Investor Logins and the Disposition Effect

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Abstract

Using data from an online brokerage, we examine the role of investor logins in trading behavior. We find that a new reference point is created when an investor logs in and views their portfolio. We observe this as a disposition effect on returns since last login, in addition to the traditional disposition effect on returns since purchase. Further, these reference points produce a strong interaction such that even a small loss since last login nullifies the positive effect of a gain since purchase. This interaction follows if investors select the higher, more aspirational price as a reference point.

Keywords: reference point, disposition effect, attention, login, investor behavior

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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, and because they display diminishing sensitivity to both (Tversky and Kahneman, 1991), the reference point against which gains and losses are determined can have a dramatic impact on the decisions they make.

Individuals evaluate different types of outcomes relative to different reference points, and in some cases evaluate specific outcomes relative to multiple reference points.[1] Yet, despite evidence documenting the impact of diverse reference points in settings as varied as consumer products marketing (Hardie et al., 1993), tax compliance (Yaniv, 1999), food choices (Van Herpen et al., 2014), effort in sports (Allen et al., 2016), and rental choices Bordalo et al. (2019), very few empirical papers have examined the creation of reference points and the interplay between multiple reference points in financial decisions.[2] Previous studies have shown how the price of a recently sold stock influences the sale decisions for other stocks (Frydman et al., 2018), or how non-price reference points influence decisions, such as the rank position in returns within an investor's portfolio (Hartzmark, 2015), or the performance of a stock in the context of portfolio performance (An et al., 2019).

We study the creation and interaction between multiple reference points – specifically multiple prices – in the context of one of the most important and robust reference point effects: the disposition effect. The disposition effect refers to the reluctance of purchasers of an asset

[1] For example, the literature on personnel economics documents how people evaluate the pay they receive from work relative to what they received in the past (Bewley, 2009; DellaVigna et al., 2017), but also relative to what others receive (Brown et al., 2008; Card et al., 2012; Bracha et al., 2015), what they expected to receive (Kőszegi and Rabin, 2006; Mas, 2006; Crawford and Meng, 2011), and what they would like to receive (aspirations) (March and Shapira, 1992; Heath et al., 1999). In a book summarizing research on negotiation, Neale and Bazerman (cited in Kahneman, 1992) identify fully five possible points of reference that might influence a union's response to a wage offer made by management: last year's wage; management's initial offer; the union's estimate of management's reservation point; the union's reservation point; and the union's publicly announced bargaining position.

[2] Moreover, to the extent that this issue has been addressed, all prior research, to the best of our knowledge, has involved hypothetical choices (see. e.g., Sullivan and Kida, 1995; Ordóñez et al., 2000) or stylized laboratory experiments (Koop and Johnson, 2012). A small number of studies consider how multiple reference points affect choices on separate dimensions, such as income vs. leisure (Crawford and Meng, 2011) or goals vs experience (Markle et al., 2018). Yet none of the limited research involving naturalistic decisions made in economically meaningful contexts has examined the effect of multiple reference points operating within the same domain – e.g., different salient wage rate comparisons or, as in the current study, different prices against which a stock's current price could be compared.

to sell it at a loss (Shefrin and Statman, 1985). In displaying a disposition effect against some reference point, investors reveal to us as researchers the existence of that reference point. The purchase price has been assumed to be the relevant reference point in the vast majority of studies. Most of these studies have focused on the behavior of financial investors (e.g., Barber and Odean, 2000; Shapira and Venezia, 2001; Feng and Seasholes, 2005; Chang et al., 2016), but the disposition effect occurs in other domains (see, e.g., Genesove and Mayer, 2001; Quispe-Torreblanca et al., 2021, for its application to housing). Yet performance against more recent points might be relevant for selling decisions. For example, Heath et al. (1999) show that the decision of employees to exercise stock options is positively related to short-term stock performance and negatively related to performance over longer time horizons.

We first present a new model of the disposition effect in which new reference points are created and in which decisions are made in the context of multiple reference points. Our model implements prospect theory preferences in a multi-period setting in which investors experience realization utility from selling (Barberis and Xiong, 2012; Ingersoll and Jin, 2013; Frydman et al., 2014a; Imas, 2016). A key innovation in our model is that paying attention to stock prices can generate a new reference point against which future decisions are evaluated. Specifically, if, when paying attention, the investor observes a higher price than the purchase price, that price becomes a reference point against which future decisions are evaluated. Our model predicts that investors will, in such cases, display a disposition effect against the new reference point.

Focusing on the behavior of retail investors, in empirical analyses we explore the impact of the price the investor saw at his or her latest account login (our measure of paying attention to the stock's held by the investor) on selling behaviour. Our focus on attention to the prices of individual stocks arises from the tendency of investors to hold only a few stocks (the median in our sample is four, consistent with samples used in the previous literature, see Barber and Odean, 2013) and therefore the value of each holding they see when they login is likely to stay in their memory in the short-term. The majority of the time, when the investor subsequently makes a login, the change in the value of the holding reflects the change in the price of the stock.[3] We present two novel findings. First, investors are more disposed to sell stocks that

[3] Exceptions include low-frequency events such as in cases where dividend payouts are automatically reinvested.

have gained value since they last logged in to their account. That is, they show a disposition effect against the price at their last login. Second, the purchase price and the price at the last login interact as reference points, such that investors are more likely to sell stocks that have gained on *both* margins relative to those that have lost on *either* margin.

Thus our first empirical contribution is therefore to identify a new reference point that influences the behavior of investors. 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. This result is important because, given that people pay attention to their accounts selectively and not at random (Sicherman et al., 2015), it means that when people look has consequences for their actions, because it creates a new and meaningful reference point against which future prices are evaluated. Of course, investors may attend to price information off platform and create new reference points as a result. We do not observe off-platform attention. However, logging in is, given we see a strong disposition effect against the price at the last login, a likely indicator of significant attention being paid.

Our second empirical contribution is to determine how these two reference points jointly influence investor behavior. Given the operation of multiple reference points, an important question is how they jointly influence behavior. One could imagine, for example, that multiple reference points could be combined into a single composite reference point against which outcomes are evaluated (e.g., Tryon, 1994), that each reference point is evaluated against the outcome in question and then the different evaluations are averaged according to some weighting scheme (Ordóñez et al., 2000), or that, as we find, multiple reference points interact with one another in a more complicated fashion.

We show that there exists a very strong interaction effect between returns since purchase and returns since latest login in their effect on selling behaviour: 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) on selling behavior are not independent, but interactive. The interaction effect is so strong that even a small negative return since latest login is sufficient to almost eliminate the disposition effect for returns since purchase that are an order of magnitude larger.

We interpret these findings in light of the model we develop, which builds on an explanation of the disposition effect offered by Barberis and Xiong (2009), who draw on insights from prospect theory. 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, scaled-up by the risk-free rate) in combination with a utility function in which utility is determined by realized gains and losses. In our simplification of their framework, we focus on psychological considerations only, and incorporate a second reference point (the price at latest login). Specifically, drawing on insights from psychology as well as disposition effects in other domains, we assume that, when deciding whether or not to sell a stock at a particular point in time, an investor who is exposed to more than one salient reference point focuses on the highest, most aspirational reference point which, in this case, makes the current price look worst.

Holding on to a stock in our model represents a gamble – that the stock may rise or fall in value (we assume that the individual transfers proceeds from a sale to a comparatively safe asset). If the investor's effective reference point is high, so they feel that they have lost money, prospect theory predicts they will be risk-seeking, which, in our model, will encourage holding the stock. However, if the individual's reference point is low or close to the current value of the stock, the individual will tend to be risk-averse (due to value function concavity or loss aversion), encouraging selling the stock. Combined with the assumption that the investor cares only about the higher reference point, the model generates the prediction that the individual will only sell when the current price exceeds both of the reference points.

A complication, in testing whether the price at the 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; Gherzi et al., 2014; 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.[4] Note that this problem applies equally when it comes to the disposition

[4] In a related piece of work, we provide an extensive analysis of look up choices for a large panel of investors that incorporates the pool of investors we employ here (see Quispe-Torreblanca et al., 2020). We demonstrate that

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 they learn about the value of the asset when they look. In our sample, returns since purchase and returns since latest login both have means of zero and are close to normally distributed, indicating that investors cannot buy stocks, or time their logins, to achieve a systematically positive distribution of returns.

Crucially, to address directly the endogeneity in investors selecting when to log in, 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" type investors. Second, we use a Heckman selectivity correction to control for non-random selection into logging in 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 log in 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 enables 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 their account. The majority of assets (both in terms of number and value) held by investors in the trading

investors devote disproportionate attention to already-known positive information about the performance of individual stocks within their portfolios.

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 makes it possible 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. Investors also log in much more frequently than they trade, and, usefully, 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 $\times$ stock $\times$ 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 baseline estimates from OLS regression models are robust to the inclusion of individual fixed effects, rich controls for returns since purchase and controls for 1-day returns (indicating that the effects we estimate arising from returns since latest login do not simply proxy for effects from 1-day returns). Our results are also robust to the use of a selectivity correction specification which models investor logins, and to the use of a Cox proportional hazard model specification, as in Seru et al. (2010).

We also explore the sensitivity of our main results across a broad range of subsamples. 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).

Second, we examine the sensitivity of our estimates to splitting the sample according to the number of days since the stock was purchased and, separately, the number of days since the latest login day. In each of these analyses, 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. The analysis dividing the sample according to the number of days since latest login similarly shows a disposition effect even for those who logged in a comparatively long time in the past.

Third, we present estimates for subsamples of low- and high-volatility stocks and find that the patterns in selling behaviour in our baseline sample are present in both high- and low-volatility subsamples.

Fourth, we present estimates for subsamples which cut the data by 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. Importantly, we also show that the effect of the price observed in the last login day is stronger when investors paid higher attention to their stocks' prices, which we proxy by counting the number of logins to the account during the last login day.

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). Explanations for the disposition effect focusing on the importance of realization utility and loss aversion include Barberis and Xiong (2009) and Frydman et al. (2014b).[5] Frydman and 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. Odean (1998) demonstrates that the disposition effect does not arise due to transaction costs, portfolio rebalancing, a preference for realizing gains more frequently than losses, or due to different beliefs about expected future returns. The disposition effect tends to be stronger among individual, as compared

[5] 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).

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 sales of individual stocks rather than index funds or mutual funds.

Our study also contributes to an expanding literature examining the consequences of limitations on, and motivational directors of, attention. This research includes work on differential consumer attention to explicit versus shrouded good attributes (Gabaix and Laibson, 2018), the impact of taxes and payment medium on consumer demand (Chetty et al., 2009; Finkelstein, 2009), and market segmentation (Bordalo et al., 2013). In the domain of finance, attention-related research has examined the impact of attention-grabbing features of stocks on short- and long-term returns (Barber et al., 2007), and of the day on which earnings are announced (DellaVigna and Pollet, 2009), as well as the aforementioned research on the ostrich effect. At a theoretical level, 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 (Ebbinghaus, 1913; Murdock, 1962; Ward, 2002;). 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 introduces the model of the disposition effect which incorporates multiple reference points. Section 3 describes the Barclays Stockbroking data and presents summary statistics. Section 4 presents the econometric specification used in the analysis and describes the sample selection restrictions. Section 5 presents the main results and the additional robustness and sensitivity tests. Section 6 interprets and discusses the empirical results. Section 7 concludes.

2 A Model of Investor Behavior with Multiple Reference Points

Beginning with Odean (1998), analyses of the disposition effect have focused upon the purchase price as the reference point against which investors evaluate selling decisions. Barberis and Xiong (2009) show that an implementation of prospect theory in a model of trading behavior in which investor preferences are defined over realized gains and losses can reliably predict a disposition effect based upon the purchase price of the stock.[6]

Here we develop a model of realization utility which incorporates prospect theory preferences, but with two innovations. First, we allow for the creation of new reference points when investors log in and attend to their portfolio. Second, we describe the selection of reference points in the context of multiple reference points.

A key assumption in our model concerns the interaction between multiple reference points. We assume that an investor who is exposed to more than one salient reference point focuses on the highest, most aspirational price – here meaning the highest price – when deciding whether or not to sell a stock at a particular point in time. This price represents the best price achieved to date and hence it is actually the least favourable for a comparison of the investor's current position. Research in psychology on aspirations, goal-setting, and social comparison, all find that people generally do not select inferior points of comparison that make them feel good in the present, but, typically, referents that are superior to their own current position (e.g., Collins, 1996; Lopes and Oden, 1999). [7]

Of course, the assumption that investors focus on the most aspirational price implies that investors do not endogenously choose a reference point so as to make their current position most favourable. To do so, investors would optimally focus on a *lower* price than the current

[6] The authors also show that a model in which preferences are defined over annual paper gains and losses does not generate a disposition effect.

[7] In other applications, the most aspirational reference point might be the lowest price when, for example, going short on a stock or the period of most price volatility when, for example, trading a volatility-linked security.

stock price (and lower than the purchase price) – at the limit, focusing on a price of zero. Thaler (1985) proposed the concept of "hedonic editing" to refer to the idea that when different options for mental accounting exist, people choose the approach that makes them feel best, hedonically. But Thaler and Johnson (1990) find that people do not, in fact, frame decision in ways that, theory would say, should maximize their utility.

To illustrate our assumption with an intuitive example, a worker learning of her yearly bonus might have as salient reference points both her own bonus from the previous year and her office-mate's bonus in the current year. According to the assumption of selection of the most aspirational reference point, if one of these reference points was higher than her bonus this year but the other was lower, she would focus on the higher reference point virtually to the exclusion of the lower.[8]

Figure 1 presents a four-period model for the case of investors' selling decisions, as follows:

Period 0. The investor purchases a stock at $t = 0$ at a price p_0. This purchase price constitutes a salient reference point. Between Period 0 and Period 1, the price then either rises or falls to a price p_1 at time $t = 1$.

Period 1. In period 1, the individual either looks or does not look at her portfolio (which contains this single stock). If the investor chooses to look, then p_1 becomes a second salient reference point[9]. Between Period 1 and Period 2, the price then either rises or falls to a price p_2.

Period 2. In period 2, the investor looks up the value of the stock, then chooses whether or not to sell the stock. Between Period 2 and Period 3, the price then either rises or falls to a price p_3.

Period 3. In this final period, the investor liquidates any remaining position in the stock.

For tractability, we apply a number of simplifying assumptions. We assume that at the

[8] Although the selection of reference points is a behavioral feature of the model, in Section 5.3.5 we provide a number of tests that rule out the possibility that our results are driven by the potential endogenous choice of login days.

[9] At each point in time, prices can go up or down with equal likelihood, e.g., p_1 can be either $p_0 + 1$ or $p_0 - 1$; p_2 can be either $p_0 + 2$, p_0, or $p_0 - 2$; etc.

start of period 0 the investor purchases a stock which takes the form of a single share and that prior to each period the price rises or falls with equal likelihood (independent of the price history) by a fixed amount (for simplicity, normalized to 1). We further assume that once having sold the stock, the receipts are held in a risk-free asset, as is most commonly the case with modern brokerage accounts.[10] With the assumption of realization utility, the investor is only concerned with the utility experienced from selling the stock, either in period 2 or 3.

Figure 1 Panel A illustrates the events in the model. Beginning from p_0 at time $t = 0$, the price of the stock rises or falls through periods $t = 1, 2, 3$, resulting in the investor arriving at a node in each time period, dependent on the evolution of the price of the stock. Panel B describes the investor's selling decision under prospect theory preferences at each node in the period $t = 2$.

At $t = 2$, the investor maximises a prospect theory value function given by

$$\begin{aligned} &|p - r|^{\delta} \ \text{ if } \ p - r > 0, \\ -\lambda &|p - r|^{\delta} \ \text{ if } \ p - r < 0, \end{aligned} \tag{1}$$

where δ $(0 < \delta < 1)$ and λ respectively determine the curvature of the value function and the degree of loss aversion. The reference point r, is determined by the price in period $t = 1$ and whether the investor looks in period $t = 1$. If the individual does not look at the stock value in period $t = 1$, then $r = p_0$. If the investor looks, then the reference point is given by:

$$r = \gamma p_1 + (1 - \gamma) p_o \tag{2}$$

where γ is an indicator that takes a value of 1 if $p_1 > p_0$ and 0 otherwise.

The sell/no-sell predictions of the model should not be viewed as predictions about whether the investor will sell or not, but rather as reflecting the propensity to sell or not sell that is contributed by the reference points an investor is subject to. A specific individual might have a

[10] In the Barclays Stockbroking data used in this study, proceeds from sales are automatically transferred to a liquid account paying money market returns.

general tendency to hold onto, or sell, stocks, and other idiosyncratic factors may be in play, such as liquidity constraints or tax considerations. The model identifies selling or holding tendencies above and beyond such considerations that arise from the investor's contemplation of where the stock's price stands relative to the operative reference point.

The model has two degenerate cases, labeled Node -2 and Node $+2$. These result from the price either falling prior to both $t = 1$ and $t = 2$, or rising prior to both $t = 1$ and $t = 2$. In the former Node -2 case, the relevant reference price is the purchase price (whether or not the individual looks at $t = 1$). In the latter Node $+2$ case, the reference price is the purchase price if the investor did not look at $t = 1$ but is the price upon looking if the investor looked ($p_0 + 1$). At Node -2 the individual is in the domain of losses. As a result of the convexity of the value function, the individual is risk-seeking in this situation, which means holding the stock and risking the possibility of an increase prior to $t = 3$. At Node $+2$ the individual is in the domain of gains (against p_o if the individual did not look or $p_o + 1$ if the individual did look). As a result of the concavity of the value function, the individual is risk-averse and hence sells the stock, shifting receipts to the safe asset.

The most interesting situation is Node 0. At this node, whether the investor is in loss or gain depends on the price history of the stock and whether or not the investor looked. If the individual did not look, then her reference price is the same as the current stock price, making the individual extremely risk adverse due to loss aversion. If the individual did look, however, the reference price depends on whether the stock price has risen or fallen between $t = 0$ and $t = 1$. If the stock price rose, then the reference point is $p_o + 1 > p_0$, the individual is in the risk-seeking domain of losses, and doesn't sell. If the stock price fell, then the reference point is equal to the purchase price, which is equal to the sell price and the individual sells (due to the concavity of the value functions). Hence, an investor looking at the price of her stock holding may generate a reference point for future selling decisions. This is determined by the price of the stock upon looking relative to the purchase price.

While for tractability the model only incorporates three periods, we expect that the effect of prices observed through sequential logins during the holding period will fade over time. Therefore, at any point in time, the last price observed is generally more salient than its predecessors and more likely to influence trading choices. However, prices might generate reference points through other mechanisms apart from the investor looking at her stock portfolio. In a related paper, Quispe-Torreblanca et al. (2021), we examine the role of highest prices in the disposition effect in the housing market and market for securities, applying the model presented here to the case where investors form a reference point around all-time high prices during their holding period. Our model describes the key general rule for the selection of reference points when more than one salient reference point is in place.

The model has two main implications which we take to the empirical analysis. First, the model implies the existence of a disposition effect defined over returns since purchase, but also a disposition effect defined over returns since the price when the investor last looked. Investors who do not look at the stock price have no opportunity to form a new reference point, whereas investors who do look may form a new reference point, depending on whether the price has risen or fallen since purchase.

Second, the model implies that an investor may not sell even when the stock is in the domain of gains since purchase if the reference point formed when the investor last paid attention is higher (this is the case at Node 0 when the price of the stock rose before $t = 1$, then fell back before period $t = 2$). In such cases, the positive effect on utility of the return since purchase is nullified by the loss since looking. Hence, the investor chooses not to sell due to the reference point formed by looking. Panel B of Figure 1 summarizes these predictions. Further details and simulation of the model using a prospect theory value function are provided in the Online Appendix, see Table A1.

3 Data

Data were provided by Barclays Stockbroking, an execution-online brokerage service operating in the United Kingdom. The data cover the period April 2012 to March 2016 and include daily-level records of all trades and quarterly-level records of all positions in the portfolio. The vast majority of positions held are in common stocks.[11] 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

[11] 5.6% of all positions (by value) held are in mutual funds.

on each day of the sample period.[12] 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 on all stocks held within the account, which is required for the estimation of the disposition effect. This provides a baseline sample of approximately 8,200 accounts.[13]

3.1 Summary Statistics

Table A2 shows summary statistics for the baseline sample. Approximately 85% of account holders are male and the average age of an account holder is 45 years. A similar profile of account holders is observed in the Barber and Odean trading data set (for example, Barber and Odean, 2001).[14] Accounts holders have held their accounts with Barclays for, on average, approximately two-and-a-half years. The average portfolio value is approximately £42,000, 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 tendency of individual investors to concentrate their holdings in a few stocks is common in previous studies (for a review, see Barber and Odean, 2013).[15]

The summary statistics for login and transaction behavior shows that investors log in much more frequently than they trade. Investors log in on average approximately once every

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

[13] 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 those stocks purchased before the beginning of the sample period in 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 of purchase, meaning that we cannot calculate gains since purchase. We further restrict the sample to accounts with at least two stocks in their portfolio and for which we have complete data, including demographic data, and data on trades and logins. Outliers in returns since purchase (1 and 99 percentiles) and in the distance from the portfolio day to the last transaction day (99 percentile) were also excluded. In Section 7 we show results for the sample of existing accounts restricting only to stocks purchased within the sample period.

