# Investor Attention, Reference Points and the Disposition Effect

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**Abstract**

Using login data from an online trading brokerage, we test whether investors have a greater propensity to sell assets when they have made a gain rather than a loss relative to the price at their latest login to their account. This disposition effect on returns since latest login exists alongside the widely-documented disposition effect on returns since purchase. We also show a strong interaction effect: investors tend to hold on to stocks that have made either a negative return since latest login or a negative return since purchase. Even a small loss since latest login annuls the disposition effect of a much larger gain since purchase. We interpret these findings in a Prospect Theory inspired model of realization utility with enhanced loss aversion.

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# 1 Introduction

In a variety of settings, individuals evaluate outcomes relative to reference points. Reference points arise when a particular price, or quantity, becomes a benchmark for future decisions. Because decision makers treat gains differently than they do losses (Tversky and Kahneman, 1991), the reference point against which gains and losses are determined by a decision maker in a particular situation can have a dramatic impact on the decisions they make. In finance, the best-documented form of reference-dependent behaviors is the disposition effect: the greater tendency of investors to sell assets that have made a gain relative to those that have made a loss (Shefrin and Statman, 1985).

In virtually all past research on the disposition effect, the purchase price has been assumed to be the relevant reference point (Barber and Odean, 2000; Shapira and Venezia, 2001; Feng and Seasholes, 2005; Chang et al., 2016). However, in many settings outside of finance, individuals evaluate outcomes relative to multiple reference points. For example, people evaluate the pay they receive from work relative to what they received in the past (Bewley, 2009), but also relative to what others receive (Brown et al., 2008; Bracha et al., 2015) and what they expected to receive (Mas, 2006; Crawford and Meng, 2011). In finance, however, there has been little if any research examining the potential for multiple reference points in investor decision making.

In this paper, we explore the role of an additional, empirically powerful, reference point that enters into investor behavior: the price the investor saw at their latest login to their account. Specifically, we show that prices of stocks held in individuals' portfolios on the days they login to their stockbroking account create reference prices against which investors are disposed to sell stocks that make a subsequent gain, compared to when they have made a loss. Our first contribution is therefore to shed light on a new form of the disposition effect. Our results replicate the disposition effect arising from gains and losses relative to purchase price, but demonstrate an additional disposition effect based on whether an asset has gained or lost value since the investor's latest login.

Our second contribution is to show that there exists a very strong interaction effect between returns since purchase and returns since latest login in their effect on selling behaviour. Estimates show that investors tend to hold on to stocks that have made either a negative return since latest login or a negative return since purchase. Hence, the effects of the two reference prices (the purchase price and the price at latest login) are not independent. The interaction effect is so strong that even a small negative return since login is sufficient to almost eliminate the disposition effect for returns since purchase.

We interpret these findings in light of an explanation for the disposition effect based upon insights from Prospect Theory offered by Barberis and Xiong (2009). They show that the disposition effect can arise in a model in which investors exhibit reference-dependent preferences (where the reference point is the purchase price) in combination with a utility function in which utility is determined by realized gains and losses. If we introduce to this framework a second reference point (the price at latest login), then, when deciding whether to sell a stock, investors evaluate the net utility of experiencing a gain, or loss, relative to both purchase price and latest login price.

This model provides an explanation for the strong interaction effect. A stock which is in gain relative to one reference price but in loss relative to the other reference price may not be sold if the net realization utility from the sale would be negative. This interpretation of the interaction effect relies on a high degree of loss aversion in the individual's utility function. Returns since latest login tend to be much smaller in magnitude compared to returns since purchase, because returns since latest login are over a much shorter time horizon. Despite this, even a small loss since latest login is sufficient to overturn the effect that a large gain since purchase has on the probability of selling. In a standard Prospect Theory utility function, for a small loss to render the positive utility of a large gain net negative in overall utility requires a very high degree of loss aversion.

We therefore discuss alternative explanations for the interaction effect based upon a *qualitative* difference in the experienced utility of a loss versus a gain. If the negative utility of a loss is greater than the positive utility of a gain at *any* value of gain, then even a small loss is sufficient to render the positive utility of a large gain net negative in overall utility. An insight from studies in psychology is that, in some circumstances, losses qualitatively nullify gains. For example, the psychologist Paul Rozin observed that "*a teaspoon of sewage will spoil a barrel of wine, but a teaspoon of wine will do nothing for a barrel of sewage*" (Rozin and Fallon, 1987). Hence, the interaction effect may reflect the unwillingness of investors to make a sale that results in a loss of any magnitude on either margin relative to purchase price or price at latest login.

A complication, in testing whether price at last login serves as a reference-point, is that when an investor looks up the value of stocks in their portfolio is itself a matter of choice. Moreover, prior research has shown that this decision is by no means random; research on the "ostrich effect" (Karlsson et al., 2009; Sicherman et al., 2015) shows that most investors are more likely to login to their accounts, without transacting, when the market is up than when it is down. Note that this is also a problem when it comes to the disposition effect associated with purchase price; when an individual buys an asset is also a matter of choice.

However, just as investors can decide when to buy, but not what happens to the value of the asset after they buy, investors can decide when to look, but not what happens to the value of the asset after they look. In our sample, returns since purchase and returns since latest login are both normally distributed with means close to zero, indicating that investors cannot buy stocks, or time their logins, to achieve a systematically positive distribution of returns. We also conduct a series of robustness and sensitivity tests which illustrate that our results are not driven by factors determining when investors login. First, we show that the disposition effect arising from returns since latest login occurs for both for logins on days following increases in the market index and on days following decreases in the market index. Hence, the results are not driven only by "ostrich" types. Second, we use a Heckman selectivity correction to control for non-random selection into login on a particular day. We use daily weather conditions as the exclusion restriction in a first-stage selection equation. This offers exogenous variation in the propensity to login on a particular day, allowing us to correct for selection. The selectivity-corrected estimates are very similar to the main estimates. Third, we show that our estimates are robust to the inclusion of individual fixed effects. Hence, our results are not due to unobservable between-investor differences in login behavior.

Our study uses individual investor account data over a four year period provided by Barclays Stockbroking, an execution-only discount brokerage operating in the United Kingdom. In addition to detailed information on trades and positions held by investors, which allow us to calculate returns on purchased stocks at daily frequency, the data also contain records of daily login activity. This allows us to calculate both the return on a stock since the stock was purchased (the standard measure of returns used in the previous literature on the disposition effect), and also the return on a stock since the investor last made a login to her account. The majority of assets (both in terms of number and value) held by investors in the trading accounts in our sample are common stocks, as opposed to mutual funds or index funds, for which evidence of the disposition effect is much weaker (Chang et al., 2016). Hence, our sample is particularly suited to the study of the disposition effect.

Importantly, the richness of our data set allows us to estimate returns on stocks at the daily level, which is crucial for our analysis. Some investors log in to their accounts multiple times per week. Hence, estimation of the effects of returns since login requires data that enable the calculation of returns on stocks at the daily level.[1] Investors also log in much more frequently than they trade, and returns since latest login are only weakly correlated with returns since purchase.

We estimate the disposition effect on returns since purchase and returns since latest login using regression models and observations at the account × stock × day level. Our baseline regression model includes dummy variables to indicate a gain since purchase and a gain since latest login, together with the interaction of the two dummies. We restrict the samples to i) observations from days on which investors made at least one sale (Sell-days) and, separately, ii) observations from days on which investors made a login to their account (Login-days). Our results show that our baseline estimates from OLS regression models are robust to the inclusion of individual fixed effects, rich controls for returns since purchase and a selectivity correction for investor logins.

We also explore the sensitivity of our main results across a broad range of sub-samples. First, we show that our main results hold across sub-samples split by whether the market index increased or decreased on the day prior to the latest login. Previous studies show that individuals are less likely to login when the market index has fallen the previous day (Sicherman et al., 2015). We find that the disposition effect arising from returns on a stock since latest login

[1] Many data sets of individual investor accounts allow only for calculation of returns at lower frequency (for example, returns at the monthly level as in Barber and Odean (2000)).

is of very similar magnitude when the latest login occurred on days after the market index rose and when the market index fell.

Second, we examine the sensitivity of our estimates to the number of days since the stock was purchased and, separately, the number of days since the latest login day, conducting a median-split of the sample on number of days since purchase, which splits the sample at 91 days. Both subsamples show a disposition effect arising from both returns since purchase and returns since latest login. The results on the longer sample show that the strength of both forms of disposition effect – arising from returns since purchase and returns since latest login – persist over long time periods. A parallel analysis dividing the sample according to the number of days since latest login, which divides the sample at prior logins occurring before or after one working week, similarly shows a disposition effect on both margins for both subsamples.

Third, we show that our estimates hold across a variety of investor characteristics and portfolio characteristics. These include investor gender, age and trading experience, as well as the number of stocks held in the investor's portfolio and the value of the portfolio. We find evidence for a stronger disposition effect when investors hold fewer stocks, plausibly because gains since purchase and latest login on individual stocks are more salient when fewer stocks are held in the portfolio.

Our study contributes new insights to the large previous literature on the disposition effect. The disposition effect has been demonstrated across multiple countries and time periods (Grinblatt and Keloharju, 2001; Brown et al., 2006; Barber et al., 2007; Calvet et al., 2009), as well as in experimental laboratory settings, such as in Weber and Camerer (1998). It tends to be stronger among individual, as compared with institutional, investors (Shapira and Venezia, 2001), less-experienced investors (Feng and Seasholes, 2005) and investors with lower wealth (Dhar and Zhu, 2006). The disposition effect has, however, been shown to not occur – indeed, there seems to be an effect going in the opposite direction – for mutual funds (Chang et al., 2016). Our focus in this paper is on purchases and sales of individual stocks.

Explanations for the disposition effect focusing on the importance of realization utility and loss aversion include Barberis and Xiong (2009) and Frydman et al. (2014).[2] Frydman and

[2] Other studies present mixed evidence on whether these features of Prospect Theory preferences would give rise to a disposition effect (Kaustia, 2010; Hens and Vlcek, 2011; Henderson, 2012).

Rangel (2014) explore the role of the salience of prices in the disposition effect, showing in a laboratory experiment that reduced salience diminishes the strength of the disposition effect.

A number of recent studies explore investor attention. Karlsson et al. (2009) present a model that links information acquisition decisions on the part of individuals to the hedonic utility of information. Sicherman et al. (2015) show that investor attention is affected by day-on-day movements in market indices. Pagel (2018) presents a model in which investors are loss-averse over news and do not pay attention to their portfolios in order to avoid bad news utility.

Previous studies suggest that first and last prices act as reference points.In a laboratory experiment that examined the determinants of investor reference points by exposing subjects to hypothetical sequences of stock prices, Baucells et al. (2011) find that a stock's starting and ending prices are the two most important inputs into an investor's reference point. Studies in the psychology literature suggest that individuals exposed to a series of stimuli tend to be better at recalling the first and the most recent values (Murdock, 1962; Ward, 2002; Ebbinghaus, 2013). For our investors, the purchase price is most likely the first price seen in the holding episode, and the price at latest login is most likely the last.

The remainder of the paper proceeds as follows. Section 2 describes the Barclays Stockbroking data and presents summary statistics. Section 3 presents the econometric specification used in the analysis and describes the sample selection restrictions. Section 4 presents the main results and the additional robustness and sensitivity tests. Section 5 interprets and discusses the empirical results. Section 6 concludes.

## 2 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 July 2016 and include daily-level records of all trades and quarterly-level records of all positions in the portfolio. The vast majority of positions held are in common stock.[3] 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

[3] 5.6% of all positions (by value) held are in mutual funds, investment trusts or other non-common stock securities

on each day of the sample period.[4] The data also contain a daily-level dummy variable for whether the investor made a login to the trading account.

We focus on new accounts that open after the beginning of April 2012, as this sample restriction allows us to calculate returns since purchase, which is required for the estimation of the disposition effect. This provides in total a baseline sample of approximately 8,200 accounts.[5]

### 2.1 Summary Statistics

Table A1 shows summary statistics for the baseline sample. Approximately 85% of account holders are male. The average age of an account holder is 45 years. Accounts holders have held their accounts with Barclays for, on average, approximately two-and-a-half years. The average portfolio value is approximately £43,000, with portfolios containing on average five stocks.

Investors in the sample overwhelmingly hold positions in a few common stocks. Holding mutual funds is uncommon, comprising only 5.6% of the average portfolio size (by value). This feature of individual investors choosing to concentrate their holdings on a few stocks is common in previous studies (for a review, see Barber and Odean, 2013).[6]

The summary statistics for login and transaction behavior show that investors login much more frequently than they trade. Investors login on average approximately once every five days (the median is approximately six days).[7] Investors made a transaction on average approximately once every 25 market open days (i.e., approximately once every five weeks), with the median investor making a transaction approximately once every fifty days. This pattern of investors paying attention to their accounts much more frequently than they make transactions is consistent with the pattern of login and transaction behavior observed among investors in the United States (US) by Sicherman et al. (2015).[8]

[4] The individual investor data used in Barber and Odean (2000) permit the reconstruction of the value of each stock position at monthly frequency.

[5] This sample restriction is necessary because in order to calculate returns since purchase we need to observe the purchase price and quantity. We do not have this information for existing accounts already open at the start of the sample period. These accounts enter the sample with stocks in the investor's portfolio but no information on date and price and/of purchase, meaning that we cannot calculate gains since purchase. We further restrict the sample to accounts for which we have complete data, including data on logins.

