Attention Utility: Evidence From Individual Investors

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Abstract

Attention utility is the hedonic pleasure or pain derived purely from paying attention to information. Using data on brokerage account logins by individual investors, we show that individuals devote disproportionate attention to already-known positive information about the performance of individual stocks within their portfolios. This aversion to paying attention to unfavorable information, through its effect on logins, has consequences for trading activity; it reduces trading after recent losses and increases trading after recent gains. Attention utility is distinct from models of belief-based utility and information aversion (in which information not sought is not fully known), and implies that the pleasure and pain of attending to known information may be important for individual behavior.

Keywords: information utility, attention, login, investor behavior

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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 eschewing medical tests (Ganguly and Tasoff, 2016, Kőszegi, 2003, Oster et al., 2013), investors who avoid looking at financial portfolios when the stock market declines (Karlsson et al., 2009, Olafsson and Pagel, 2017, Sicherman et al., 2015,) 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.[1] 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). A second is that people may form motivatedly optimistic beliefs (Brunnermeier and Parker, 2005), and may be reluctant to burst their 'optimism bubble' with realistic information they can't ignore (Oster et al., 2013).[2]

Yet, beyond the utility of obtaining good or bad news, the act of attending to information,

[1] 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 ?Pagel2018) draws out implications of their model for information avoidance.

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

even when it is already known – i.e., not 'news' – may directly confer utility to individuals. "Attention utility" is the hedonic pleasure, or displeasure, derived purely from looking at, or thinking about – i.e., paying attention to – information. Casual observation suggests that individuals enjoy spending time looking at positive information even when this information is already known, with examples including exam scores, sports results and journal acceptance letters. 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 looking – savouring the information. Attention-based utility is not entirely separable from belief-based utility;[3] but what one pays attention to at a particular moment is very different from the overall set of beliefs that one has cumulatively developed at any point in time.

Examining the portfolio look-up behavior of retail investors, we show that individuals devote disproportionate attention to already-known positive information about stocks, and by the same token, relatively less attention to information known to be negative, and that this pattern of behavior has significant economic consequences. Using detailed data on investor portfolio performance together with login records, we examine the relationship between stock returns and investor attention. Our first contribution is to show that investors are more likely to pay attention – ie., 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.

Our second contribution is to show that attention utility has implications for consequential behavior on the part of investors. Specifically, we show that decreased attention to bad information – losses on recently acquired stocks – leads to decreased trading activity, on both the buy and sell dimensions. We show, further, that the effect of losses on trading is wholly mediated by reduced attention. By reducing attention to their brokerage accounts to avoid

[3] To the extent that people selectively pay attention to different beliefs (whether for motivational reasons or as a function of cognitive constraints), the beliefs they hold will constrain the range of what they can pay attention to. By the same token, what information people pay attention to over time is very likely to affect the beliefs they come to hold.

the disutility of paying attention to their losses, investors reduce their trading activity (which 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 covers a large sample of investors over a multi-year panel, with detailed information on investor characteristics and records of daily login behaviour. A key advantage of our data is that we can observe the exact portfolio holdings of investor 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 our study is that we draw 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

[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 cover typically 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 examine 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

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 with stocks which make losses *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 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 purchase, such as top-up of an existing stock and purchase of a new stock, and occurs in both thin and thick portfolios.

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; conditioning 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, therefore, investors neglect to use the trading platform, and, as a result, reduce trading activity on other stocks.

Our study relates to the growing literature on financial attention. Recent models develop preference-based explanations for information aversion. Pagel (2018) develops a news-utility theory for inattention in which investors have a preference to ignore their portfolios due to aversion to potential news about losses. Andries and Haddad (2019) develop a life-cycle model in which preference-based utility costs of information can generate under-diversification because investors choose only a few stocks in order to reduce the likelihood of receiving disappointing information. Hence they show that, theoretically, a model of information aversion has implications for real activity (for reviews of the literature on information avoidance see

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).

Sweeny et al., 2010; and Golman et al., 2017). To our knowledge, with only one exception we are aware of (Golman and Loewenstein, 2015), the literature has yet to see the development of models of attention utility.

Our results have implications for models 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 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), that people also tend to focus attention on things that make them feel good. Such a motivated focus on the positive likely contributes to 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), most investors hold only a few stocks in their portfolio (Goetzmann and Kumar, 2008; Barber and Odean, 2013). Investors also exhibit biases in their trading behaviour, such as over-trading and rank effects (Barber and Odean, 2000, 2001; Hartzmark, 2015). Our findings contribute to the study of the role of psychology in investor behaviour (Barberis, 2018) and more broadly to the application of psychology to economic decision making (DellaVigna and Pollet, 2009). 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.

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. Section 1 describes the individual investor data, steps in sample selection and presents summary statistics. Section 2 describes patterns in investor attention, presenting results on the relationships between attention and demographic characteristics, and also portfolio diversification. Section 3 presents our main results on attention utility and login behavior. Section 4 presents results on the relationship between stock gains, attention and trading activity. Section 5 concludes the paper.

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.[7] 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.

1.1 Sample Selection

Our starting sample, provided by Barclays, contains approximately 155,000 accounts which are active 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

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

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.[8] 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 accounts by the average value of the total portfolio over the whole data period, in order to remove extreme outlier values.[9]

Table A1 reports the effects of these steps in sample selection. The columns report 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 removing 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 71.8% of buy-days from the starting sample.

2 Summary Statistics on Investor Attention

In this section, we provide summary statistics for investors in our sample and summarize patterns in investor attention.

2.1 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

[8] This sample restriction is necessary to ensure completeness in our calculation of portfolio values.
[9] Our main results are not sensitive to this sample restriction.

age of an account holder is 54 years (median 57 years).[10] Account holders have held their accounts for, on average, 5 years (median 3 years). Twenty five percent of account holders had held their accounts for more than six years. This profile of account holders is similar to that seen in US data (see Barber and Odean, 2001).[11]

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 holding are of 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 low number of stocks held in the sample is consistent with evidence from previous studies that individual investors tend to hold under-diversified portfolios (Goetzmann and Kumar, 2008, Barber and Odean, 2013).