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

[15] Goetzmann and Kumar (2008) also show that US investors tend to hold under-diversified portfolios with positions concentrated in only a few stocks. More than 50% of investor portfolios contain one to three stocks. For most investors in their sample, under-diversification is financially costly.

five days (the median is approximately six days),[16] but make a transaction, on average, only once every 18 market open days (i.e., approximately once every four weeks; median, once every thirty market open days). This pattern of much more frequent logins than transactions is consistent with behavior observed among investors in the United States (Sicherman et al., 2015).[17]

4 Econometric Specification and Estimation Sample

4.1 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:

$$Sale_{ijt} = b_0 + b_1 GainSincePurchase_{ijt} + \epsilon_{ijt}, \tag{3}$$

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. *Sale* is a dummy equal to 1 if the investor holding account *(i)* reduced holding of stock *(j)* on day *(t)*. *GainSincePurchase* is a dummy variable indicating whether, for the investor holding account *(i)*, stock *(j)* had made a gain on day *(t)* compared to the price on the day the stock was purchased by the investor.

We modify the baseline specification in Equation 3 by adding a dummy variable indicating whether the stock was in gain on day *(t)* 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*.

[16] 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.

[17] Sicherman et al. (2015) explore login and transaction behavior among defined contribution retirement savings 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 is now:

$$Sale_{ijt} = b_0 + b_1 GainSincePurchase_{ijt} + b_2 GainSinceLatestLogin_{ijt} + \epsilon_{ijt} \tag{4}$$

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

The modified specification therefore adds a new concept to the econometric estimation of the disposition effect, the concept of *gain since latest login.* The dummy variables for *gain since purchase* and *gain since latest login* are not collinear: due to the high login frequency displayed by individual investors relative to their trading frequency, as seen in the summary statistics in Table 2, the correlation of gain since purchase and gain since latest login is low. 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 4 the dummy variables indicating where an account × stock × day is in gain since purchase and gain since latest login enter independently. This specification therefore assumes independent effects from the two measures of gains. In an additional specification, we also include an interaction term on the two measures of gains. We return later to the economic interpretation of the independent and interacted effects.

We estimate both Equation 3 and Equation 4, allowing us first to replicate the standard estimation of the disposition effect from Equation 3 before introducing results from the revised specification in Equation 4. In subsequent robustness analysis in Section 5.3, 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 analyses of estimates of these econometric models in Section 5.4.

4.2 Estimation Sample

The econometric specifications in Equation 3 and Equation 4 have as the unit of observation an account × stock × day. Given that we can observe the value of stock positions at daily frequency, we can estimate Equation 3 and Equation 4 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 on which the market is open.

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. As discussed in (Chang et al., 2016), on days with no sales, we cannot tell whether the absence of a sale is a deliberate choice on the part of the investor, or whether it is due to inattention. Consequently, previous studies (beginning with Odean, 1998), restrict the sample to account × stock × time units on which the investor sold at least *one* stock in their portfolio. This sample restriction ensures 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.

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*. However, given that we have daily-level data available, we also show results for two other samples. First, we show results for login-days, restricting the sample to account × stock × days on which the investor made a login. An argument in support of this sample selection is that on login days we know that the investor was paying attention to the portfolio, and hence a decision not to sell is more likely to be an active choice. 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 (and gains new information on stock prices). We call this sample the *Login-Day sample*. Second, we show results for all days on which the market was open, with the caveat described above. We call this sample the *All-Day sample*. Results are consistent across all three samples. We show results from the Sell-Day sample in the main text, with results from the Login-Day sample mostly shown in Section 7 and results from the

All-Day sample shown in Appendix B.[18]

The Sell-Day sample provides approximately 349,983 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 5,894,175 account × stock × days for investors who made at least one login on the day. Both data samples pool 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.

4.3 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.[19] 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.[20] However, this is not the case in our sample in which investors login much more frequently than they trade. The Pearsons' ρ coefficient is 0.18 in

[18] As described above, we also show results from the Login-Day sample for existing accounts in Appendix C. The analysis in that appendix restricts to stocks purchased within the sample period, a subset of all stocks held in existing accounts.

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

[20] 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.

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.

5 Results

5.1 Main Results

This subsection presents estimates of the disposition effect. Before showing the regression estimates, Figure 2 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.[21] The plot shows a very large increase in the probability of sale when returns since purchase are positive.

Figure 3 Panel A shows the analogous relationship for stock returns since latest login. That is, Figure 3 Panel A plots the probability that a stock is sold as a function of its return since latest login. Initial scrutiny of the figure suggests that its shape is very different from that of Figure 2, which shows sales as a function of returns since purchase; the plot shows a "v-shape" centered upon zero in contrast to the step-shape of Figure 2. 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 3) also displays a v-shape pattern.[22] 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

[21] Figure A2 shows the equivalent plot using the Login-Day sample.
[22] Figure A3 shows the equivalent plots using the Login-Day sample.

login are positive than when they are negative. This can be seen in the asymmetry in the v-shape, with the loss side always lower than the gain side at any magnitude of return since lastest login. 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 3. 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 11.6 percentage points more likely to be sold compared with a stock in loss. Against the base probability of selling a stock in loss from the constant in the regression of 14.2%, this represents an increase of 81%. In the Login-Day sample in Panel B, the equivalent increase is 69%.

The model in Column 2 Panel A replaces the gain since purchase dummy from Equation 3 with the gain since latest login dummy. The coefficient on this dummy variable is again positive and precisely defined. The coefficient on the gain since latest login dummy in Column 2 of Panel A implies that a stock which is in gain since latest login is approximately 5.2 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 approximately 34%.

Estimates of Equation 4 are shown in Column 3 in each panel. Results show a positive coefficient on both the gain since purchase and gain since latest login dummies, which are both precisely estimated. The inclusion of both gain since purchase and gain since latest login 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 gain since purchase dummy remains stronger than the coefficient on the gain since latest login dummy. For example, in Panel A, the coefficients imply that a stock in gain since purchase is eleven percentage points more likely to be sold, while a stock in gain since latest login is 3 percentage points more likely to be sold. This pattern holds in the Sell-Day and Login-Day samples.

5.2 Interaction Results

The specification shown in the final column of Table 3 adds the term for the interaction of the gain since purchase and gain since latest login dummies to Equation 4. The coefficients for the main effects and the interaction are each precisely defined. With the inclusion of the interaction term, the coefficient on gain since latest login variable becomes negative, while the coefficient on the interaction term is positive. Investigation of the coefficient magnitudes implies that the probability of sale is only substantially increased when *both* gain since purchase and gain since latest login are positive. In particular, if the gain since latest login dummy takes a value of zero, the effect of a gain since purchase on the probability of sale is greatly diminished.

To visualize the interaction between gain since purchase and gain since latest login, Figure 4 reproduces the illustration in Figure 2, separating out account × stock × day observations by whether the stock was in gain or in loss since latest login.[23] Strikingly, the clear 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 evidence of only a very small disposition effect arising from positive returns since purchase when the stock has made a loss since latest login, compared with the very large jump in probability of sale when the stock has made a gain since latest login.

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

5.3 Robustness Tests

5.3.1 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 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 that the positive effect of a gain since purchase diminishes when the stock also exhibits a loss since latest login. In

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

Panel A Column 4, the probability of sale increases by twice as much when the stock is in gain since purchase and in gain since latest login when compared to being in loss since latest login.

5.3.2 Controlling for Returns and Individual Fixed Effects

The second robustness test adds linear controls for returns to the econometric models in Equation 3 and Equation 4. 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 A3. 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.

5.3.3 Controlling for 1-day Returns

Returns since latest login might proxy for 1-day returns, if investors form a reference point from the stock price on the previous day. To control for this, Table 6 adds returns since the latest market day, which we call "returns since yesterday" to the baseline model. Results in Column 1 show that in a specification including the gains since purchase and a gain since yesterday dummy only, the coefficient on the gain since yesterday dummy is positive and precisely defined. However, this coefficient becomes much smaller and less precisely defined with the addition of the gain since latest login dummy in Columns 2-4. The coefficients on the gain since purchase and gain since latest login dummies in specification, and their interaction in Column 4 (the baseline specification plus the gain since yesterday dummy) are consistent with those in the baseline model (Table 3). This is also the case when returns since yesterday replace the gain since yesterday dummy in Columns 5 - 8. In these models the coefficient on the return since yesterday variable is positive and very small, whereas the coefficients on the gain since purchase and gain since latest login dummies in specification and their interaction are of much larger magnitude.[24]

[24] These same patterns are also seen when using the Login-Day Sample, with results shown in Table A4, and when using the All-Day sample and Older Accounts Sample.

5.3.4 Additional Control Variables

We show estimates from econometric specifications incorporating a broad set of control variables in Table 7. Previous studies suggest important control variables in econometric specifications of the disposition effect include the stock holding period (see Ben-David and Hirshleifer, 2012) and investor experience (see Da Costa Jr et al., 2013). In a series of econometric models, we control for the holding period (days since purchase), the period since latest login (days since latest login), account tenure, investor characteristics (age and gender) and portfolio characteristics (portfolio value and number of stocks held).

Results show that the coefficients on our main variables of interest, the dummies for gain since purchase and gain since latest login, together with the interaction between the two, are stable across econometric specifications which add these additional controls. In Table 7 the coefficient on gain since purchase is in the range 0.05 - 0.06, increasing to 0.08 with the inclusion of individual fixed effects. The coefficient on gain since latest login is in the range -0.016 to -0.026 across specifications, and the coefficient on the interaction term is in the range 0.09 to 0.12 across specifications. In all specifications we see a large coefficient on the interaction effect, consistent with the main results. Results for the Login-Day sample, which resemble those from the Sell-Day sample, are shown in Table A5.

5.3.5 Login Selectivity Correction

As discussed in the introduction, 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.[25] 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 they learn about the value of the asset when they look. For the interaction effect we observe to arise endogenously, it must be that investors who are more likely to login when experiencing gains are also more predisposed to the disposition effect. While this might be the case for a certain group of unsophisticated investors, with individual fixed effects this result could only arise due

[25] For an exhaustive analysis on how investors allocate attention to their portfolio, see Quispe-Torreblanca et al. (2020), where we analyse look up choices for a large panel of investors that incorporates the pool of investors we employ here. We find that investors devote disproportionate attention to already-known positive information about the performance of individual stocks within their portfolios.

to time-varying investor characteristics correlated with the propensity to login, which seems implausible.

We also provide two sets of empirical evidence that our results are not due to the choice of when to look. Figure A5 reproduces the main result for sub-samples of observations split by whether the stock was in gain or loss since the previous day, week, month or quarter. The same effect is seen across all sub-samples, indicating that our main result is not dependent on the pattern of returns over the period (in particular, not dependent on a sample of positive returns only).

As a second test, we add a Heckman selectivity correction term to control for non-random selection into making a login on a given day. [26] 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 4, 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 involved (e.g., outside leisure activities). The assumption implicit in the exclusion is that, for individual investors, weather affects sale decisions only through an affect on investors paying attention to their accounts (i.e., logins), with no direct effect on sales other than through attention. This is consistent with previous studies which find evidence of direct effects of the weather on trading behaviour of institutional investors (Goetzmann et al., 2015), but not individual investors (Goetzmann and Zhu, 2005).

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

[26] Although our main analysis uses sell days and login days for new accounts, in Appendix B we replicate our main results using all days in which the market is open and the accounts are active.

weather.[27]

Estimates of the probit model for the decision to login are shown in Table A6. 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 8 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.[28]

5.3.6 Cox Proportional Hazard Model Estimates

To provide a more exhaustive treatment of potential confounds introduced by the holding period, which has been shown to be relevant for stock selling decisions (Ben-David and Hirshleifer, 2012), we also estimate a stratified Cox proportional hazard model with time-varying covariates. The Cox model allows us to estimate the time-varying probability of a sell event without imposing any structure on the baseline hazard (i.e., without specifying the exact form of the distribution of the sell event times). Specifically, we estimate the investor i's probability of selling position j at time t (conditional on not selling the position until time t, h_{ijt}). In the model, we count every purchase of an stock as the beginning of a new position, and we assume

[27] 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.

[28] 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.

that a position ends on the date the investor first sells part or all of his holdings (as in Seru et al. (2010)). Estimates are stratified by account. That is, coefficients are equal across accounts but baseline hazard functions are unique to each account, ϕ_i. Thus, the stratified analysis is analogous to the fixed effect analysis described above.

$$h_{ijt} = \phi_i \exp\{b_1 GainSincePurchase_{ijt} + b_2 GainSinceLatestLogin_{ijt}\} \tag{5}$$

Time-varying covariates, like the gain since purchase and gain since latest login variables, are incorporated into the Cox regression model by dividing the follow-up time of each account into shorter time intervals. We split the data at the observed login and selling days. Table A7 in the Online Appendix shows stratified estimates by account for the Sell-Day and Login-Day samples. Column 3 in Panel A of Table A7 shows estimates of Equation 5. Column 4 incorporates the interaction between the gain since purchase and the gain since latest login dummies. The coefficient of the gain since purchase dummy in Column 4 is 0.366, which indicates that when there is a loss since the latest login day, investors are $\exp(0.366) \approx 1.441$ times more likely to sell a winning stock (since purchase) compared to a losing stock. However, the coefficient of the interaction is large in magnitude, 0.654, and indicates that, when there is a gain since the latest login day, investors are $\exp(0.366 + 0.654) \approx 2.774$ times more likely to sell a winning stock (since purchase) compared to a losing stock. This results are qualitatively similar to those obtained under the linear probability analysis[29].

5.3.7 All-Day and Existing Accounts Samples

We have shown results for the Sell-Day and Login-Day samples for new accounts. In Appendix B, we show additional results for the All-Day sample for new accounts; and in Appendix C, we replicate our results for Existing Accounts samples (accounts that opened before April 2012). These additional replication exercises help to provide robust evidence that the pattern of results we observe are not restricted to new accounts, which could incorporate a larger portion of less

[29] The size of the effect of a gain since purchase (conditional on a gain since the latest login) is also qualitatively similar to results obtained by Seru et al. (2010). Seru et al. (2010) estimated a Cox model using data from 11,000 individual investors in Finland. Specifically, they estimated the hazard ratio for selling a winning stock (since purchase) for each investor and year in the data, that the median investor has a hazard ratio of about 2.8.

experienced and unsophisticated investors. In the All-Day sample Figure B3 resembles Figure 4, showing a strong interaction effect in the unconditional plot. Table B3 -Table B5 replicate the coefficient patterns seen in the main regression table, including in the Cox Proportional Hazard model. The same patterns are also seen in the Existing Accounts sample, with the caveat that this sample selects only recently purchased stocks held within existing accounts (see Section 3 for the description of sample construction).

5.4 Sensitivity Tests

In this section we explore the sensitivity of our main results to subsamples defined by a range of characteristics including market characteristics, investor characteristics and trading portfolio characteristics. By analysing different subsamples of the data, this exercise is equivalent to the incorporation of these additional characteristics into our main equation in an interactive fashion.

5.4.1 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, 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 9. 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 A8 shows the same patterns occur in the Login-Day sample.

5.4.2 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.[30]

Table 10 reports results where 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 the Sell-Day and the Login-Day samples. Table A9 shows the same patterns occur in the Login-Day sample.

Table 11 reports results where the sample is split by the number of days since latest login.[31] 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 5 days previously. The effect of a gain since last login (relative to the probability of a gain since purchase but a loss since last login in each subsample) is stronger in Panel A. This result might indicate that the effect of the last price observed is larger when it is easy to recall. However, because the magnitude of this effect doesn't decrease monotonically across subsamples, these estimates do not provide conclusive evidence that the disposition effect on returns since latest login fades over this time window. Nevertheless, we cannot rule out the possibility that the disposition effect on gains since latest login would fade over longer time horizons.[32]

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[30] 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.

[31] Table A10 shows the estimates for the Login-Day sample.

[32] 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.

5.4.3 The Role of Attention Intensity on the Last Price Observed

While Table 11 explores the effect of salience (given by the recency of the login event) on the disposition effect on returns since the latest login, to provide a direct test of the effect of salience on the main interaction effect, we split the data by the degree of attention paid to the prices observed in the last login day. We proxy the level of attention by the number of logins investors made to their account on their previous login day. Figure 5 displays three panels describing interaction patterns for cases in which the investor login once, twice, and three (or more) times on the previous login day, respectively. We observe that the interaction effect increases monotonically with the degree of attention, with the interaction effect in high-attention days (right panel) being twice as large as the effect in low-attention days (left panel).

5.4.4 Stock Price Volatility

Third, we test the sensitivity of our main results to stock price volatility, following Chang et al. (2016). High volatility stocks may exhibit different propensities to sell, and hence the patterns we see in selling behaviour might differ across high- and low-volatility samples. Additional analysis in the Appendix, Table A11 and Table A12, confirms that the patterns in selling behaviour in our baseline sample are seen in both high- and low-volatility subsamples.

5.4.5 Investor and Portfolio Characteristics

Fourth, 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, Mottola, Utkus, and Yamaguchi, Mitchell et al.). 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 coefficients on the main effects and interaction terms (Column 4 of Table 3) are shown in Table 12. 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 and below-median number of stocks held. To gauge the magnitude of the difference in effect size across samples by number of stocks held and portfolio value, in Table 12 the coefficient on the interaction term is approximately twice as large for the below-median portfolio value. The coefficient is also larger among the sample containing below-median number of stocks held. Note that this might occur mechanistically because the unconditional probability of sale of each stock is higher the fewer the number of stocks, as shown by the much higher intercept in the below-median sample.[33]

5.5 Alternative Mechanisms

Finally, we consider two alternative explanations that do not arise from reference dependent preferences: expectation formation (leading to different trading strategies) and portfolio rebalancing strategies.

5.5.1 Expectation Formation

Different from the purchase price, which can barely be used to forecast returns, the evolution of prices observed in the short term (i.e., rolling realized return) can be used by investors to predict future prices. The patterns we observe in the data could reflect the beaviour of contrarian investors. Recent evidence suggests that retail investors tend to trade as contrarians around news announcements, buying stocks on large negative earnings surprises and selling stocks on

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

large positive earnings surprises (Luo et al., 2020).). If investors in our data expect prices to rise after a recent short-term loss, they will be reluctant to sell. Likewise, if investors expect prices to drop after a recent short-term gain, they will be prone to cash in the stock profits quickly. However, the patterns observed in Figure A5 rule out this alternative explanation. Figure A5 splits the data by whether the stock was in gain/loss in the previous day, week, month, and quarter. Contrarian investors should be reluctant to sell after experiencing recent losses; we observe, however, sizeable interaction effects in each of the panels of the figure (in both the gain and loss domains of short-term returns).

5.5.2 Rebalancing Strategies

A second alternative mechanism concerns portfolio rebalancing strategies. When investors look at their accounts, they observe the entire portfolio, which enables them to compare the relative performance of their assets against each other. Therefore, investors might be inclined to rebalance their portfolio and sell stocks displaying extreme positive returns in order to reduce their risk exposure (which could correspond to stocks in gain since purchase and in gain since the last login day). To account for this possibility, in Table A14 we replicate our main specification but considering only complete sales (following Odean, 1998). By excluding partial sales, we discard trading strategies that might be consistent with the desire to rebalance portfolios. The pattern of estimates in Table A14 remain consistent with our main findings.

6 Discussion

In this section, we interpret and discuss our results. In summary, our analysis yields two main results. First, investors 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. The interaction is strong, such that even a small loss since latest login overturns the effect of large gains since purchase.

6.1 Experimental Studies of Multiple Reference Points

The purchase price and price at latest login act as reference points. That these prices act as reference points is also consistent with previous studies showing that "first" and "last" prices act as reference points.[34]

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 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 neutral selling 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, 1913).[35]

In addition, our results are consistent with the notion of investors making selling choices using the last price observed as a reference point when this is higher than the purchase price. This finding is consistent with studies exploring the dynamics of reference point adaptation. For instance, Arkes et al. (2008) explore the shift in each subject's reference point following prior gains or losses, using both questionnaires and real money incentives. They find that reference point adaptation is asymmetric: reference point adapts to prior gains to a greater extent than to prior losses.

6.2 Theoretical Discussion

Barberis and Xiong (2009) propose a Prospect Theory-based explanation of the disposition effect. They show that the disposition effect can arise in a model in which investors engage

[34] There is also evidence for a peak-end rule in the psychological evaluation of a time series of events, where the evaluation of the episode is determined by the worst and last pain experienced (Kahneman et al., 1993). Thus, the latest login is an important reference for the evaluation of a stock, but also raises the issue of peak and trough prices as reference points, which we explore in Quispe-Torreblanca et al. (2021).