[6] Goetzmann and Kumar (2008) show that US investors tend to hold under-diversified portfolios with positions concentrated in only a few stocks. For most investors in their sample, under-diversification is financially costly.

[7] The variable "Login Days" measures the proportion of days the investor has an account with Barclays which is open in the sample period and makes a login. On average, investors login on 20.7% of days.

[8] Sicherman et al. (2015) explore login and transaction behavior among defined contribution retirement savings

# 3 Econometric Specification and Estimation Sample

## 3.1 Econometric Specification

In this section we explain the econometric specification used to estimate the disposition effect and the choice of estimation sample. Our interest is in whether investors have a higher tendency to sell stocks on which they have made a gain compared with those on which they have made a loss. Following the recent literature on the disposition effect (Chang et al., 2016), our baseline econometric specification which we use to estimate the disposition effect arising from returns since purchase is:

$$Sale_{ijt} = b_0 + b_1 GainSincePurchase_{ijt} + \epsilon_{ijt} \tag{1}$$

in which the unit of observation is at the account *(i)*, stock *(j)* and date *(t)* level. Note that, given the detailed account data, we can construct daily measures of returns since purchase. Hence the unit of analysis in Equation 1 is an account × stock × day. *Sale* is a dummy equal to 1 if the investor holding account *(i)* reduced holding of stock *(j)* stock on day *(t)*. *GainSincePurchase* is a dummy variable indicating whether, for the investor holding account *(i)*, stock *(j)* had made a gain on the day *(t)* compared to price on the day the stock was purchased by the investor.

We modify the baseline specification in Equation 1 by adding a dummy variable indicating whether the stock was in gain on day compared to the price on the most recent day on which the investor made a login to the account. We call this dummy variable *GainSinceLatestLogin*. The modified econometric specification is now:

$$Sale_{ijt} = b_0 + b_1 GainSincePurchase_{ijt} + b_2 GainSinceLatestLogin_{ijt} + \epsilon_{ijt} \tag{2}$$

in which *GainSinceLatestLogin* is a dummy indicating whether, for the investor holding account *(i)*, stock *(j)* was in gain on day *(t)* compared to price on the day when the investor made her most recent login.

account holders in the US using data provided by Vanguard. They find that, on average, over a two year period investors login to their accounts on 85 days while over the same period making only 2 trades. The higher levels of login and trading activity in our sample most likely reflect different behaviors among investors in their retirement savings accounts compared with their trading accounts.

The modified econometric specification therefore adds a new concept to the econometric estimation of the disposition effect, the concept of *Gain Since Latest Login (GSLL)*. The dummy variables for *Gain Since Purchase (GSP)* and GSLL are not collinear: due to the high login frequency displayed by individual investors relative to their trading frequency, as seen in the summary statistics, the correlation of GSP and GSLL is low (see summary statistics below). A stock held by an investor may have, for example, made a gain since purchase due to long-term market trends, yet have lost in value since latest login, due to short-term volatility in the prices of (most) stocks. Conversely, a persistently under-performing stock which has delivered a loss since purchase might be in gain since the latest login.

In the modified econometric specification in Equation 2 the dummy variables indicating where an account × stock × day is in GSP and GSLL enter independently. This specification therefore assumes independent effects from the two measures of gain. In an additional specification, we also include an interaction term on the two measures of gain. We return later to the economic interpretation of the independent and interacted effects.

We estimate both Equation 1 and Equation 2, allowing us first to replicate the standard estimation of the disposition effect from Equation 1 before introducing results from the revised specification in Equation 2. In subsequent robustness analysis in Section 4.3, we also estimate models that add i) individual fixed effects to control for individual-specific time invariant heterogeneity in selling behavior, ii) continuous measures of returns since purchase above and below the zero threshold, iii) a selectivity correction (Inverse Mills Ratio) to control for selection into making a login. We also present additional sub-sample analysis of estimates of these econometric models in Section 4.4.

### 3.2 Estimation Sample

The econometric specifications in Equation 1 and Equation 2 have as the unit of observation an account × stock × day. Given that we can observe the value of stock positions at daily frequency, we could estimate Equation 1 and Equation 2 using all account × stock × days in the data i.e. for each stock held by each investor a separate observation for each day of the sample period. This would provide a very large estimation sample.

However, a common concern raised in the previous literature relating to the selection of account × stock × time unit (here day), is that on most days investors do not make a sale, and may not pay any attention to their portfolio. Hence, on non-sale days, the effective likelihood of a sale may be zero. Consequently, previous studies restrict the sample to account × stock × time units on which the investor sold at least *one* stock in their portfolio, as this indicates that the investor was paying attention to the portfolio at those points in time and there was some risk that the investor would sell *any* stock (Chang et al., 2016).

We therefore use a baseline sample restriction of account × stock × days on which the investor made a sale of at least one stock, which we refer to as the *Sell-Day sample*. Given that we have login data, we can also restrict the sample to account × stock × days on which the investor made a login, as on these days we know that the investor was paying attention to the portfolio, which we refer to as the *Login-Day sample*. Of course, a login event does not imply that the investor had some intention to make a trade, but the likelihood of a trade increases when the investor pays attention to their portfolio. Results from the Login-Day samples resemble results from the Sell-Day sample.

The Sell-Day sample provides approximately 320,000 account × stock × days for by investors who sold at least one stock on the day, whereas the login sample is much larger (because login days are much more common than sale days). The Login-Day sample provides 2,315,276 account × stock × days for investors who made at least one login on the day. Both data samples pools together investors and days, hence we cluster standard errors at the account and date level. For concreteness, our results will focus on estimates using the Sell-Day sample. However, in Appendix A, we present analogous estimates using the Login-Day sample.

### 3.3 Summary Statistics for Measures of Returns

Figure A1 illustrates the distributions of returns since purchase and returns since latest login in the Sell-Day sample and in the Login-Day sample. The distributions are centred on zero and appear very close to normal, with a wider range of returns since purchase compared with returns since latest login day. Given the greater frequency of logins than trades, this difference reflects the longer time period over which returns since purchase occur.

Table 1 provides summary statistics for returns since purchase and returns since latest login in the Sell-Day (Panel A) and Login-Day (Panel B) samples. In both samples, close to 45% of account × stock × days are for stocks which show a gain since purchase.[9] The percentage of account × stock × days showing a gain since latest login is close to the percentage of account × stock × days showing a gain since purchase.

Table 2 summarizes the correlation between returns since purchase and returns since latest login. Given that most investors only hold a few stocks in their portfolios, if investors were to log in only to make trades, we would expect a high correlation between returns since purchase and returns since latest login.[10] However, this is not the case in our sample in which investors login much more frequently than they trade. The Pearsons' $\rho$ coefficient is 0.18 in the Sell-Day sample and 0.11 in the Login-Day sample. The correlation is higher among the top decile of accounts by trading frequency, as expected, because there are fewer login days between transactions.

## 4 Results

### 4.1 Main Results

This subsection presents estimates of the disposition effect. Before showing the regression estimates, Figure 1 illustrates the unconditional relationship between stock returns since purchase and the probability of the stock being sold. The plot pools all account × stock × day observations in the Sell-Day sample.[11] The plot shows a very large increase in the probability of sale when returns since purchase are positive.

Figure 2 Panel A shows the analogous relationship for stock returns since latest login. That is, Figure 2 Panel A plots the probability that a stock is sold as a function of its return since latest login. Initially scrutiny of the figure suggests that its shape is very different from that of Figure 1, which shows sales as a function of returns since purchase; the plot shows a

[9] The equivalent statistic is is 49% in Chang et al. (2016).

[10] As a limit example, an investor who buys only one stock, making a login on the buy-day in order to place the buy order, and does not login until the the day on which she sells the stock, would have a correlation of 1 between returns since purchase and returns since latest login.

[11] Figure A2 shows the equivalent plot using the Login-Day sample.

"v-shape" centered upon zero in contrast to the step-shape of Figure 1. However, the difference is misleading. Returns since latest login, whether positive or negative, tend to be much smaller than returns since purchase. This is because people log in much more frequently than they trade, so the time interval since purchase is on average much longer than the time interval since last login. When we make the trade since last purchase figure more comparable, by only examining purchases made in the last 30 days, the graph of likelihood of selling as a function of returns since purchase (Panel B of Figure 2) also displays a v-shape pattern.[12] We conjecture that both figures show a reluctance to sell stocks that have gained or lost very little since either purchase or last login. Ben-David and Hirshleifer (2012) also find that the probability of selling as a function of returns since purchase is v-shaped over short holding periods.

The key feature of Figure 2 Panel A of relevance here, which can be seen on closer inspection, is that the probability of the stock being sold is higher when returns since latest login are positive than when they are negative. This disposition effect is very clear in the regression estimates, which are shown in Table 3.

Panel A of Table 3 shows results from the Sell-Day sample and Panel B shows results from the Login-Day sample. Column 1 of each panel shows the estimates of Equation 1. The coefficient on the Gain Since Purchase dummy is positive in both panels. The coefficient of on the Gain Since Purchase dummy in Column 1 of Panel A implies that a stock which is in gain since purchase is approximately 11.5 percentage points more likely to be sold compared with a stock in loss. Against the base probability of selling a stock from the constant in the regression of 14.2%, this represents an increase of 80.9%. In the Login-Day sample in Panel B, the equivalent increase is 68.9%.

The model in Column 2 Panel A replaces the GSP dummy from Equation 1 with the GSLL dummy. The coefficient on this dummy variable is again positive and precisely defined. The coefficient of on the GSLL dummy in Column 2 of Panel A implies that a stock which is in gain since latest login is approximately 5.1 percentage points more likely to be sold compared with a stock in loss. Against the base probability of selling a stock of 17%, this represents a 30% increase in the likelihood of a sale. In the Login-Day sample, the equivalent increase is

[12] Figure A3 shows the equivalent plots using the Login-Day sample.

approximately 34%.

Estimates of Equation 2 are shown in Column 3 in each panel. Results show a positive coefficient on both the GSP and GSLL dummies, which are both precisely estimated. The inclusion of both GSP and GSLL dummies increases the model fit, measured by $R^2$. In keeping with the results in Columns 1 and 2, in Column 3 the coefficient on the GSP dummy remains stronger than the coefficient on the GSLL dummy. This is pattern holds in the Sell-Day and Login-Day samples. In Panel A, the coefficients imply that a stock in GSP is eleven percentage points more likely to be sold, while a stock in GSLL is 3 percentage points more likely to be sold.

### 4.2 Interaction Results

The specification shown in the final column of Table 3 adds the term for the interaction of the GSP and GSLL dummies to Equation 2. The coefficients for the main effects and the interaction are precisely defined. Investigation of the coefficient magnitudes implies that the probability of sale is only increased when both GSP and GSLL are positive.

To visualize the interaction between GSP and GSLL, Figure 3 reproduces the illustration in Figure 1, separating out account $\times$ stock $\times$ day observations by whether the stock was in gain or in loss since latest login.[13] Strikingly, the discrete jump in probability of sale around zero on the x-axis is seen only for the sample of observations in gain since latest login. Hence there is no evidence for a disposition effect arising from positive returns since purchase when the stock has made a loss since latest login.

Before turning to the interpretation of these results, we first present the results from robustness test and sensitivity tests.

### 4.3 Robustness Tests

#### *4.3.1 Individual Fixed Effects*

The first robustness test adds individual fixed effects to control for individual-specific time invariant heterogeneity in selling behavior. Results are shown in Table 4. The table reports

[13] Figure A4 shows the equivalent plot from the Login-Day Sample.

results for the same four specifications as those shown in Table 3. Results from the Sell-Day sample are shown in Panel A, with results from the Login-Day sample shown in Panel B. The inclusion of individual fixed effects does not alter the qualitative pattern in results in either sample.

#### *4.3.2 Controlling for Returns*

The second robustness tests adds linear controls for returns to the econometric models in Equation 1 and Equation 2. Linear controls are added for returns either side of zero, for both returns since purchase and returns since latest login. Results are shown in Table 5 for the Sell-Day sample. Table 5 reports estimates both without individual fixed effects (shown in Columns 1-4) and with the addition of individual fixed effects (shown in Columns 5-8). Results for the Login-Day sample are shown in Table A2. The pattern in the results remains qualitatively the same as those shown in Table 3 even after controlling for the magnitude of gains and losses.

#### *4.3.3 Login Selectivity Correction*

Not all investors login to their accounts on each day and this could potentially create a source of bias in our main estimates if the propensity to login on a particular day is related to the disposition effect. Given that we only observe selling choices when the investor makes a login into the account, a third robustness test adds a Heckman selectivity correction term to control for non-random selection into making a login on a given day. The first step of the Heckman (two-step) correction procedure consists on defining a probit model for selection, followed by the calculation of a correction factor: the inverse Mills ratio. The second step estimates our equation of interest, Equation 2, including the correction factor. For identification, we need an exclusion restriction, one variable that affects the selection into the sample—the decision to login on the day— but that does not affect the decision to sell otherwise. As an exclusion restriction we use the weather in the locality in which the investor resides. Individuals are more likely to login to their trading accounts on poor weather days due to the lower opportunity cost (e.g. outside leisure activities).

