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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 the investor's 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.

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

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 examine the creation of reference points and the interplay between multiple reference points in financial decisions.[2]

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 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 is assumed to be the relevant reference point in the vast majority of studies.[3] Yet performance against more recent points might be relevant for selling decisions.[4] Recent papers show that the disposition effect varies across settings. For example, the disposition effect is absent following a stock split, suggesting investors fail to adjust their reference point (Birru 2015). The price of a recently sold stock influences the sale decisions for other stocks (Frydman et al. 2018). Nonprice reference points also 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. 2024). The disposition effect is also stronger among investors who participate in social trading web platforms, suggesting that social interaction contributes to the disposition effect (Heimer 2016).

We first present a new framework of the disposition effect that considers the role of investor attention in generating reference points. Our framework implements prospect theory preferences in a multiperiod setting in which investors experience realization utility from selling (Barberis and Xiong 2012, Ingersoll and Jin 2013, Frydman et al. 2014, Imas 2016). A key innovation in our framework 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 framework predicts that investors, 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 the investor's latest account login (our measure of paying attention to the stocks held by the investor) on selling behavior. 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 previous literature; see Barber and Odean 2013), and therefore, the value of each holding they see when they log in 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.[5] We present two novel findings. First, investors are more disposed to sell stocks that 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 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, the fact that we do see a strong disposition effect against the price at the last login suggests that logging in is, in fact, an important determinant and 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.[6] We show that there exists a very strong interaction effect between returns since purchase and returns since latest login in their effect on selling behavior: 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, in the absence of such a negative lookup effect, are an order of magnitude larger.

We interpret these findings in light of a theoretical framework that builds on the 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 (in which 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 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 worse.

Holding on to a stock in our framework 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 the investor feel that the investor has lost money, prospect theory predicts the investor will be risk-seeking, which, in our framework, encourages holding the stock. However, if the individual's reference point is low or close to the current value of the stock, the individual tends to be risk-averse (because of value function concavity or loss aversion), which encourages selling the stock. Combined with the assumption that the investor cares only about the higher reference point, the framework generates the prediction that the individual is more likely to 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 the investor's portfolio is itself a matter of choice. Moreover, prior research shows that this decision is not 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 log in to their accounts without transacting when the market is up than when it is down.[7] Note that this problem applies equally when it comes to the disposition effect associated with purchase price; when an individual buys an asset is also a matter of choice. However, just as investors can decide when to buy but not what happens to the value of the asset after they buy, investors can decide when to look but not what 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.

To address directly the endogeneity in investors selecting when to log in, we conduct a series of robustness and sensitivity tests that illustrate our results are not driven by factors determining when investors log in. First, we show that the disposition effect arising from returns since latest login occurs 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 nonrandom 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 the investor's account. The majority of assets (in terms of both number and value) held by investors in the trading accounts in our sample are common stocks, as opposed to mutual funds or index funds, for which evidence of the disposition effect is much weaker (Chang et al. 2016). Hence, our sample is particularly suited to the study of the disposition effect.

Our study contributes new insights to the large previous literature on the disposition effect. The disposition effect is 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. (2014).[8] 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. Heimer et al. (2023) provide evidence from field and laboratory studies that the disposition effect is also the result of a self-control problem in dynamic risk taking when planned and actual behaviors differ (see also Barberis 2012). Odean (1998) demonstrates that the disposition effect does not arise because of transaction costs, portfolio rebalancing, a preference for realizing gains more frequently than losses, or different beliefs about expected future returns. The disposition effect tends to be stronger among individual as compared with institutional investors (Shapira and Venezia 2001), less-experienced investors (Feng and Seasholes 2005), and investors with lower wealth (Dhar and Zhu 2006). The disposition effect is, however, shown not to occur—indeed, there seems to be an effect going in the opposite direction—for mutual funds. In extended analysis, we corroborate this result in our data and also show that the effect of the price at the latest login is present for stocks but not for funds, consistent with Chang et al. (2016).

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 examines 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, and both Golman et al. (2020) and Bolte and Raymond (2023) propose models in which risk-taking behavior is influenced by decision makers' awareness that their risk-taking and risk-avoiding decisions naturally draw their attention to specific types 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.[9]

The remainder of the paper proceeds as follows. Section 2 introduces the framework 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 additional robustness and sensitivity tests. Section 6 interprets and discusses the empirical results. Section 7 concludes.

2. A Framework of Investor Behavior with Multiple Reference Points

Beginning with Odean (1998), analyses of the disposition effect have focused on 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.[10]

Here, we develop a framework of realization utility that 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 framework 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 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 favorable for a comparison of the investor's current position. Research in psychology on aspirations, goal-setting, and social comparison finds 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).[11]

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 favorable. To do so, investors would optimally focus on a lower price than the current stock price (and also lower than the purchase price) — at the limit, focusing on a price of zero. Thaler (1985) proposes 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 the worker's yearly bonus might have as salient reference points both the worker's own bonus from the previous year and the worker's 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 is higher than the worker's bonus this year but the other was lower, the worker would focus on the higher reference point virtually to the exclusion of the lower.[12]

In Figure 1, we illustrate our framework with a basic 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 periods 0 and 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 the individual's portfolio (which contains this single stock). If the investor chooses to look, then p_1 becomes a second salient reference point.[13] Between periods 1 and 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 and then chooses whether to sell the stock. Between periods 2 and 3, the price then either rises or falls to a price p_3.