[35] 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).

in narrow framing, exhibit reference-dependent preferences in combination with a Prospect Theory realization utility function.[36]

The explanation for the disposition effect in Barberis and Xiong (2009), which is relevant to our discussion here, is as follows. Due to diminishing sensitivity to gains, investors prefer to realise their gains in many small sales. For gains, 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. Due to diminishing sensitivity to losses, investors prefer to realise their loss in one single sale.[37] 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 gain since purchase and gain since latest login? 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 the purchase price and the 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 an abnormal steeper convexity below the reference point, 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 gain since purchase and gain since latest login, it does not

[36] 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 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).

[37] 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. 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.

immediately account for the strength of the interaction effect.[38] An alternative explanation is that there is a discrete downwards jump in utility to the left of the reference point, illustrated in the modified Prospect Theory utility function in Figure A8 Panel B suggested by Homonoff (2018) and discussed in Markle et al. (2018).[39] 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.[40]

In our discussion of a possible extension of the Barberis and Xiong (2009) model – either with a high level of loss aversion or with a Homonoff step at zero – we are assuming investors evaluate today's price against both the purchase price and the peak price, and then quantitatively combine the two subjective evaluations. Another possibility is of a more qualitative integration, where any loss leaves bad feeling. Research in psychology shows that small losses can effectively nullify large gains (Baumeister et al., 2001). Rozin and Fallon (1987) observe that "a teaspoon of sewage will spoil a barrel of wine, but a teaspoon of wine will do nothing for a barrel of sewage." Such a qualitative integration of the subjective values from comparisons against multiple reference points is indeed consistent with the strong interaction we see, where a loss against either purchase or last login price is sufficient to eliminate the effect of any gains.

However, rather than hypothesizing the effect of two reference points acting in parallel (and the required abnormal degree of convexity in the value functions below each reference point, or some qualitative comparison), the model we propose here shows that by assuming that

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[38] 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, 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 Prospect Theory model. In a standard Prospect Theory utility function, such as that shown in Figure A8 Panel A, 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 A8 Panel A, the net utility of a small loss in combination with a large gain will be positive – thus, much more loss aversion is required for the small loss to render the net utility negative.

[39] Homonoff (2018) examines the impact of a $0.05 tax 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. Markle et al. (2018) examine reported satisfaction with finishing times compared with expressed goals (the reference point) among marathon runners. The authors find evidence of a discrete jump in satisfaction at the goal value.

[40] Shampanier et al. (2007) also suggest that the value function may exhibit a discrete jump at zero.

investors care only about the highest reference point (or the price which represents maximum paper returns), we are able to fully elucidate the patterns observed in the data, that the investors are more likely to sell when both of the relevant reference points – the purchase price and the price when the investor last looked up the value of the stock – are lower than the current price.

7 Conclusion

In this paper, we investigate the role of multiple reference points in the disposition effect. We present a new model of the disposition effect in which paying attention can create a new reference point against which future decisions are evaluated. Our model describes how people choose between reference points when making trading decisions. 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 logged in to his 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, as predicted by our model: 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 even a small negative return since latest login is sufficient to almost eliminate the effect of much larger gains in most of our estimates. That is, small negative returns since the last login almost eliminate the conventional disposition effect.

Our findings provide new data and insights to the literature in finance showing 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. More generally, our paper contributes to a growing literature documenting the importance of attention for economic behavior and outcomes.

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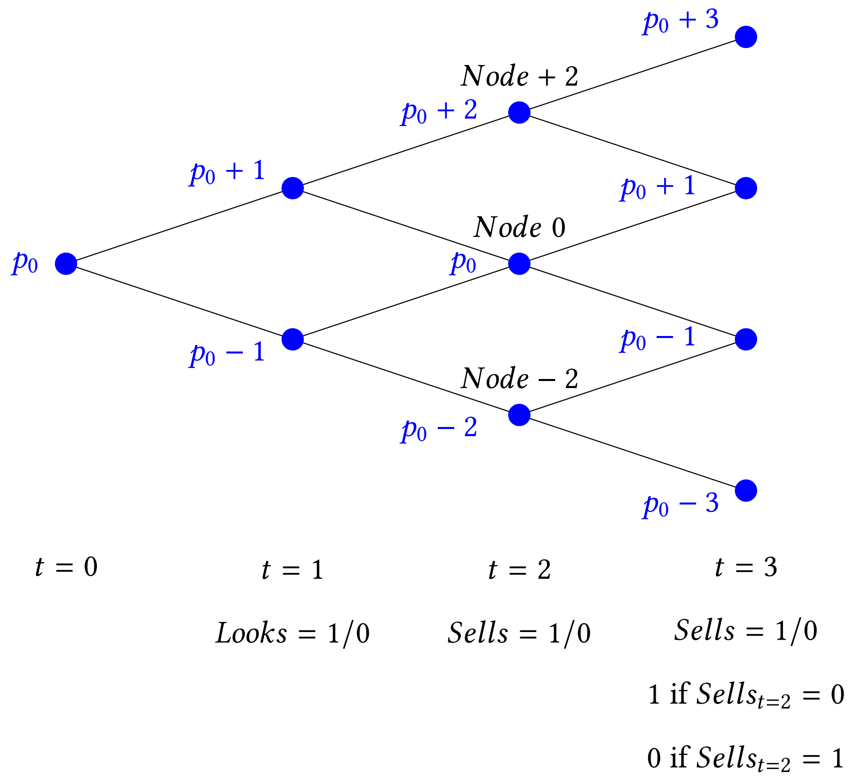
Figure 1: Illustration of the Model of Multiple Reference Points

(A) Model Structure

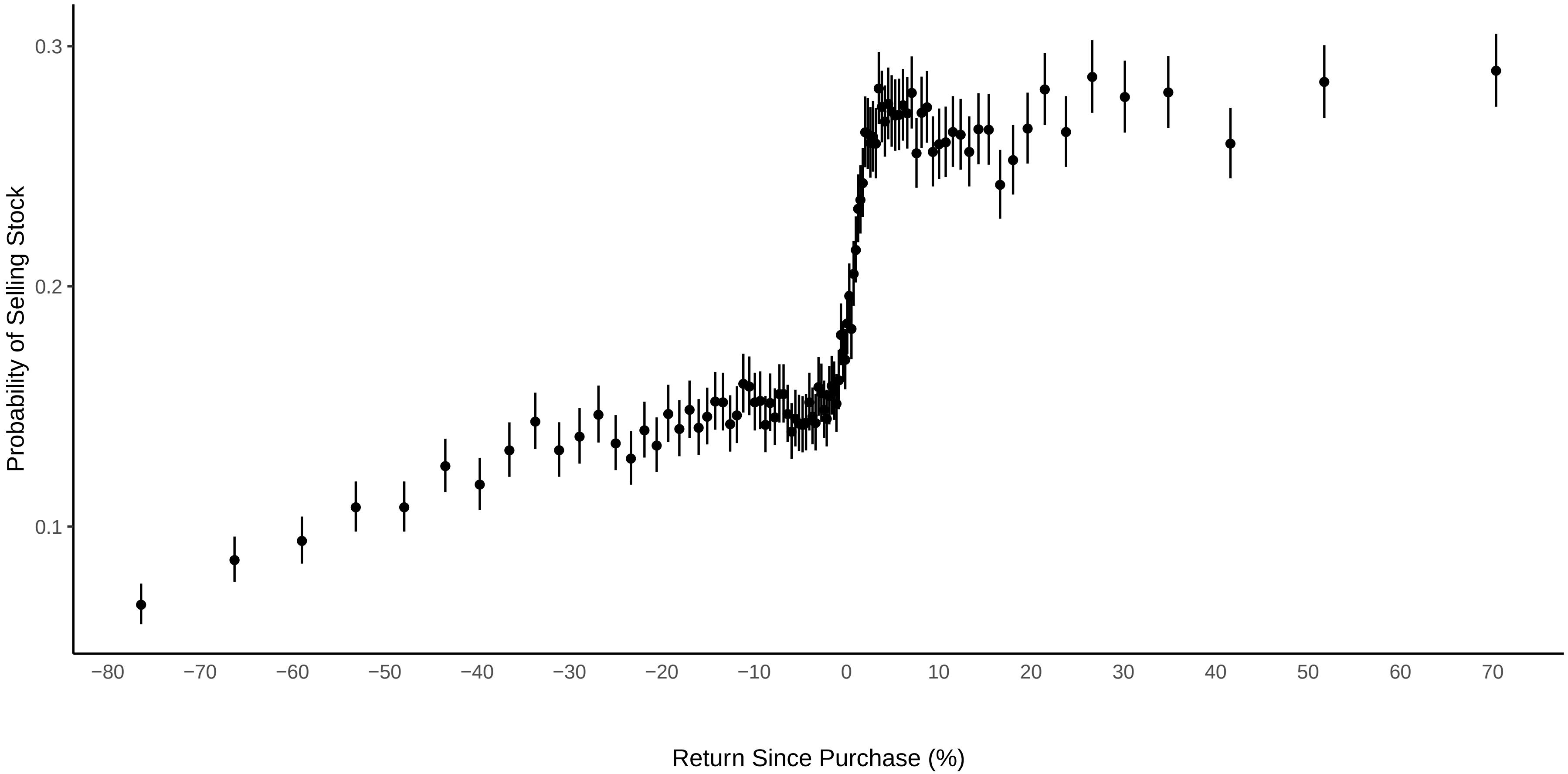


(B) Sell Decisions for Different Reference Points

		Price at $t = 2$		
Attention at $t = 1$	Reference point at $t = 2$	Node -2	Node 0	Node +2
Doesn't look	P_0	Don't Sell	Sell	Sell
Looks, $P_0 + 1$	$P_0 + 1$	Don't Sell	Don't sell	Sell
Looks, $P_0 - 1$	P_0	Don't Sell	Sell	Sell

Note: The figure illustrates the four-period model of multiple reference points. In Panel A, at $t = 0$ the individual purchases an asset at a price p_0, which constitutes a first reference point. At $t = 1$, if he observes his portfolio, the price observed becomes a new reference point. At $t = 2$, he chooses whether or not to sell the asset, and at $t = 3$ he liquidates any remaining position in the asset. Panel B displays the predictions of the model under which an individual with prospect theory preferences based his selling decisions using the highest reference point.

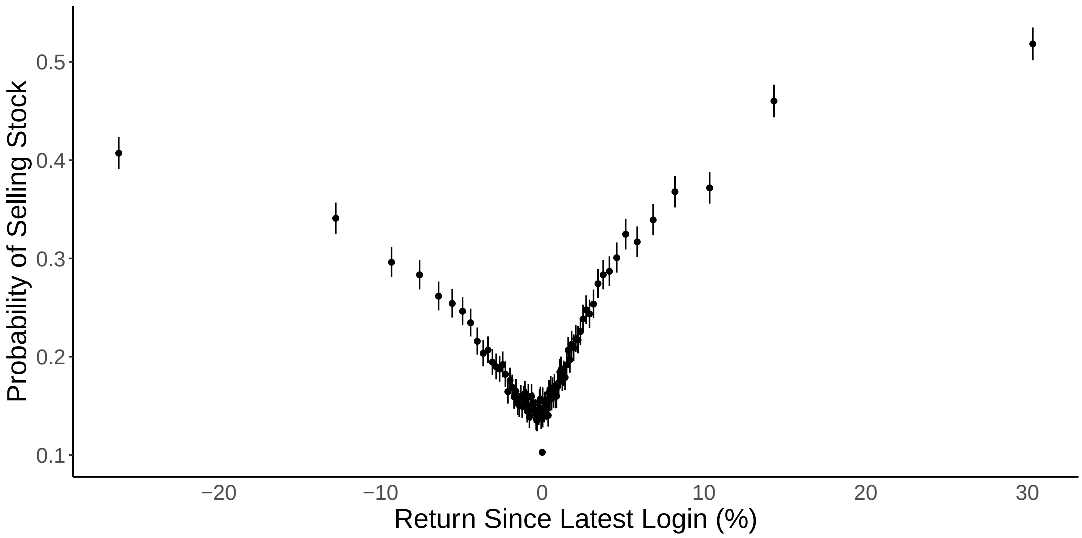
Figure 2: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Purchase in the Sell-Day Sample



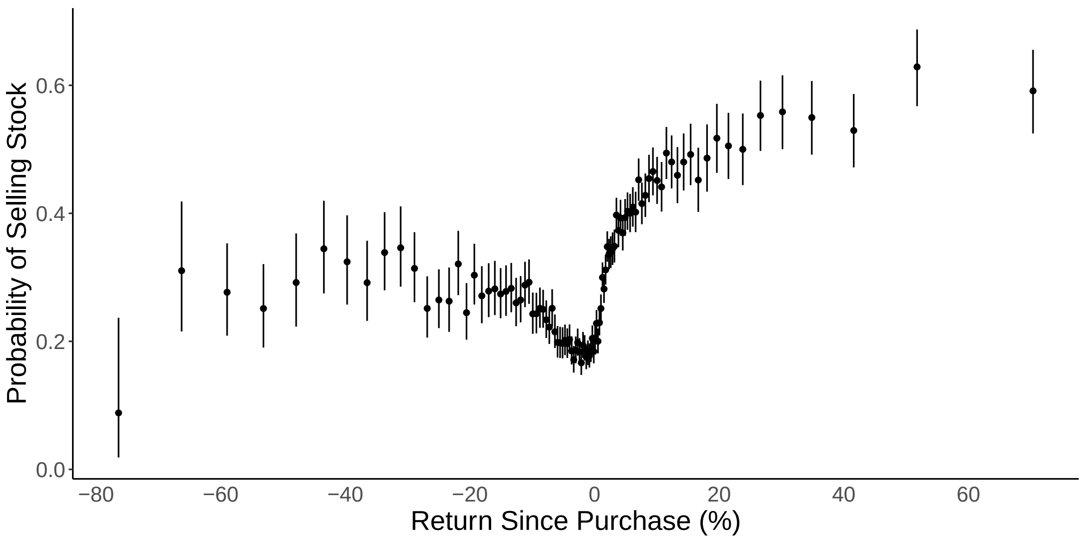
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. Sell-day sample includes all investor × stock × days on which the investor sold at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

Figure 3: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Latest Login in the Sell-Day Sample

(A) Returns Since Latest Login

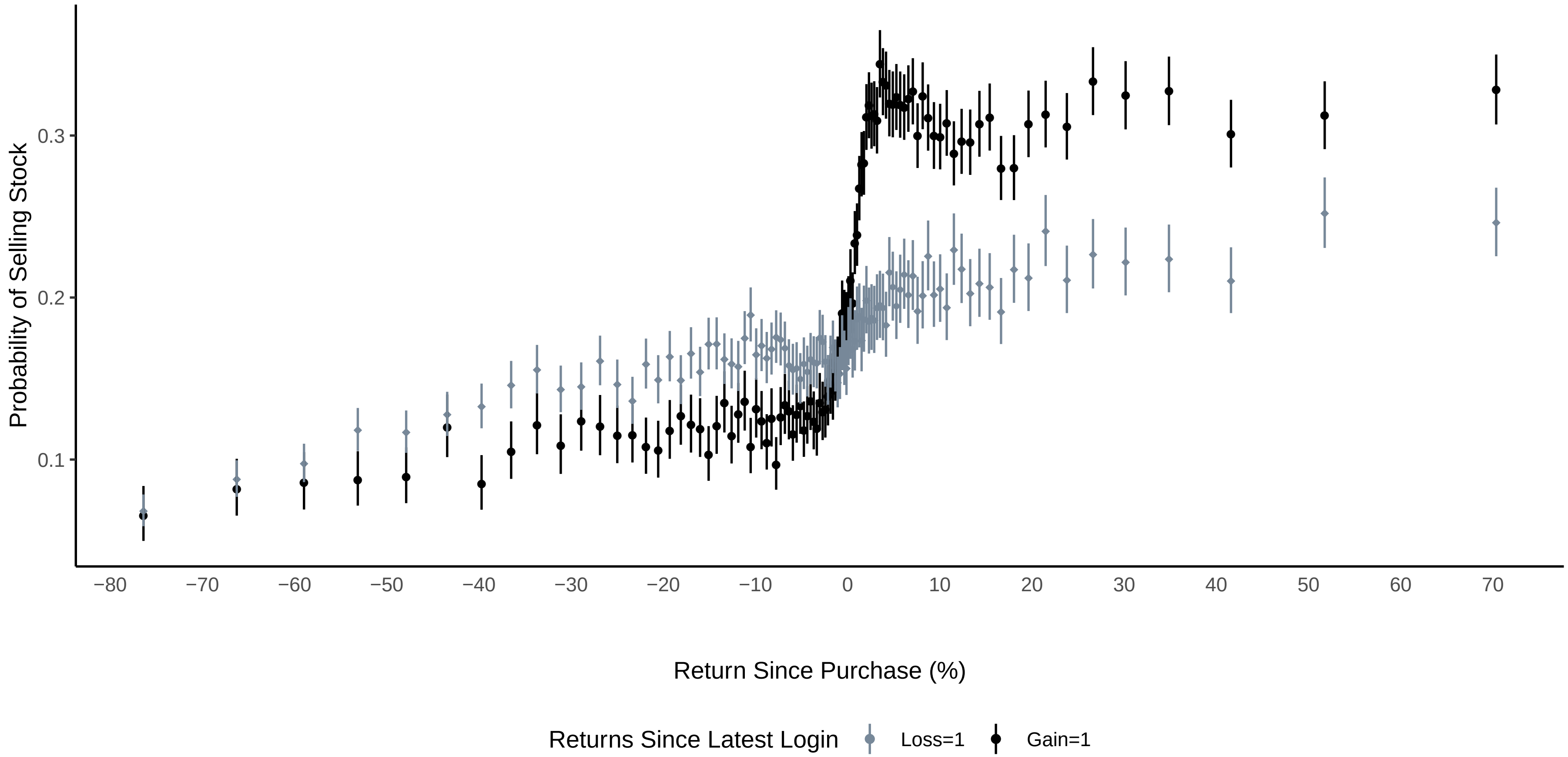


(B) Returns Since Purchase (Up to 30 Days Since Purchase)



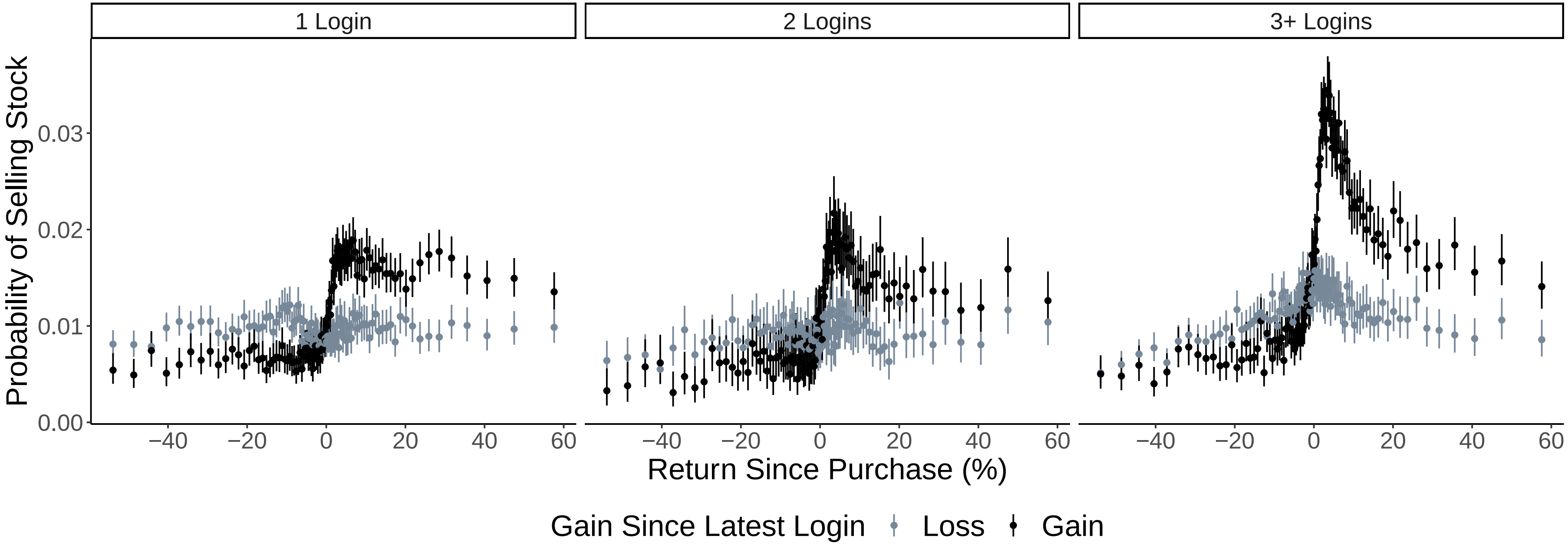
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. In Panel A the X-axis variable is the returns on the stock since latest login. In Panel B the X-axis variable is the returns on the stock since purchase. 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 4: 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 5: Interaction Effect by Intensity of Attention in the Latest Login Day 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 the number of times the investor login to their account in the latest login day: one time in the left panel, two times in the middle panel and three or more times in the right panel (which correspond to 43%, 21%, and 36% of observations). Login-day sample includes all investor × stock × days on which the investor made at least one login to their account. Returns since purchase and returns since latest login are calculated at the daily level.