2.2 Summarizing Investor Attention and Trading

We summarize ther 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).[12] Because our account data contain account openings and closings, the panel is unbalanced. We calculate the frequency of logins as the account-level average distance (in days) between login-days and the frequency of transactions as the account-level average distance (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 bin contains an equal number of observations.[13] 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

[10] 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).

[11] 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).

[12] 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.

[13] 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.

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).[14] Panels B and C of Figure A1 illustrate the distributions of login frequency and trading frequency.[15] Table 2 provides summary statistics for the frequency of logins and frequency of trades. The account-level average number of days between login (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.

3 Results

In this section, we present our first main result that investors are more likely to pay attention to winning stocks compared with losing stocks. Our research design focuses on 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 over subsequent days compared with stocks which make losses *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 the performance of individual stocks.[16] In this way, we can detect excess logins arising purely from the desire to *look* at portfolios as distinct from the desire to *discover* how movement in the market index translate into changes in the value of the individual's imperfectly correlated portfolio.

[14] 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.

[15] 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.

[16] 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.

3.1 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. 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. Login activity spikes around buy-days, as illustrated in Figure A2 in the Online Appendix.[17]

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.[18] 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 shown as day zero, 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% on the

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

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

average login probability of 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 on the previous day on the x-axis. The plot illustrates an positive relationship between returns and the probability of login, with evidence of a jump in the probability of login when the stock return becomes positive.

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. 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 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). Results are shown in Table 3. 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 8.9% on the baseline probability calculated from the constant term in the model.

Columns 2-6 of Table 3 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, apart from 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 purchase stock increases the likelihood of login by approximately 1.5 percentage points, an increase of 6.7% on the baseline probability calculated from the constant term in the model.

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.[19] These estimates demonstrate that recently purchased stocks that have gained value generate excess logins compared with those that have lost value, consistent with login behavior being driven by attention utility.

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 seem to be proxying for an effect of returns on the market index, or returns on other stocks. 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 channel explored by Sicherman et al., 2015). Third, the effect is not driven by the intention to buy or sell the recently purchased stocks, since during the periods no other transaction has taken place. Fourth, given the robustness of the result to the inclusion of individual fixed effects, the effect does not seems to be picking 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.

[19] Regressions in this main analysis and in the robustness and sensitivity tests exclude account × day outliers in returns, removing observations outside of percentiles 1 and 99.

3.2 Robustness and Sensitivity Tests

3.2.1 Functional Form

Our baseline estimates in Table 3 control for the daily return on the FTSE100 and for the daily return on the other stocks in the portfolio. In Table 4, 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 4 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 then 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 5.8% on the baseline probability calculated from the constant term in the model.

3.2.2 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.[20] We observe the same pattern over this longer time horizon as that seen in the main results.[21] Table 5 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

[20] 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.

[21] Additional figures presented in the Online Appendix shows that we see the same result for login behaviour in this extended period sample. Figure A3 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 purchase stock is in loss.

positive and precisely defined in each sample, with the coefficient magnitude stable across the four weekly period subsamples.

3.2.3 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, 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 A4 to Figure A7. Regression estimates are reported in Table 6. Once again, the coefficient on the gain dummy for the most recently purchase 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.

3.2.4 Returns Since Purchase

In the main empirical specification stock returns are measured as returns on the previous day. Investors may instead evaluate gains and losses against other reference prices, such as the purchase price.[22] 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,

[22] 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).

the correlation between the two measures of returns is 0.495. Results presented in the Online Appendix reveal very similar patterns when this alternative measure of returns is used in the analysis. Figure A8 reproduces the same patterns as those seen in Figure 1 using returns since purchase. Table A2 reports regression results based upon Table 3 in which the measure of daily returns is replaced with returns since purchase, again with very similar results. Finally, Table A3 shows similar results to Table 6 in a specification in which returns on the previous day are replaced by returns since purchase.

3.2.5 Sunday Logins

As an additional test, we analyse Sunday logins, following Sicherman et al. (2015). The rationale for examining logins on Sunday is as follows. Markets are closed at weekends; hence the value of an individual's stock holdings is unchanged from Friday close under Monday opening. We can therefore treat Sunday login events, conditional on the investor having made a login on Saturday, 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 a Saturday cannot receive any new information by making a login to the account on a Sunday, due to the market being closed over the whole interval. Therefore, any effect of stock price returns during the week (here the return between Thursday and Friday) on the probability of a login on a Sunday conditional on having made a login on the Saturday represents a pure effect of attention-utility preferences for looking at gains compared with looking at losses.

Table A4 presents estimates of our main econometric specification but in which the dependent variable is whether the investor made a login on a Sunday and the sample is restricted to investors who made a login on Saturday (the sample includes the four Sundays following the purchase of the stock). Results show that investors who made a gain on the most recent stock between Thursday and Friday are more likely to login on a Sunday. The coefficient of 0.0137 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 1.4 percentage points, or 6.1%, more likely to login on the Sunday.

3.3 Further Extensions

3.3.1 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 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 7 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 rejects the null hypotheses of equality of coefficients at only the the 80% confidence level. In the subsequent columns, the coefficient estimates for the weeks two-to-four subsamples fail to reject the null hypothesis of equality even at lower confidence level. This evidence is therefore inconclusive, but suggestive that people attend relatively more to their most recent stock in the period immediately after purchase.

3.3.2 Interaction Terms

As a further extension to our main analysis, we test whether out main result that stocks in gain generate excess logins compared with those in loss varies by 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) the number of stocks held and, iii) portfolio value.

Estimates are presented in Table 8. 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 the main effect of the gain dummy for females. This indicates that the excess logins generates by stocks in gain is an effect attributable only 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 A5 replicates these results using returns since purchase.

4 From Attention to Action in Trading Behavior

In this section we 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. Conversely, and more definitively, when trading using an online interface, it is not possible to trade stocks if one fails to log in.