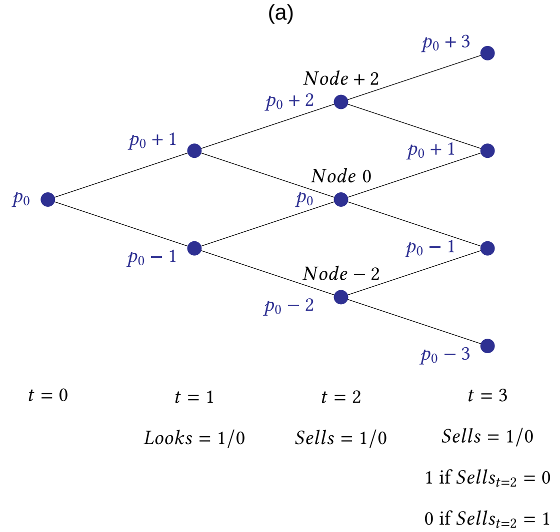
Period 3: In this final period, the investor liquidates any remaining position in the stock.

For tractability, we apply a number of simplifying assumptions. We assume that, at the start of period 0, the investor purchases a stock that takes the form of a single share and, 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 one). 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.[14] With the assumption of realization utility, the investor is only concerned with the utility experienced from selling the stock in either period 2 or 3.

Figure 1(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)

Figure 1. (Color online) Illustration of the Model of Multiple Reference Points

(a)



(b)

		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

Notes. 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 the individual observes the individual's portfolio, the price observed becomes a new reference point. At $t = 2$, the individual chooses whether to sell the asset, and at $t = 3$, the individual liquidates any remaining position in the asset. Panel (b) displays the predictions of the model under which an individual with prospect theory preferences based the individual's selling decisions using the highest reference point. (a) Model structure. (b) Sell decisions for different reference points.

describes the investor's selling decision under prospect theory preferences at each node in the period $t = 2$.

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

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

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 one if $p_1 > p_0$ and zero 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 to which an investor is subject. A specific individual might have a 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 (regardless of whether 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 the investor looked. If the individual did not look, then the individual's reference price is the same as the current stock price, making the individual extremely risk adverse because of 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 $p_o + 1 > p_0$, and 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 (because of the concavity of the value function). Hence, an investor looking at the price of their 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.

Whereas, 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 the investor's stock portfolio. In a related paper, Quispe-Torreblanca et al. (2023) 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 in which 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 that we take to the empirical analysis. First, the model implies the existence of a disposition effect defined over returns since purchase and 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 the disposition effect with respect to returns since purchase will not come into play if the reference point formed when the investor last paid attention is higher than the stock's current value (this is the case at node 0 when the price of the stock rose before $t = 1$ and 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 because of 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 Online 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.[15] Combining the account-level data with daily stock price data allows us to calculate the value of each stock position in an investor's portfolio on each day of the sample period.[16] 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.[17]

3.1. Summary Statistics

Table 1 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).[18] Account holders have held their accounts with Barclays for, on average, approximately two and a half years. The average portfolio value is approximately £42,000, and portfolios contain 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).[19]

The summary statistics for login and transaction behavior show that investors log in much more frequently than they trade. Investors log in, on average, approximately once every five days (the median is approximately six days)[20] but make a transaction, on average, only once every 18 market open days (i.e., approximately once every four weeks; median, once every 30 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).[21]

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. *Sale* is a dummy equal to one 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 with 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 with the price on the most recent day on which the investor made a login to the account. We call this dummy variable

Table 1. Baseline Sample Summary Statistics

	Mean	Minimum	p25	p50	p75	Maximum
Panel 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
Panel B. Account characteristics						
Portfolio value, £10,000	4.247	0.000	0.346	0.918	2.120	5,742.635
Investment in mutual funds, £10,000	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	1,257.464
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
Number of accounts	8,242					

Notes. 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. Because of a high degree of skewness, portfolio turnover statistics exclude the top 1% 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.

GainSinceLatestLogin. The modified econometric specification is now

$$Sale_{ijt} = b_0 + b_1 GainSincePurchase_{ijt} + b_2 GainSinceLatestLogin_{ijt} + \epsilon_{ijt} \qquad (4)$$

in which *GainSinceLatestLogin* is a dummy indicating whether, for the investor holding account (i), stock (j) was in gain on day (t) compared with the price on the day when the investor made the investor's 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: because of the high login frequency displayed by individual investors relative to their trading frequency, as seen in the summary statistics in Online Table A2, 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 because of long-term market trends yet have lost value since latest login because of short-term volatility in the prices of (most) stocks. Conversely, a persistently underperforming stock that 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 Equations (3) and (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 analyses in Section 7, 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; and (iii) a selectivity correction (inverse Mills ratio) to control for selection into making a login. We also present additional subsample analyses of estimates of these econometric models in Section 7.