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

Panel (A): Sell-Day Sample

	Mean	SD	Median
Sale=1	0.195		
Return Since Purchase			
Return Since Purchase (%)	−3.643	21.730	−1.214
Gain Since Purchase Day=1	0.449		
Return Since Latest Login			
Return Since Latest Login Day (%)	0.118	5.545	0.000
Gain Since Latest Login Day=1	0.463		
N Investor × Stock × Day	349,983		

Panel (B): Login-Day Sample

	Mean	SD	Median
Sale=1	0.012		
Return Since Purchase			
Return Since Purchase (%)	−2.620	23.095	−0.849
Gain Since Purchase Day=1	0.466		
Return Since Latest Login			
Return Since Latest Login Day (%)	−0.009	4.016	0.000
Gain Since Latest Login Day=1	0.456		
N Investor × Stock × Day	5,894,175		

Note: This table presents summary statistics for returns since purchase and returns since latest login in the sell-day 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.

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

Panel (A): Sell-Day Sample

	Pearson's ρ
All	0.179
Bottom Decile Trade Frequency	0.137
Top Decile Trade Frequency	0.230

Panel (B): Login-Day Sample

	Pearson's ρ
All	0.115
Bottom Decile Trade Frequency	0.074
Top Decile Trade Frequency	0.208

Note: This table presents correlation coefficients (Pearson's ρ) for returns since purchase and returns since latest login. Panel A reports for the sell-day sample of 349,983 investor × stock × days. Panel B reports for the login-day sample of 5,894,175 investor × stock × 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	0.1162***		0.1103***	0.0507***
	(0.0058)		(0.0056)	(0.0052)
Gain Since Latest Login=1		0.0517***	0.0306***	-0.0263***
		(0.0037)	(0.0032)	(0.0038)
Gain Since Purchase=1 ×				0.1239***
Gain Since Latest Login=1				(0.0051)
Constant	0.1425***	0.1706***	0.1309***	0.1524***
	(0.0054)	(0.0057)	(0.0060)	(0.0064)
Observations	349,983	349,983	349,983	349,983
R^2	0.0213	0.0042	0.0227	0.0286

Panel (B): Login-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0060***		0.0057***	0.0010***
	(0.0004)		(0.0003)	(0.0003)
Gain Since Latest Login=1		0.0034***	0.0027***	-0.0022***
		(0.0003)	(0.0003)	(0.0003)
Gain Since Purchase=1 ×				0.0102***
Gain Since Latest Login=1				(0.0004)
Constant	0.0087***	0.0100***	0.0077***	0.0096***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	5,894,175	5,894,175	5,894,175	5,894,175
R^2	0.0008	0.0003	0.0009	0.0015

Note: This table presents ordinary least squares regression estimates of Equation 4. 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	0.1240***		0.1183***	0.0734***
	(0.0055)		(0.0053)	(0.0045)
Gain Since Latest Login=1		0.0507***	0.0292***	-0.0130***
		(0.0033)	(0.0028)	(0.0031)
Gain Since Purchase=1 ×				0.0922***
Gain Since Latest Login=1				(0.0046)
Observations	349,983	349,983	349,983	349,983
R^2	0.1610	0.1435	0.1622	0.1653

Panel (B): Login-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0095***		0.0092***	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 ×				0.0066***
Gain Since Latest Login=1				(0.0004)
Observations	5,894,175	5,894,175	5,894,175	5,894,175
R^2	0.0459	0.0445	0.0461	0.0463

Note: This table presents fixed effects regression estimates of Equation 4. 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	0.0901***		0.0880***	0.0344***	0.0939***		0.0904***	0.0482***
	(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***	0.0141***	0.0140***		0.0116***	0.0110***	0.0110***
		(0.0005)	(0.0005)	(0.0005)		(0.0005)	(0.0004)	(0.0004)
Gain Since Latest Login=1		0.0397***	0.0203***	-0.0304***		0.0342***	0.0178***	-0.0220***
		(0.0033)	(0.0029)	(0.0032)		(0.0029)	(0.0025)	(0.0027)
Gain Since Purchase=1 ×				0.1072***				0.0844***
Gain Since Latest Login=1				(0.0047)				(0.0043)
Constant	0.1591***	0.1417***	0.1248***	0.1466***				
	(0.0058)	(0.0053)	(0.0059)	(0.0062)				
Account FE	NO	NO	NO	NO	YES	YES	YES	YES
Observations	349,983	349,983	349,983	349,983	349,983	349,983	349,983	349,983
R^2	0.0228	0.0298	0.0551	0.0594	0.1629	0.1572	0.1791	0.1817

Note: This table presents ordinary least squares regression estimates of Equation 4 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:
Including Continuous Returns Since the Preceding Day, Sell-Day Sample

	$Sale_{ijt}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain Since Purchase=1	0.1116***		0.1103***	0.0507***	0.1121***		0.1092***	0.0484***
	(0.0056)		(0.0056)	(0.0052)	(0.0056)		(0.0056)	(0.0051)
Gain Since Latest Login=1		0.0486***	0.0276***	-0.0302***		0.0391***	0.0212***	-0.0380***
		(0.0039)	(0.0036)	(0.0042)		(0.0035)	(0.0031)	(0.0038)
Gain Since Purchase=1 ×				0.1239***				0.1260***
Gain Since Latest Login=1				(0.0051)				(0.0051)
Gain Since Yesterday=1	0.0273***	0.0036	0.0034	0.0044				
	(0.0032)	(0.0037)	(0.0036)	(0.0037)				
Return Since Yesterday (%)					0.0034***	0.0031***	0.0024***	0.0028***
					(0.0005)	(0.0005)	(0.0005)	(0.0005)
Constant	0.1319***	0.1704***	0.1307***	0.1521***	0.1437***	0.1759***	0.1353***	0.1578***
	(0.0060)	(0.0058)	(0.0060)	(0.0064)	(0.0055)	(0.0056)	(0.0058)	(0.0062)
Observations	349,982	349,982	349,982	349,982	349,982	349,982	349,982	349,982
R^2	0.0225	0.0042	0.0227	0.0286	0.0228	0.0052	0.0233	0.0293

Note: This table presents ordinary least squares regression estimates of Equation 4 with the addition of control variables for the return of the stock since the preceding day (independently of whether the investor log in to their account on the preceding day). 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 7: Estimates of the Disposition Effect
Including Portfolio and Demographic Controls, Sell-Day Sample

	$Sale_{ijt}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain Since Purchase=1	0.0513***	0.0537***	0.0556***	0.0574***	0.0533***	0.0535***	0.0535***	0.0545***	0.0734***	0.0816***
	(0.0052)	(0.0050)	(0.0049)	(0.0049)	(0.0048)	(0.0048)	(0.0048)	(0.0046)	(0.0044)	(0.0044)
Gain Since Latest Login=1	-0.0266***	-0.0226***	-0.0203***	-0.0195***	-0.0193***	-0.0193***	-0.0193***	-0.0184***	-0.0121***	-0.0168***
	(0.0039)	(0.0037)	(0.0036)	(0.0035)	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0031)	(0.0031)
Gain Since Purchase=1 ×	0.1249***	0.1159***	0.1110***	0.1096***	0.1040***	0.1040***	0.1040***	0.1029***	0.0897***	0.0894***
Gain Since Latest Login=1	(0.0051)	(0.0048)	(0.0048)	(0.0046)	(0.0045)	(0.0045)	(0.0045)	(0.0045)	(0.0044)	(0.0042)
Days Since Purchase (100 days)		-0.0171***	-0.0186***	-0.0173***	-0.0141***	-0.0151***	-0.0149***	-0.0151***	-0.0069***	-0.0031***
		(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0014)	(0.0008)	(0.0007)
Days Since Latest Login (100 days)			0.2594***	0.2385***	0.1794***	0.1791***	0.1794***	0.1722***	0.0932***	0.0899***
			(0.0155)	(0.0145)	(0.0138)	(0.0138)	(0.0138)	(0.0132)	(0.0121)	(0.0121)
Portfolio Value (£10000)				-0.0022***	-0.0008**	-0.0008**	-0.0008**	-0.0008***	-0.0021***	-0.0020***
				(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0006)
Number of Stocks (10 stocks)					-0.0472***	-0.0474***	-0.0474***	-0.0459***	-0.0228	-0.0219
					(0.0103)	(0.0103)	(0.0102)	(0.0097)	(0.0150)	(0.0148)
Account Tenure (years)						0.0050	0.0049	0.0070**		
						(0.0035)	(0.0035)	(0.0033)		
Female=1							-0.0100	-0.0025		
							(0.0068)	(0.0060)		
Age (10 years)								-0.0161***		
								(0.0024)		
Constant	0.1533***	0.1819***	0.1752***	0.1893***	0.2487***	0.2442***	0.2455***	0.3183***		
	(0.0064)	(0.0072)	(0.0072)	(0.0068)	(0.0117)	(0.0123)	(0.0119)	(0.0125)		
Account FE	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Stock FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES
Observations	346,445	346,445	346,445	346,445	346,445	346,445	346,445	346,445	346,445	346,445
R^2	0.0289	0.0359	0.0397	0.0492	0.0786	0.0787	0.0788	0.0817	0.1680	0.1926

Note: This table presents ordinary least squares regression estimates of Equation 4 with the addition of demographic controls and (daily level) portfolio controls. Sample of all investor × stock × days on which the investor sold at least one login to the account. Outliers (investor × stock × days) in the first and 99 percentiles of daily portfolio values are excluded. Gender and age (calculated from decades of birth) are within individual time invariant. Standard errors are clustered by account and day.

Table 8: 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***
	(0.0004)		(0.0004)	(0.0003)
Gain Since Latest Login=1		0.0034***	0.0027***	-0.0022***
		(0.0003)	(0.0003)	(0.0003)
Gain Since Purchase=1 × Gain Since Latest Login=1				0.0103***
				(0.0005)
Inverse Mills Ratio	-0.0099***	-0.0108***	-0.0095***	-0.0096***
	(0.0024)	(0.0023)	(0.0024)	(0.0024)
Constant	0.0188***	0.0210***	0.0174***	0.0194***
	(0.0024)	(0.0023)	(0.0024)	(0.0024)
Observations	5,697,583	5,697,583	5,697,583	5,697,583
R^2	0.0008	0.0003	0.0010	0.0016

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 9: 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	0.1283***		0.1219***	0.0597***
	(0.0062)		(0.0060)	(0.0055)
Gain Since Latest Login=1		0.0563***	0.0325***	-0.0239***
		(0.0043)	(0.0038)	(0.0043)
Gain Since Purchase=1 ×				0.1222***
Gain Since Latest Login=1				(0.0063)
Constant	0.1351***	0.1665***	0.1220***	0.1447***
	(0.0054)	(0.0058)	(0.0061)	(0.0065)
Observations	185,289	185,289	185,289	185,289
R^2	0.0261	0.0051	0.0278	0.0335

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

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.1024***		0.0970***	0.0418***
	(0.0064)		(0.0063)	(0.0059)
Gain Since Latest Login=1		0.0470***	0.0292***	-0.0269***
		(0.0043)	(0.0039)	(0.0046)
Gain Since Purchase=1 ×				0.1231***
Gain Since Latest Login=1				(0.0062)
Constant	0.1504***	0.1746***	0.1402***	0.1598***
	(0.0060)	(0.0061)	(0.0066)	(0.0069)
Observations	164,141	164,141	164,141	164,141
R^2	0.0164	0.0035	0.0177	0.0234

Note: This table presents ordinary least squares regression estimates of Equation 4 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 10: 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	0.1313***		0.1216***	0.0394***
	(0.0080)		(0.0077)	(0.0069)
Gain Since Latest Login=1		0.0690***	0.0366***	-0.0471***
		(0.0050)	(0.0041)	(0.0046)
Gain Since Purchase=1 ×				0.1717***
Gain Since Latest Login=1				(0.0065)
Constant	0.1760***	0.2059***	0.1635***	0.1922***
	(0.0066)	(0.0068)	(0.0074)	(0.0076)
Observations	175,564	175,564	175,564	175,564
R^2	0.0237	0.0065	0.0254	0.0348

Panel (B): Above Median Days Since Purchase

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0921***		0.0895***	0.0648***
	(0.0049)		(0.0048)	(0.0052)
Gain Since Latest Login=1		0.0324***	0.0221***	-0.0004
		(0.0035)	(0.0032)	(0.0038)
Gain Since Purchase=1 ×				0.0521***
Gain Since Latest Login=1				(0.0047)
Constant	0.1117***	0.1358***	0.1026***	0.1118***
	(0.0048)	(0.0053)	(0.0053)	(0.0056)
Observations	174,419	174,419	174,419	174,419
R^2	0.0162	0.0020	0.0171	0.0184

Note: This table presents ordinary least squares regression estimates of Equation 4 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 11: 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	0.1209***		0.1153***	0.0602***
	(0.0064)		(0.0061)	(0.0057)
Gain Since Latest Login=1		0.0522***	0.0326***	-0.0188***
		(0.0041)	(0.0036)	(0.0042)
Gain Since Purchase=1 ×				0.1136***
Gain Since Latest Login=1				(0.0059)
Constant	0.1282***	0.1574***	0.1154***	0.1355***
	(0.0059)	(0.0064)	(0.0064)	(0.0070)
Observations	241,822	241,822	241,822	241,822
R^2	0.0243	0.0046	0.0260	0.0312

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

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.1084***		0.1026***	0.0454***
	(0.0071)		(0.0068)	(0.0066)
Gain Since Latest Login=1		0.0492***	0.0276***	-0.0310***
		(0.0052)	(0.0048)	(0.0059)
Gain Since Purchase=1 ×				0.1234***
Gain Since Latest Login=1				(0.0082)
Constant	0.1549***	0.1823***	0.1451***	0.1659***
	(0.0055)	(0.0058)	(0.0064)	(0.0066)
Observations	73,919	73,919	73,919	73,919
R^2	0.0179	0.0037	0.0190	0.0246

Panel (C): >6 Days Since Latest Login

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0933***		0.0843***	0.0050
	(0.0086)		(0.0084)	(0.0092)
Gain Since Latest Login=1		0.0551***	0.0297***	-0.0489***
		(0.0070)	(0.0065)	(0.0079)
Gain Since Purchase=1 ×				0.1640***
Gain Since Latest Login=1				(0.0110)
Constant	0.2201***	0.2378***	0.2104***	0.2361***
	(0.0059)	(0.0061)	(0.0067)	(0.0068)
Observations	34,242	34,242	34,242	34,242
R^2	0.0112	0.0039	0.0122	0.0200

Note: This table presents ordinary least squares regression estimates of Equation 4 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 12: The Disposition Effect:
Sub-Sample Analysis, Sell-Day Sample

	Gain Since Purchase		Gain Since Latest Login		Interaction		Constant	
Gender								
Female	0.0714***	(0.0134)	-0.0133*	(0.0080)	0.1226***	(0.0121)	0.1215***	(0.0136)
Male	0.0472***	(0.0055)	-0.0284***	(0.0042)	0.1239***	(0.0055)	0.1577***	(0.0071)
Age								
Below Median	0.0504***	(0.0068)	-0.0314***	(0.0049)	0.1303***	(0.0067)	0.1777***	(0.0096)
Above Median	0.0500***	(0.0073)	-0.0192***	(0.0053)	0.1146***	(0.0068)	0.1253***	(0.0079)
Experience								
Below Median	0.0537***	(0.0068)	-0.0362***	(0.0042)	0.1385***	(0.0062)	0.1716***	(0.0069)
Above Median	0.0474***	(0.0063)	-0.0163***	(0.0052)	0.1050***	(0.0064)	0.1338***	(0.0084)
Portfolio Value								
Below Median	0.0753***	(0.0070)	-0.0405***	(0.0048)	0.1524***	(0.0064)	0.2143***	(0.0073)
Above Median	0.0394***	(0.0051)	-0.0022	(0.0043)	0.0748***	(0.0059)	0.0848***	(0.0061)
Number of Stocks								
Below Median	0.0677***	(0.0058)	-0.0425***	(0.0044)	0.1542***	(0.0062)	0.2396***	(0.0047)
Above Median	0.0376***	(0.0045)	-0.0019	(0.0036)	0.0558***	(0.0057)	0.0623***	(0.0046)

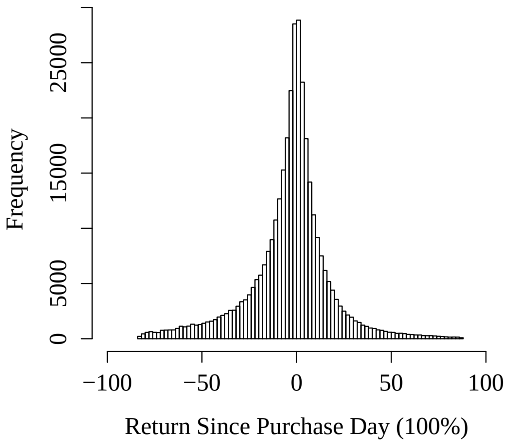
Note: This table presents ordinary least squares regression estimates for separate samples by gender, age, trading experience and portfolio value. Each row reports coefficients and standard errors from a single regression in which the dependent variable takes a value of 1 if the investor made a sale 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.

Online Appendix A: Supplementary Items for Login-Days and Sell-Days in the New Accounts Sample

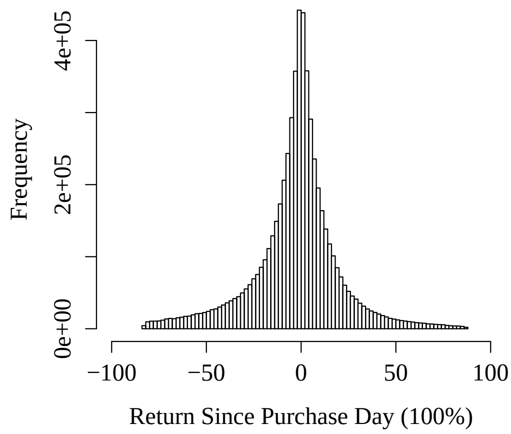
Figure A1: Returns Since Purchase and Returns Since Latest Login

(I) Returns Since Purchase

(A) Sell-Day Sample

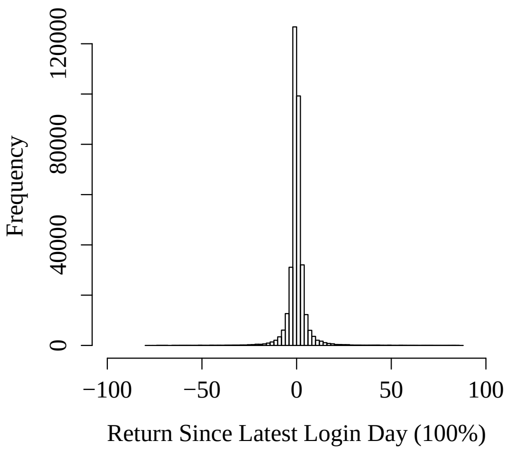


(B) Login-Day Sample

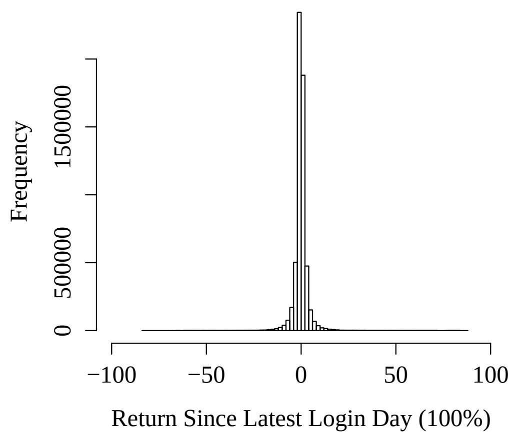


(II) Returns Since Latest Login

(C) Sell-Day Sample

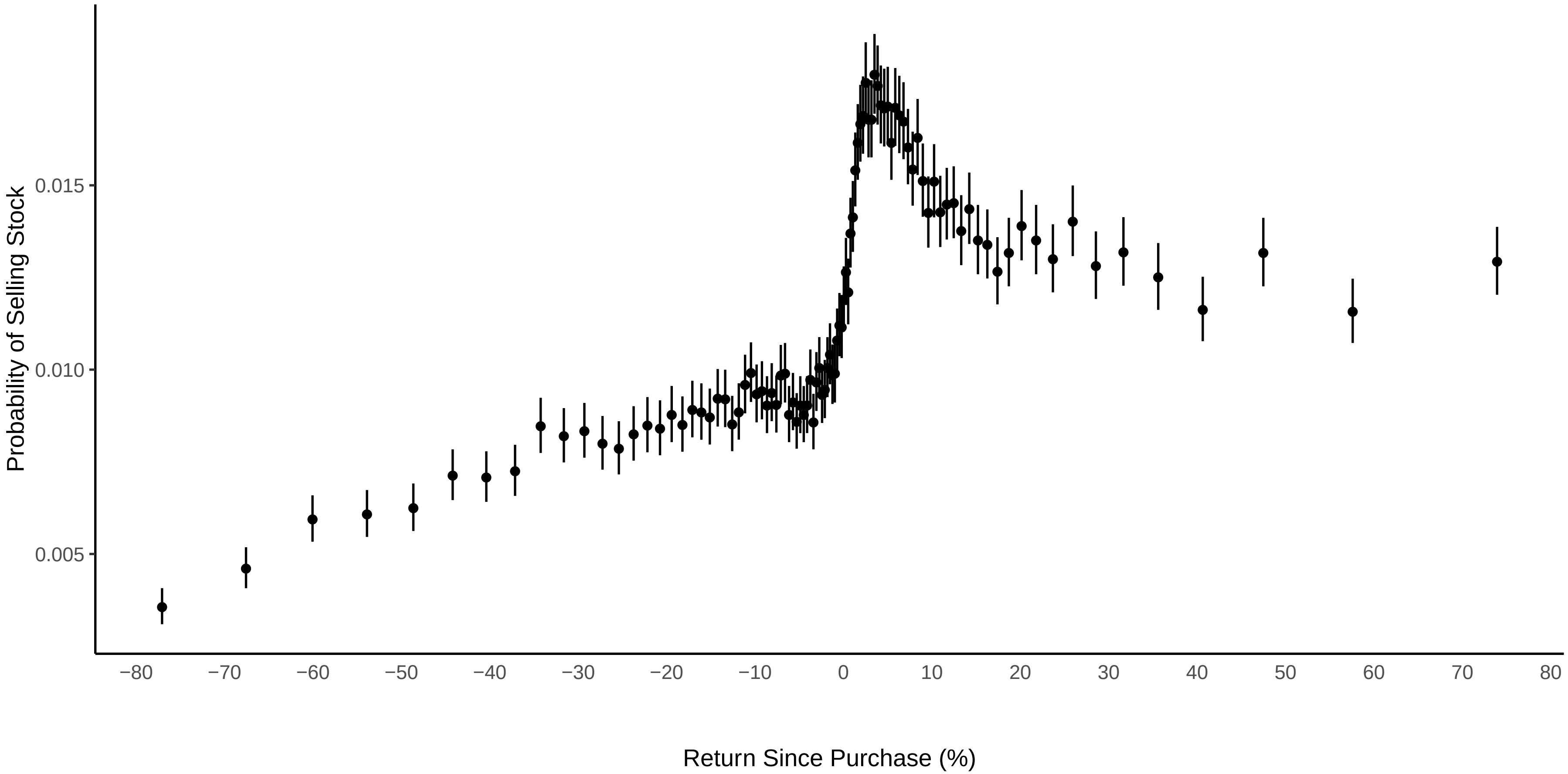


(D) Login-Day Sample



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.