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 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 about 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.[23]

Results for trading activity are shown in Table 9. 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. 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 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 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. The inclusion of the login dummy in the specifications in Columns 4, 5 and 6 changes the sign of the coefficient on the target stock, which becomes negative in Column 4, not precisely defined in Column 5, and about zero but again not precisely defined in Column 6. This effect on the coefficient on the gain dummy for the target stock of including the login dummy suggests that returns on the target stock influence trading via its influence on attention to the trading account (captured by the login dummy).

Results from models estimated separately for selling and buying activity are shown in the two panels of Table 10. 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 in positive in Columns 1, 2,

[23] 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. This is to avoid any bias that might be introduced by selecting out samples in which stock purchases were followed by subsequent purchases.

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 reduces the coefficient on the target stock in both the top and bottom panels. 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 A7 and Table A8 we replicate the analysis from Table 9 and Table 10 but shorten the time period of analysis to two weeks. When we do so, results are unchanged.[24]

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

5 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 the attention utility from looking at the good news about their investment choices.

In addition, our results demonstrate that 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

[24] As a further sensitivity test, we replace returns on the previous day in this specification with returns since purchase. Results are shown in Table A6 and Table A9. In these specification, 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 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 specification.

looking at their portfolio when their most recent stock has declined in value discourages investors from looking, and hence trading.

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.

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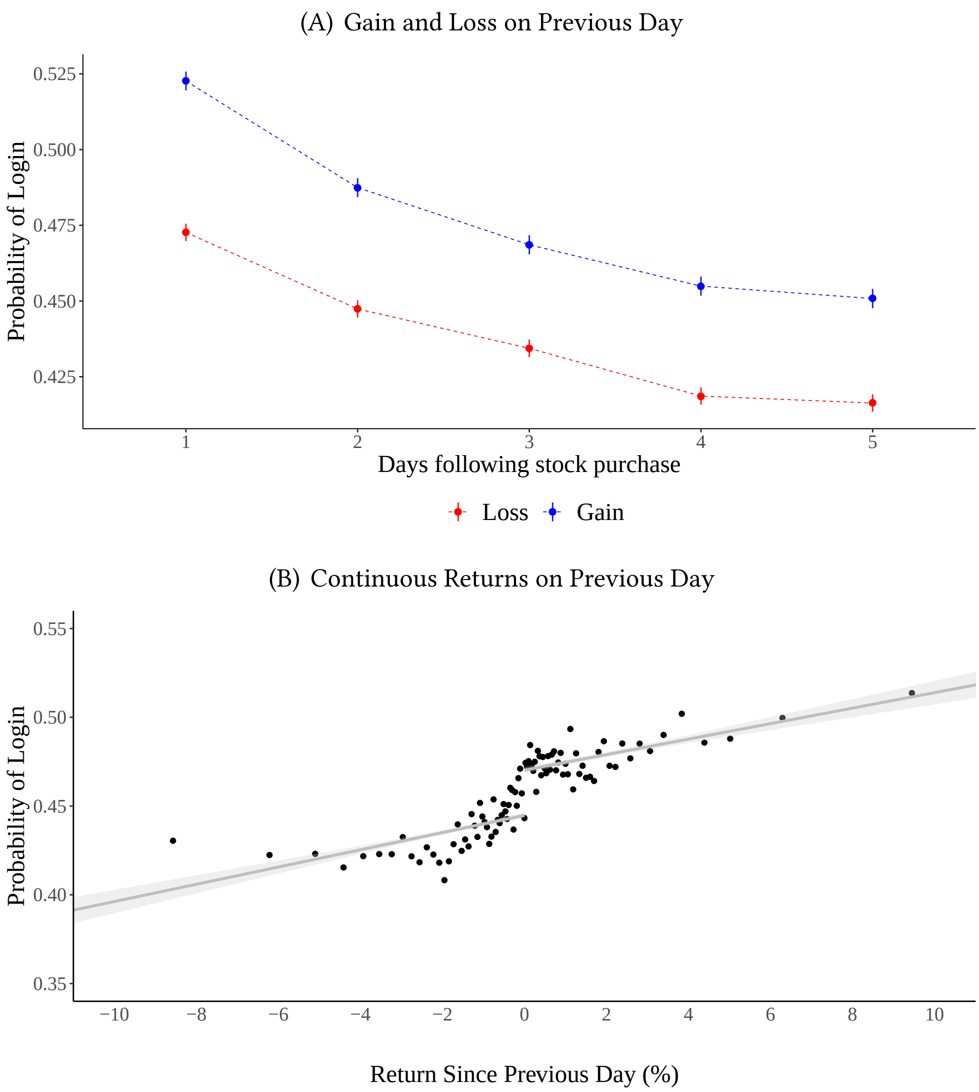
Figure 1: Probability of Login by Stock Returns



Note: Figure illustrates the relationship between returns on a recently purchased stock, and the probability of an account login, over the following five market open days after the purchase day. Panel A shows the probability of a login on each of the five market open days following the purchase of a stock, by 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 by 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.

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 for that account in the sample period.

Table 2: 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 3: Logins and Returns on 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, 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 4: Logins and Returns on 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 5: Logins and Returns on 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 in 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 6: Logins and Returns on 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 7: Logins and Returns on 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 in 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 8: Logins and Returns on 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)	
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 3, 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 9: Logins and Spillovers: Trades of Other Stocks and Returns on 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)
A 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 in 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 and Returns on Previous Day