4.2. Estimation Sample

The econometric specifications in Equations (3) and (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 Equations (3) and (4) using all account × stock × days in the data, that is, 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 the investor's 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 is 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 the investor's 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 earlier. 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 Online Appendix B.[22]

The sell-day sample provides approximately 349,983 account × stock × days for 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 focus on estimates using the sell-day sample. However, in Online Appendix A, we present analogous estimates using the login-day sample.

4.3. Summary Statistics for Measures of Returns

Table 2 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 that show a gain since purchase.[23] 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.[24]

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.[25] However, this is not the case in our sample in which investors login much more frequently than they trade. The Pearson ρ coefficient is 0.18 in the sell-day sample and 0.11 in the login-day sample. The correlation is higher among the top decile of accounts by trading

Table 2. Summary Statistics for Returns Since Purchase and Returns Since Latest Login

	Mean	Standard deviation	Median
	Panel A. Sell-day sample		
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		
Number of investor × stock × days	349,983		
	Panel B. Login-day sample		
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		
Number of investor × stock × day	5,894,175		

Notes. 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.

frequency as expected because there are fewer login days between transactions.[26]

5. Results

5.1. Main Results

This section 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.[27] The plot shows a very large increase in the probability of sale when returns since purchase are positive.[28]

Estimates of Equation (3) are shown in Table 3 (panel A 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 that 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%.

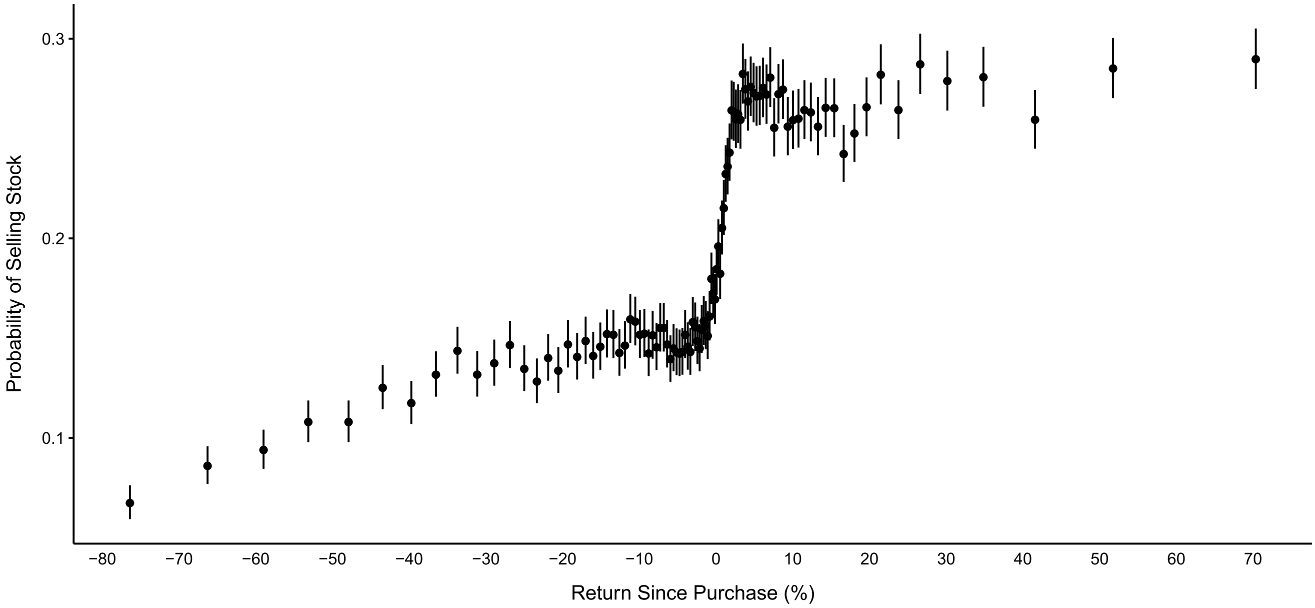
The model in column (2) in panel A replaces the gain since purchase dummy from Equation (3) with the gain since latest login dummy. The coefficient on this dummy variable is again positive and precisely defined. The coefficient on the gain since latest login dummy in column (2) of panel A implies that a stock that 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 11 percentage points more likely to be sold, whereas 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

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



Notes. The figure shows a binned scatterplot with 95% confidence intervals. The *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. The 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.

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

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Panel A. Sell-day sample				
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 × Gain since latest login = 1				0.1239***
				(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				
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 × Gain since latest login = 1				0.0102***
				(0.0004)
Constant	0.0087***	0.0100***	0.0077***	0.0096***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	5,894,175	5,894,175	5,894,175	5,894,175
R^2	0.0008	0.0003	0.0009	0.0015

Notes. This table presents ordinary least squares regression estimates of Equation (4). The dependent variable takes a value of one 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.

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

login variable becomes negative, whereas 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 3 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.[29] 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.