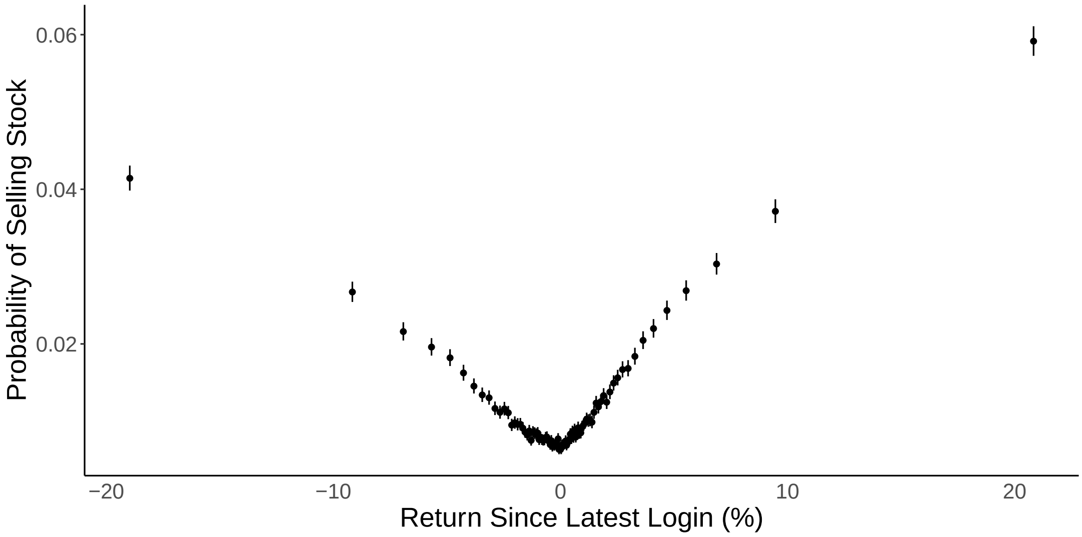
Figure A2: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Purchase in the Login-Day Sample



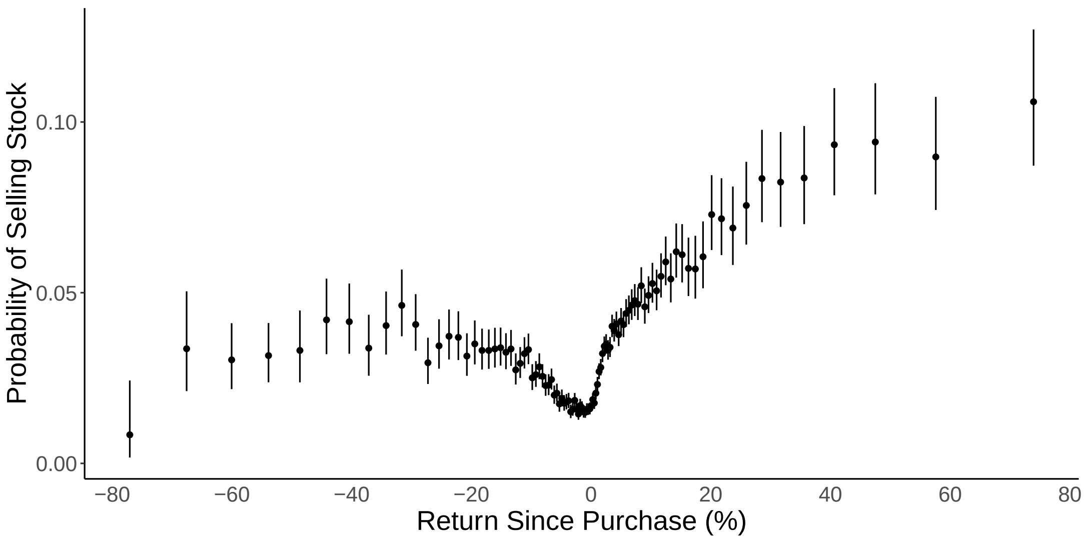
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. Login-day sample includes all investor × stock × days on which the made a login to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

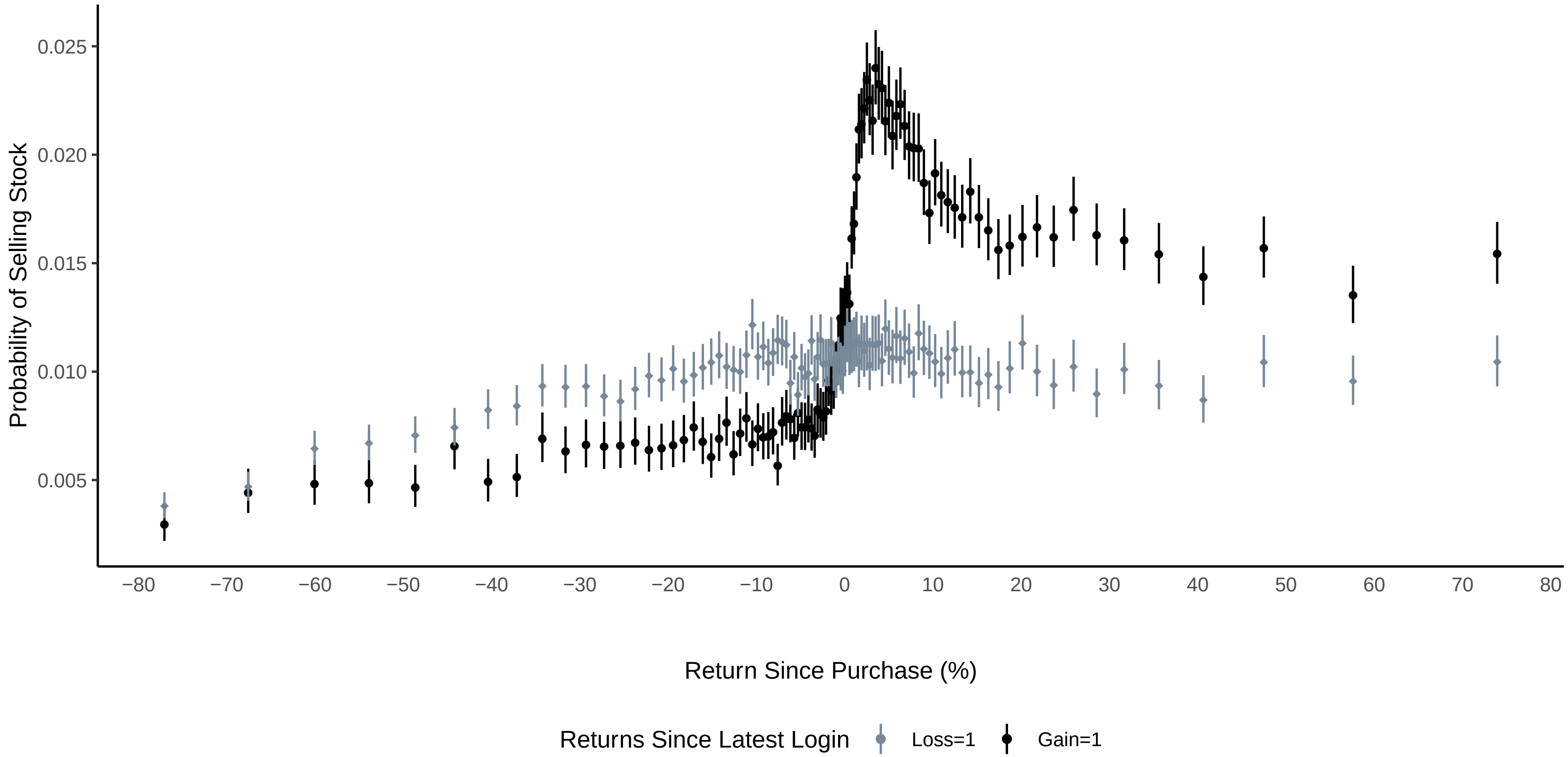


(B) Returns Since Purchase (Up to 30 Days Since Purchase)



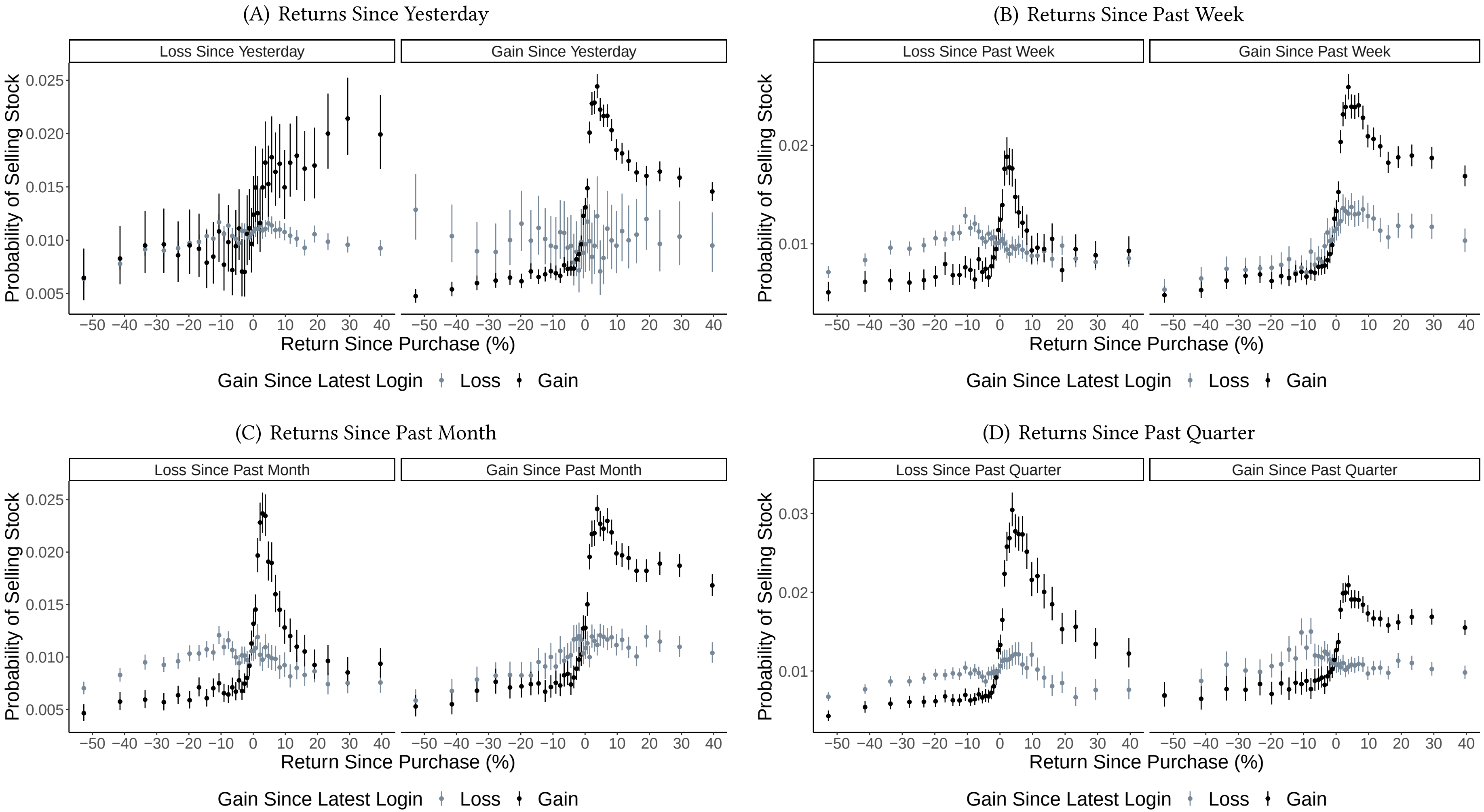
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. In Panel A the X-axis variable is the returns on the stock since latest login. In Panel B the X-axis variable is the returns on the stock since purchase. 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.

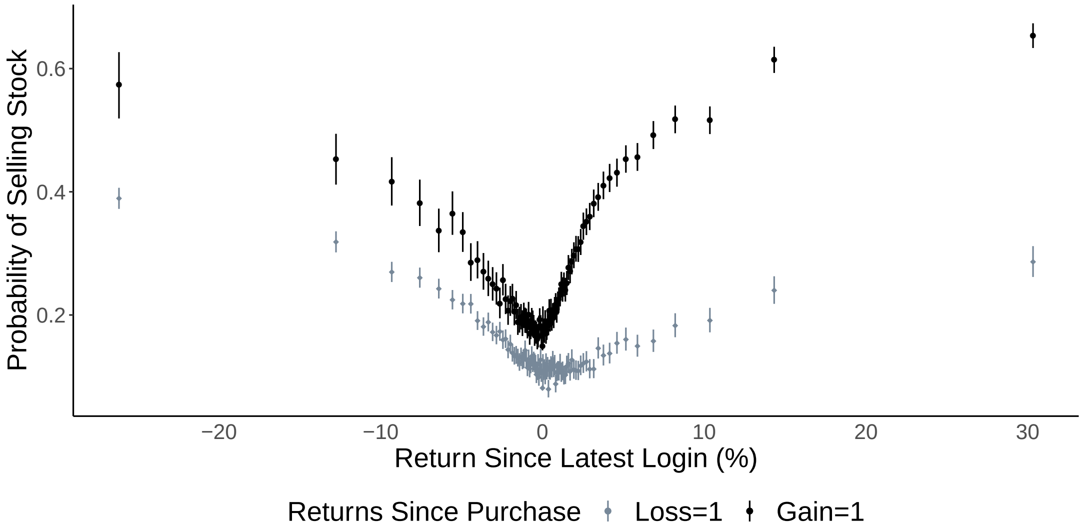
Figure A5: Disposition Effect:
Splits by Recent Performance of Stocks in the Login-Day Sample



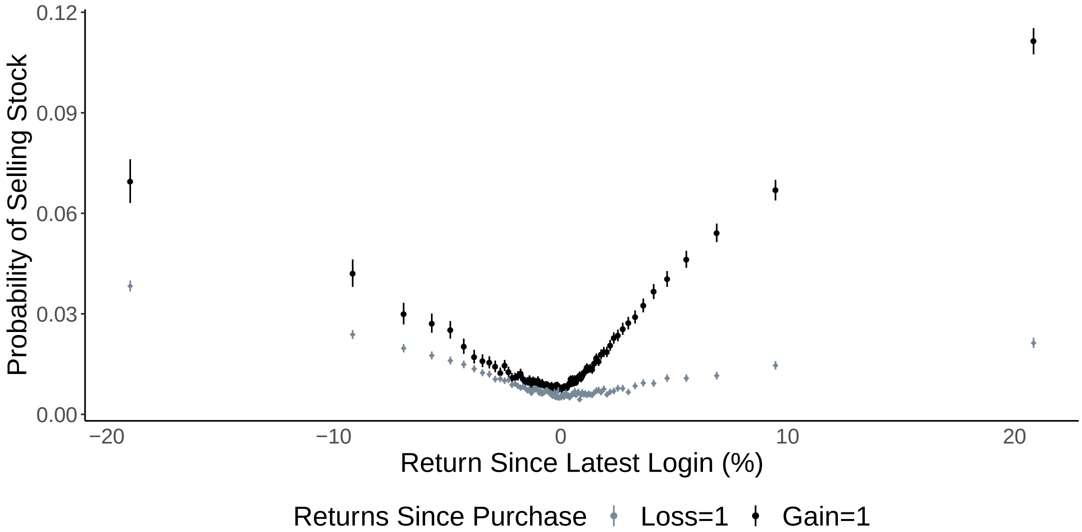
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. Across panels, the X-axis variable is the returns on the stock since purchase. Panels A, B, C, and D, split the data by returns since yesterday, the past week, the past month, and the past quarter, respectively. Login-day sample includes all investor × stock × days on which the investor made at least one login to the account. Returns since purchase and since latest login are calculated at the daily level.