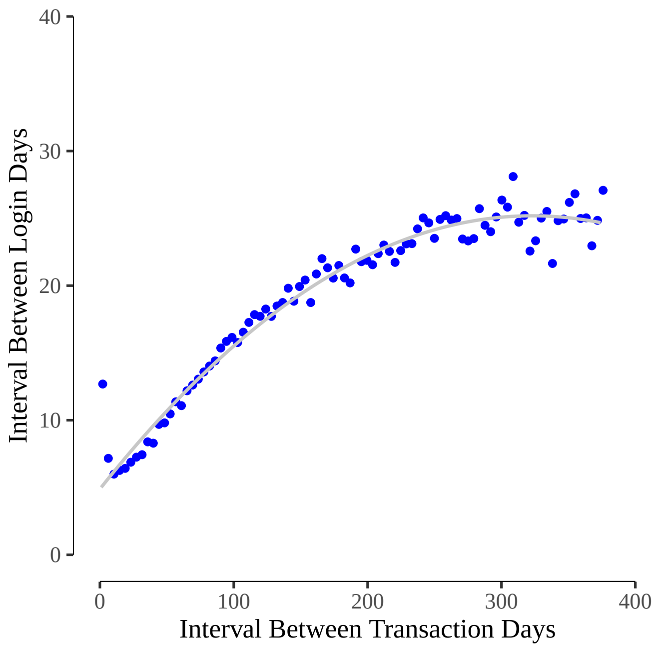
	Sell Other Stock$_{it}$ = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Target Stock, %Δ + = 1	0.0026***	0.0032***	0.0037***	0.0003	0.0008***	0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Target Stock, %Δ +		0.0007***	0.0007***		0.0003***	0.0002**
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Target Stock, %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

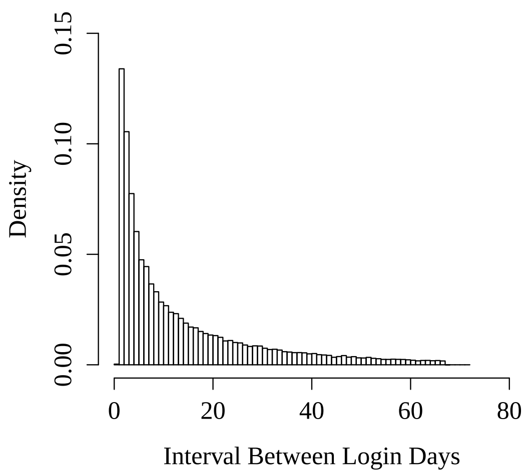
Note: The table shows the effect of a gain in a target stock on trades on others stocks in the days following the purchase of the target stock. The target stock is defined as the first stock purchased in the month. Target stocks exclude those stocks purchased in days in which the investor traded multiple stocks. The sample includes the 30 days subsequent to the purchase of the target stocks. Outliers in 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.

Figure A1: Frequency of Logins vs. Frequency of Trades

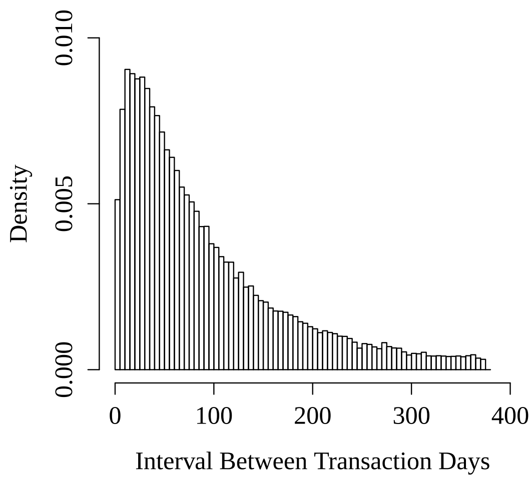
(A) Login Frequency vs. Trading Frequency