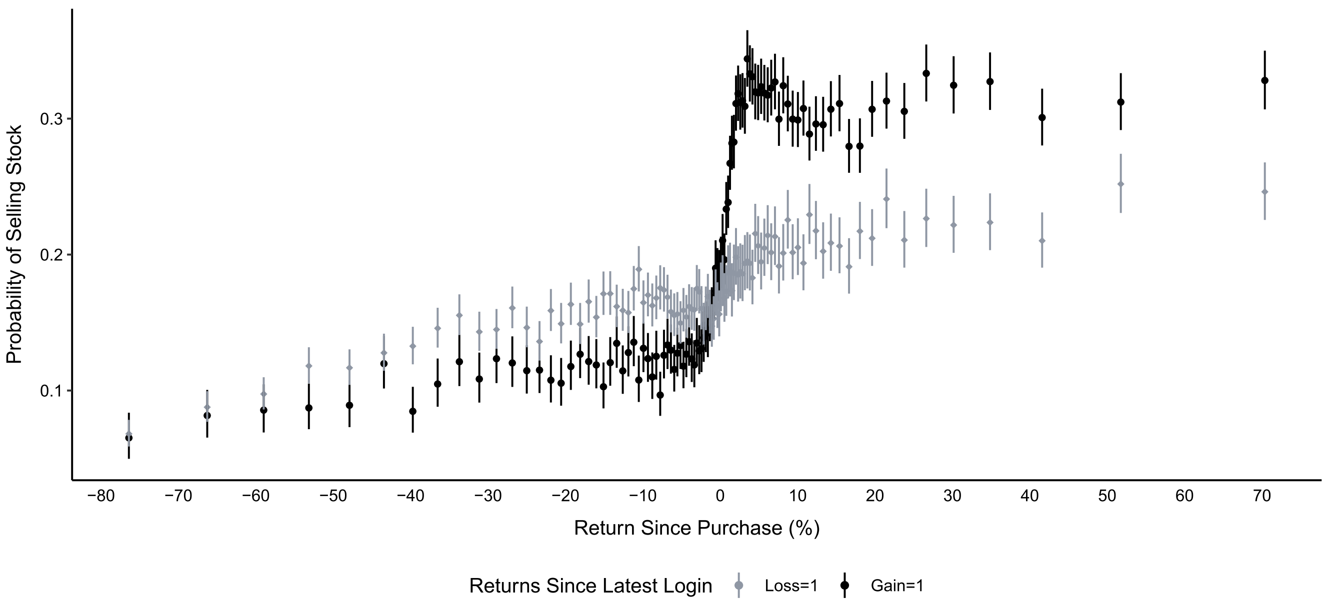
5.3. Investor and Portfolio Characteristics

We test the sensitivity of our main results to investor characteristics and investor portfolio characteristics, initially focusing on the impact of investor gender and age. Previous studies show gender and age differences in trading behavior (Barber and Odean 2001, Agnew et al. 2003, Dorn and Huberman 2005, Mitchell et al. 2008). 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 4. The estimates reveal slightly higher coefficients for the main effects in females compared to males, with similar interaction terms across genders (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 subsamples.

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

Figure 3. (Color online) Illustration of the Interaction Effect in the Sell-Day Sample



Notes. The figure shows a binned scatterplot with 95% confidence intervals. The 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.

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 4, 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.[30]

Table 4. The Disposition Effect: Subsample 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)

Notes. 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 one if the investor made a sale of the stock and zero otherwise and there are three covariates (a dummy for gains since purchase, another for gains since the latest login, and their interaction) 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.

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

5.4. Extension I: Prices at Other Time Points

The effect we observe arising from gain since latest login might indicate that prices at a number of time points are important for the investor trading decision, such as gains and losses relative to the price on the previous day, week, or month. Login events may be particularly important as they generate attention to the price, but prices at other time points may also be important.

To investigate this, in Table 5, we add to our main models a series of dummy variables for whether the stock was in gain compared with the price on the previous day, week, month, or quarter. We also interact these dummy variables with gain since purchase. Results indicate no clear pattern from the gain dummy for the other time points, which vary in sign and statistical significance. The inclusion of these dummy variables and their interactions does not substantially alter the coefficients on the main variables of interest. In additional analysis shown in Online Table A22, we focus on the samples of stocks that have suffered losses over the respective time period (day, week, month, quarter) and reestimate our main models. If these potential reference points are more relevant to investors' decisions, we should observe that gains since purchase and since latest login have little influence on investors' sales. These results show the same pattern of a consistent interaction term between gains since purchase and gain since latest login.

This analysis does not rule out the existence of other relevant reference prices apart from interim prices as suggested by Gneezy (2005). One example might be the highest price experienced by the investor during the investor's holding period or peak price, which we examine in both housing and stock markets elsewhere (Quispe-Torreblanca et al. 2023).[31]

5.5. Extension II: Endogeneity of Logins

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 the investor's portfolio is itself a matter of choice.[32] However, just as investors can decide when to buy but not what happens to the value of the asset after

