The Portfolio-Driven Disposition Effect*

Li An, Joseph Engelberg, Matthew Henriksson,

Baolian Wang, and Jared Williams‡

May 25, 2019

Abstract: In simple univariate tests, the disposition effect for a stock nearly disappears if the portfolio is at a gain. We find a large disposition effect when the portfolio is at a loss. The portfolio-driven disposition effect that we document is not explained by extreme returns, portfolio rebalancing, simultaneous transactions, or investor sophistication/skill. We consider hedonic mental accounting and preferences over both paper and realized gains/losses as potential explanations for our findings.

* This paper is a combination of two earlier working papers that simultaneously documented the same phenomenon: one by Engelberg, Henriksson, and Williams, and the other by An and Wang (titled, "Hedonic Mental Accounting"). We thank Nick Barberis, Justin Birru, James Choi, Vasu Ellapulli, Cary Frydman, Samuel Hartzmark, Matti Keloharju (discussant), Dong Lou, Elena Pikulina (discussant), Tarun Ramadorai, David Solomon (discussant), Eshwar Venugopal (discussant), Neng Wang, Jianfeng Yu, Ning Zhu, and seminar participants at the 2019 AFA conference, 2018 CEPR Household Finance Conference, 2018 NFA conference, PBC Tsinghua, and 2018 Florida Finance Conference for their helpful feedback. We especially thank Terry Odean for sharing the individual trading data.

‡ Contact: Li An, Tsinghua University, PBC School of Finance, (email) anl@pbcsf.tsinghua.edu.cn; Joseph Engelberg, University of California – San Diego, Rady School of Management, (Email) jengelberg@ucsd.edu (Tel) 858-822-7912; Matthew Henriksson, University of South Florida, Muma College of Business, (Email) mhenriksson@mail.usf.edu; Baolian Wang, University of Florida, Warrington College of Business, (Email) baolian.wang@warrington.ufl.edu; and Jared Williams, University of South Florida, Muma College of Business, (Email) jwilliams25@usf.edu.

I. Introduction

There is perhaps no more robust trading phenomenon than the disposition effect, the observation that investors are more likely to sell an asset when it is at a gain than when it is at a loss (Shefrin and Statman, 1985). The disposition effect has been documented among US retail stock investors (Odean, 1998), foreign retail investors (Grinblatt and Keloharju, 2001), institutional investors (Shapira and Venezia, 2001), homeowners (Genesove and Mayer, 2001), corporate executives (Heath, Huddart, and Lang, 1999), and in experimental settings (Frydman, Hartzmark, and Solomon, 2018).

Standard explanations for the disposition effect – such as tax considerations, portfolio rebalancing, and informed trading – have been proposed and dismissed (Odean, 1998), leaving explanations that rely on investor preferences.[1] For example, Barberis and Xiong (2009) show that the disposition effect is most reliably generated in a model of prospect theory preferences with realization utility.

While much of the empirical and theoretical work related to the disposition effect focuses on individual assets, most households hold a portfolio of assets. This paper then asks a simple question: does the disposition effect operate at the individual asset level or at the portfolio level? In doing so we ask the related question of whether investors have preferences over their individual stocks or over the portfolio as a whole.

To illustrate the idea, consider an investor with three stocks: X_1, X_2, and X_3. The disposition effect says $\Pr(X_i \text{ is sold} \mid X_i \text{ is at a gain}) > \Pr(X_i \text{ is sold} \mid X_i \text{ is at a loss})$ for all *i*. If the investor has preferences over each individual stock, then we would expect those three probabilistic statements to be independent of each other. However, if she has preferences over the

1 Belief-based interpretations have also been proposed. Odean (1998) discusses that the disposition effect is consistent with investors having an irrational belief in price mean reversion. Ben-David and Hirshleifer (2012) argue that belief-based interpretations can offer a possible explanation for the V-shapes of both the selling and buying schedules that they document.

portfolio, we'd expect the disposition effect for Stock X_1 to depend on the state of the remaining portfolio (X_2 and X_3).