Specifically, we match into the Barclays investor data set weather data recorded by the UK

Meteorological Office at 150 weather station locations geographically distributed across the UK. We match the 2,009 unique postcodes (at the 4-digit level) of the investors in our sample to the nearest weather station and join data on daytime visibility, a commonly used measure of weather.[14]

Estimates of the probit model for the decision to login are shown in Table A3. The dependent variable in the model is an account × day dummy for whether the investor made a login to the account on the day, with a sample size of 3.2 million account × days. The model includes the modal visibility on the day. The model also includes fixed effects for the month of the year and the day of the week when the login occurred. The omitted visibility category in the model is "Excellent." The coefficients on the other visibility categories are each positive and precisely defined, with larger magnitudes for the higher visibility ratings, implying that investors are more likely to login to their trading accounts on poor weather days. From this model, we calculate the Inverse Mills Ratio that is added to our equation of interest.

Table 6 shows estimates of the main equation of interest for the Login-Day sample with the inclusion of the Inverse Mills Ratio as the additional control. The qualitative pattern in the coefficient estimates is once more the same as in Table 3. The coefficient on the Inverse Mills Ratio is negative and precisely defined, implying that the main results may suffer from negative selection, i.e. downward-bias in the coefficient estimates.[15]

### 4.4 Sensitivity Tests

#### *4.4.1 Market Movements*

As a first sensitivity test, we examine the sensitivity of our main results to days following market upturns and market downturns. Recent evidence shows that investors pay more attention to their accounts on days following a gain in the market index (Sicherman et al., 2015). To explore whether our main results hold on both days following market upturns and market downturns,

[14] Visibility at the weather station is measured on a 6-point scale between "Excellent" and "Very Poor" based on visibility (in meters. Due to some missing data, the sample for this analysis is reduced from 5.9 million account × sock × days to 5.7 million account × stock × days.) We calculate the modal visibility level on the day (between 8am and 8pm) and use this variable as the exclusion restriction.

[15] We do not have equivalent selectivity-corrected estimates for the Sell-Day sample as we do not have an exclusion restriction offering a source of exogenous variation in making a login on a day conditional upon making a sale, which would be the necessary feature of an exclusion restriction in the Sell-Day sample.

we join data on the level of the Financial Times Stock Exchange 100 Index, which tracks the value of shares among the UK's largest 100 publicly listed firms by market capitalization. We then split the sample into observations of days following a rise in the FTSE 100 Index and days following a fall in the FTSE 100 Index.

Results are shown in Table 7. Panel A shows results from the sample of days following a rise in the FTSE 100 Index, Panel B shows results from the sample of days following a fall in the FTSE 100 Index. The results are very similar across all columns of the two panels. Table A4 shows the same patterns occur in the Login-Day sample.

#### *4.4.2 Days Since Purchase and Days Since Latest Login*

Second, we test the sensitivity of our main results to the number of days since the investor purchased the stock and the number of days since the latest login. The strength of the disposition effect might plausibly decline over time if investors forget the value of their positions in each stock or pay less attention to older positions in their portfolio.[16]

Table 8 reports results where in the sample is split into two by the median number of days since purchase. Panel A shows results from the sample of below-median days since purchase (where the median days since purchase is 100 days) with Panel B showing results from the sample of above median days since purchase. The qualitative pattern in the results is the same across the two sub-samples, but the coefficient magnitudes are smaller in Panel A for the coefficients on both GSP and GSLL.Table A5 shows the same patterns occur in the Login-Day sample.

Table 9 reports results where the sample is split by the number of days since latest login. Many investors login to their account every day, so the table shows three panels: Panel A shows observations for which the latest login was the previous day, Panel B shows observations for which the latest login was two to five days previously and Panel C shows observations for which the latest login was more than 6 days previously.

The coefficient on GSLL dummy does not decline across the samples: it is small in Panel B (two-to-five days since latest login), but is similar size in Panel C (more than six days since

[16] However, this will not be the case if the online brokerage interface displays the purchase price, as is the case with most online brokerage interfaces, including Barclays Stockbroking.

latest login) as that in Panel A (one day since latest login). These estimates do not suggest, therefore, that the disposition effect on returns since latest login fades over this time window.[17] Table A6 shows the same patterns occur in the Login-Day sample.

#### *4.4.3 Investor and Portfolio Characteristics*

Third, we test the sensitivity of our main results to investor characteristics and investor portfolio characteristics.

We explore the sensitivity of our main results to investor gender and age. Previous studies show gender and age differences in trading behavior (Barber and Odean, 2001; Agnew et al., 2003; Dorn and Huberman, 2005; Mitchell et al., 2006). To investigate, we split the sample by investor gender and also, separately, by investor age (splitting the sample at the age of the median investor). We then estimate our main models on both samples separately. This approach allows the coefficients on all variables to vary across the samples. Results for the estimates of Equation 2 are reported in the top rows of Table 10. Results for the coefficients on the main effects and interaction terms (Column 4 of Table 3) are shown in Table 11. The estimates reveal slightly higher coefficients on the main effects and on the interaction term for females (though the much smaller sample size for females results in larger standard errors). The coefficients on the main effects and interaction terms are very similar in the age sub-samples.

We also explore the sensitivity of our main results to investor trading experience (measured by the number of years for which the investor has held the trading account with Barclays Stockbroking), portfolio value and the number of stocks held in the portfolio. Previous studies suggest that the disposition effect declines with trading experience (Feng and Seasholes, 2005; Seru et al., 2010).

Results show very similar coefficient estimates across samples by investor experience. Results by portfolio value and number of stocks held show larger coefficient values for below-median portfolios by portfolio value and below-median portfolios by number of stocks held. To gauge the magnitude of the difference in effect size across samples by number of stocks held

[17] We cannot rule out the possibility that the disposition effect on gains since latest login would fade over longer time horizons. However, due to the high frequency with which investors login to their accounts in the Sell-Day and Login-Day samples, we do not have a large number of observations in which we could test for the effects of longer time horizons.

and portfolio value, in Table 11 the coefficient on the interaction term is approximately twice as large for the below-median portfolio value and number of stocks held samples compared with the above-median. This suggests that the disposition effects are stronger when investors hold fewer stocks, plausibly because gains since purchase and latest login are more salient when fewer stocks are held in the portfolio.[18] Table A7 and Table A8 show the same patterns occur in the Login-Sample sample.

# 5 Interpretation and Discussion

In this section we interpret and discuss our results. Our analysis yields two main results. First, investors to have a greater propensity to sell assets when they have made a gain compared to when they have made a loss relative to the price at their latest login to their account. In other words, there is a "returns since latest login" disposition effect alongside a "returns since purchase" disposition effect. Second, there is a strong interaction effect between these two outcomes: investors tend to hold on to stocks that have made either a negative return since latest login or a negative return since purchase.

## 5.1 Multiple Reference Points

Our first result shows that the purchase price is not the only reference point relevant to investors when making decisions over which stocks to sell. The fact that the purchase price is the first price seen by the investor (at least, the first price in investor's history of returns for the current episode of holding that stock) and that the price at latest login is the most recent price seen by the investor is consistent with previous studies showing that "first" and "last" prices act as reference points.[19]

For example, in a laboratory study closely related to our current study, Baucells et al. (2011) presented participants with a price sequence for an imaginary stock on a graph on a computer screen, and ask them to imagine that they had purchased the stock for the first price

[18] Portfolio value correlates with the number of stocks held, so we should not interpret these results as isolating the independent effect of either variable.

[19] The "purchase price" in the calculation of the disposition effect is a weighted average of prices paid each time the investor buys the stock. In the majority of account × stock × days investors hold positions originating from one purchase event, hence, on these days, the first price and the purchase price are the same.

in the sequence. At the conclusion of the sequence, participants were asked to state the "*at what selling price would you feel neutral about the sale of the stock, i.e., be neither happy nor unhappy about the sale*." They find that reference price is best described as a combination of the first and the last price of the time series, with intermediate prices receiving lower weights. Earlier studies in the psychology literature suggest that individuals exposed to a series of stimuli tend to be better at recalling the first and the most recent values (primacy and recency effects—Murdock, 1962; Ward, 2002; Ebbinghaus, 2013).[20]

### 5.2 Interaction Effect

Our second result is that the effects of the two reference prices are not independent. The interaction effect is so strong that either a negative return since latest login or a negative return since purchase is sufficient to almost eliminate the disposition effect seen in the other variable in most of our estimates. This is seen most clearly in Figure 3, which plots unadjusted probability of sale on a particular day as a function of return since purchase, plotting separately days on which returns since latest login were positive or negative. In the remainder of this section we discuss how this strong interaction effect can be interpreted in light of recent models of the disposition effect based upon insights from Prospect Theory.

#### *5.2.1 Prospect Theory Interpretation*

In a recent paper, Barberis and Xiong (2009) explore Prospect Theory-based explanations of the disposition effect. They show that the disposition effect can arise in a model in which investors engage in narrow framing, exhibit reference-dependent preferences in combination with a Prospect Theory realization utility function (the form of which is shown in Figure 4 Panel A), with the purchase price acting as the reference price.[21]

[20] Of course, reference prices need not be limited to first and last prices. There may be other relevant reference prices. For example, market analysts commonly make reference to moving averages defined over recent time windows (e.g., 30-day and 60-day moving averages). There may be individual-specific reference prices arising from points in time most salient to the individual. In another example, in the hedonic evaluation of a sequence of events, there is a peak-end effect, where the *worse* and the last event strongly influence the overall evaluation (Kahneman et al., 1993).

[21] As Barberis and Xiong (2009) observe, while people commonly refer to Prospect Theory as an explanation for the disposition effect, it is not immediately apparent how Prospect Theory can explain the disposition effect. Prospect Theory preferences can explain why individuals do not take gambles with positive expected pay-off, because the convexity of utility over losses implies that the gamble may not have positive expected utility. However, the

The explanation for the disposition effect in Barberis and Xiong (2009), which is relevant to our discussion here, is as follows. Due to loss aversion, the investor prefers to realize a loss via one sale of the total position in the stock (the convexity of utility in the loss domain means that the utility loss of realizing a $ loss in one sale is *lower* than the sum of utility losses from realizing the same $ loss in two or more sales). For gains, the investor prefers to realize a gain via many partial sales of the position in the stock (the concavity of utility in the gain domain means that the sum of the utility gains from realizing a $ gain in two or more sales is *higher* than utility gain from realizing the same $ gain in one sale). That is, investors prefer one big aggregated loss over many small segregated losses and prefer many small segregated gains over one big aggregated gains—in both cases because of diminishing marginal utility from the zero point. Hence, when deciding which stock to sell on a given day, investors will tend to sell a little of a stock that is in gain spreading the sale over many time periods, but prefer to hold on to their stocks in loss until the last time period (at which they will realize the entire aggregated loss through a terminal sale).

How does this model shed light on the interaction effect between GSP and GSLL? If we introduce a second reference price into the framework in Barberis and Xiong (2009), the price at latest login, then investors weigh the net utility of experiencing a gain, or loss, relative to both purchase prices and latest login price when deciding whether to sell a stock. A stock which is in gain relative to one price but in loss relative to the other price may not be sold if the net realization utility from the sale would be negative. With loss aversion, a stock which makes a larger gain relative to one price but a smaller (absolute value) loss relative to the other price may not be sold because the negative utility of the small loss is larger in magnitude than the positive utility of a larger gain due to loss aversion.

While this account provides an explanation for an interaction effect between GSP and GSLL, it does not immediately account for the strength of the interaction effect. In our estimates, either a negative return since latest login or a negative return since purchase is sufficient to almost eliminate the disposition effect. While gains experienced since a purchase can be large,

disposition effect refers to investors choosing to sell “risks” that have already resolved. For example, Barberis and Xiong (2009) show that the disposition effect does not arise in a model of Prospect Theory reference-dependent preferences in combination with realization utility in which utility is defined over annualized gains and losses (not gains and losses relative to the purchase price).

losses experienced since the last login are nearly always smaller in magnitude because of the much shorter time horizon. Despite the smaller magnitude, a small loss since latest login can overturn the effect of a much larger gain since purchase, and this requires substantial, perhaps implausible, loss aversion in the standard Propect Theory model.

### *5.2.2 Alternative Interpretations*

In a standard Prospect Theory utility function, for a small loss to render the positive utility of a large gain net negative in overall utility requires a very high degree of loss aversion. For example, in Figure 4 Panel A, the net utility of a small loss in combination with a large gain will be positive. One alternative interpretation of the interaction effect, therefore, is that individuals experience a very high degree of loss aversion. A high degree of loss aversion could be modelled as either i) the slope of the utility function in loss must be very steep close to the origin, or, ii) there is a discrete downwards jump in utility at zero, illustrated in the modified Prospect Theory utility function in Panel B suggested by Homonoff (2018).[22] In the utility function illustrated in Panel B, the utility loss of a small loss will outweigh the utility gain of a large gain due to the discrete drop in utility at zero. In this way, a small loss relative to one reference price could outweigh in net utility a large gain relative to the other reference price, resulting in the investor deciding not to make a sale.

One alternative interpretation of the strength of the interaction effect is that there is a *qualitative* difference in the experienced utility of a loss versus a gain. If the negative utility of a loss is greater than the positive utility of a gain at *any* value of gain, then even a small gain is sufficient to render the positive utility of a large gain net negative in overall utility. An insight from studies in psychology is that, in some circumstances, losses qualitatively nullify gains. For example, the psychologist Paul Rozin observed that "*a teaspoon of sewage will spoil a barrel of wine, but a teaspoon of wine will do nothing for a barrel of sewage*" (Rozin and Fallon, 1987).