(B) Login Frequency

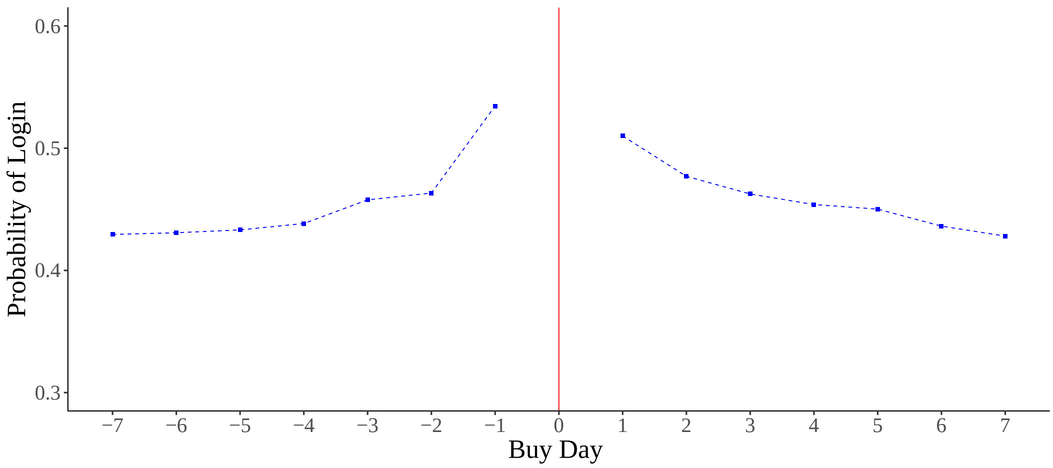


(C) Trading Frequency



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

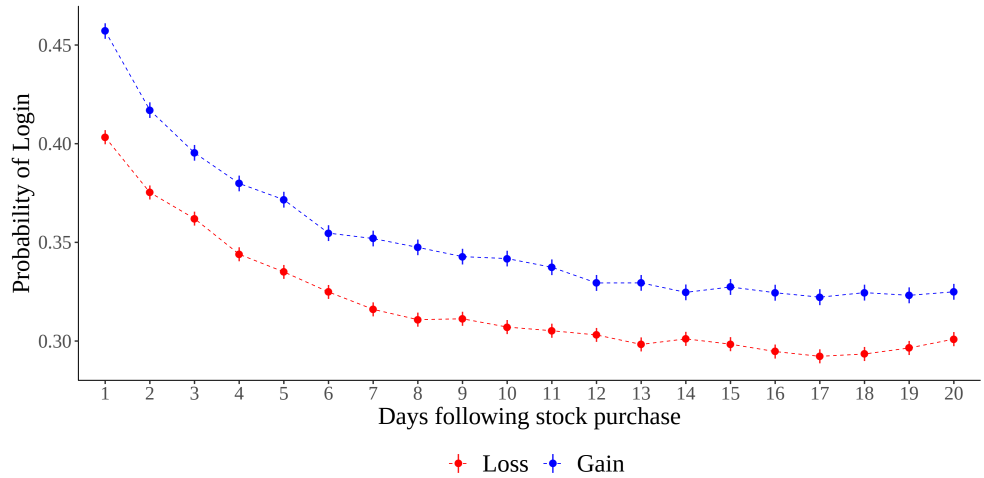


Days From Buy Transaction

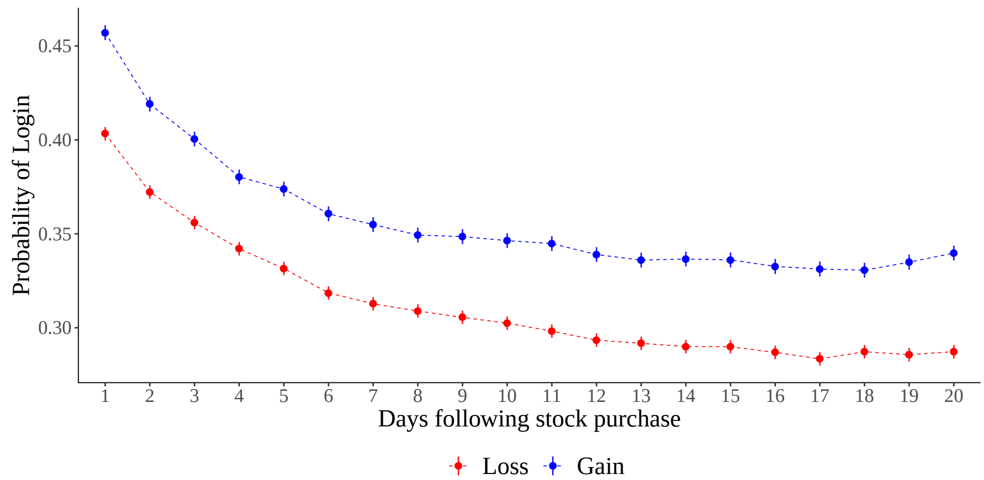
Note: Figure shows the probability of logging in the seven days before and after a buy transaction, conditional on no transaction the week before and after. Weekends are excluded. Lines spanning 95% confidence intervals are included but are not visible. The figures includes 6,434,283 account × days.

Figure A3: Daily Stock Returns and Logins Over 20 Days

(A) Return on Previous Day



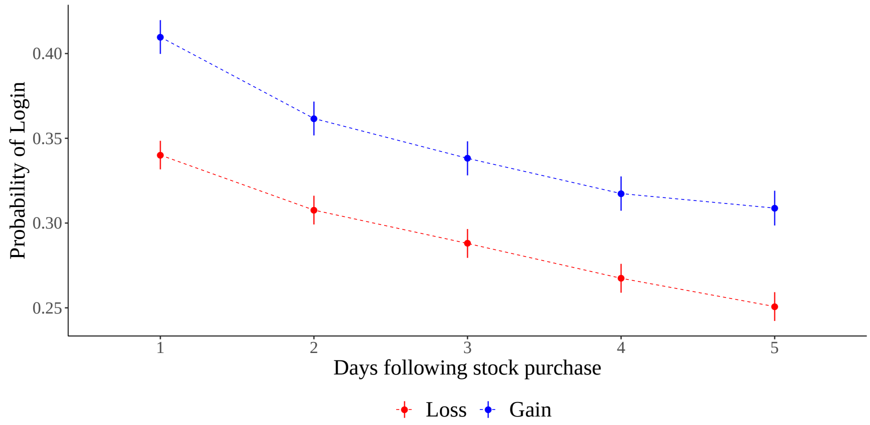
(B) Return Since Purchase



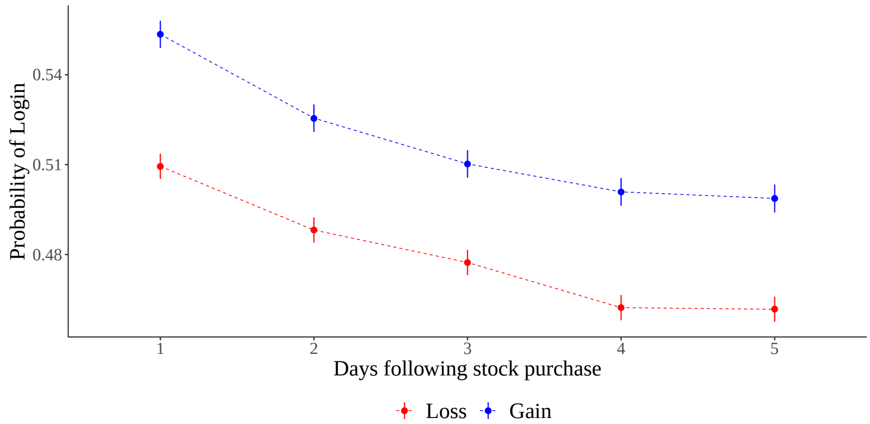
Note: Figure illustrates the relationship between returns on a recently purchased stock, and the probability of an account login, over the following twenty market open days after the purchase day. Panel A shows the probability of a login on each of the twenty market open days following the purchase of 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.

Figure A4: Daily Stock Returns and Logins for Top-Up Buys

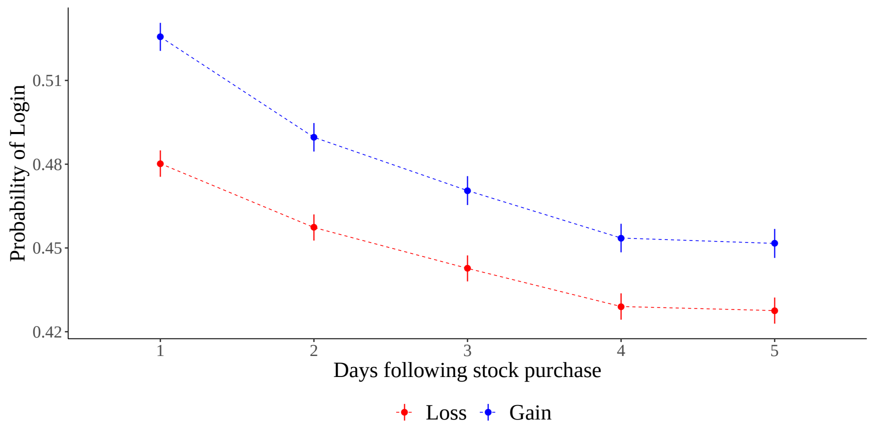
(A) Top-Up Buy of Single Stock-Portfolio