The latter is precisely what we find in the data. When we examine the trading among the roughly 78,000 households in the Barber and Odean (2000) dataset, we find a trivial disposition effect for Stock X if the investor's portfolio is up. In this case, Stock X is almost as likely to be liquidated when it is at a paper gain as a paper loss. However, if the portfolio is down, Stock X is more than twice as likely to be liquidated when it is at a paper gain as a paper loss. Given how pervasive the disposition effect is, it is surprising to find that the disposition effect largely disappears among the 61% of observations in which portfolios are up in the Barber and Odean (2000) dataset. We find similar patterns using data from a Chinese retail brokerage firm between 2000 and 2009.

We document this relationship between the performance of an investor's portfolio and her tendency to exhibit a disposition effect in both univariate analysis and regressions with a host of fixed effects. Perhaps the cleanest way to see our finding is via a matched-sample analysis. More specifically, we compare selling decisions across investors made on the same day for the same stock that is also purchased on the same day (i.e., controlling for stock×day×time-owned fixed effects). In other words, our identification comes exclusively from the fact that different investors face different portfolio-level capital gains due to the other stocks in their portfolio. The results are nearly identical to those from the baseline analysis.

We next show that this "portfolio-driven disposition effect" (PDDE) is not merely a repackaging of earlier research on the disposition effect. Specifically, we show that it is distinct from the rank effect documented by Hartzmark (2015); it is not driven by tax considerations or portfolio rebalancing; and we provide evidence that it is not driven by correlations between investor sophistication or skill and the disposition effect (Dhar and Zhu, 2006; Grinblatt, Keloharju, and Linnainmaa, 2012).

Because the PDDE is strong evidence that investors do not exclusively engage in narrow framing when making their liquidation decisions, we propose two models where investors engage in broader portfolio-level framing that might explain the PDDE.

The first is a form of hedonic mental accounting (Thaler 1985; 1999). When investors liquidate a stock, they have a choice: they can frame their gain/loss narrowly - at the stock level - or broadly - at the portfolio level. Hedonic mental accounting (HMA) predicts they will frame their transaction in a way that makes them feel best. For example, an investor who sells a losing stock as part of a broader winning portfolio, would prefer broad framing to narrow framing under HMA. Because utility functions are increasing in asset returns, she would rather think about her transaction as liquidating part of her winning portfolio than think about her transaction as realizing a loss. [2] We show that a model which extends Barberis and Xiong (2009) with preferences like these naturally generates a PDDE. The intuition is straightforward: if an investor's portfolio is at a gain and she can think about selling any stock within it as realizing part of this gain, she won't care if the individual stock she sells is a winner or a loser. Hence, there will be more of a disposition effect when the portfolio is at a loss.

If the moderating effect of portfolio performance on the disposition effect indeed originates from mental accounting, we should expect to see a stronger moderating effect from assets that investors find easier to put into the same mental account as US common stocks.[3] Presumably, it is easier for an investor to combine capital gains from one US stock with those from other US stocks, compared with capital gains from other assets. Among other assets, it is

[2] One reason investors might strategically frame their decisions this way is cognitive dissonance. Cognitive dissonance is defined as the discomfort that arises when a person recognizes that he or she makes choices and/or holds beliefs that are inconsistent with each other (Festinger, 1957). When investors face losses, there is a disconnect between the belief that the investor makes good decisions and the fact that the investor has now lost money on the position. When selling a losing stock in a winning portfolio, investors can avoid cognitive dissonance by thinking of the portfolio as a whole. Chang, Solomon, and Westerfield (2016) provide both empirical and experimental evidence that cognitive dissonance affects the strength of the disposition effect among investors.

[3] This approach is reminiscent of the widely used method in economics to test whether money from different sources is fungible (see Thaler [1999] for a review and Hastings and Shapiro [2018] for a recent example). Tversky and Kahneman (1981) and Thaler (1999) argue that one important purpose of mental accounting is to economize on time and thinking costs, and notional boundaries can alter decisions.

easier to combine US stock-generated gains with those from foreign stocks than those from mutual funds. Empirically, we find that the moderating role of portfolio performance on the disposition effect monotonically decreases as the source of the capital gain bears less resemblance to US common stocks. The moderating effect of a one-dollar capital gain generated by other common stocks is twice as large as the same one-dollar gain generated by foreign stocks or other stock-type securities, and it is four times as large as a one-dollar gain from investment in mutual funds.