These alternative interpretations share the common characteristic that small losses are sufficient to offset the positive utility effects of large gains, providing a theoretical framework

[22] Homonoff (2018) examines the impact of a $0.05 taxe vs. a $0.05 bonus on the use of disposable plastic bags. She finds that while the tax decreased disposable bag use by over forty percentage points, the bonus generated virtually no effect on behavior. This result is consistent with a loss aversion only if the utility drop in the loss domain is very large at the very small $0.05 loss.

for interpretation of the strong interaction effect we see in our empirical estimates.

## 6 Conclusion

In this paper we use detailed daily-level trading data from an online trading brokerage to show that investors have a tendency to hold on to stocks that have made negative returns since the investor last made a login to their account. This new form of disposition effect based on returns since latest login exists alongside the well-known disposition effect on returns since purchase, identifying another reference price that is relevant for investor trading decisions.

We further show a strong interaction effect: investors tend to hold on to stocks that have made either a negative return since latest login *or* a negative return since purchase. The interaction effect is so strong that a negative return since latest login is sufficient to almost eliminate the conventional disposition effect in most of our estimates.

We interpret these findings in a Prospect Theory-inspired model of realization utility with enhanced loss aversion. We introduce a second reference point (the price at latest login) into a model of the disposition effect based upon reference-dependent preferences and a Prospect Theory realization utility function. Under this modified model investors weigh the net utility of experiencing a gain, or loss, relative to both purchase prices and latest login price when deciding whether to sell a stock. Due to loss aversion, a stock which is in gain relative to one reference price but in loss relative to the other reference price may not be sold if the negative realization utility from the second reference price outweighs the positive realization utility from the first reference price.

Our findings imply that investor attention is important for understanding trading behaviour. The act of paying attention to one's trading account generates an empirically important reference point that bears on future behaviour. Our paper contributes to a growing literature showing how attention matters for economic behavior and outcomes.

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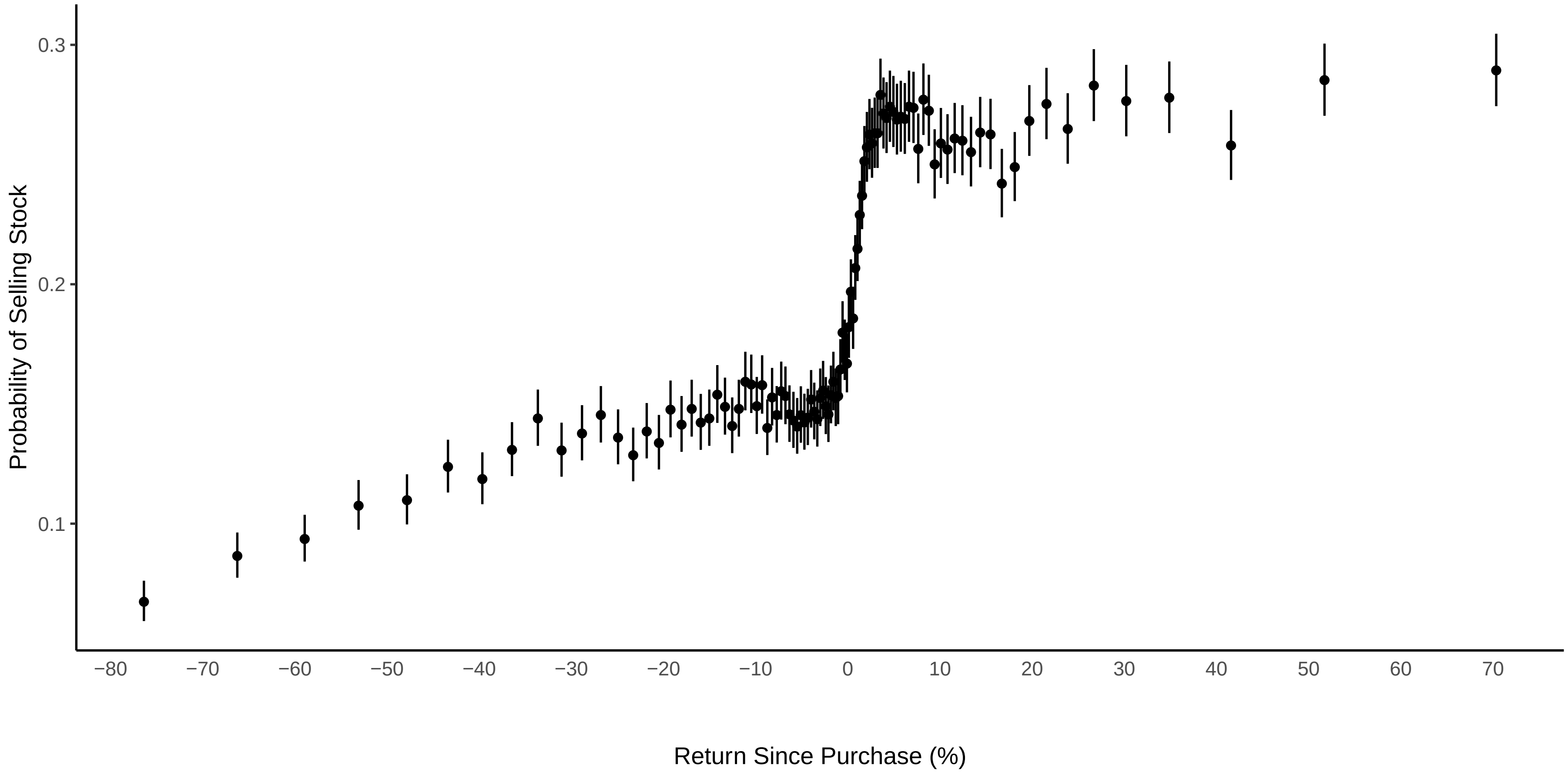
Figure 1: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Purchase in the Sell-Day Sample

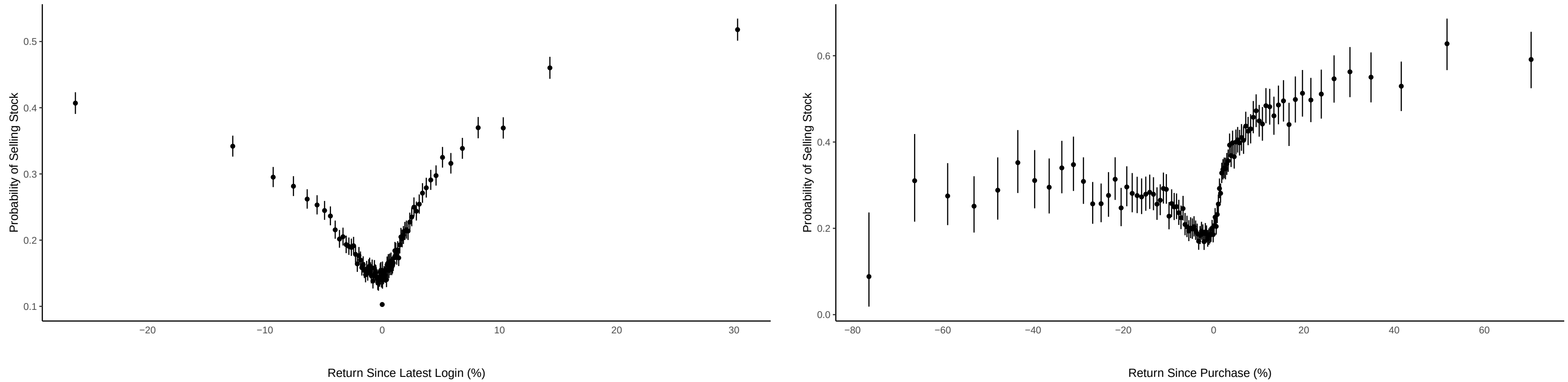



*Note:* Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. Sell-day sample includes all investor × stock × days on which the investor sold at least one position in the portfolio. Returns since purchase are calculated at the daily level.

Figure 2: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Latest Login in the Sell-Day Sample

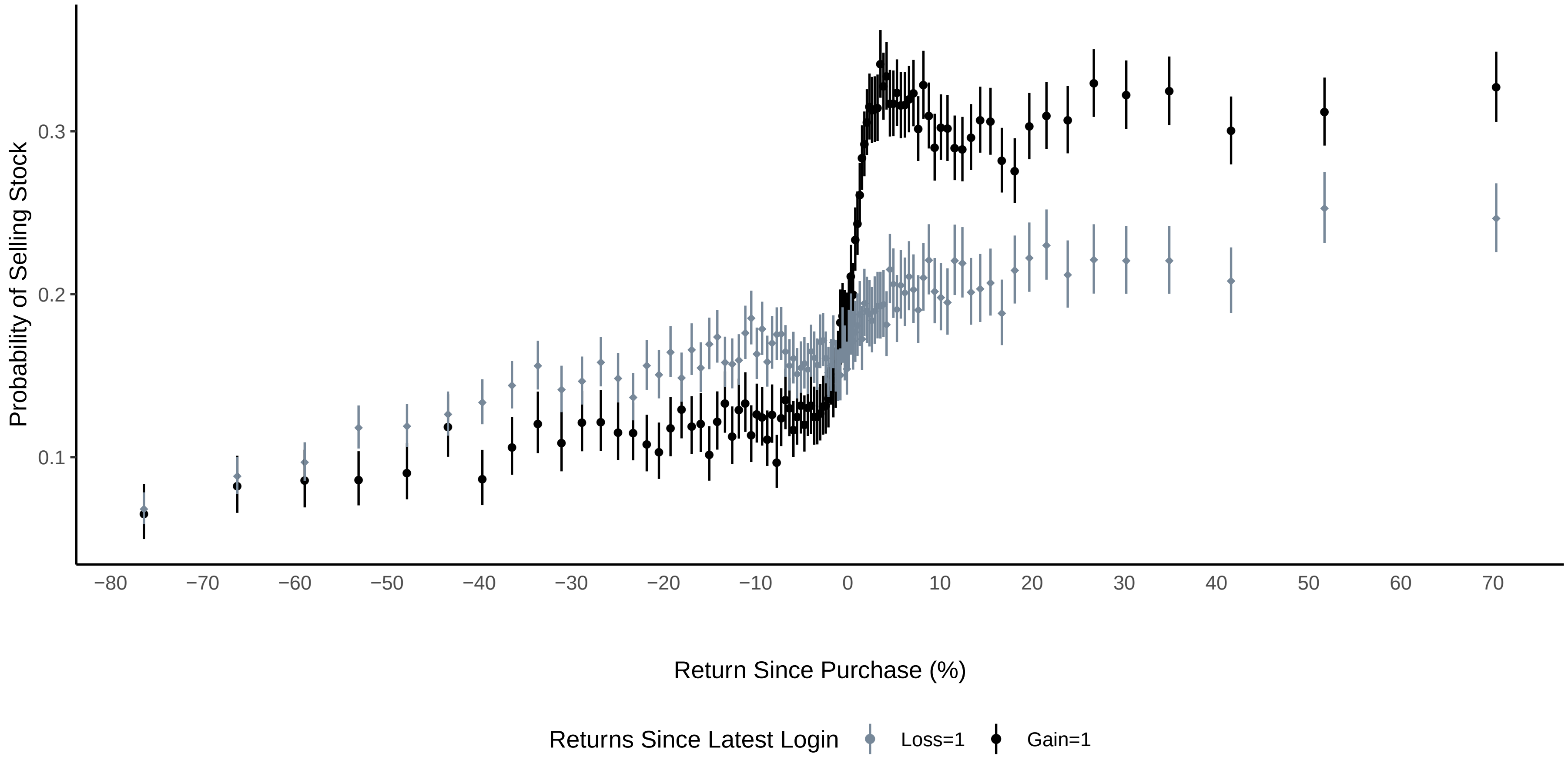
(A) Returns Since Latest Login

(B) Returns Since Purchase (Up to 30 Days Since Purchase)




*Note:* Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. in Panel A the X-axis variable is the returns on the stock since latest login. In Panel B the X-axis variable is the returns on the stock since purchase. Panel B restricts to stocks purchased within the past 30 days only. Sell-day sample includes all investor × stock × days on which the investor sold at least one position in the portfolio. Returns since purchase and since latest login are calculated at the daily level.