Table 5. The Disposition Effect: Prices at Other Time Points, Login-Day Sample

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain since purchase = 1	0.0009***	−0.0016***	−0.0009***	0.0028***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Gain since latest login = 1	−0.0017***	−0.0019***	−0.0022***	−0.0023***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Gain since purchase = 1 × Gain since latest login = 1	0.0090***	0.0081***	0.0098***	0.0104***
	(0.0005)	(0.0004)	(0.0004)	(0.0005)
Gain since yesterday				
Gain since yesterday = 1	−0.0006**			
	(0.0003)			
Gain since purchase = 1 × Gain since yesterday = 1	0.0014***			
	(0.0005)			
Gain since past week				
Gain since past week = 1		−0.0009***		
		(0.0002)		
Gain since purchase = 1 × Gain since past week = 1		0.0064***		
		(0.0003)		
Gain since past month				
Gain since past month = 1			0.0003	
			(0.0002)	
Gain since purchase=1 × Gain since past month=1			0.0030***	
			(0.0003)	
Gain since past quarter				
Gain since past quarter=1				0.0022***
				(0.0003)
Gain since purchase=1 × Gain since past quarter=1				−0.0041***
				(0.0005)
Constant	0.0096***	0.0098***	0.0095***	0.0090***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	5,894,168	5,892,466	5,881,815	5,845,014
R^2	0.0015	0.0018	0.0016	0.0016

Notes. This table presents ordinary least squares regression estimates of Equation (4) controlling for other reference points. Columns (1)–(4) control for gains since yesterday, the past week, the past month, and the past quarter, respectively. 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.

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

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. Whereas this might be the case for a certain group of unsophisticated investors with individual fixed effects, this result could only arise because of time-varying investor characteristics correlated with the propensity to login, which seems implausible.

We also provide two sets of analyses presenting evidence that our results are not a result of the choice of when to look. First, we reproduce the main result for subsamples of observations split by whether the stock was in gain or loss since the previous day, week, month, or quarter (see Online Figure A6). The same effect is seen across all subsamples, 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). Likewise, we replicate the same patterns across subsamples that condition the data on the stock's performance prior to the last login day (see Online Figure A7). The persistence of the interaction effect across subsamples implies, again, that our results are not driven by the choice of when to look.

As a second test, we add a Heckman selectivity correction term to control for nonrandom selection into making a login on a given day.[33] The first step of the Heckman (two-step) correction procedure consists of 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 log in 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 log in to their trading accounts on poor weather days because of 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 effect 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 that find evidence of direct effects of the weather on trading behavior of institutional investors (Goetzmann et al. 2015) and mutual fund investors (Li et al. 2021) 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 United Kingdom. We match the 2,009 unique postcodes (at the four-digit level) of the investors in our sample to the nearest weather station and join data on daytime visibility, a commonly used measure of weather.[34]

The first stage models the decision to log in. 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 log in to their trading accounts on poor weather days.[35] From this model, we calculate the inverse Mills ratio that is added to our equation of interest.

Table 6 shows estimates of the main equation of interest for the login-day sample with the inclusion of the inverse Mills ratio as the additional control. The qualitative pattern in the coefficient estimates is once more the same as in Table 3. The coefficient on the inverse Mills ratio is negative and precisely defined, implying that the main results may suffer from negative selection, that is, downward bias in the coefficient estimates.[36]

5.6. Extension III: Stocks and Funds

Evidence from recent studies suggests that the disposition effect is not seen in mutual fund trades (Chang et al. 2016). We investigate whether the effect of gains since latest login is also seen in mutual fund trades. In Table 7, we reestimate our main models separately for samples of stocks and funds (panel A).[37] Consistent with Chang et al. (2016), we find no clear evidence of a disposition effect in trades of funds and no clear evidence of an effect arising from gain since latest login or the interaction between gain since purchase and gain since latest login. Coefficient signs and precision are variable across specifications (see columns (6)–(10)) with no clear pattern of effect sign and precision.[38]

We further investigate whether the absence of a disposition effect relative to gain since purchase or gain since latest login arises because of differences across investors who hold stocks and funds or differences across stocks and funds themselves. To investigate this, in panel B, we limit of our sample to days on which investors simultaneously held stocks and funds. Here, we observe the same pattern as earlier: consistent evidence across specifications of a disposition effect since purchase and since latest login for stocks but no clear evidence of an effect for funds. Our evidence is, therefore, consistent with that presented in Chang et al. (2016) and suggests that investors have different reactions to gains relative to both purchase price and price at latest login depending on asset class. One reason for this may be that investors have different attitudes to

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

	$Sale_{ijt}$			
	(1)	(2)	(3)	(4)
Gain since purchase = 1	0.0061***		0.0057***	0.0010***
	(0.0003)		(0.0002)	(0.0002)
Gain since latest login = 1		0.0034***	0.0027***	−0.0022***
		(0.0002)	(0.0002)	(0.0002)
Gain since purchase = 1 × Gain since latest login = 1				0.0103***
				(0.0003)
Inverse Mills ratio	−0.0099***	−0.0108***	−0.0095***	−0.0096***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Constant	0.0188***	0.0210***	0.0174***	0.0194***
	(0.0013)	(0.0012)	(0.0013)	(0.0013)
Observations	5,697,583	5,697,583	5,697,583	5,697,583
R^2	0.0008	0.0003	0.0010	0.0016

Notes. This table presents selectivity correction estimates for which 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 one 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. Because the Heckman correction is a two-step estimation method, we present panel bootstrap-based standard errors in parenthesis.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

realizing gains and losses on undelegated assets (e.g., individual stock choices) compared with delegated assets (e.g., mutual funds), an interpretation further explored in Chang et al. (2016).