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



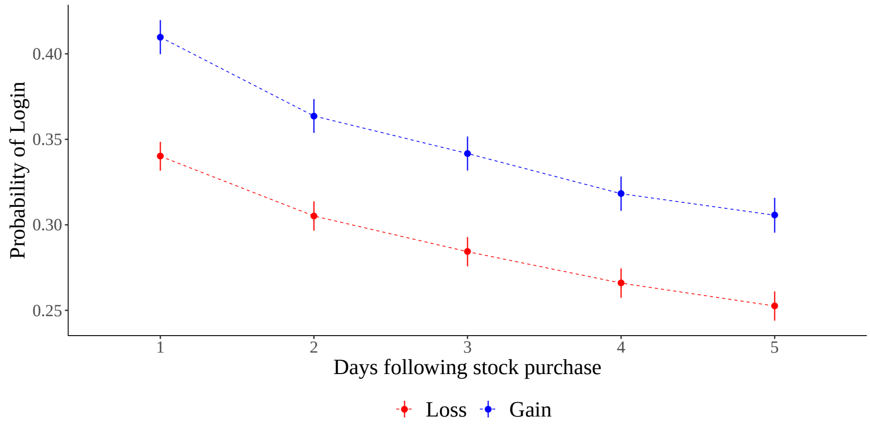
(C) New Buy Adding to Multiple-Stock Portfolio



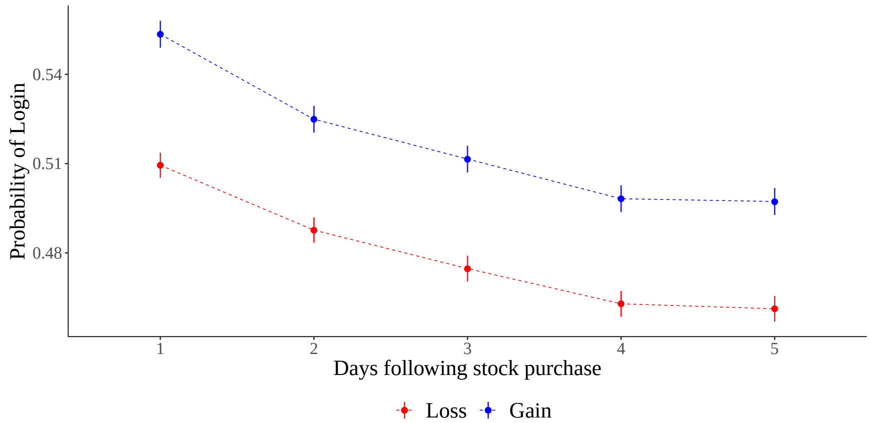
Note: The panels shows the raw likelihood of logging in during the 5 business days following the purchase of an stock, excluding bank holidays, according to changes in the daily return of that stock. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio 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 A5: Returns Since Purchase and Logins for Top-Up Buys

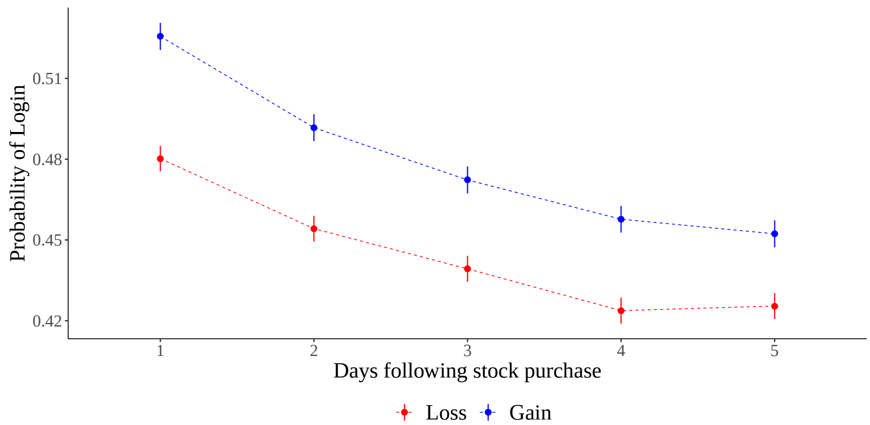
(A) Top-Up Buy of Single Stock-Portfolio