Figure 3: Illustration of the Interaction Effect in the Sell-Day Sample

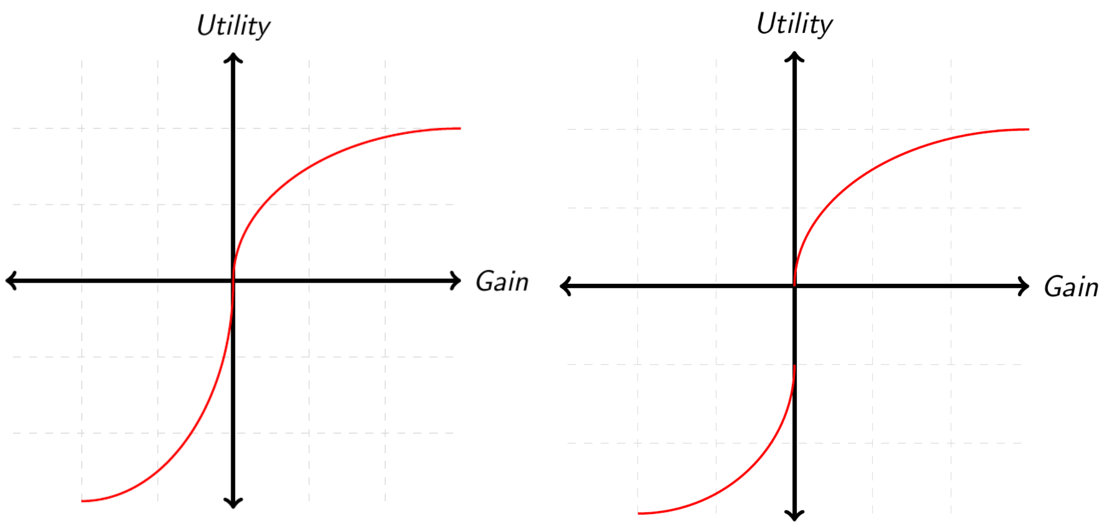



*Note:* Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. Observations are divided by whether the investor made a gain or not since the latest login day. Sell-day sample includes all investor × stock × days on which the investor sold at least one position in the portfolio. Returns since purchase and returns since latest login are calculated at the daily level.

Figure 4: Prospect Theory Utility Functions

(A) Utility Function I

(B) Utility Function II




*Note:* Figure shows two versions of a Prospect Theory utility function. Panel A shows the standard case in which the curvature of the utility function is concave in the domain of gains and convex in the domain of losses. Panel B shows a modified case in which in utility jumps discretely at zero.

Table 1: Summary Statistics for Returns Since Purchase and Returns Since Latest Login

Panel (A): Sell-Day Sample

| | Mean | SD | Median |
|---|---|---|---|
| Sale = 1 | 0.193 | | |
| *Return Since Purchase* | | | |
| Return Since Purchase (%) | −3.601 | 21.726 | −1.187 |
| Gain Since Purchase = 1 | 0.450 | 0.497 | 0 |
| *Return Since Latest Login* | | | |
| Return Since Latest Login (%) | 0.116 | 5.535 | 0.000 |
| Gain Since Latest Login = 1 | 0.463 | 0.499 | 0 |
| N Investor × Stock × Day | 351,556 | | |

Panel (B): Login-Day Sample

| | Mean | SD | Median |
|---|---|---|---|
| Sale = 1 | 0.012 | | |
| *Return Since Purchase* | | | |
| Return Since Purchase (%) | −2.598 | 23.089 | −0.835 |
| Gain Since Purchase = 1 | 0.467 | 0.499 | 0 |
| *Return Since Latest Login* | | | |
| Return Since Latest Login (%) | -0.009 | 4.013 | 0.000 |
| Gain Since Latest Login = 1 | 0.456 | 0.498 | 0 |
| N Investor × Stock × Day | 5,910,268 | | |

*Note:* This table presents summary statistics for returns since purchase, returns since latest login and investor attention in the sell-day sample and login-day samples. The unit of analysis is an investor × stock × day. The sell-day sample in Panel A includes all investor × stock × days on which the investor sold at least one position in the portfolio. The login-day sample in Panel B includes all investor × stock × days on which the investor made a login. Returns since purchase and returns since latest login are calculated at the daily level. The attention rate since purchase measures the proportion of days the investor has made a login since the day on which the position was purchased.

Table 2: Correlation Returns Since Purchase
and Returns Since Latest Login

Panel (A): Sell-Day Sample

| | Pearson's $\rho$ |
|---|---|
| All | 0.179 |
| Bottom Decile Trade Frequency | 0.137 |
| Top Decile Trade Frequency | 0.230 |

Panel (B): Login-Day Sample

| | Pearson's $\rho$ |
|---|---|
| All | 0.115 |
| Bottom Decile Trade Frequency | 0.074 |
| Top Decile Trade Frequency | 0.208 |

*Note:* This table presents correlation coefficients (Pearson's $\rho$) for returns since purchase and returns since latest login. Panel A reports for the sell-day sample of 351,335 investor $\times$ stock $\times$ days. Panel B reports for the login-day sample of 5,910,268 investor $\times$ stock $\times$ days.

Table 3: Ordinary Least Squares Regression Estimates of the Disposition Effect

Panel (A): Sell-Day Sample

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase = 1 | 0.1149*** | | 0.1091*** | 0.0495*** |
| | (0.0059) | | (0.0057) | (0.0052) |
| Gain Since Latest Login = 1 | | 0.0514*** | 0.0306*** | -0.0265*** |
| | | (0.0037) | (0.0032) | (0.0038) |
| Gain Since Purchase = 1 × Gain Since Latest Login = 1 | | | | 0.1239*** |
| | | | | (0.0051) |
| Constant | 0.1423*** | 0.1702*** | 0.1308*** | 0.1523*** |
| | (0.0054) | (0.0057) | (0.0060) | (0.0064) |
| Observations | 351,556 | 351,556 | 351,556 | 351,556 |
| $R^2$ | 0.0209 | 0.0042 | 0.0223 | 0.0282 |

Panel (B): Login-Day Sample

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase = 1 | 0.0060*** | | 0.0057*** | 0.0009*** |
| | (0.0004) | | (0.0003) | (0.0003) |
| Gain Since Latest Login = 1 | | 0.0034*** | 0.0026*** | -0.0022*** |
| | | (0.0003) | (0.0003) | (0.0003) |
| Gain Since Purchase = 1 × Gain Since Latest Login = 1 | | | | 0.0102*** |
| | | | | (0.0004) |
| Constant | 0.0087*** | 0.0100*** | 0.0077*** | 0.0096*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Observations | 5,910,268 | 5,910,268 | 5,910,268 | 5,910,268 |
| $R^2$ | 0.0008 | 0.0002 | 0.0009 | 0.0015 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Panel A shows sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Panel B shows sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

Table 4: The Disposition Effect: Fixed Effects Estimates

Panel (A): Sell-Day Sample

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase = 1 | 0.1233*** | | 0.1177*** | 0.0731*** |
| | (0.0055) | | (0.0053) | (0.0044) |
| Gain Since Latest Login = 1 | | 0.0504*** | 0.0290*** | -0.0132*** |
| | | (0.0033) | (0.0028) | (0.0031) |
| Gain Since Purchase = 1 × | | | | 0.0920*** |
| Gain Since Latest Login = 1 | | | | (0.0045) |
| Observations | 351,556 | 351,556 | 351,556 | 351,556 |
| $R^2$ | 0.1611 | 0.1437 | 0.1623 | 0.1654 |

Panel (B): Login-Day Sample

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0095*** | | 0.0091*** | 0.0061*** |
| | (0.0005) | | (0.0004) | (0.0004) |
| Gain Since Latest Login=1 | | 0.0039*** | 0.0029*** | -0.0003 |
| | | (0.0003) | (0.0003) | (0.0002) |
| Gain Since Purchase=1 × | | | | 0.0065*** |
| Gain Since Last Login=1 | | | | (0.0004) |
| Observations | 5,910,268 | 5,910,268 | 5,910,268 | 5,910,268 |
| $R^2$ | 0.0459 | 0.0445 | 0.0460 | 0.0463 |

*Note:* This table presents fixed effects regression estimates of Equation 2. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Fixed effects are at account level. Panel A includes sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Panel B includes sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

Table 5: The Disposition Effect:
Including Continuous Returns Since Purchase, Sell-Day Sample

| | $Sale_{ijt}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Return Since Purchase < 0 (%) | 0.0010*** | | 0.0020*** | 0.0021*** | 0.0010*** | | 0.0016*** | 0.0016*** |
| | (0.0001) | | (0.0001) | (0.0001) | (0.0001) | | (0.0001) | (0.0001) |
| Return Since Purchase > 0 (%) | 0.0008*** | | -0.0001 | -0.0000 | 0.0013*** | | 0.0007*** | 0.0007*** |
| | (0.0002) | | (0.0002) | (0.0002) | (0.0002) | | (0.0002) | (0.0002) |
| Gain Since Purchase=1 | 0.0890*** | | 0.0870*** | 0.0334*** | 0.0933*** | | 0.0899*** | 0.0478*** |
| | (0.0062) | | (0.0058) | (0.0049) | (0.0059) | | (0.0055) | (0.0046) |
| Return Since Latest Login < 0 (%) | | -0.0122*** | -0.0156*** | -0.0148*** | | -0.0086*** | -0.0113*** | -0.0107*** |
| | | (0.0005) | (0.0005) | (0.0005) | | (0.0005) | (0.0005) | (0.0005) |
| Return Since Latest Login > 0 (%) | | 0.0137*** | 0.0142*** | 0.0141*** | | 0.0116*** | 0.0111*** | 0.0111*** |
| | | (0.0005) | (0.0005) | (0.0005) | | (0.0005) | (0.0004) | (0.0004) |
| Gain Since Latest Login=1 | | 0.0394*** | 0.0203*** | -0.0307*** | | 0.0339*** | 0.0177*** | -0.0223*** |
| | | (0.0033) | (0.0029) | (0.0032) | | (0.0029) | (0.0025) | (0.0027) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1073*** | | | | 0.0843*** |
| | | | | (0.0047) | | | | (0.0043) |
| Constant | 0.1588*** | 0.1412*** | 0.1246*** | 0.1464*** | | | | |
| | (0.0058) | (0.0053) | (0.0059) | (0.0061) | | | | |
| Account FE | NO | NO | NO | NO | YES | YES | YES | YES |
| Observations | 351,556 | 351,556 | 351,556 | 351,556 | 351,556 | 351,556 | 351,556 | 351,556 |
| R2 | 0.0224 | 0.0299 | 0.0548 | 0.0591 | 0.1630 | 0.1574 | 0.1792 | 0.1817 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 with the addition of continuous control variables for the return since purchase when the return since purchase is negative and, in a separate variable, when the return since purchase is positive. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors are clustered by account and day.

Table 6: The Disposition Effect:
Selectivity Correction Estimates, Login-Day Sample

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0061*** | | 0.0057*** | 0.0010*** |
| | (0.0001) | | (0.0001) | (0.0001) |
| Gain Since Latest Login=1 | | 0.0034*** | 0.0026*** | -0.0022*** |
| | | (0.0001) | (0.0001) | (0.0001) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0103*** |
| | | | | (0.0002) |
| Inverse Mills Ratio | -0.0058*** | -0.0064*** | -0.0056*** | -0.0057*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Constant | 0.0155*** | 0.0174*** | 0.0142*** | 0.0162*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Observations | 5,713,274 | 5,713,274 | 5,713,274 | 5,713,274 |
| $R^2$ | 0.0008 | 0.0003 | 0.0010 | 0.0015 |

*Note:* This table presents selectivity correction estimates where a selection equation models login to the account. The selection equation includes the weather in the locality × day as the exclusion restriction. In the second-stage equation the dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor made a login. Standard errors are clustered by account and day.

Table 7: The Disposition Effect: Sample Split by Previous Day FTSE100 Index Returns, Sell-Day Sample

Panel (A): FTSE100 Return in $t-1>0$

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.1269*** | | 0.1205*** | 0.0584*** |
| | (0.0063) | | (0.0061) | (0.0056) |
| Gain Since Latest Login=1 | | 0.0559*** | 0.0324*** | -0.0240*** |
| | | (0.0043) | (0.0038) | (0.0043) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1220*** |
| | | | | (0.0063) |
| Constant | 0.1349*** | 0.1661*** | 0.1218*** | 0.1446*** |
| | (0.0053) | (0.0058) | (0.0061) | (0.0064) |
| Observations | 186,128 | 186,128 | 186,128 | 186,128 |
| $R^2$ | 0.0256 | 0.0050 | 0.0272 | 0.0329 |

Panel (B): FTSE100 Return in $t-1<0$

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.1013*** | | 0.0959*** | 0.0407*** |
| | (0.0065) | | (0.0063) | (0.0059) |
| Gain Since Latest Login=1 | | 0.0469*** | 0.0293*** | -0.0271*** |
| | | (0.0043) | (0.0038) | (0.0046) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1234*** |
| | | | | (0.0062) |
| Constant | 0.1502*** | 0.1741*** | 0.1400*** | 0.1597*** |
| | (0.0060) | (0.0061) | (0.0066) | (0.0069) |
| Observations | 164,875 | 164,875 | 164,875 | 164,875 |
| $R^2$ | 0.0161 | 0.0034 | 0.0174 | 0.0231 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 for separate samples of observations from days on which the FTSE 100 posted a one-day positive returns (Panel A) and days on which the FTSE 100 posted one-day negative return (Panel B). The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors are clustered by account and day.