5.7. Extension IV: Investor "Ostricity" and Price at Latest Login

The tendency of investors to exhibit a sensitivity to gain since latest login could potentially reflect differences in

Table 7. The Disposition Effect for Stocks and Funds

	Stocks					Funds				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A. All days					
Gain since purchase = 1	0.0080***		0.0076***	0.0019***	0.0072***	−0.0006*		−0.0005	−0.0015***	−0.0004
	(0.0004)		(0.0004)	(0.0003)	(0.0004)	(0.0003)		(0.0003)	(0.0004)	(0.0004)
Gain since latest login=1		0.0043***	0.0033***	−0.0022***	−0.0002		−0.0004	−0.0004	−0.0017***	−0.0010***
		(0.0004)	(0.0003)	(0.0003)	(0.0002)		(0.0003)	(0.0003)	(0.0004)	(0.0004)
Gain since purchase=1 × Gain since latest login=1				0.0122***	0.0082***				0.0021***	0.0006
				(0.0005)	(0.0004)				(0.0005)	(0.0004)
Constant	0.0091***	0.0106***	0.0078***	0.0099***		0.0061***	0.0060***	0.0063***	0.0068***	
	(0.0003)	(0.0003)	(0.0003)	(0.0003)		(0.0004)	(0.0004)	(0.0004)	(0.0005)	
Account fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
Observations	5,016,419	5,016,419	5,016,419	5,016,419	5,016,419	877,756	877,756	877,756	877,756	877,756
R^2	0.0013	0.0004	0.0015	0.0022	0.0492	0.0000	0.0000	0.0000	0.0001	0.0394
					Panel B. Days simultaneously holding stocks and funds					
Gain since purchase = 1	0.0037***		0.0036***	0.0011***	0.0030***	−0.0004		−0.0004	−0.0012***	−0.0003
	(0.0004)		(0.0004)	(0.0004)	(0.0005)	(0.0003)		(0.0003)	(0.0003)	(0.0004)
Gain since latest login = 1		0.0013***	0.0009***	−0.0017***	−0.0007**		−0.0004	−0.0003	−0.0014***	−0.0008**
		(0.0003)	(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0002)	(0.0004)	(0.0003)
Gain since purchase = 1 × Gain since latest login = 1				0.0054***	0.0037***				0.0018***	0.0005
				(0.0005)	(0.0004)				(0.0004)	(0.0004)
Constant	0.0055***	0.0066***	0.0051***	0.0062***		0.0052***	0.0051***	0.0053***	0.0058***	
	(0.0003)	(0.0003)	(0.0003)	(0.0004)		(0.0003)	(0.0003)	(0.0004)	(0.0004)	
Account fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
Observations	1,493,524	1,493,524	1,493,524	1,493,524	1,493,524	699,834	699,834	699,834	699,834	699,834
R^2	0.0005	0.0001	0.0005	0.0008	0.0298	0.0000	0.0000	0.0000	0.0001	0.0453

Notes. This table presents ordinary least squares regressions for our baseline regressions separately for stocks and funds. Panel A includes all login days. Panel B includes all login days during which the investor holds individual stocks and funds simultaneously (funds include mutual funds, unit trusts, investment trusts, and exchange-traded funds). In addition, columns (1)–(5) limit the sample to individual stocks, whereas columns (6)–(10) to funds. Standard errors are clustered by account and day.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

the drivers of investor login behavior. Sicherman et al. (2015) show that investors vary in the responsiveness of their logins to upturns and downturns in market prices, coining the term "ostrich effect" to describe investors who are less likely to log in to their accounts following a recent market downturn. One interpretation of this result is that these investors are averse to viewing paper losses and experiencing the hedonic disutility of the information.

The tendency to avoid looking at losses/gains might be related to the response of investors to future losses/gains since latest login. An investor who dislikes viewing losses, for example, may be more likely to hold the stock. Aversion to viewing losses may correlate with the aversion to realizing losses. Hence, we might find a relationship between login behavior and the response to gains and losses since latest login. Previous studies suggest that experiencing losses causes changes in future behavior (Barberis and Xiong 2012, Heimer 2016, Imas 2016).

We, therefore, investigate the role of ostricity in sensitivity to gain since latest login for investors in our sample. To do so, estimate the sensitivity of each investor's login behavior to changes in the value of their more recently traded stock. We do so by estimating a separate regression for each investor, thereby obtaining an individual-specific ostricity coefficient. Splitting the sample at the median by this coefficient value, we reestimate our main models on the two samples. Estimates shown in Table 8 reveal that both samples yield significant results for the effects of gain since purchase, gain since latest login, and the interaction of the two dummies. The high-ostricity sample, however, shows slightly larger coefficients, hinting at the possibility that selective information avoidance may, to some extent, moderate the strength of the login-based disposition effect. There is, however, evidence that ostrich-type investors sell stocks more frequently than non–ostrich-type investors as indicated by the larger intercepts (i.e., they have a higher baseline rate). When compared with their baseline rates, a gain since the last login has largely similar effects across the two samples.

