.0016***	0.0016***	-0.0009***	-0.0011***	-0.0011***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Target Stock, %Δ +		0.0004***	0.0004***		0.0002***	0.0002***
		(0.0000)	(0.0001)		(0.0000)	(0.0000)
Target Stock, %Δ -		0.0000	0.0001		-0.0002***	-0.0002***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
A Login = 1				0.1517***	0.1517***	0.1514***
				(0.0010)	(0.0010)	(0.0010)
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	4,042,412	4,042,412	4,042,412	4,042,412	4,042,412	4,042,412
R^2	0.1223	0.1223	0.1257	0.1760	0.1760	0.1788
Adjusted R^2	0.1092	0.1093	0.1116	0.1637	0.1637	0.1656

Note: The table shows the effect of a gain in a target stock on trades on others stocks in the days following the purchase of the target stock. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes the 30 days subsequent to the purchase of the target stocks. 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 A10: Logins and Spillovers:
Trades of Other Stocks - Following Two Weeks - Returns Since Previous Day

	$Trade\ Other\ Stock_{it} = 1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0034***	0.0055***	0.0062***	-0.0028***	-0.0008*	-0.0002
	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Target Stock, %Δ +		0.0015***	0.0016***		0.0002	0.0003
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
Target Stock, %Δ -		-0.0036***	-0.0039***		-0.0018***	-0.0021***
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
A Login = 1				0.1480***	0.1479***	0.1474***
				(0.0011)	(0.0011)	(0.0011)
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	1,903,882	1,903,882	1,903,882	1,903,882	1,903,882	1,903,882
R^2	0.1331	0.1333	0.1385	0.1832	0.1833	0.1878
Adjusted R^2	0.1052	0.1054	0.1084	0.1569	0.1570	0.1594

Note: The table shows the effect of a gain in a target stock on trades on others stocks in the days following the purchase of the target stock. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes the 10 business days subsequent to the purchase of the target stocks. 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 A11: Logins and Spillovers:
Trades of Other Stocks - Following Two Weeks - Returns Since Previous Day

	Sell Other Stock$_{it}$ = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0022***	0.0029***	0.0034***	-0.0002	0.0004	0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Target Stock, %Δ +		0.0008***	0.0008***		0.0003**	0.0003**
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Target Stock, %Δ -		-0.0016***	-0.0016***		-0.0009***	-0.0009***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
A Login = 1				0.0574***	0.0573***	0.0569***
				(0.0006)	(0.0006)	(0.0006)
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	1,903,882	1,903,882	1,903,882	1,903,882	1,903,882	1,903,882
R^2	0.1018	0.1020	0.1068	0.1189	0.1190	0.1234
Adjusted R^2	0.0729	0.0731	0.0756	0.0906	0.0906	0.0928

	Buy Other Stock$_{it}$ = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0019***	0.0036***	0.0041***	-0.0028***	-0.0011**	-0.0007
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Target Stock, %Δ +		0.0009***	0.0010***		-0.0000	0.0000
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
Target Stock, %Δ -		-0.0026***	-0.0029***		-0.0013***	-0.0015***
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
A Login = 1				0.1108***	0.1107***	0.1104***
				(0.0009)	(0.0009)	(0.0008)
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	1,903,882	1,903,882	1,903,882	1,903,882	1,903,882	1,903,882
R^2	0.1057	0.1059	0.1109	0.1427	0.1427	0.1473
Adjusted R^2	0.0769	0.0771	0.0798	0.1151	0.1151	0.1175

Note: The table shows the effect of a gain in a target stock on trades on others stocks in the days following the purchase of the target stock. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes the 10 business days subsequent to the purchase of the target stocks. 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 A12: Logins and Spillovers:
Trades of Other Stocks - Following Two Weeks - Returns Since Purchase

	$Trade\ Other\ Stock_{it} = 1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0028***	0.0018***	0.0020***	-0.0018***	-0.0012**	-0.0011*
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
Target Stock, %Δ +		0.0003***	0.0003***		0.0000	0.0000
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Target Stock, %Δ -		0.0000	0.0001		-0.0002**	-0.0002**
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
A Login = 1				0.1477***	0.1477***	0.1473***
				(0.0011)	(0.0011)	(0.0011)
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	1,890,958	1,890,958	1,890,958	1,890,958	1,890,958	1,890,958
R^2	0.1333	0.1333	0.1385	0.1833	0.1833	0.1878
Adjusted R^2	0.1052	0.1053	0.1082	0.1569	0.1569	0.1593

Note: The table shows the effect of a gain in a target stock on trades on others stocks in the days following the purchase of the target stock. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes the 10 business days subsequent to the purchase of the target stocks. 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 A13: Sample Selection in LDB Dataset

	N
Starting Sample	2080
Drop due to:	
Excluding participants with multiple records	1
Excluding participants who took part in the pilot study	2
Excluding participants who have not held stocks for six months or did not report their stocks names	251
Excluding participants who reported stocks for which historical pricing data was not available	46
Remaining Sample (Survey 2 recipients)	1780
Excluding participants who failed to pass the checks verifying their understanding of the plots displaying their stock performance	21
Baseline Sample	1759

Note: The table details the steps in sample selection. The starting sample includes all participants recruited via Prolific. We conducted a pilot study with 12 participants to estimate the completion time of the surveys before launching our main study. Step 2 excludes participants who participated in an initial pilot study. The largest drop in Step 3 corresponds to participants who have not held stocks in the last six months. Participants could enter their stocks manually or choose from a drop-down menu. Step 4 excludes participants (manually) reporting stocks that were not associated with a known ticker symbol. Price data was scrapped from the Yahoo Finance website using stock ticker symbols. The final drop excludes participants who failed to pass the checks verifying they understood the plots (e.g., when actual performance was declining, it was reported as increasing).