Table 8: The Disposition Effect:
Days Since Stock Purchase, Sell-Day Sample

Panel (A): Below Median Days Since Purchase (100 Days)

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.1310*** | | 0.1213*** | 0.0391*** |
| | (0.0080) | | (0.0077) | (0.0069) |
| Gain Since Latest Login=1 | | 0.0688*** | 0.0365*** | -0.0473*** |
| | | (0.0050) | (0.0041) | (0.0046) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1718*** |
| | | | | (0.0065) |
| Constant | 0.1760*** | 0.2059*** | 0.1635*** | 0.1922*** |
| | (0.0066) | (0.0068) | (0.0073) | (0.0075) |
| Observations | 175,789 | 175,789 | 175,789 | 175,789 |
| $R^2$ | 0.0236 | 0.0065 | 0.0253 | 0.0347 |

Panel (B): Above Median Days Since Purchase

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0902*** | | 0.0877*** | 0.0630*** |
| | (0.0050) | | (0.0049) | (0.0053) |
| Gain Since Latest Login=1 | | 0.0320*** | 0.0220*** | -0.0005 |
| | | (0.0035) | (0.0032) | (0.0037) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0521*** |
| | | | | (0.0047) |
| Constant | 0.1115*** | 0.1352*** | 0.1025*** | 0.1117*** |
| | (0.0048) | (0.0052) | (0.0053) | (0.0056) |
| Observations | 175,767 | 175,767 | 175,767 | 175,767 |
| $R^2$ | 0.0156 | 0.0020 | 0.0166 | 0.0178 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 for separate samples by days since purchase of the stock. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors are clustered by account and day.

Table 9: The Disposition Effect: Days Since Latest Login, Sell-Day Sample

Panel (A): 1 Day Since Latest Login

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.1197*** | | 0.1141*** | 0.0590*** |
| | (0.0064) | | (0.0062) | (0.0057) |
| Gain Since Latest Login=1 | | 0.0520*** | 0.0326*** | -0.0189*** |
| | | (0.0041) | (0.0036) | (0.0042) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1136*** |
| | | | | (0.0059) |
| Constant | 0.1281*** | 0.1570*** | 0.1153*** | 0.1354*** |
| | (0.0058) | (0.0063) | (0.0064) | (0.0069) |
| Observations | 242,802 | 242,802 | 242,802 | 242,802 |
| $R^2$ | 0.0238 | 0.0045 | 0.0256 | 0.0308 |

Panel (B): 2-5 Days Since Latest Login

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.1070*** | | 0.1013*** | 0.0440*** |
| | (0.0071) | | (0.0069) | (0.0066) |
| Gain Since Latest Login=1 | | 0.0487*** | 0.0275*** | -0.0313*** |
| | | (0.0052) | (0.0048) | (0.0059) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1235*** |
| | | | | (0.0081) |
| Constant | 0.1546*** | 0.1817*** | 0.1449*** | 0.1657*** |
| | (0.0055) | (0.0058) | (0.0064) | (0.0066) |
| Observations | 74,365 | 74,365 | 74,365 | 74,365 |
| $R^2$ | 0.0175 | 0.0036 | 0.0186 | 0.0242 |

Panel (C): >6 Days Since Latest Login

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0921*** | | 0.0831*** | 0.0039 |
| | (0.0086) | | (0.0084) | (0.0092) |
| Gain Since Latest Login=1 | | 0.0549*** | 0.0300*** | -0.0491*** |
| | | (0.0069) | (0.0065) | (0.0079) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1642*** |
| | | | | (0.0111) |
| Constant | 0.2199*** | 0.2372*** | 0.2101*** | 0.2359*** |
| | (0.0059) | (0.0061) | (0.0067) | (0.0068) |
| Observations | 34,389 | 34,389 | 34,389 | 34,389 |
| $R^2$ | 0.0109 | 0.0039 | 0.0119 | 0.0198 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 for separate samples by days since latest login to the account. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors are clustered by account and day.

Table 10: The Disposition Effect:
Sub-Sample Analysis, Sell-Day Sample

| | Returns Since Purchase | Returns Since Latest Login |
|---|---|---|
| *Gender* | | |
| Male | 0.1052*** (0.0061) | 0.0286*** (0.0035) |
| Female | 0.1312*** (0.0136) | 0.0427*** (0.0068) |
| *Age* | | |
| Below Median | 0.1119*** (0.0071) | 0.300*** (0.0037) |
| Above Median | 0.1036*** (0.0082) | 0.319*** (0.0048) |
| *Experience* | | |
| Below Median | 0.1200*** (0.0071) | 0.0294*** (0.0033) |
| Above Median | 0.0958*** (0.0069) | 0.0304*** (0.0045) |
| *Portfolio Value* | | |
| Below Median | 0.1483*** (0.0068) | 0.0290*** (0.0038) |
| Above Median | 0.0740*** (0.0058) | 0.0709*** (0.0057) |

*Note:* This table presents ordinary least squares regression estimates for separate samples by gender, age, trading experience and portfolio value. Each row reports coefficients and standard errors from a single regression in which the dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise, there are two covariates (returns since purchase and returns since latest login). Investor experience is measured by months since account opening. Sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors are clustered by account and day.

Table 11: The Disposition Effect:
Sub-Sample Analysis, Sell-Day Sample

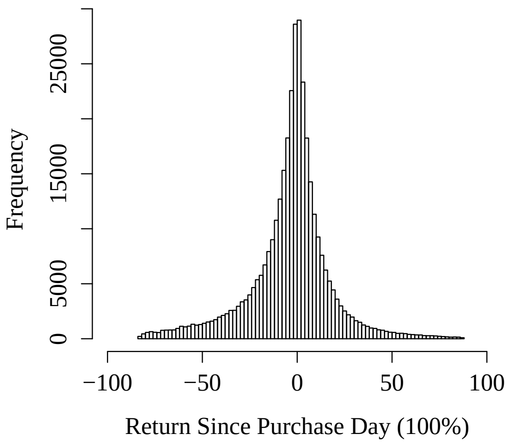
| | Gain Since Purchase | Gain Since Latest Login | Interaction |
|---|---|---|---|
| *Gender* | | | |
| Male | 0.0457*** (0.0055) | -0.0286*** (0.0042) | 0.1240*** (0.0055) |
| Female | 0.0714*** (0.0134) | -0.0133*** (0.0080) | 0.1226*** (0.0121) |
| *Age* | | | |
| Below Median | 0.0499*** (0.0068) | -0.0314*** (0.0049) | 0.1303*** (0.0067) |
| Above Median | 0.0483*** (0.0073) | -0.0195*** (0.0053) | 0.1145*** (0.0068) |
| *Experience* | | | |
| Below Median | 0.0531*** (0.0067) | -0.0362*** (0.0042) | 0.1383*** (0.0062) |
| Above Median | 0.0458*** (0.0064) | -0.0165*** (0.0053) | 0.1050*** (0.0064) |
| *Portfolio Value* | | | |
| Below Median | 0.0752*** (0.0070) | -0.0406*** (0.0048) | 0.1521*** (0.0064) |
| Above Median | 0.0380*** (0.0052) | -0.0025*** (0.0043) | 0.0747*** (0.0059) |
| *Number of Stocks* | | | |
| Below Median | 0.0677*** (0.0058) | -0.0425*** (0.0044) | 0.1542*** (0.0062) |
| Above Median | 0.0366*** (0.0045) | -0.0023*** (0.0036) | 0.0557*** (0.0057) |

*Note:* This table presents ordinary least squares regression estimates for separate samples by gender, age, trading experience and portfolio value. Each row reports coefficients and standard errors from a single regression in which the dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise, there are two covariates (returns since purchase and returns since latest login) and an intercept term. Investor experience is measured by months since account opening. Sample of all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors are clustered by account and day.

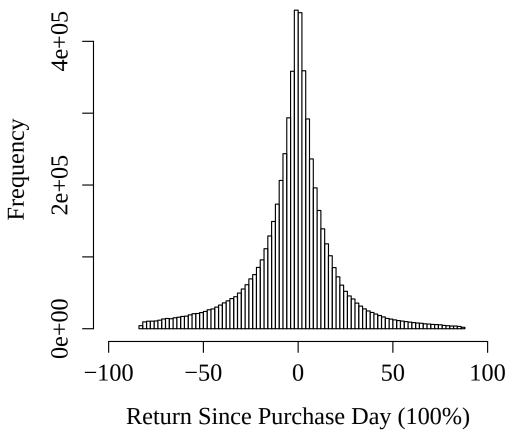
Figure A1: Returns Since Purchase and Returns Since Latest Login

(I) Returns Since Purchase

(A) Sell-Day Sample

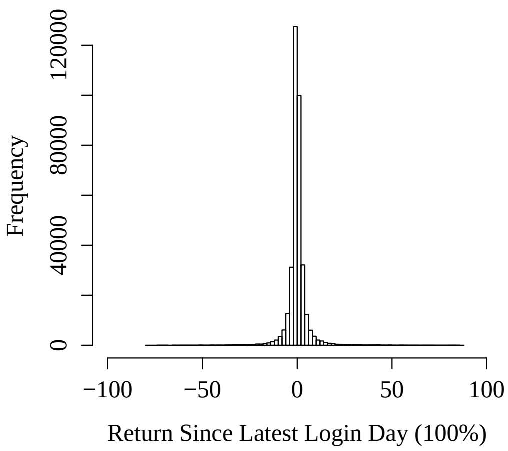



(B) Login-Day Sample

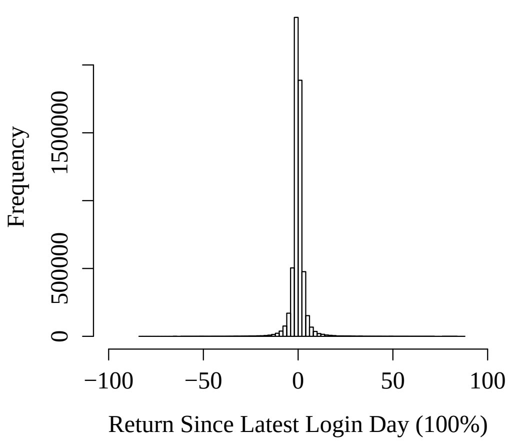



(II) Returns Since Latest Login

(C) Sell-Day Sample

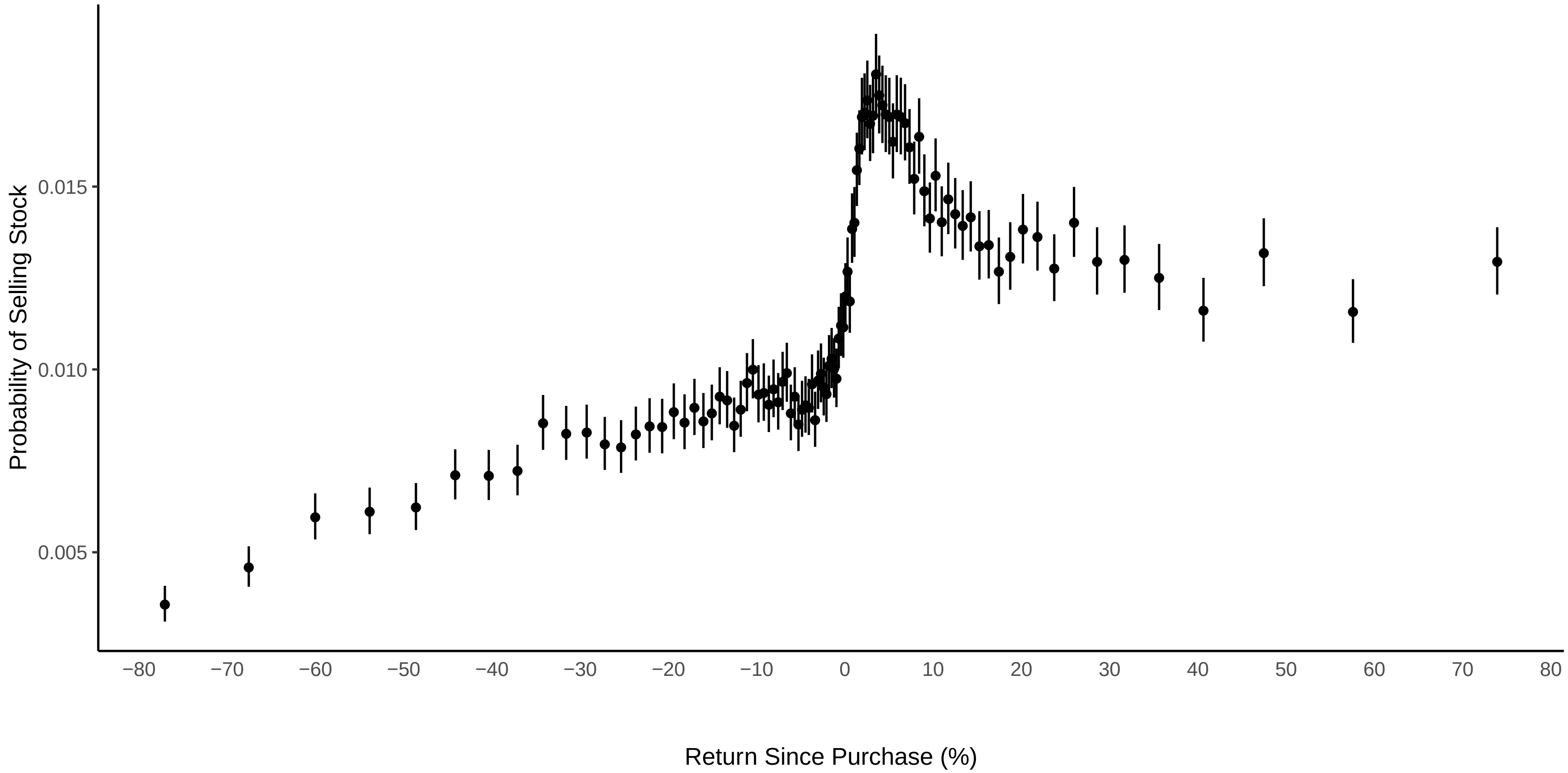



(D) Login-Day Sample




*Note:* Figure shows distribution of returns since purchase (top panel) and returns since latest login (bottom panel) for the sell-day sample and the login-day sample. The sell-day sample includes all investor × stock × days on which the investor sold at least one position in the portfolio. The login-day sample includes all investor × stock × days on which the investor made a login. Returns since purchase and returns since latest login are calculated at the daily level.