Table 8. The Effect of Gains Since the Last Login for Ostrich-Type Investors, Login-Day Sample

	$Sale_{ijt}$	
	Investors with below-median ostrich effect coefficients (1)	Investors with above-median ostrich effect coefficients (2)
Gain since purchase = 1	0.0010***	0.0012***
	(0.0004)	(0.0004)
Gain since latest login = 1	−0.0020***	−0.0023***
	(0.0003)	(0.0004)
Gain since purchase = 1 × Gain since latest login = 1	0.0082***	0.0124***
	(0.0005)	(0.0007)
Constant	0.0083***	0.0109***
	(0.0004)	(0.0004)
Observations	3,276,662	2,531,372
R^2	0.0012	0.0020

Notes. This table presents ordinary least squares regression estimates of Equation (4) for ostrich-type investors. Ostrich effect estimates were computed for each investor by regressing the probability of logging in on the day on the daily returns of the most recent stock traded. Investors who traded multiple stocks on the same day were excluded. Column (1) includes investors with below-median ostrich effect coefficients (3,751 investors), whereas column (2) includes investors with above-median ostrich effect coefficients (3,752 investors). Further, the sample includes investor × stock × days on which the investor made at least one login to the account. Standard errors are clustered by account and day.

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

5.8. Additional Extensions

5.8.1. Expectation Formation. The patterns we observe in the data could reflect the behavior 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 large positive earnings surprises (Luo et al. 2020). If investors in our sample 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, additional analysis rules out this alternative explanation. We split 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, consistent interaction effects exist in both the gain and loss domains of short-term returns (see Online Figure A6).

5.8.2. 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, 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 remains consistent with our main findings (see Online Table A21).

5.8.3. Additional Robustness and Sensitivity Tests. Additional robustness and sensitivity tests are presented in the online appendix accompanying this paper.

6. Discussion

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.[39]

For example, in a laboratory study closely related to our current study, Baucells et al. (2011, p. 508) presented participants with a price sequence for an imaginary stock on a graph on a computer screen and asked 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, "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; Ebbinghaus 1913, Murdock 1962, Ward 2002).[40]

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. (2010) 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: a reference point adapts to prior gains to a greater extent than to prior losses. This finding is also consistent with laboratory experiments conducted by Weber and Camerer (1998) in which subjects made portfolio decisions over multiple periods. They find evidence consistent with the hypothesis that the previous period's price of the stock served as a reference point.

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 in narrow framing and exhibit reference-dependent preferences in combination with a prospect theory realization utility function.[41]

The explanation for the disposition effect in Barberis and Xiong (2009), which is relevant to our discussion here, is as follows. Because of diminishing sensitivity to gains, investors prefer to realize 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. Because of diminishing sensitivity to losses, investors prefer to realize their loss in one single sale.[42] Hence, when deciding which stock to sell on a given day, investors tend to sell a little of a stock that is in gain, spreading the sale over many time periods, but prefer to hold onto their stocks in loss until the last time period (at which they 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 that 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 that 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 because of loss aversion. Whereas this account provides an explanation for an interaction effect between gain since purchase and gain since latest login, it does not immediately account for the strength of the interaction effect.[43] An alternative explanation is that there is a discrete downward jump in utility to the left of the reference point, illustrated in the modified prospect theory utility function in Online Figure A13, panel (b), suggested by Homonoff (2018) and discussed in Markle et al. (2018).[44] In the utility function illustrated in panel (b), the utility loss of a small loss outweighs the utility gain of a large gain because of 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.[45]

In our discussion of a possible extension of the Barberis and Xiong (2009) model—with either a high level of loss aversion or 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, in which any loss leaves a bad feeling. Research in psychology shows that small losses can effectively nullify large gains (Baumeister et al. 2001). Rozin and Fallon (1987, p. 32) 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, in which 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 framework we propose here shows that, by assuming that investors care only about the highest reference point (or the price that 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 framework of the disposition effect in which paying attention can create a new reference point against which future decisions are evaluated. Our framework 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 onto stocks that have made negative returns since the investor last logged in to the investor's 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 framework: investors tend to hold onto 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 behavior. The act of paying attention to one's online trading account generates an empirically important reference point that bears on future behavior. More generally, our paper contributes to a growing literature documenting the importance of attention for economic behavior and outcomes. In modern markets, attention is related to technology as is the case with online trading accounts and also attention to one's position relative to others via online social networks as in Heimer (2016). A natural extension to this work would be to consider whether investor attention is important among different types of investors, such as institutional and retail investors, as has been examined in the literature on the disposition effect (on which see Barber and Odean 2013). We suggest this as an avenue for future research.

Acknowledgments

An earlier version of this paper was titled "Investor Attention, Reference Points and the Disposition Effect."

Endnotes

[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 1999, DellaVigna et al. 2017) and 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 want 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 considers how multiple reference points affect choices on separate dimensions, such as income versus leisure (Crawford and Meng 2011) or goals versus experience (Markle et al. 2018). Yet none of the limited research involving naturalistic decisions made in economically meaningful contexts examines the effect of multiple reference points operating within the same domain, for example, different salient wage rate comparisons or, as in the current study, different prices against which a stock's current price could be compared.