Figure A6: Illustration of the Interaction Effect:
Probability of Sale by Returns Since Login, by Gain / Loss Since Purchase

(A) Sell-Day Sample

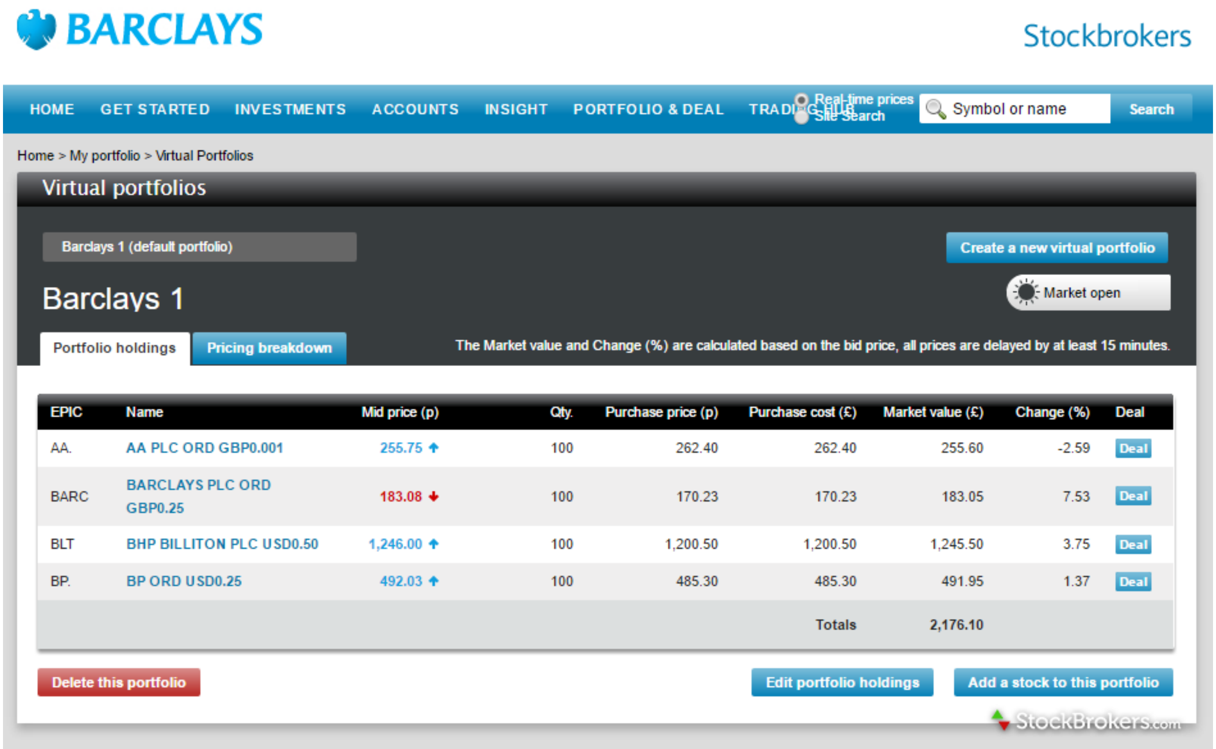


(B) Login-Day Sample



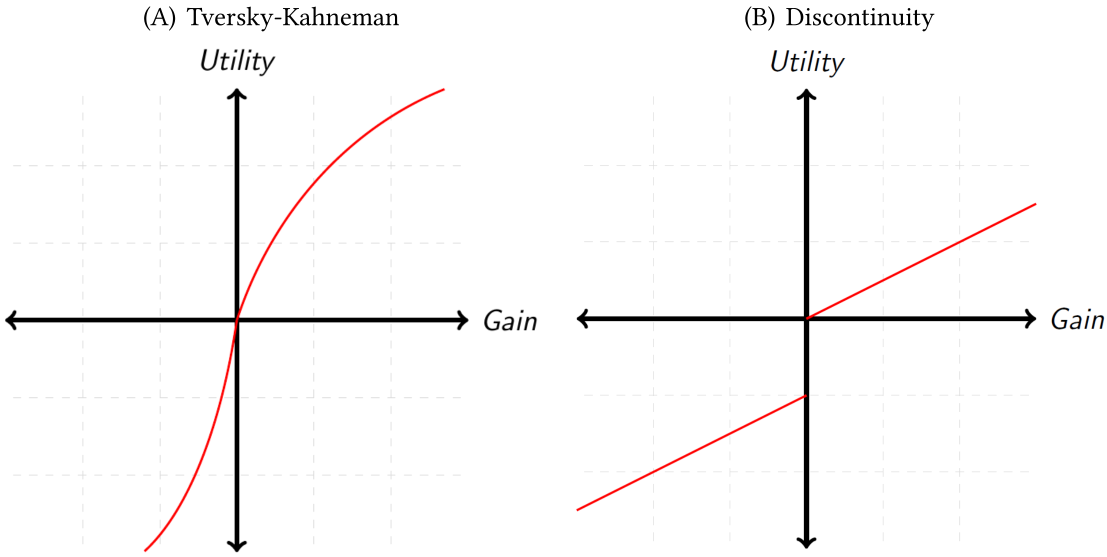
Note: Figure shows binned scatter plot with 95% confidence intervals. The X-axis variable is the returns on the stock since the latest login day. Observations are divided by whether the investor made a gain or not since purchase. Returns since purchase and returns since latest login are calculated at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

Figure A7: Screenshot of Barclays Portfolio Dashboard



Note: Picture shows an example portfolio dashboard from Barclays Stockbroking. Used with permission.

Figure A8: Reference-Dependent Utility Functions



Note: Figure shows two versions of reference-dependent utility functions. 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, as in Tversky and Kahneman (1991). Panel B shows a modified case in which in utility jumps discretely at zero, as in Homonoff (2018).

Table A1: Example of Trading Strategy for Different Reference Points With Prospect Theory Preferences

		Price at $t = 2$								
		Node -2			Node 0			Node +2		
		PT Value			PT Value			PT Value		
Attention at $t = 1$	Reference point at $t = 2$	If sell at $t = 2$	If sell at $t = 3$	Decision at $t = 2$	If sell at $t = 2$	If sell at $t = 3$	Decision at $t = 2$	If sell at $t = 2$	If sell at $t = 3$	Decision at $t = 2$
Doesn't look	P_0	-2.83	-2.73	Don't sell	0	-0.50	Sell	1.41	1.37	Sell
Looks at $P_0 + 1$	$P_0 + 1$	-3.46	-3.41	Don't sell	-2	-1.41	Don't sell	1	0.71	Sell
Looks at $P_0 - 1$	P_0	-2.83	-2.73	Don't sell	0	-0.50	Sell	1.41	1.37	Sell

Note: Table illustrates selling strategies for different reference points in the model (described in Section 2 in the main text). In the simulation, the investor solves a value function $|p - r|^{\delta}$ for cases where $p - r > 0$ and a value function $-\lambda|p - r|^{\delta}$ for cases where $p - r < 0$. We conservatively choose parameters for risk aversion and loss aversion of $\delta = 0.5$ and $\lambda = 2$. In the model, if the individual does not look at the stock value in period $t = 1$, then $r = p_0$. If the investor looks, then the reference point is given by $r = \gamma p_1 + (1 - \gamma)p_o$, where γ takes a value of 1 if $p_1 > p_0$ and 0 otherwise.

Table A2: Baseline Sample Summary Statistics

	Mean	Min	p25	p50	p75	Max
A. Account Holder Characteristics						
Female	0.145					
Age (years)	44.995	22.000	33.000	44.000	54.000	83.000
Account Tenure (years)	2.259	0.348	1.496	2.222	3.025	3.995
B. Account Characteristics						
Portfolio Value (£10000)	4.247	0.000	0.346	0.918	2.120	5742.635
Investment in Mutual Funds (£10000)	0.171	0.000	0.000	0.000	0.000	84.529
Investment in Mutual Funds (%)	5.551	0.000	0.000	0.000	0.000	100.000
Number of Stocks	5.205	2.000	2.375	3.500	6.000	102.182
Portfolio Turnover (%)	89.071	0.000	12.330	39.975	100.928	1257.464
Login days (% all days)	20.697	0.081	6.452	15.347	31.673	75.000
Transaction days (% all market open days)	5.733	0.196	1.786	3.275	6.481	100.000
N Accounts	8242					

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. 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. Portfolio turnover is the account average annual portfolio turnover. Due to a high degree of skewness, portfolio turnover statistics exclude the top 1 percent of observations. 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 A3: 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***	0.0078***		0.0076***	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 ×				0.0099***				0.0068***
Gain Since Latest Login=1				(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	5,894,175	5,894,175	5,894,175	5,894,175	5,894,175	5,894,175	5,894,175	5,894,175
R^2	0.0009	0.0053	0.0073	0.0078	0.0460	0.0468	0.0488	0.0491

Note: This table presents ordinary least squares regression estimates of Equation 4 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 A4: The Disposition Effect:
Including Continuous Returns Since the Preceding Day, Login-Day Sample

	$Sale_{ijt}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain Since Purchase=1	0.0058***		0.0057***	0.0010***	0.0057***		0.0056***	0.0005*
	(0.0004)		(0.0003)	(0.0003)	(0.0004)		(0.0003)	(0.0003)
Gain Since Latest Login=1		0.0033***	0.0026***	-0.0023***		0.0016***	0.0009***	-0.0046***
		(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)
Gain Since Purchase=1 ×				0.0102***				0.0110***
Gain Since Latest Login=1				(0.0004)				(0.0005)
Gain Since Yesterday=1	0.0023***	0.0001	0.0000	0.0001				
	(0.0003)	(0.0003)	(0.0003)	(0.0003)				
Return Since Yesterday (%)					0.0007***	0.0006***	0.0006***	0.0007***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	0.0078***	0.0100***	0.0077***	0.0096***	0.0089***	0.0108***	0.0085***	0.0107***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	5,894,168	5,894,168	5,894,168	5,894,168	5,894,168	5,894,168	5,894,168	5,894,168
R^2	0.0009	0.0003	0.0009	0.0015	0.0012	0.0005	0.0012	0.0018

Note: This table presents ordinary least squares regression estimates of Equation 4 with the addition of control variables for the return of the stock since the preceding day (independently of whether the investor log in to their account on the preceding day). 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: Estimates of the Disposition Effect
Including Portfolio and Demographic Controls, Login-Day Sample

	$Sale_{ijt}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain Since Purchase=1	0.0012***	0.0017***	0.0018***	0.0020***	0.0019***	0.0021***	0.0021***	0.0021***	0.0060***	0.0071***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Gain Since Latest Login=1	-0.0018***	-0.0014***	-0.0013***	-0.0013***	-0.0013***	-0.0013***	-0.0013***	-0.0013***	-0.0001	-0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Gain Since Purchase=1 × Gain Since Latest Login=1	0.0092***	0.0084***	0.0081***	0.0081***	0.0080***	0.0080***	0.0080***	0.0080***	0.0061***	0.0063***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Days Since Purchase (100 days)		-0.0019***	-0.0019***	-0.0019***	-0.0018***	-0.0021***	-0.0021***	-0.0021***	-0.0002***	-0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Days Since Latest Login (100 days)			0.0323***	0.0316***	0.0293***	0.0291***	0.0291***	0.0285***	0.0023	0.0023
			(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0016)	(0.0016)
Portfolio Value (£10000)				-0.0002***	-0.0001*	-0.0001**	-0.0001*	-0.0001*	-0.0007***	-0.0007***
				(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Number of Stocks (10 stocks)					-0.0025***	-0.0026***	-0.0026***	-0.0025***	0.0019***	0.0020***
					(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Account Tenure (years)						0.0016***	0.0016***	0.0017***		
						(0.0003)	(0.0003)	(0.0003)		
Female=1							-0.0007	-0.0005		
							(0.0005)	(0.0005)		
Age (10 years)								-0.0008***		
								(0.0002)		
Constant	0.0084***	0.0127***	0.0118***	0.0126***	0.0150***	0.0137***	0.0138***	0.0176***		
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0006)	(0.0009)		
Account FE	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Stock FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES
Observations	5,776,300	5,776,300	5,776,300	5,776,300	5,776,300	5,776,300	5,776,300	5,776,300	5,776,300	5,776,300
R^2	0.0015	0.0033	0.0037	0.0040	0.0047	0.0048	0.0048	0.0050	0.0376	0.0406

Note: This table presents ordinary least squares regression estimates of Equation 4 with the addition of demographic controls and (daily level) portfolio controls. Sample of all investor × stock × days on which the investor made at least one login to the account. Outliers (investor × stock × days) in the first and 99 percentiles of daily portfolio values are excluded. Gender and age (calculated from decades of birth) are within individual time invariant. Standard errors are clustered by account and day.

Table A6: Selectivity Correction
Selection Equation

	(1)
Omitted: Excellent	
2 Very good	0.0164***
	(0.0018)
3 Good	0.0146***
	(0.0023)
4 Moderate	0.0092***
	(0.0029)
5 Poor and Very poor	0.0168***
	(0.0050)
Constant	-0.3510***
	(0.0031)
Observations	3,164,622
Log Likelihood	-2,078,221
Akaike Inf. Crit.	4,156,481

Note: This table presents estimates of the selection equation for the results shown in Table 8. The dependent variable is a dummy indicator for login.

Table A7: The Disposition Effect: Cox Proportional Hazard Model

Panel (A): Sell-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.7032***		0.6743***	0.3659***
	(0.0100)		(0.0103)	(0.0142)
Gain Since Latest Login=1		0.2787***	0.1236***	-0.2632***
		(0.0098)	(0.0101)	(0.0162)
Gain Since Purchase=1 ×				0.6544***
Gain Since Latest Login=1				(0.0207)
Observations	297,089	297,089	297,089	297,089
R^2	0.0171	0.0028	0.0176	0.0210

Panel (B): Login-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.8318***		0.7870***	0.5786***
	(0.0099)		(0.0102)	(0.0140)
Gain Since Latest Login=1		0.3662***	0.1595***	-0.1070***
		(0.0094)	(0.0098)	(0.0158)
Gain Since Purchase=1 ×				0.4502***
Gain Since Latest Login=1				(0.0205)
Observations	5,429,747	5,429,747	5,429,747	5,429,747
R^2	0.0014	0.0003	0.0014	0.0015

Note: This table presents Cox Proportional Hazard regression estimates of Equation 5 with time varying covariates. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Coefficients show stratified estimates by account. That is, coefficients are equal across accounts but baseline hazard functions are unique to each account. In the model, we count every purchase of a stock as the beginning of a new position, and we assume a position ends on the date the investor first sells part or all of his holdings. 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.

Table A8: 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	0.0069***		0.0065***	0.0014***
	(0.0004)		(0.0004)	(0.0003)
Gain Since Latest Login=1		0.0035***	0.0026***	-0.0023***
		(0.0004)	(0.0003)	(0.0003)
Gain Since Purchase=1 ×				0.0102***
Gain Since Latest Login=1				(0.0005)
Constant	0.0085***	0.0101***	0.0074***	0.0095***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	3,048,680	3,048,680	3,048,680	3,048,680
R^2	0.0010	0.0003	0.0011	0.0017

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

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0053***		0.0050***	0.0006*
	(0.0004)		(0.0004)	(0.0003)
Gain Since Latest Login=1		0.0031***	0.0025***	-0.0022***
		(0.0004)	(0.0004)	(0.0003)
Gain Since Purchase=1 ×				0.0101***
Gain Since Latest Login=1				(0.0005)
Constant	0.0091***	0.0102***	0.0082***	0.0099***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Observations	2,782,737	2,782,737	2,782,737	2,782,737
R^2	0.0006	0.0002	0.0007	0.0013

Note: This table presents ordinary least squares regression estimates of Equation 4 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 A9: 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	0.0095***		0.0088***	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 ×				0.0162***
Gain Since Latest Login=1				(0.0007)
Constant	0.0122***	0.0141***	0.0107***	0.0136***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Observations	2,954,838	2,954,838	2,954,838	2,954,838
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***		0.0025***	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 ×				0.0025***
Gain Since Latest Login=1				(0.0003)
Constant	0.0053***	0.0059***	0.0048***	0.0053***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	2,939,337	2,939,337	2,939,337	2,939,337
R^2	0.0003	0.0001	0.0003	0.0004

Note: This table presents ordinary least squares regression estimates of Equation 4 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 A10: 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***		0.0060***	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 ×				0.0097***
Gain Since Latest Login=1				(0.0005)
Constant	0.0083***	0.0096***	0.0071***	0.0090***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	3,902,134	3,902,134	3,902,134	3,902,134
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***	-0.0023***
		(0.0004)	(0.0004)	(0.0004)
Gain Since Purchase=1 ×				0.0088***
Gain Since Latest Login=1				(0.0005)
Constant	0.0079***	0.0091***	0.0072***	0.0088***
	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Observations	1,474,991	1,474,991	1,474,991	1,474,991
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***	0.0029***	-0.0048***
		(0.0006)	(0.0006)	(0.0006)
Gain Since Purchase=1 ×				0.0163***
Gain Since Latest Login=1				(0.0009)
Constant	0.0143***	0.0155***	0.0133***	0.0160***
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Observations	517,050	517,050	517,050	517,050
R^2	0.0007	0.0003	0.0008	0.0017

Note: This table presents ordinary least squares regression estimates of Equation 4 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 A11: The Disposition Effect:
Stock Volatility, Sell-Day Sample

Panel (A): Below Median Annual Stock Volatility

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0841***		0.0806***	0.0315***
	(0.0055)		(0.0054)	(0.0050)
Gain Since Latest Login=1		0.0362***	0.0249***	-0.0283***
		(0.0034)	(0.0031)	(0.0037)
Gain Since Purchase=1 ×				0.0993***
Gain Since Latest Login=1				(0.0053)
Constant	0.1263***	0.1531***	0.1156***	0.1385***
	(0.0050)	(0.0049)	(0.0055)	(0.0058)
Observations	175,120	175,120	175,120	175,120
R^2	0.0124	0.0023	0.0135	0.0177

Panel (B): Above Median Annual Stock Volatility

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.1761***		0.1670***	0.0912***
	(0.0077)		(0.0075)	(0.0069)
Gain Since Latest Login=1		0.0761***	0.0397***	-0.0204***
		(0.0049)	(0.0044)	(0.0050)
Gain Since Purchase=1 ×				0.1574***
Gain Since Latest Login=1				(0.0068)
Constant	0.1542***	0.1857***	0.1407***	0.1611***
	(0.0068)	(0.0077)	(0.0076)	(0.0080)
Observations	174,863	174,863	174,863	174,863
R^2	0.0420	0.0083	0.0442	0.0521

Note: This table presents ordinary least squares regression estimates of Equation 4 for separate samples of stocks by annual stock volatility. 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 A12: The Disposition Effect:
Stock Volatility, Login-Day Sample

Panel (A): Below Median Annual Stock Volatility

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0032***		0.0031***	0.0005**
	(0.0003)		(0.0003)	(0.0002)
Gain Since Latest Login=1		0.0019***	0.0016***	-0.0014***
		(0.0002)	(0.0002)	(0.0002)
Gain Since Purchase=1 ×				0.0054***
Gain Since Latest Login=1				(0.0003)
Constant	0.0060***	0.0069***	0.0053***	0.0066***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Observations	2,973,966	2,973,966	2,973,966	2,973,966
R^2	0.0003	0.0001	0.0004	0.0007

Panel (B): Above Median Annual Stock Volatility

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0120***		0.0114***	0.0038***
	(0.0006)		(0.0006)	(0.0004)
Gain Since Latest Login=1		0.0061***	0.0044***	-0.0023***
		(0.0005)	(0.0004)	(0.0004)
Gain Since Purchase=1 ×				0.0166***
Gain Since Latest Login=1				(0.0008)
Constant	0.0108***	0.0128***	0.0092***	0.0116***
	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Observations	2,920,209	2,920,209	2,920,209	2,920,209
R^2	0.0023	0.0006	0.0026	0.0036

Note: This table presents ordinary least squares regression estimates of Equation 4 for separate samples of stocks by annual stock volatility. 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 A13: The Disposition Effect:
Sub-Sample Analysis, Login-Day Sample

	Gain Since Purchase		Gain Since Latest Login		Interaction		Constant	
Gender								
Female	0.0024***	(0.0006)	-0.0010**	(0.0004)	0.0093***	(0.0010)	0.0071***	(0.0006)
Male	0.0007**	(0.0003)	-0.0024***	(0.0003)	0.0104***	(0.0005)	0.0101***	(0.0003)
Age								
Below Median	0.0007*	(0.0004)	-0.0028***	(0.0003)	0.0114***	(0.0006)	0.0115***	(0.0005)
Above Median	0.0012***	(0.0004)	-0.0015***	(0.0003)	0.0089***	(0.0006)	0.0077***	(0.0004)
Experience								
Below Median	0.0007**	(0.0003)	-0.0029***	(0.0003)	0.0120***	(0.0006)	0.0114***	(0.0004)
Above Median	0.0011***	(0.0003)	-0.0014***	(0.0003)	0.0080***	(0.0005)	0.0079***	(0.0003)
Portfolio Value								
Below Median	0.0021***	(0.0004)	-0.0036***	(0.0003)	0.0144***	(0.0006)	0.0131***	(0.0005)
Above Median	0.0009***	(0.0003)	-0.0004	(0.0003)	0.0056***	(0.0004)	0.0056***	(0.0003)
Number of Stocks								
Below Median	0.0015***	(0.0004)	-0.0037***	(0.0004)	0.0150***	(0.0006)	0.0142***	(0.0004)
Above Median	0.0012***	(0.0003)	-0.0004	(0.0003)	0.0044***	(0.0004)	0.0047***	(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.