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

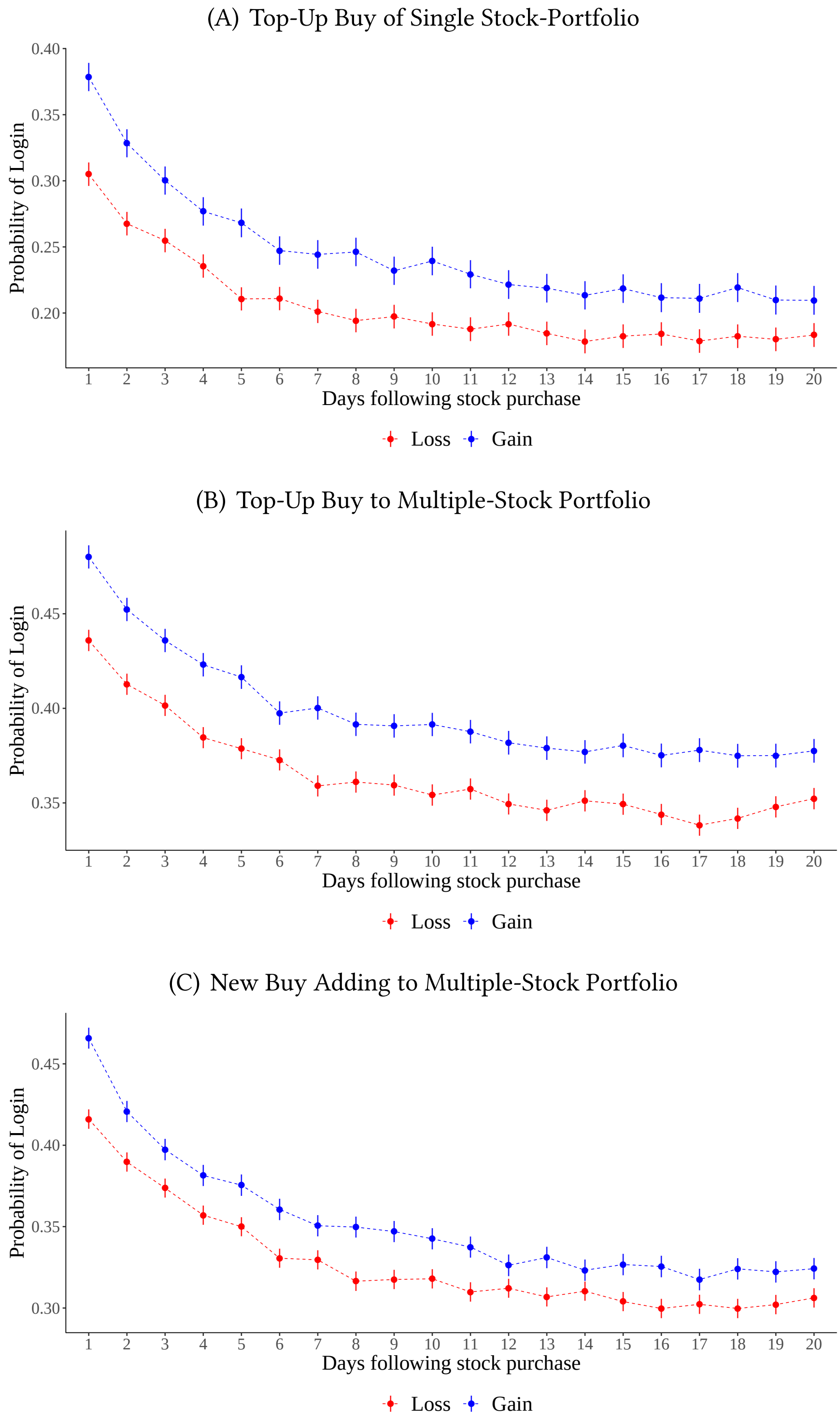


(C) New Buy Adding to Multiple-Stock Portfolio



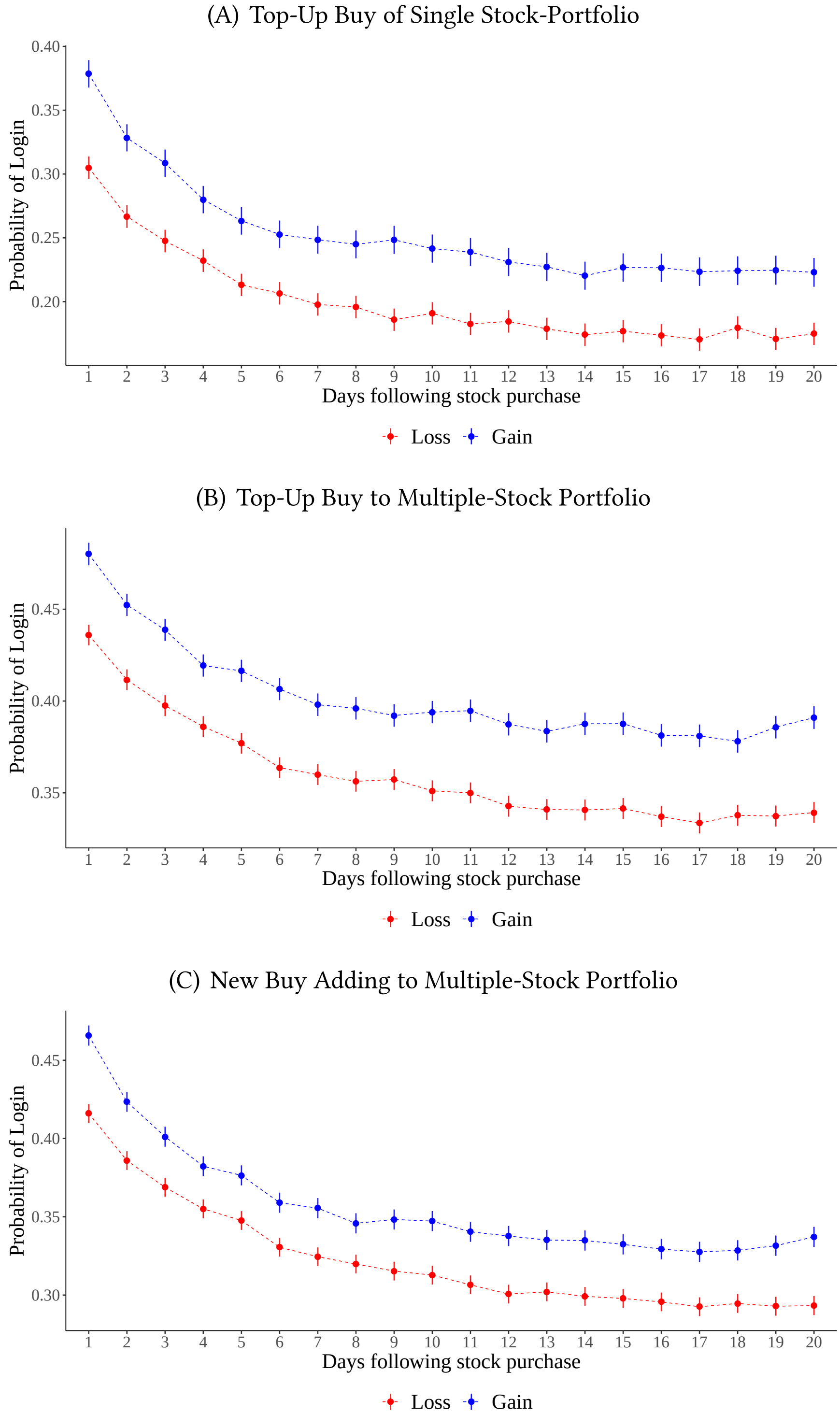
Note: The panels shows the raw likelihood of logging in during the 5 business days following the purchase of an stock, excluding bank holidays, according to changes in the return of the stock since the purchase day. The probability is displayed for the cases in which the trader (A) has only one stock in his portfolio and increases his position in that stock (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 A6: Daily Stock Returns and Logins for Top-Up Buys Over 20 Days



Note: The panels shows the raw likelihood of logging in during the 20 business days following the purchase of an stock, excluding bank holidays, according to changes in 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.