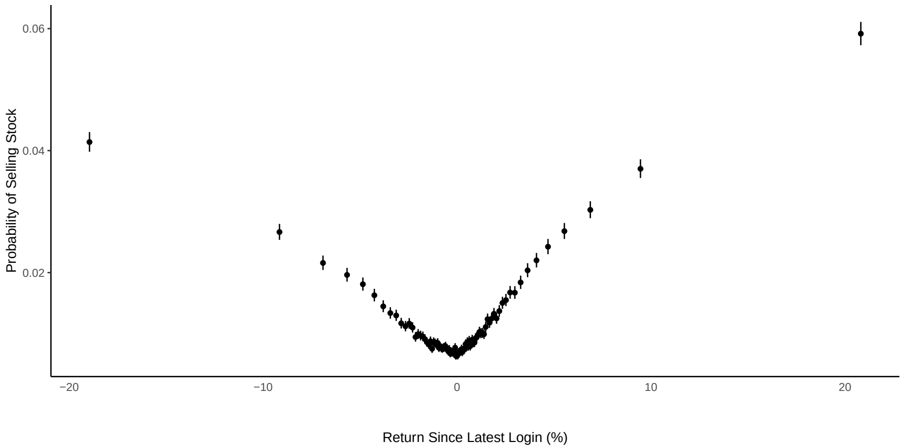
Figure A2: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Purchase in the Login-Day Sample



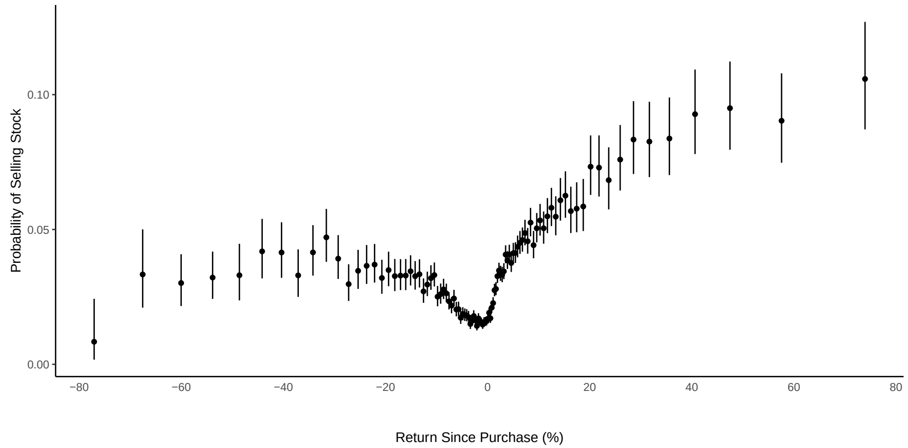

*Note:* Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. Sell-day sample includes all investor × stock × days on which the made a login to the account. Returns since purchase are calculated at the daily level.

Figure A3: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Latest Login in the Login-Day Sample

(A) Returns Since Latest Login

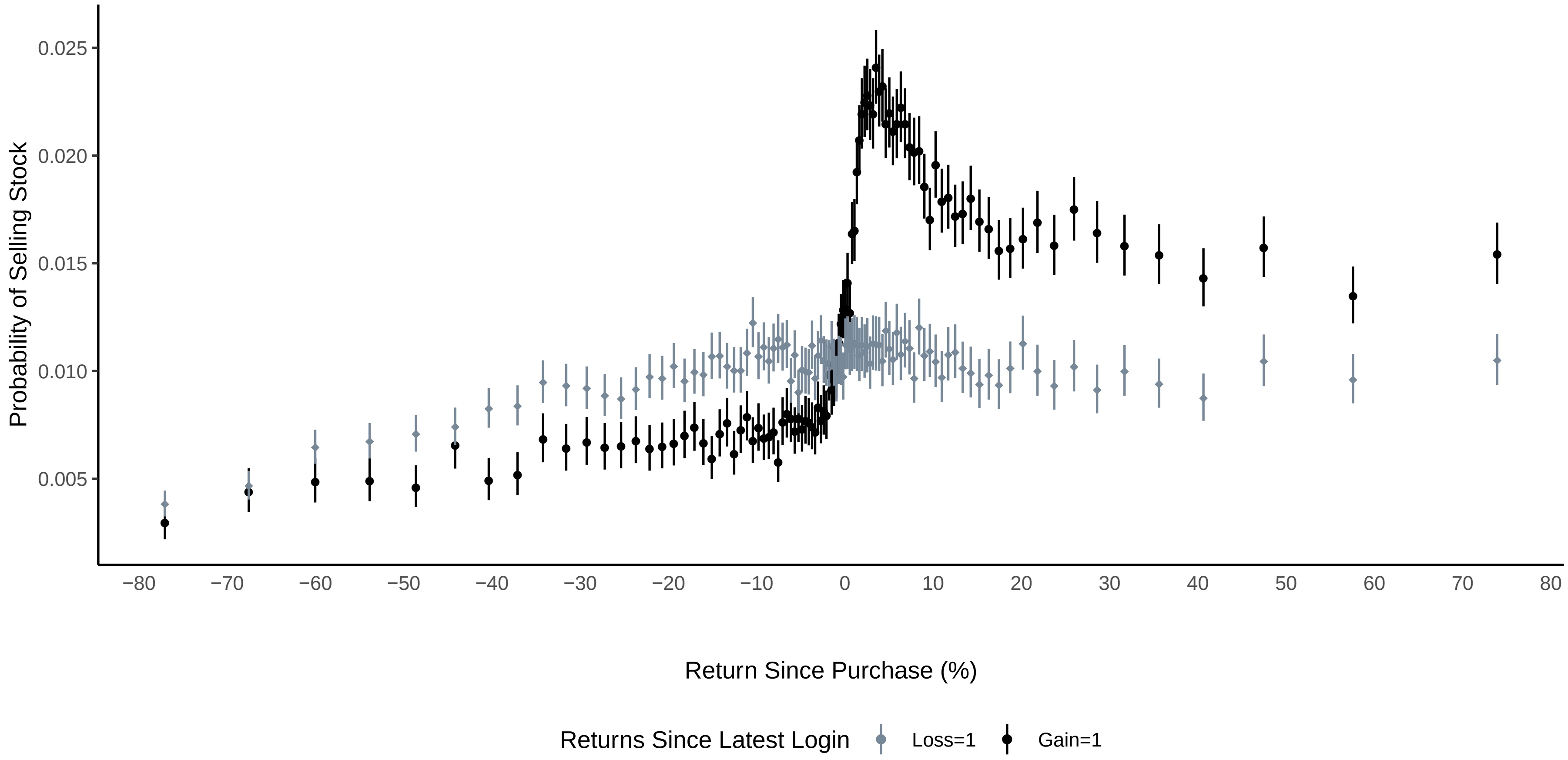



(B) Returns Since Purchase (Up to 30 Days Since Purchase)




*Note:* Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. In Panel A the X-axis variable is the returns on the stock since latest login. In Panel B the X-axis variable is the returns on the stock since purchase. Panel B restricts to stocks purchased within the past 30 days only. Login-day sample includes all investor × stock × days on which the investor made a login to the account. Returns since purchase and since latest login are calculated at the daily level.

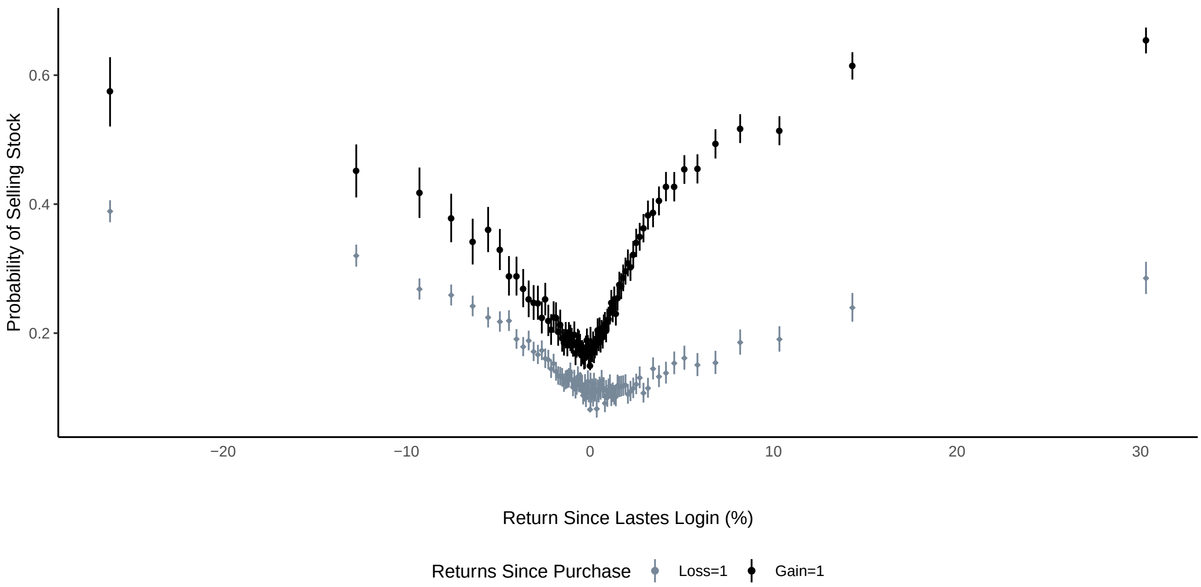
Figure A4: Illustration of the Interaction Effect in the Login-Day Sample



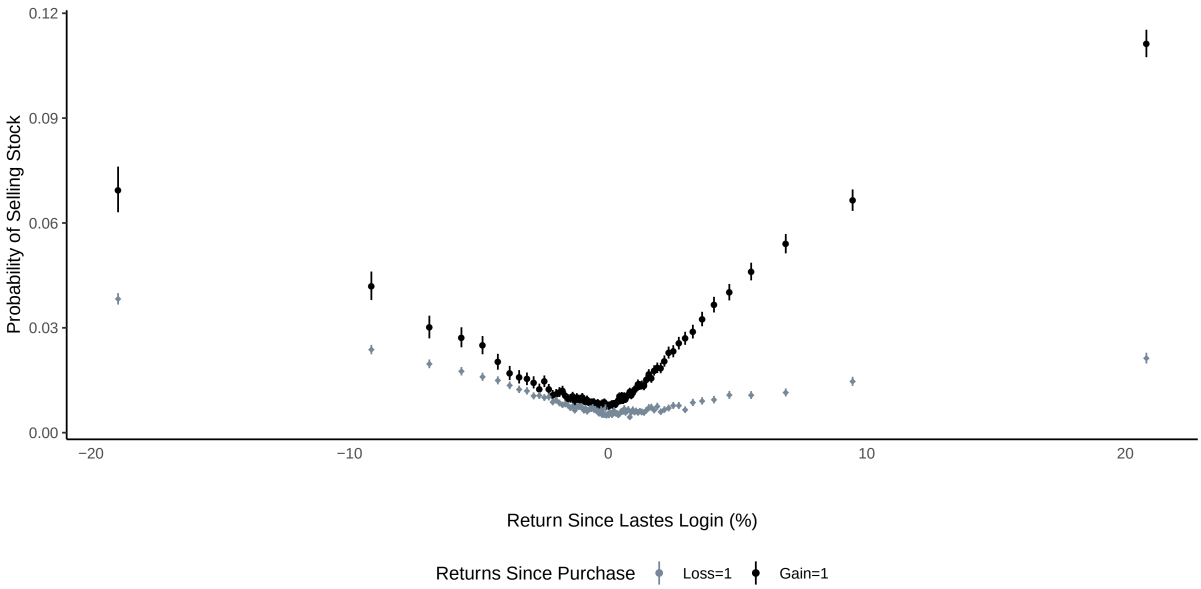

*Note:* Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. Observations are divided by whether the investor made a gain or not since the latest login day. Login-day sample includes all investor × stock × days on which the investor made a login to the account. Returns since purchase and returns since latest login are calculated at the daily level.

Figure A5: Illustration of the Interaction Effect:
Probability of Sale by Returns Since Login, by Gain / Loss Since Purchase

(A) Sell-Day Sample




(B) Login-Day Sample




*Note:* Figure shows binned scatter plot with 95% confidence intervals. The X-axis variable is the returns on the stock since the latest login day. Observations are divided by whether the investor made a gain or not since purchase. Returns since purchase and returns since latest login are calculated at the daily level.