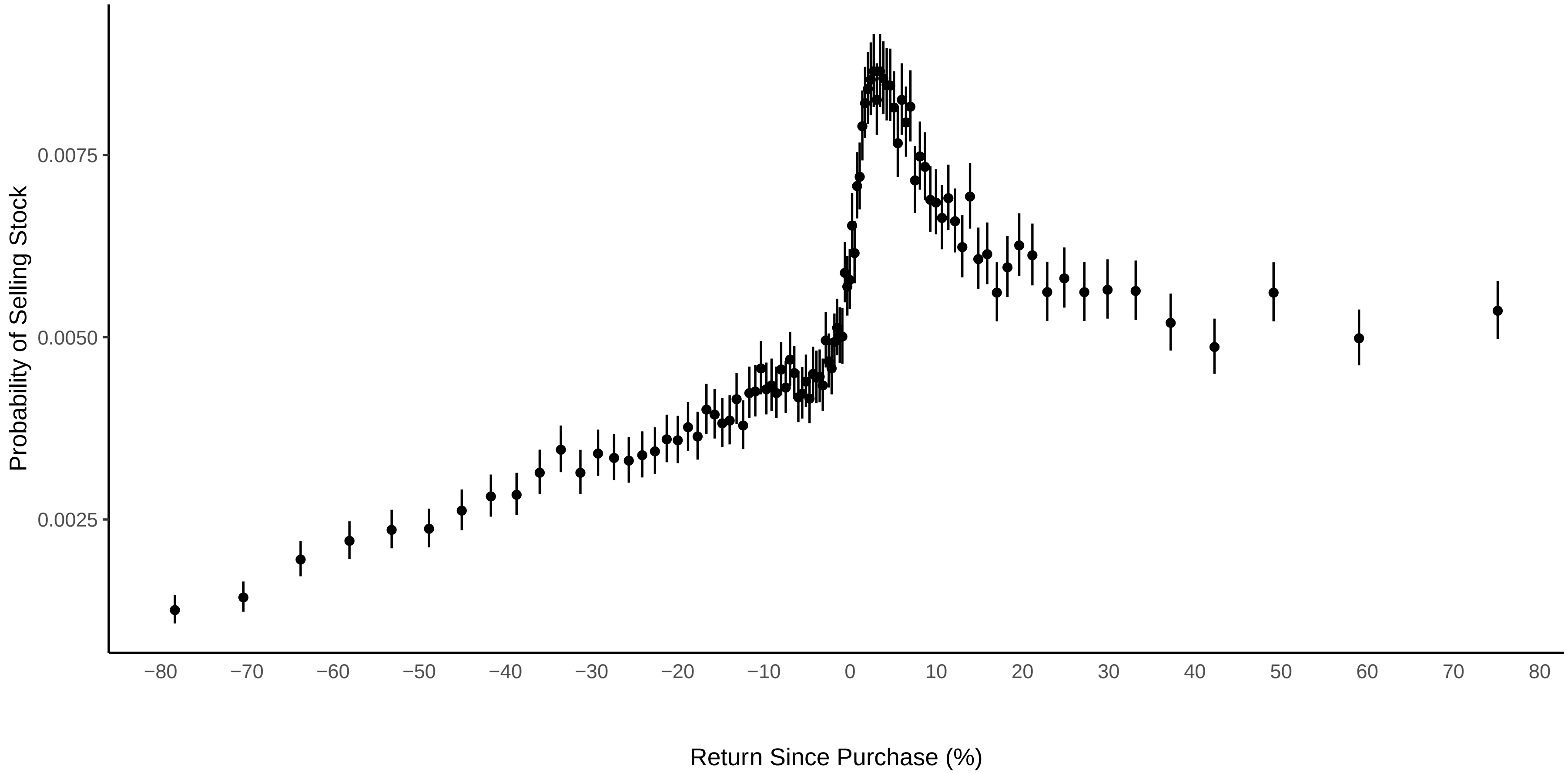
Table A14: The Disposition Effect: Testing Rebalancing of Portfolios as Alternative Mechanism, Login-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.0078***		0.0075***	0.0046***
	(0.0004)		(0.0004)	(0.0003)
Gain Since Latest Login=1		0.0026***	0.0018***	-0.0012***
		(0.0002)	(0.0002)	(0.0002)
Gain Since Purchase=1 × Gain Since Latest Login=1				0.0063***
				(0.0003)
Account FE	YES	YES	YES	YES
Observations	5,894,175	5,894,175	5,894,175	5,894,175
R^2	0.0399	0.0386	0.0400	0.0403

Note: This table presents fixed effects regression estimates of Equation 4. The dependent variable takes a value of 1 if the investor made a complete sale of the stock and zero otherwise (i.e., excluding partial sells). 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.

Online Appendix B: Supplementary Items for All-Days in the New Accounts Sample

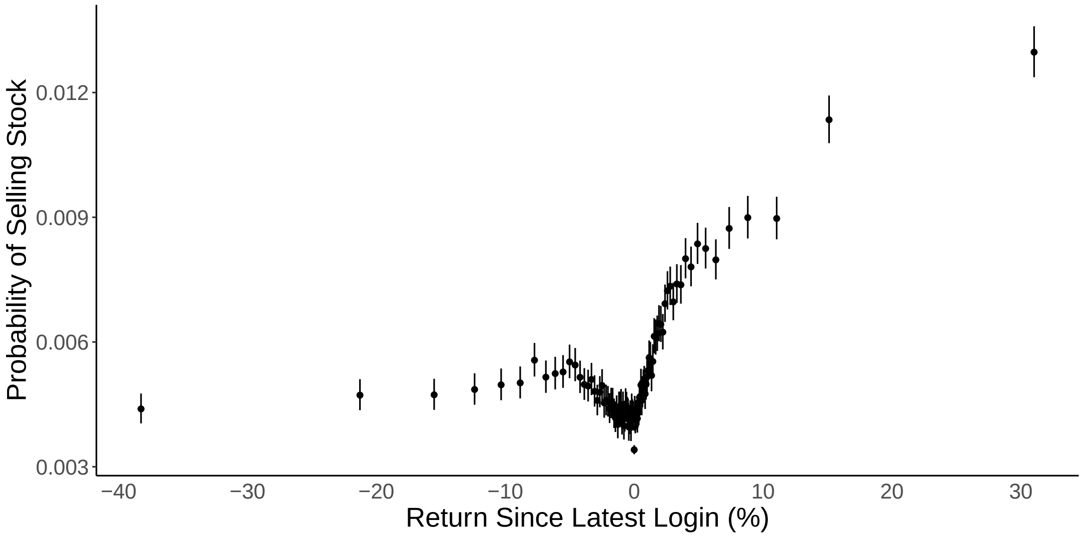
Figure B1: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Purchase in the All-Day Sample



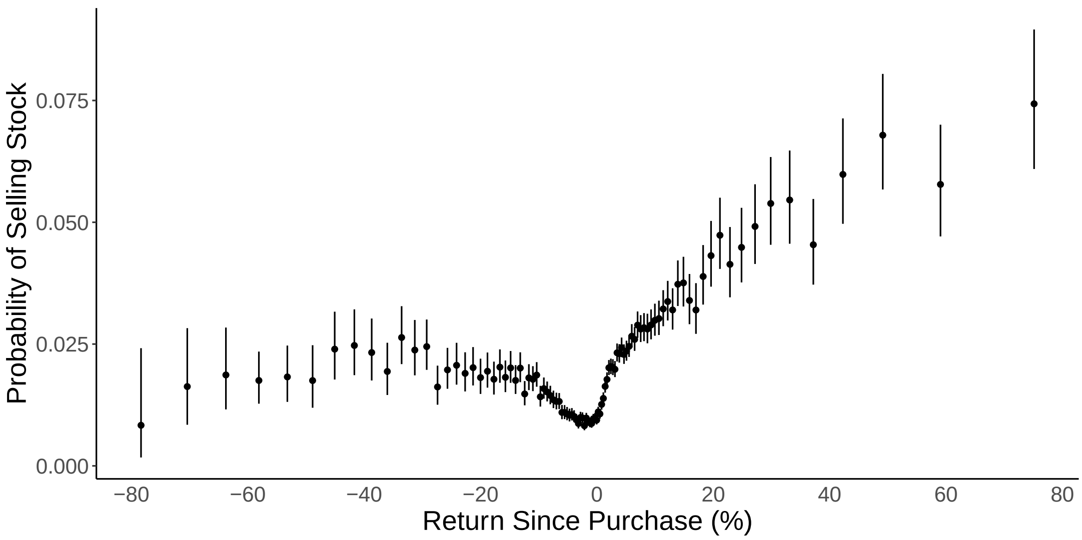
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. All-day sample includes all investor × stock × days in which the market is open and the account is active. Returns since purchase are calculated at the daily level.

Figure B2: Illustration of the Disposition Effect:
Probability of Sale and Returns Since Latest Login in the All-Day Sample

(A) Returns Since Latest Login

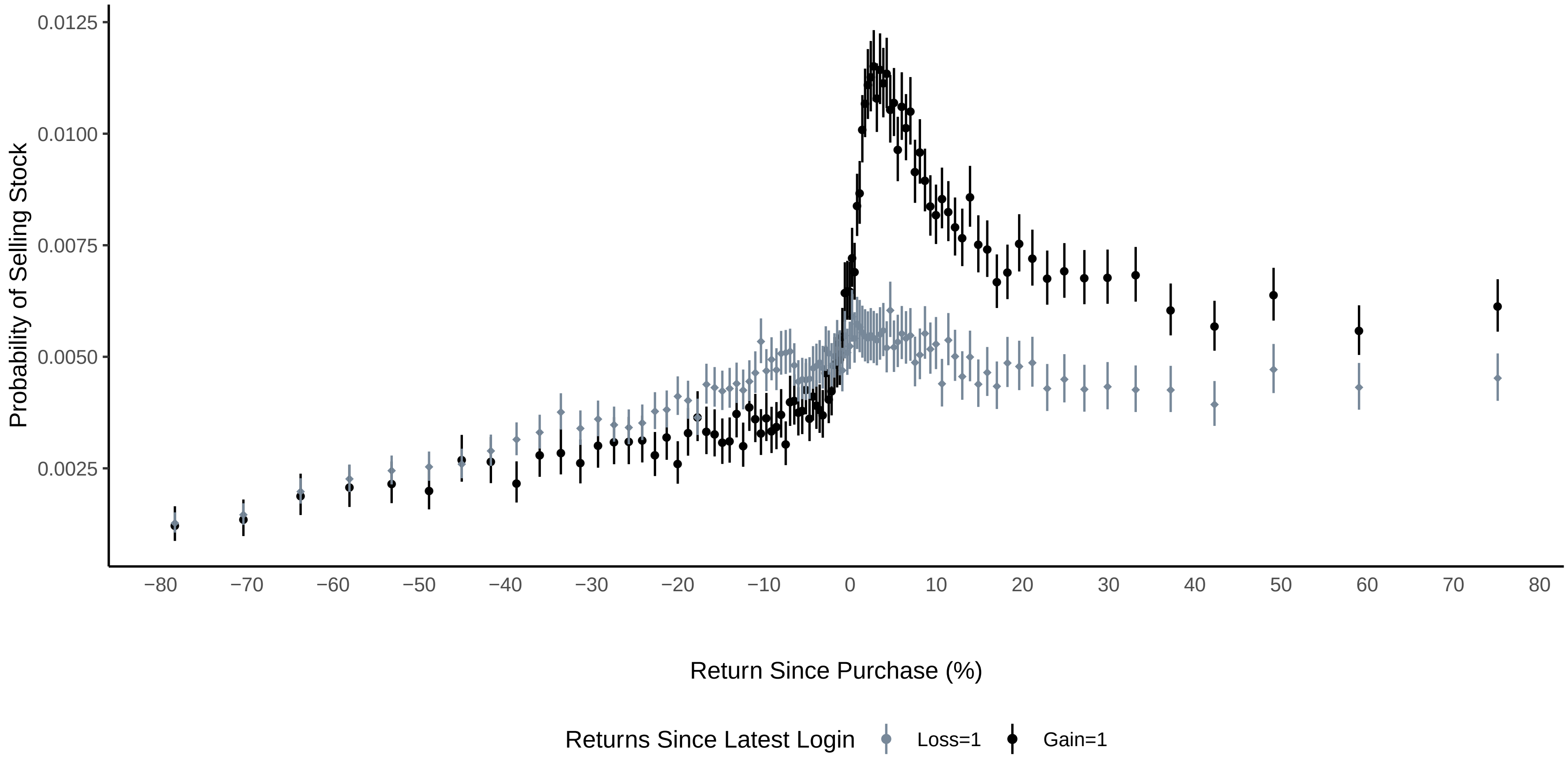


(B) Returns Since Purchase (Up to 30 Days Since Purchase)



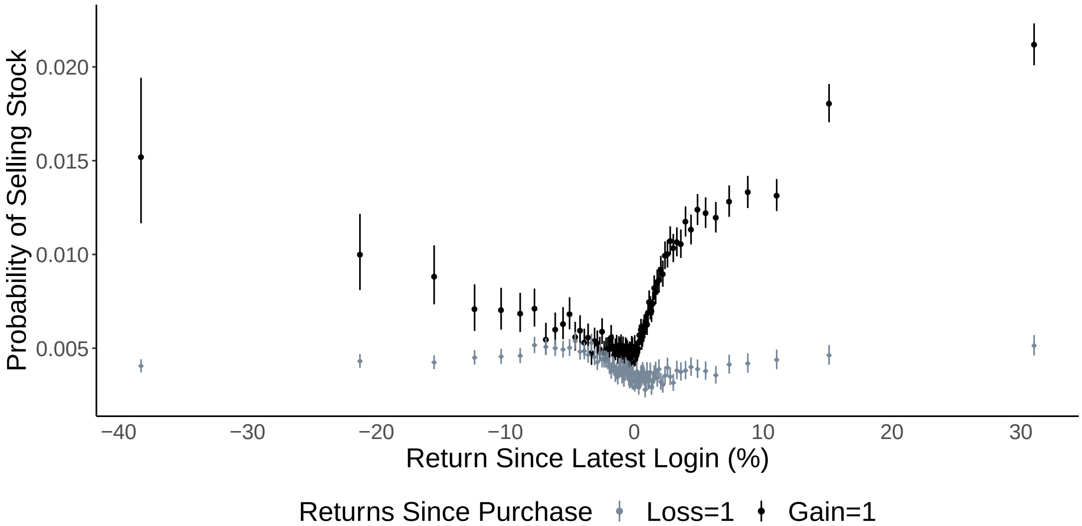
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. In Panel A the X-axis variable is the returns on the stock since latest login. In Panel B the X-axis variable is the returns on the stock since purchase.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

Figure B3: Illustration of the Interaction Effect in the All-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. All-day sample includes all investor × stock × days in which the market is open and the account is active. Returns since purchase and returns since latest login are calculated at the daily level.

Figure B4: Illustration of the Interaction Effect:
Probability of Sale by Returns Since Login, by Gain / Loss Since Purchase, All-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 B1: Summary Statistics for Returns Since Purchase and Returns Since Latest Login, New Accounts, All-Day Sample

	Mean	SD	Median
Sale=1	0.005	0.072	0
Return Since Purchase			
Return Since Purchase (%)	−3.585	24.564	−1.362
Gain Since Purchase Day=1	0.453		
Return Since Latest Login			
Return Since Latest Login Day (%)	−0.551	6.923	0.000
Gain Since Latest Login Day=1	0.437		
N Investor × Stock × Day	13275767		

Note: This table presents summary statistics for returns since purchase and returns since latest login. The unit of analysis is an investor × stock × day. All-day sample includes all investor × stock × days in which the market is open and the account is active. Returns since purchase and returns since latest login are calculated at the daily level.

Table B2: Correlation Returns Since Purchase and Returns Since Latest Login, All-Day Sample

	Pearson's ρ
All Sample	0.23419
Bottom Decile Trade Frequency	0.11114
Top Decile Trade Frequency	0.3731

Note: This table presents correlation coefficients (Pearson's ρ) for returns since purchase and returns since latest login. All-day sample includes all investor × stock × days in which the market is open and the account is active.

Table B3: The Disposition Effect:
Including Continuous Returns Since Purchase, All-Day Sample

	$Sale_{ijt}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return Since Purchase < 0 (%)	0.0000***		0.0001***	0.0001***	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***	0.0000		-0.0000	-0.0000*
	(0.0000)		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
Gain Since Purchase=1	0.0029***		0.0027***	0.0008***	0.0041***		0.0038***	0.0024***
	(0.0002)		(0.0002)	(0.0001)	(0.0002)		(0.0002)	(0.0002)
Return Since Latest Login < 0 (%)		-0.0000***	-0.0001***	-0.0001***		-0.0000***	-0.0002***	-0.0001***
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Return Since Latest Login > 0 (%)		0.0003***	0.0004***	0.0004***		0.0003***	0.0003***	0.0003***
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
Gain Since Latest Login=1		0.0010***	0.0006***	-0.0015***		0.0015***	0.0010***	-0.0006***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Gain Since Purchase=1 × Gain Since Latest Login=1				0.0041***				0.0032***
				(0.0002)				(0.0002)
Constant	0.0048***	0.0043***	0.0042***	0.0050***				
	(0.0002)	(0.0001)	(0.0002)	(0.0002)				
Account FE	NO	NO	NO	NO	YES	YES	YES	YES
Observations	13,275,767	13,275,767	13,275,767	13,275,767	13,275,767	13,275,767	13,275,767	13,275,767
R^2	0.0006	0.0004	0.0011	0.0012	0.0252	0.0245	0.0256	0.0257

Note: This table presents ordinary least squares regression estimates of Equation 4 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. All-day sample includes all investor × stock × days in which the market is open and the account is active. Standard errors are clustered by account and day.

Table B4: Estimates of the Disposition Effect
Including Portfolio and Demographic Controls, All-Day Sample

	$Sale_{ijt}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain Since Purchase=1	0.0010***	0.0012***	0.0010***	0.0011***	0.0011***	0.0012***	0.0012***	0.0012***	0.0031***	0.0038***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Gain Since Latest Login=1	-0.0004***	-0.0002*	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***	0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Gain Since Purchase=1 ×	0.0036***	0.0031***	0.0036***	0.0035***	0.0035***	0.0035***	0.0035***	0.0035***	0.0030***	0.0031***
Gain Since Latest Login=1	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Days Since Purchase (100 days)		-0.0010***	-0.0010***	-0.0009***	-0.0009***	-0.0010***	-0.0010***	-0.0010***	-0.0002***	-0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Days Since Latest Login (100 days)			-0.0045***	-0.0048***	-0.0051***	-0.0052***	-0.0052***	-0.0052***	-0.0040***	-0.0040***
			(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Portfolio Value (£10000)				-0.0001***	-0.0000**	-0.0000***	-0.0000**	-0.0000**	-0.0004***	-0.0004***
				(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Number of Stocks (10 stocks)					-0.0010***	-0.0011***	-0.0011***	-0.0010***	0.0016***	0.0017***
					(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Account Tenure (years)						0.0006***	0.0006***	0.0006***		
						(0.0001)	(0.0001)	(0.0001)		
Female=1							-0.0007***	-0.0006***		
							(0.0002)	(0.0002)		
Age (10 years)								-0.0002**		
								(0.0001)		
Constant	0.0036***	0.0062***	0.0067***	0.0069***	0.0078***	0.0073***	0.0073***	0.0081***		
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)		
Account FE	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Stock FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES
Observations	13,010,268	13,010,268	13,010,268	13,010,268	13,010,268	13,010,268	13,010,268	13,010,268	13,010,268	13,010,268
R^2	0.0007	0.0019	0.0022	0.0022	0.0024	0.0025	0.0025	0.0025	0.0214	0.0231

Note: This table presents ordinary least squares regression estimates of Equation 4 with the addition of demographic controls and (daily level) portfolio controls. All-day sample includes all investor × stock × days in which the market is open and the account is active. Outliers (investor × stock × days) in the first and 99 percentiles of daily portfolio values are excluded. Gender and age (calculated from decades of birth) are within individual time invariant. Standard errors are clustered by account and day.

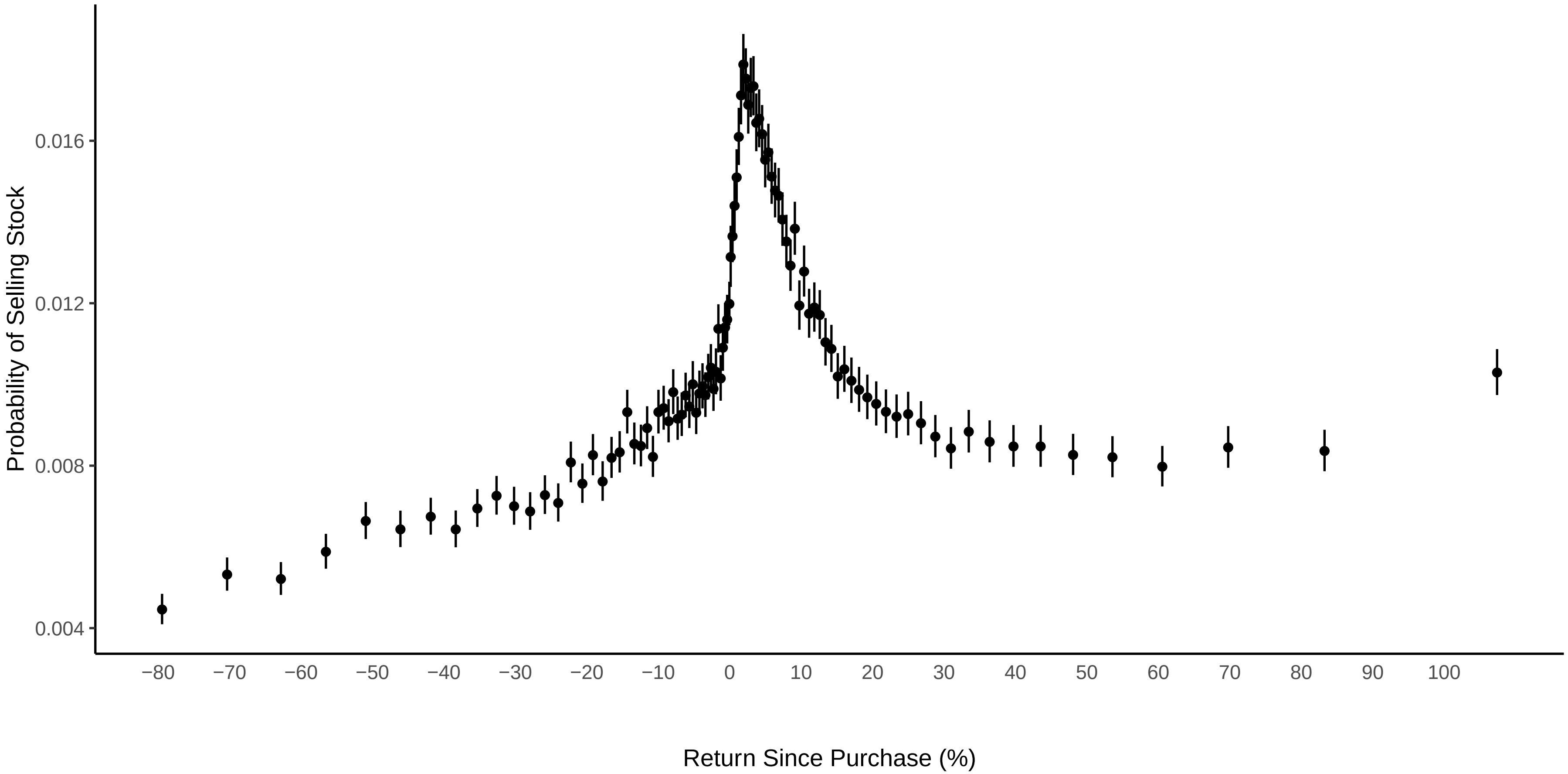
Table B5: The Disposition Effect: Cox Proportional Hazard Model, All-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.8380***		0.7767***	0.5127***
	(0.0098)		(0.0101)	(0.0138)
Gain Since Latest Login=1		0.4250***	0.2409***	-0.0981***
		(0.0092)	(0.0096)	(0.0156)
Gain Since Purchase=1 × Gain Since Latest Login=1				0.5720***
				(0.0202)
Observations	12,257,380	12,257,380	12,257,380	12,257,380
R^2	0.0006	0.0002	0.0007	0.0007

Note: This table presents Cox Proportional Hazard regression estimates of Equation 5 with time varying covariates. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Coefficients show stratified estimates by account. That is, coefficients are equal across accounts but baseline hazard functions are unique to each account. In the model, we count every purchase of a stock as the beginning of a new position, and we assume a position ends on the date the investor first sells part or all of his holdings. All-day sample includes all investor × stock × days in which the market is open and the account is active. Standard errors are clustered by account.