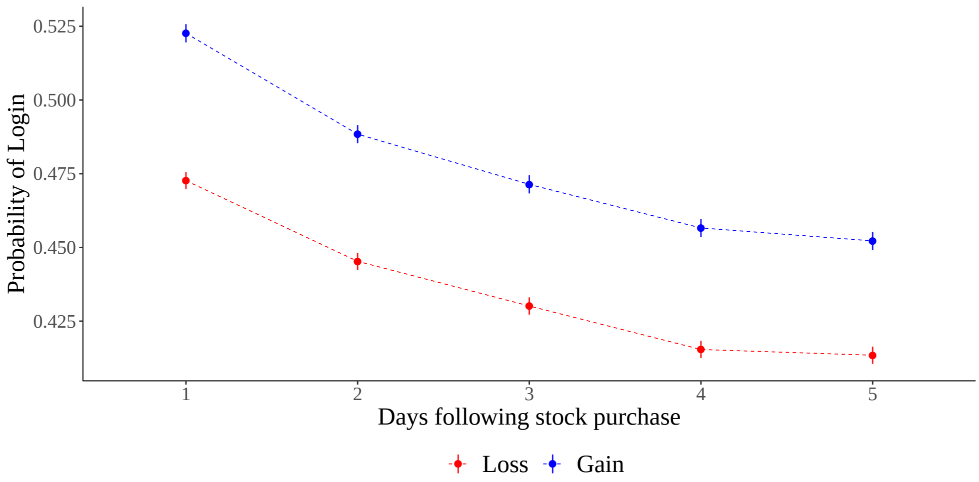
Figure A7: Returns Since Purchase and Logins for Top-Up Buys Over 20 Days



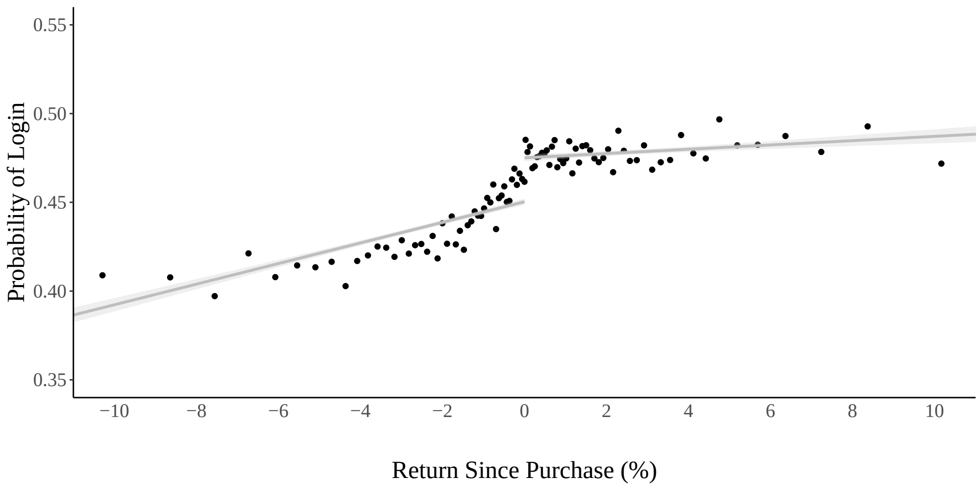
Note: The panels shows the raw likelihood of logging in during the 20 business days following the purchase of an stock, excluding bank holidays, according to changes in the return of the stock since the purchase day. The probability is displayed for the cases in which the trader (A) has only one stock 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 A8: Returns Since Purchase and Logins

(A) Gain and Loss Since Purchase



(B) Continuous Returns Since Purchase



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.

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 1.1 for a detaile description of the steps in sample selection.

Table A2: 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, 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 A3: 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 A4: Sunday Logins

	$Login_{it} = 1$ (1)
Most Recent Stock, %Δ + = 1	0.0137***
	(0.0052)
Most Recent Stock, %Δ +	-0.0079***
	(0.0019)
Most Recent Stock, %Δ -	0.0070***
	(0.0022)
Remaing Stocks, %Δ + = 1	0.0110**
	(0.0056)
Remaing Stocks, %Δ +	-0.0169***
	(0.0036)
Remaing Stocks, %Δ -	0.0172***
	(0.0046)
FTSE100, %Δ + = 1	0.0005
	(0.0056)
FTSE100, %Δ +	0.0037
	(0.0046)
FTSE100, %Δ -	-0.0060
	(0.0055)
Constant	0.2228***
	(0.0351)
Customer Controls	YES
Account Controls	YES
Observations	45,509
R^2	0.0140
Adjusted R^2	0.0131

Note: Table reports ordinary least squares regression estimates. The dependent variable is a dummy variable indicating whether the account made a login on a Sunday. The sample is restricted to the four Sundays following the week in which the investor buys new stock (day zero), either through the purchase of a new stock or top-up of an existing stock. The sample is further restricted to observations whereby the investor made a login to the account on the Saturday immediately prior to the Sunday. *p<0.1; **p<0.05; ***p<0.01.

Table A5: 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)	
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 A2, 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 A6: 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 in 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 A7: Logins and Spillovers: Trades of Other Stocks - Following Two Weeks - Returns on 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 in 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 A8: Logins and Spillovers: Trades of Other Stocks - Following Two Weeks - Returns on 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 in 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 A9: 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 in 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.