Table A14: Demographic Differences for People Completing Survey 2

	Total Sample	Completed Survey 2				
		No	Yes	Difference	Statistic	*p*-value
Gender:						
Female	0.37	0.40	0.29	0.11	$\chi^2(1)$=16.96	<.001
Male	0.62	0.59	0.70	-0.11	$\chi^2(1)$=17.96	<.001
Other/Unreported	0.00	0.01	0.00	0.00	$\chi^2(1)$=0.28	0.594
Education:						
Secondary school	0.05	0.05	0.06	-0.01	$\chi^2(1)$=1.3	0.254
A-levels	0.18	0.19	0.17	0.02	$\chi^2(1)$=0.64	0.424
University	0.51	0.51	0.50	0.01	$\chi^2(1)$=0.2	0.659
Post-graduate degree	0.26	0.25	0.27	-0.02	$\chi^2(1)$=0.65	0.422
Unreported	0.00	0.00	0.00	0.00	$\chi^2(1)$=0.74	0.389
Ethnicity:						
White	0.85	0.86	0.83	0.03	$\chi^2(1)$=3.06	0.08
Asian	0.07	0.07	0.09	-0.03	$\chi^2(1)$=3.29	0.07
Black	0.03	0.03	0.04	-0.01	$\chi^2(1)$=0.85	0.357
Mixed	0.03	0.03	0.03	0.00	$\chi^2(1)$=0	1
Other/Unreported	0.01	0.01	0.01	0.00	$\chi^2(1)$=0.01	0.923
N	1759	1282	477			

Note: The table shows the demographic characteristics of the baseline sample. Columns 4 to 6 show a comparison of Survey 2 respondents and non-responders.

Table A15: Effect of Gains on Participation on Survey 2

	Including Participants Failing Verification Checks		Replacing Actual Stock Gains with Perceived Stock Gains	
	(1)	(2)	(3)	(4)
Gain = 1	0.0501**			
	(0.0248)			
Gain Relative to $FTSE100$ = 1		0.0574**		
		(0.0251)		
Perceived Gain = 1			0.0768***	
			(0.0244)	
Perceived Gain Relative to $FTSE100$ = 1				0.0627**
				(0.0249)
Gender (Ref: Male)				
Female	-0.1021***	-0.1022***	-0.1017***	-0.1090***
	(0.0221)	(0.0221)	(0.0220)	(0.0220)
Other/Unreported	-0.1075	-0.1089	-0.1098	-0.1093
	(0.1815)	(0.1815)	(0.1807)	(0.1797)
Ethnicity (Ref: White)				
Asian	0.0869**	0.0868**	0.0831**	0.0829**
	(0.0407)	(0.0407)	(0.0407)	(0.0406)
Black	0.0831	0.0850	0.0743	0.0936
	(0.0606)	(0.0606)	(0.0608)	(0.0600)
Mixed	0.0181	0.0176	0.0035	-0.0053
	(0.0623)	(0.0623)	(0.0626)	(0.0628)
Other/Unreported	0.0368	0.0368	0.0404	0.0443
	(0.1077)	(0.1076)	(0.1071)	(0.1065)
Education (Ref: Secondary school)				
A-levels	-0.0894*	-0.0886*	-0.0887*	-0.0692
	(0.0528)	(0.0528)	(0.0526)	(0.0530)
University	-0.0841*	-0.0837*	-0.0849*	-0.0668
	(0.0490)	(0.0490)	(0.0488)	(0.0493)
Post-graduate degree	-0.0534	-0.0530	-0.0522	-0.0379
	(0.0513)	(0.0512)	(0.0510)	(0.0515)
Unreported	-0.3138	-0.3113	-0.3063	-0.2932
	(0.2416)	(0.2416)	(0.2405)	(0.2393)
Constant	0.3693***	0.3676***	0.3602***	0.3451***
	(0.0471)	(0.0471)	(0.0470)	(0.0474)
Observations	1,780	1,780	1,773	1,760
R^2	0.0211	0.0217	0.0244	0.0236

Note: The table displays ordinary least-squares regression estimates for the effect of stock gains on participation in Survey 2. The dependent variable is a dummy that takes the value of 1 if the participant replied to Survey 2. Columns 1 and 2 include participants who did not pass the checks verifying their understanding of the plots that display the performance of their stocks (e.g., those reporting that the performance increased when, in fact, it decreased). Columns 3 and 4 replace the gain dummies with the perceived gains for all participants who responded to Survey 2. Participants who reported not remembering their performance were excluded from the analysis. *p<0.1; **p<0.05; ***p<0.01