Online Appendix C: Supplementary Items for the Existing Accounts Sample

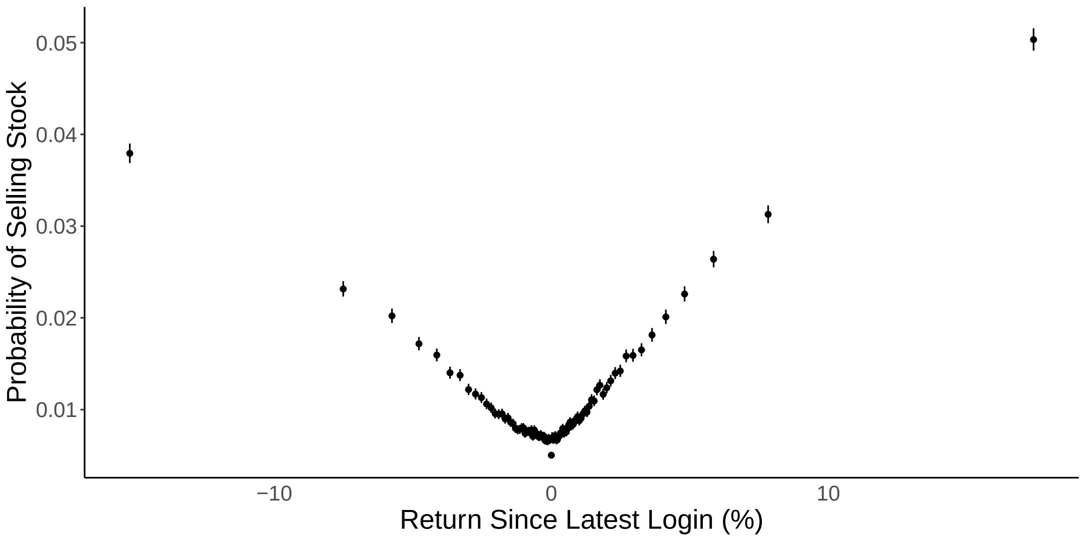
Figure C1: Illustration of the Disposition Effect for Existing Accounts:
Probability of Sale and Returns Since Purchase in the Login-Day Sample



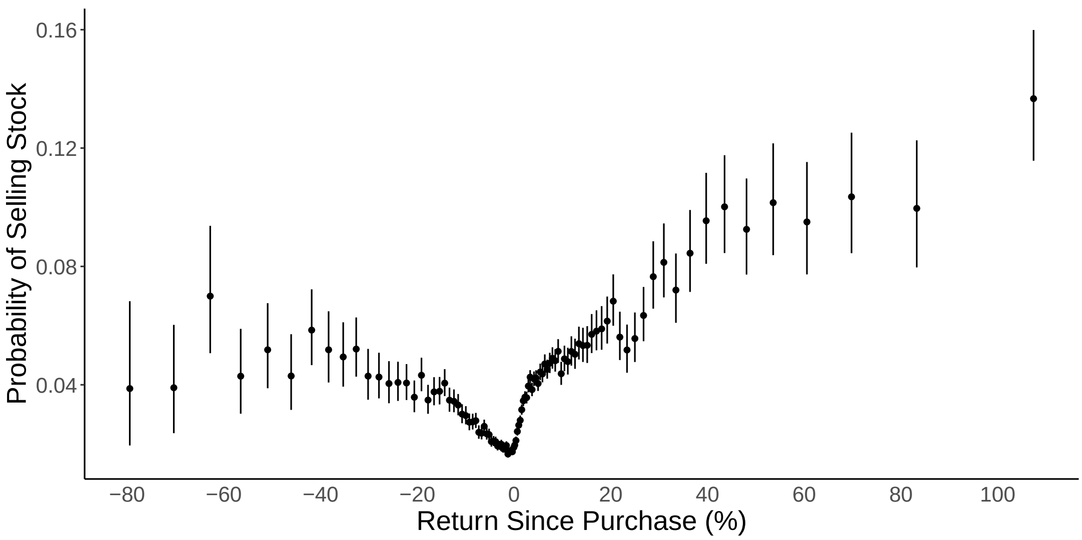
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. The X-axis variable is the returns on the stock since purchase. Login-day sample includes all investor × stock × days on which the made a login to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

Figure C2: Illustration of the Disposition Effect for Existing Accounts: Probability of Sale and Returns Since Latest Login in the Login-Day Sample

(A) Returns Since Latest Login

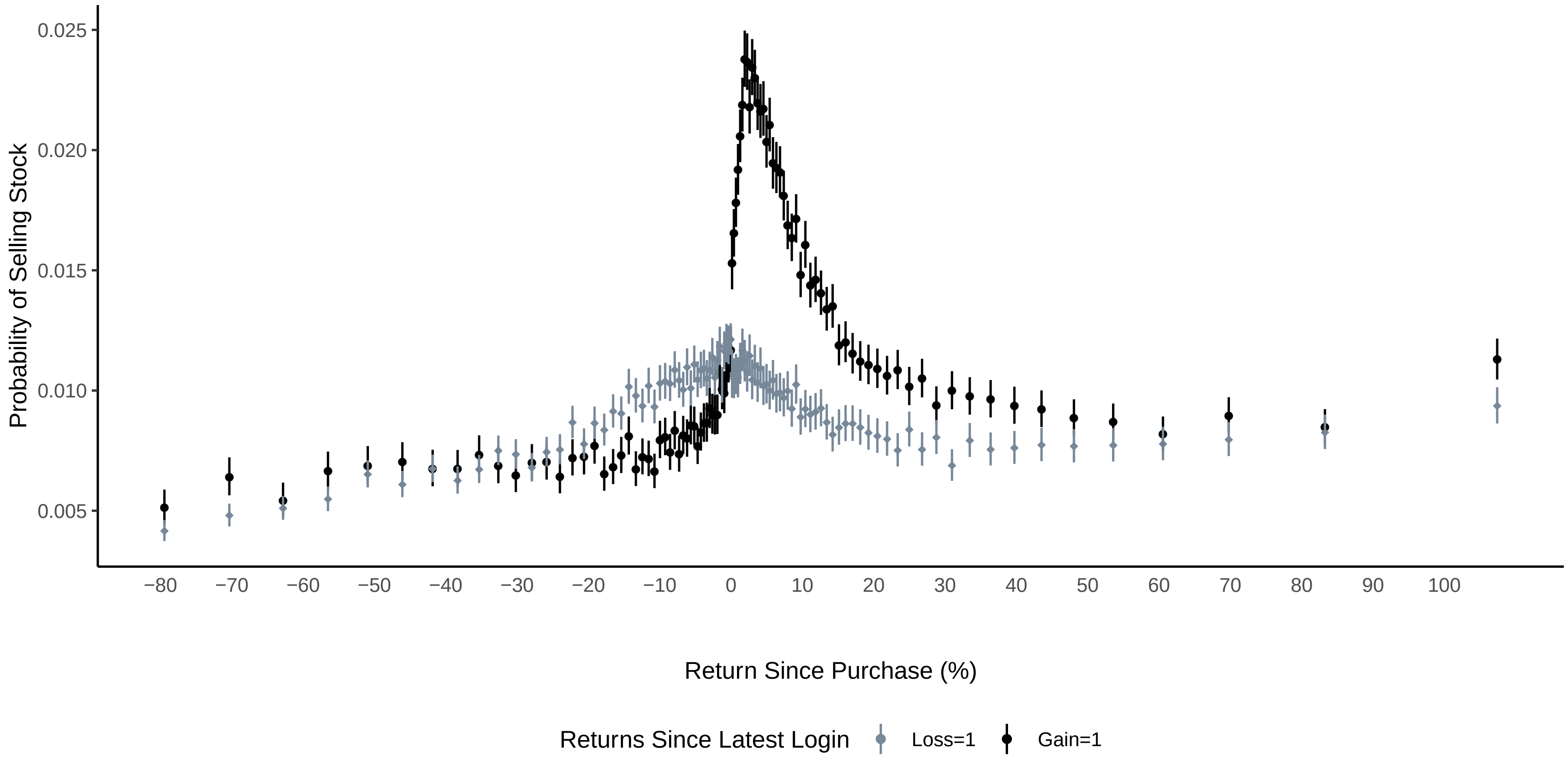


(B) Returns Since Purchase (Up to 30 Days Since Purchase)



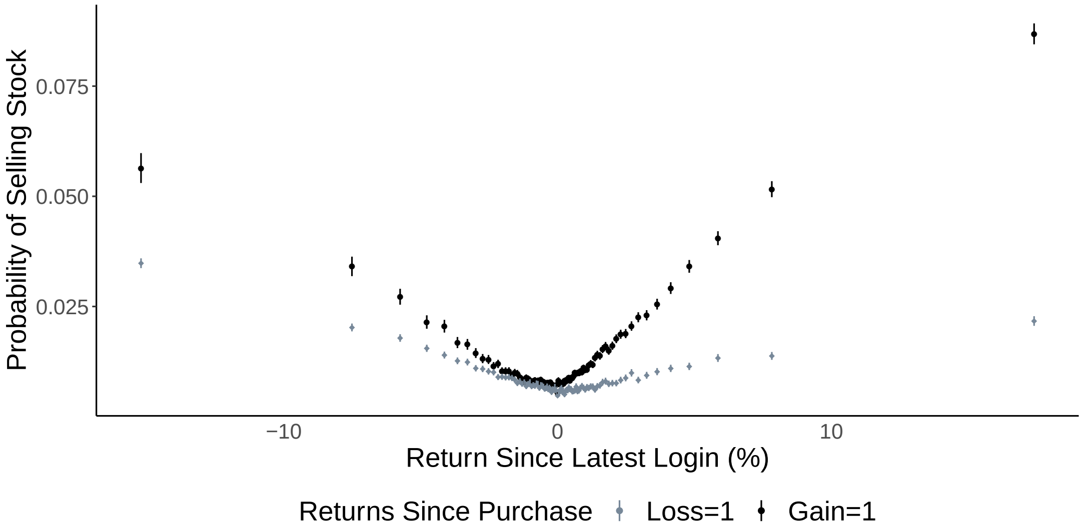
Note: Figure shows binned scatter plot with 95% confidence intervals. Y-axis variable is the probability that the stock is sold by the investor on the day. Panels include accounts opened before April 2012 and new stocks purchased since then. In Panel A the X-axis variable is the returns on the stock 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 C3: Illustration of the Interaction Effect for Existing Accounts in the Login-Day Sample



Note: Figure shows binned scatter plot with 95% confidence intervals. The plot includes accounts opened before April 2012 and new stocks purchased since then. 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 C4: Illustration of the Interaction Effect:
Probability of Sale by Returns Since Login, by Gain / Loss Since Purchase for Existing Accounts, Login-Day Sample



Note: Figure shows binned scatter plot with 95% confidence intervals. The plot includes accounts opened before April 2012 and new stocks purchased since then. 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 C1: Existing Accounts Sample Summary Statistics

	Mean	Min	p25	p50	p75	Max
A. Account Holder Characteristics						
Female	0.179					
Age (years)	56.001	17.000	47.000	57.000	67.000	87.000
Account Tenure (years)	5.954	0.052	3.816	4.984	7.455	16.951
B. Account Characteristics						
Portfolio Value (£10000)	20.893	0.000	0.742	2.232	5.920	10432.377
Investment in Mutual Funds (£10000)	0.526	0.000	0.000	0.000	0.000	1402.706
Investment in Mutual Funds (%)	4.571	0.000	0.000	0.000	0.000	100.000
Number of Stocks	6.785	2.000	2.682	4.517	8.292	115.213
Number of New Stocks	4.476	1.000	1.778	3.000	5.333	103.158
Portfolio Turnover (%)	30.789	0.000	0.000	0.000	22.717	758.615
Login days (% all days)	23.592	0.145	6.780	17.436	35.894	97.117
Transaction days (% all market open days)	4.768	0.095	1.558	2.735	5.303	100.000
N Accounts	8642					

Note: This table presents summary statistics for a 20% sample of existing accounts (accounts opened before April 2012). The same sample criteria used to define our main baseline sample of new accounts was applied. The sample includes active accounts with trading and login records and complete demographic data; and it includes portfolios with at least two stocks. However, it is restricted to accounts who purchased new stocks after April 2012. For these *new stocks* we know the purchase price and we are able to compute the return since purchase. Age is measured at 2017 (rather than at the date of account opening because of missing opening dates for some accounts). 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. Portfolio value, number of stocks, number of new 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. Number of *new stocks* reports the stocks that enter as part of the analysis presented in Table C4. Portfolio turnover is the account average annual portfolio turnover. Due to a high degree of skewness, portfolio turnover statistics exclude the top 99 percentile. 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 C2: Summary Statistics for Returns Since Purchase and Returns Since Latest Login, Existing Accounts, Login-Day Sample

	Mean	SD	Median
Sale=1	0.011		
Return Since Purchase			
Return Since Purchase (%)	1.203	28.432	0.534
Gain Since Purchase Day=1	0.517		
Return Since Latest Login			
Return Since Latest Login Day (%)	0.026	3.427	0.000
Gain Since Latest Login Day=1	0.457		
N Investor × Stock × Day	12425353		

Note: This table presents summary statistics for returns since purchase and returns since latest login for accounts opened before April 2012 and new stocks purchased from April 2012. The unit of analysis is an investor × stock × day. 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.

Table C3: Correlation Returns Since Purchase and Returns Since Latest Login, Existing Accounts, Login-Day Sample

	Pearson's ρ
All Sample	0.08659
Bottom Decile Trade Frequency	0.06534
Top Decile Trade Frequency	0.11735

Note: This table presents correlation coefficients (Pearson's ρ) for returns since purchase and returns since latest login for the Login-Day Sample of accounts opened before April 2012 and new stocks purchased from April 2012.

Table C4: The Disposition Effect for Existing Accounts:
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***	-0.0000***		-0.0000***	-0.0000***
	(0.0000)		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
Gain Since Purchase=1	0.0040***		0.0040***	0.0008**	0.0069***		0.0067***	0.0047***
	(0.0004)		(0.0004)	(0.0003)	(0.0006)		(0.0006)	(0.0005)
Return Since Latest Login < 0 (%)		-0.0021***	-0.0024***	-0.0024***		-0.0015***	-0.0018***	-0.0017***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Return Since Latest Login > 0 (%)		0.0024***	0.0026***	0.0026***		0.0019***	0.0020***	0.0020***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Gain Since Latest Login=1		0.0017***	0.0010***	-0.0028***		0.0018***	0.0011***	-0.0014***
		(0.0002)	(0.0002)	(0.0003)		(0.0002)	(0.0002)	(0.0002)
Gain Since Purchase=1 × Gain Since Latest Login=1				0.0068***				0.0044***
				(0.0004)				(0.0003)
Constant	0.0102***	0.0059***	0.0066***	0.0082***				
	(0.0004)	(0.0002)	(0.0003)	(0.0004)				
Account FE	NO	NO	NO	NO	YES	YES	YES	YES
Observations	12,425,353	12,425,353	12,425,353	12,425,353	12,425,353	12,425,353	12,425,353	12,425,353
R^2	0.0007	0.0045	0.0060	0.0063	0.0419	0.0432	0.0447	0.0448

Note: This table presents ordinary least squares regression estimates of Equation 4 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 sample includes accounts opened before April 2012 and all investor × stock × days on which the investor made at least one login to the account. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Standard errors are clustered by account and day.

Table C5: Estimates of the Disposition Effect for Existing Accounts Including Portfolio and Demographic Controls, Login-Day Sample

	$Sale_{ijt}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain Since Purchase=1	0.0004*	0.0011***	0.0011***	0.0012***	0.0013***	0.0013***	0.0013***	0.0014***	0.0050***	0.0061***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Gain Since Latest Login=1	-0.0007**	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	0.0003	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Gain Since Purchase=1 × Gain Since Latest Login=1	0.0061***	0.0053***	0.0052***	0.0051***	0.0051***	0.0051***	0.0051***	0.0050***	0.0038***	0.0039***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Days Since Purchase (100 days)		-0.0018***	-0.0018***	-0.0018***	-0.0017***	-0.0017***	-0.0017***	-0.0017***	-0.0005***	-0.0004***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Days Since Latest Login (100 days)			0.0275***	0.0270***	0.0240***	0.0240***	0.0240***	0.0230***	-0.0043**	-0.0042**
			(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0017)	(0.0017)
Portfolio Value (£10000)				-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
				(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of Stocks (10 stocks)					-0.0010***	-0.0010***	-0.0010***	-0.0009***	0.0006***	0.0006***
					(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Account Tenure (years)						-0.0000	-0.0000	0.0000		
						(0.0001)	(0.0001)	(0.0001)		
Female=1							-0.0007	-0.0008		
							(0.0007)	(0.0007)		
Age (10 years)								-0.0008***		
								(0.0002)		
Constant	0.0082***	0.0130***	0.0124***	0.0126***	0.0144***	0.0144***	0.0145***	0.0194***		
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0013)		
Account FE	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Stock FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES
Observations	12,176,865	12,176,865	12,176,865	12,176,865	12,176,865	12,176,865	12,176,865	12,176,865	12,176,865	12,176,865
R^2	0.0007	0.0030	0.0032	0.0032	0.0037	0.0037	0.0037	0.0038	0.0319	0.0353

Note: This table presents ordinary least squares regression estimates of Equation 4 with the addition of demographic controls and (daily level) portfolio controls. The sample includes accounts opened before April 2012 and all investor × stock × days on which the investor made at least one login to the account. Outliers (investor × stock × days) in the first and 99 percentiles of daily portfolio values are excluded. Gender and age (calculated from decades of birth) are within individual time invariant. Standard errors are clustered by account and day.

Table C6: The Disposition Effect for Existing Accounts: Cox Proportional Hazard Model, Login-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain Since Purchase=1	0.6855***		0.6576***	0.5016***
	(0.0071)		(0.0074)	(0.0100)
Gain Since Latest Login=1		0.2707***	0.0930***	-0.1211***
		(0.0066)	(0.0069)	(0.0116)
Gain Since Purchase=1 × Gain Since Latest Login=1				0.3481***
				(0.0149)
Observations	11,267,179	11,267,179	11,267,179	11,267,179
R^2	0.0009	0.0001	0.0009	0.0009

Note: This table presents Cox Proportional Hazard regression estimates of Equation 5 with time varying covariates. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. Coefficients show stratified estimates by account. That is, coefficients are equal across accounts but baseline hazard functions are unique to each account. The sample includes accounts opened before April 2012 and all investor × stock × days on which the investor made at least one login to the account. In the model, we count every purchase of a stock as the beginning of a new position, and we assume a position ends on the date the investor first sells part or all of his holdings. Standard errors are clustered by account.