[3] Most of these studies focuses 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. 2023 for its application to housing).

[4] 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.

[5] Exceptions include low-frequency events, such as in cases in which dividend payouts are automatically reinvested.

[6] One can 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.

[7] In a related piece of work, we provide an extensive analysis of lookup choices for the same pool of investors we employ here (see Quispe-Torreblanca et al. 2022). We demonstrate that investors devote disproportionate attention to already-known positive information about the performance of individual stocks within their portfolios.

[8] Other studies present mixed evidence on whether these features of prospect theory preferences give rise to a disposition effect (Kaustia 2010, Hens and Vlcek 2011, Henderson 2012).

[9] Previous studies suggest that first and last prices act as reference points. In a laboratory experiment that examines 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.

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

[11] 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.

[12] Although the selection of reference points is a behavioral feature of the framework, in Section 5.5, we provide a number of tests that rule out the possibility that our results are driven by the potential endogenous choice of login days.

[13] At each point in time, prices can go up or down with equal likelihood, for example, 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.

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

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

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

[17] 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 (1st and 99th percentiles) and in the distance from the portfolio day to the last transaction day (99th percentile) were also excluded. We also excluded accounts holding portfolios of zero net value on average (computed by averaging the portfolio value for the first business day of each month during the holding period). In the online appendix, we report results for existing accounts (accounts opened before April 2012), restricting only to stocks purchased within the sample period.

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

[19] Goetzmann and Kumar (2008) also show that U.S. investors tend to hold underdiversified 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, underdiversification is financially costly.

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

[21] Sicherman et al. (2015) explore login and transaction behavior among defined contribution retirement savings account holders in the United States using data provided by Vanguard. They find that, on average, over a two-year period, investors log in to their accounts on 85 days, whereas, over the same period, making only two 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.

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

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

[24] Online 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 centered 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.

[25] 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 day on which the investor sells the stock, would have a correlation of one between returns since purchase and returns since latest login.

[26] Online Table A2 summarizes the correlation between returns since purchase and returns since latest login.

[27] Online Figure A3 shows the equivalent plot using the login-day sample.

[28] Online Figure A2, panel (a), shows the analogous relationship for stock returns since latest login. The plot shows a v-shape centered on 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 Online Figure A2) also displays a v-shape pattern. 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 the figure panel (a) of relevance here, which can be seen on closer inspection, is that the probability of the stock being sold is higher when returns since latest login are positive than when they are negative. This 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 latest login. This disposition effect is very clear in the regression estimates, which are shown in Table 3.

[29] Online Figure A5 shows the equivalent plot from the login-day sample.

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

[31] Although past peak prices are not our main focus here, in Online Figure A8, we investigate the triple interaction between gains since the most recent login, gains since purchase, and gains since the past peak price (Online Figure A8). The plot uses a sample of new investors described in Quispe-Torreblanca et al. (2023). This sample is reminiscent of the sample studied here except for a few sample selection restrictions described in detail in Quispe-Torreblanca et al. (2023) (e.g., observations without a past peak price are excluded from the analysis). Results show that losses on any of these margins reduce the probability that the investor will sell even when other margins show gains. These findings are in accordance with the

predictions of our framework: that when investors are exposed to more than one salient reference point, they base their decisions using the most aspirational or demanding price as reference point.

[32] For an exhaustive analysis on how investors allocate attention to their portfolio, see Quispe-Torreblanca et al. (2022), in which we analyze lookup 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.

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

[34] Visibility at the weather station is measured on a six-point scale between "excellent" and "very poor" based on visibility (in meters). Because of 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 8 am and 8 pm) and use this variable as the exclusion restriction.

[35] Results are shown in Online Table A13. These findings are consistent with a large literature documenting an increase in indoor activities on poor weather days, for example, Cheng et al. (2022) find high Google search volume of firm names used by Yahoo Finance in Taiwan; Gilchrist and Sands (2016) show larger movie viewership; and Xu (2018) document more crowdfund-backing activities, through more internet usage, on Kickstarter).

[36] 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.

[37] We use the term "mutual fund" to refer to delegated asset classes traded in the United Kingdom, which include mutual funds, unit trusts, investment trusts, and exchange-traded funds. In our sample, mutual funds account for 6% of total security purchases by value over the sample period.

[38] Online Figure A14 illustrates these results.

[39] There is also evidence for a peak-end rule in the psychological evaluation of a time series of events, in which 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. (2023).

[40] 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- and 60-day moving averages).

[41] As Barberis and Xiong (2009) observe, whereas 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 payoff 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).

[42] 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 gain in both cases because of diminishing marginal utility from the zero point.

[43] In our estimates, either a negative return since latest login or a negative return since purchase is sufficient to almost eliminate the disposition effect. Whereas 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 Online Figure A13, 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 Online Figure A13, 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.

[44] Homonoff (2018) examines the impact of a $0.05 tax versus a $0.05 bonus on the use of disposable plastic bags. She finds that, whereas the tax decreased disposable bag use by more than 40 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.

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

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