Table A1: Baseline Sample Summary Statistics

| | Mean | Min | p25 | p50 | p75 | Max |
|---|---|---|---|---|---|---|
| *A. Account Holder Characteristics* | | | | | | |
| Female | 0.14 | | | | | |
| Age (years) | 45 | 22 | 33 | 44 | 54 | 83 |
| Account Tenure (years) | 2.3 | 0.3 | 1.5 | 2.2 | 3.1 | 4.0 |
| *B. Account Characteristics* | | | | | | |
| Portfolio Value (£10,000) | 4.250 | 0.000 | 0.346 | 0.918 | 2.122 | 5742.635 |
| Number of Stocks | 5.214 | 2.000 | 2.375 | 3.513 | 6.000 | 102.182 |
| Investment in Mutual Funds (£10,000) | 0.171 | 0.000 | 0.000 | 0.000 | 0.000 | 84.529 |
| Investment in Mutual Funds (%) | 5.600 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| Login days (% all days) | 20.696 | 0.081 | 6.452 | 15.341 | 31.673 | 75.000 |
| Transaction days (% all market open days) | 4.143 | 0.140 | 1.277 | 2.343 | 4.651 | 100.000 |
| N Accounts | 8246 | | | | | |

*Note:* This table presents summary statistics for the baseline sample of accounts. Age is measured at date of account opening. Account tenure is measured on the final day of the data period. Portfolio value is the value of all securities within the portfolio at market prices. The category Mutual Funds also includes Exchange Traded Funds and Unit Trusts. Portfolio value, number of stocks and investment in mutual funds are measured as within-account averages of values at the first day of each calendar month in the data period. Login days is the percentage of days the account is open in the data period and the account holder made at least one login. Transaction days is the percentage of market open days the account is open in the data period and the account holder made at least one trade.

Table A2: Estimates of the Disposition Effect
Including Continuous Returns Since Purchase, Login-Day Sample

| | $Sale_{ijt}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Return Since Purchase < 0 (%) | 0.0001*** | | 0.0002*** | 0.0002*** | 0.0001*** | | 0.0001*** | 0.0001*** |
| | (0.0000) | | (0.0000) | (0.0000) | (0.0000) | | (0.0000) | (0.0000) |
| Return Since Purchase > 0 (%) | -0.0001*** | | -0.0001*** | -0.0001*** | 0.0001*** | | 0.0000* | 0.0000* |
| | (0.0000) | | (0.0000) | (0.0000) | (0.0000) | | (0.0000) | (0.0000) |
| Gain Since Purchase=1 | 0.0057*** | | 0.0057*** | 0.0009*** | 0.0077*** | | 0.0075*** | 0.0043*** |
| | (0.0004) | | (0.0004) | (0.0003) | (0.0005) | | (0.0005) | (0.0004) |
| Return Since Latest Login < 0 (%) | | -0.0018*** | -0.0022*** | -0.0021*** | | -0.0011*** | -0.0014*** | -0.0014*** |
| | | (0.0001) | (0.0001) | (0.0001) | | (0.0001) | (0.0001) | (0.0001) |
| Return Since Latest Login > 0 (%) | | 0.0025*** | 0.0027*** | 0.0027*** | | 0.0018*** | 0.0019*** | 0.0019*** |
| | | (0.0001) | (0.0001) | (0.0001) | | (0.0001) | (0.0001) | (0.0001) |
| Gain Since Latest Login=1 | | 0.0015*** | 0.0004** | -0.0047*** | | 0.0019*** | 0.0010*** | -0.0025*** |
| | | (0.0003) | (0.0002) | (0.0003) | | (0.0002) | (0.0002) | (0.0002) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0099*** | | | | 0.0068*** |
| | | | | (0.0005) | | | | (0.0004) |
| Constant | 0.0100*** | 0.0067*** | 0.0066*** | 0.0088*** | | | | |
| | (0.0003) | (0.0002) | (0.0003) | (0.0003) | | | | |
| Account FE | NO | NO | NO | NO | YES | YES | YES | YES |
| Observations | 5,910,268 | 5,910,268 | 5,910,268 | 5,910,268 | 5,910,268 | 5,910,268 | 5,910,268 | 5,910,268 |
| R2 | 0.0009 | 0.0053 | 0.0073 | 0.0078 | 0.0459 | 0.0467 | 0.0488 | 0.0490 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 with the addition of continuous control variables for the return since purchase when the return since purchase is negative and, in a separate variable, when the return since purchase is positive. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

Table A3: Selectivity Correction

| | Selection Equation |
|---|---|
| | (1) |
| Omitted: Excellent | - |
| | - |
| Very good | 0.0268*** |
| | (0.0030) |
| Good | 0.0244*** |
| | (0.0037) |
| Moderate | 0.0156*** |
| | (0.0047) |
| Poor and Very poor | 0.0277*** |
| | (0.0081) |
| Observations | 3,167,026 |
| Log Likelihood | -2,079,719 |
| Akaike Inf. Crit. | 4,159,478 |

*Note:* This table presents estimates of the selection equation for the results shown in Table 6. The dependent variable is a dummy indicator for login. Sample of all investor × stock × days on which the investor made a login. Standard errors are clustered by account and day.

Table A4: The Disposition Effect: Sample Split by Previous Day FTSE100 Index Returns, Login-Day Sample

Panel (A): FTSE100 Return in $t-1>0$

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.1269*** | | 0.1205*** | 0.0584*** |
| | (0.0063) | | (0.0061) | (0.0056) |
| Gain Since Latest Login=1 | | 0.0559*** | 0.0324*** | -0.0240*** |
| | | (0.0043) | (0.0038) | (0.0043) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1220*** |
| | | | | (0.0063) |
| Constant | 0.1349*** | 0.1661*** | 0.1218*** | 0.1446*** |
| | (0.0053) | (0.0058) | (0.0061) | (0.0064) |
| Observations | 186,128 | 186,128 | 186,128 | 186,128 |
| $R^2$ | 0.0256 | 0.0050 | 0.0272 | 0.0329 |

Panel (B): FTSE100 Return in $t-1<0$

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.1013*** | | 0.0959*** | 0.0407*** |
| | (0.0065) | | (0.0063) | (0.0059) |
| Gain Since Latest Login=1 | | 0.0469*** | 0.0293*** | -0.0271*** |
| | | (0.0043) | (0.0038) | (0.0046) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.1234*** |
| | | | | (0.0062) |
| Constant | 0.1502*** | 0.1741*** | 0.1400*** | 0.1597*** |
| | (0.0060) | (0.0061) | (0.0066) | (0.0069) |
| Observations | 164,875 | 164,875 | 164,875 | 164,875 |
| $R^2$ | 0.0161 | 0.0034 | 0.0174 | 0.0231 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 for separate samples of observations from days on which the FTSE 100 posted a one-day positive returns (Panel A) and days on which the FTSE 100 posted one-day negative return (Panel B). The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

Table A5: The Disposition Effect:
Days Since Stock Purchase, Login-Day Sample

Panel (A): Below Median Days Since Purchase (160 Days)

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0094*** | | 0.0087*** | 0.0012*** |
| | (0.0006) | | (0.0005) | (0.0004) |
| Gain Since Latest Login=1 | | 0.0055*** | 0.0039*** | -0.0038*** |
| | | (0.0005) | (0.0005) | (0.0004) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0161*** |
| | | | | (0.0007) |
| Constant | 0.0122*** | 0.0141*** | 0.0107*** | 0.0136*** |
| | (0.0004) | (0.0004) | (0.0005) | (0.0005) |
| Observations | 2,960,201 | 2,960,201 | 2,960,201 | 2,960,201 |
| $R^2$ | 0.0014 | 0.0005 | 0.0016 | 0.0025 |

Panel (B): Above Median Days Since Purchase

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0025*** | | 0.0024*** | 0.0013*** |
| | (0.0002) | | (0.0002) | (0.0002) |
| Gain Since Latest Login=1 | | 0.0013*** | 0.0011*** | -0.0001 |
| | | (0.0002) | (0.0002) | (0.0002) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0025*** |
| | | | | (0.0003) |
| Constant | 0.0053*** | 0.0059*** | 0.0048*** | 0.0053*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Observations | 2,950,067 | 2,950,067 | 2,950,067 | 2,950,067 |
| $R^2$ | 0.0002 | 0.0001 | 0.0003 | 0.0004 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 for separate samples by days since purchase of the stock. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

Table A6: The Disposition Effect: Days Since Latest Login, Login-Day Sample

Panel (A): 1 Day Since Latest Login

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0063*** | | 0.0059*** | 0.0015*** |
| | (0.0004) | | (0.0004) | (0.0003) |
| Gain Since Latest Login=1 | | 0.0036*** | 0.0029*** | -0.0017*** |
| | | (0.0004) | (0.0003) | (0.0003) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0096*** |
| | | | | (0.0005) |
| Constant | 0.0083*** | 0.0096*** | 0.0071*** | 0.0090*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Observations | 3,911,365 | 3,911,365 | 3,911,365 | 3,911,365 |
| $R^2$ | 0.0009 | 0.0003 | 0.0011 | 0.0016 |

Panel (B): 2-5 Days Since Latest Login

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0051*** | | 0.0048*** | 0.0008** |
| | (0.0004) | | (0.0003) | (0.0003) |
| Gain Since Latest Login=1 | | 0.0026*** | 0.0019*** | -0.0024*** |
| | | (0.0004) | (0.0004) | (0.0004) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0089*** |
| | | | | (0.0005) |
| Constant | 0.0079*** | 0.0091*** | 0.0072*** | 0.0088*** |
| | (0.0003) | (0.0004) | (0.0004) | (0.0004) |
| Observations | 1,479,718 | 1,479,718 | 1,479,718 | 1,479,718 |
| $R^2$ | 0.0006 | 0.0002 | 0.0007 | 0.0012 |

Panel (C): >6 Days Since Latest Login

| | $Sale_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gain Since Purchase=1 | 0.0070*** | | 0.0063*** | -0.0014** |
| | (0.0006) | | (0.0006) | (0.0006) |
| Gain Since Latest Login=1 | | 0.0043*** | 0.0028*** | -0.0048*** |
| | | (0.0006) | (0.0006) | (0.0006) |
| Gain Since Purchase=1 × Gain Since Last Login=1 | | | | 0.0162*** |
| | | | | (0.0009) |
| Constant | 0.0142*** | 0.0155*** | 0.0132*** | 0.0159*** |
| | (0.0005) | (0.0005) | (0.0006) | (0.0006) |
| Observations | 519,185 | 519,185 | 519,185 | 519,185 |
| $R^2$ | 0.0007 | 0.0003 | 0.0008 | 0.0017 |

*Note:* This table presents ordinary least squares regression estimates of Equation 2 for separate samples by days since latest login to the account. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

Table A7: The Disposition Effect:
Sub-Sample Analysis, Login-Day Sample

| | Returns Since Purchase | Returns Since Latest Login |
|---|---|---|
| *Gender* | | |
| Male | 0.0.0055*** (0.0004) | 0.0025*** (0.0003) |
| Female | 0.0.0067*** (0.0008) | 0.0034*** (0.0005) |
| *Age* | | |
| Below Median | 0.0059*** (0.0005) | 0.0027*** (0.0003) |
| Above Median | 0.0053*** (0.0005) | 0.0026**8 (0.0004) |
| *Experience* | | |
| Below Median | 0.0063*** (0.0004) | 0.0030*** (0.0003) |
| Above Median | 0.0047*** (0.0004) | 0.0022*** (0.0003) |
| *Portfolio Value* | | |
| Below Median | 0.0088*** (0.0005) | 0.0030*** (0.0004) |
| Above Median | 0.0034*** (0.0003) | 0.0023*** (0.0003) |

*Note:* This table presents ordinary least squares regression estimates for separate samples by gender, age, trading experience and portfolio value. Each row reports coefficients and standard errors from a single regression in which the dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise, there are two covariates (returns since purchase and returns since latest login). Investor experience is measured by months since account opening. Sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

Table A8: The Disposition Effect:
Sub-Sample Analysis, Login-Day Sample

| | Gain Since Purchase | Gain Since Latest Login | Interaction |
|---|---|---|---|
| *Gender* | | | |
| Male | 0.0007*** (0.0003) | -0.0025*** (0.0003) | 0.0104*** (0.0005) |
| Female | 0.0024*** (0.0006) | -0.0010*** (0.0004) | 0.0093*** (0.0010) |
| *Age* | | | |
| Below Median | 0.0007*** (0.0004) | -0.0028*** (0.0003) | 0.0114*** (0.0006) |
| Above Median | 0.0012*** (0.0004) | -0.0016*** (0.0003) | 0.0088*** (0.0006) |
| *Experience* | | | |
| Below Median | 0.0007*** (0.0003) | -0.0029*** (0.0003) | 0.0120*** (0.0006) |
| Above Median | 0.0010*** (0.0003) | -0.0015*** (0.0003) | 0.0080*** (0.0005) |
| *Portfolio Value* | | | |
| Below Median | 0.0021*** (0.0004) | -0.0035*** (0.0003) | 0.0144*** (0.0006) |
| Above Median | 0.0008*** (0.0003) | -0.0004*** (0.0003) | 0.0056*** (0.0004) |
| *Number of Stocks* | | | |
| Below Median | 0.0015*** (0.0004) | -0.0037*** (0.0004) | 0.0150*** (0.0006) |
| Above Median | 0.0011*** (0.0003) | -0.0004*** (0.0003) | 0.0044*** (0.0003) |

*Note:* This table presents ordinary least squares regression estimates for separate samples by gender, age, trading experience and portfolio value. Each row reports coefficients and standard errors from a single regression in which the dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise, there are two covariates (returns since purchase and returns since latest login) and an intercept term. Investor experience is measured by months since account opening. Sample of all investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.