The second explanation we consider for the PDDE is that investors derive utility from both paper gains and realized gains, and they take utility by realizing gains when they have disutility from unrealized losses. Economists have assumed that investors derive utility from *paper* gains (Barberis and Huang, 2001; Barberis, Huang, and Santos, 2001; Barberis and Xiong, 2009) as well as *realized* gains (Barberis and Xiong, 2009; Barberis and Xiong, 2012; Henderson, 2012; Ingersoll and Jin, 2013). In an appendix, we show that loss-averse investors who hold these preferences simultaneously can also generate a PDDE. The intuition here is also straightforward: the marginal utility an investor receives from realizing a gain is not the same in all states of the world. Specifically, when a loss-averse investor is experiencing the disutility from a large portfolio of unrealized losses, the marginal realization utility from a gain will be greater than if she is sitting on a large portfolio of unrealized gains. Hence, there will be a stronger disposition effect when an investors' portfolio is down.

Following this intuition, we find that this condition – when the stock is at a gain and the portfolio is at a loss– is the one in which investors are most likely to keep their stock sale in cash. That is, in the case when their portfolio is down and they realize a gain, it is important to investors that the gain "stay" realized rather than creating a new mental account as in Frydman, Hartzmark and Solomon (2018). Conversely, when her portfolio is performing well, she receives positive utility from the paper gains, so she should feel less need for a burst of utility from realizing a gain.

Our paper is organized as follows. We describe our data and methodology in Section 2. In Section 3, we introduce the PDDE and show that it is a robust phenomenon. In Section 4, we show that the PDDE is not explained by prior research, i.e., it is a new phenomenon. In Section 5, we suggest possible explanations for the PDDE, and Section 6 concludes.

II. Data and Methodology

We begin with the large discount broker dataset utilized by Barber and Odean (2000). The raw data include trading activity for roughly 78,000 households with roughly 158,000 accounts between January 1991 and November 1996. Following Odean (1998), we restrict our main analyses to the US common stocks because the price data needed for this study are not available at a daily frequency for many other asset classes, and stock transactions account for more than half of all the transactions in the data set. In later analyses, we also examine how the performance of other asset classes affects investors' stock trading.

The unit of observation is an account-stock-day triple. Given that we have approximately 104,000 accounts that hold common stock, with an average of 3.5 stocks per account over the 1,497 trading days in our sample, we begin with approximately 545 million observations. Following Ben-David and Hirshleifer (2012), we filter the raw dataset and make several simplifying assumptions. First, we include only securities that are identified as common shares and appear in CRSP. Because prices in the discount brokerage dataset are not adjusted for splits and dividends, we rely on CRSP factor adjustments to account for these issues. Second, we remove any account-stocks with negative commissions since they may indicate a reverse transaction. Third, investor-stocks that include short sale transactions are removed to avoid any misrepresentation in the value-weighted average price (VWAP) of portfolio holdings. Fourth, we exclude positions for which we do not have information on the purchase price, which primarily arises when investors purchased stocks before the start of our sample period. Finally, since our primary area of interest is the effect of portfolio performance on investor behavior, we keep only account-days with at least two common stock holdings. After applying these filters and rules, we are left with a dataset of 118,269,397 (account, stock, day) observations. We report summary statistics in Table 1.

[Insert Table 1 Here]

The traditional regression specification for measuring the disposition effect (Birru, 2015; Chang, Solomon, and Westerfield, 2016) uses the following equation:

$$Sale_{i,j,t+1} = \beta_0 + \beta_1 Gain_{i,j,t} + \epsilon_{i,j,t+1} \qquad (1)$$

where observations occur at the account (i), stock (j), and date (t) level. For every account-stock-day, *Sale* is a dummy variable equal to one if a sale occurs (including partial sales) and zero otherwise. Additionally, *Gain* is a dummy variable equal to one if the stock's return (price / VWAP – 1) is strictly positive and zero otherwise. With this structure, the mean of the dependent variable, *Sale*, is the probability of selling a given position. Thus, β_0 (the constant) measures the probability of selling a stock whose return is less than or equal to zero, and β_1 measures the increase in probability of selling a given stock if that stock's return is strictly greater than zero. Recently, Chang, Solomon, and Westerfield (2016) and many others show that β_1 is positive and statistically significant.

Our interest is the relationship between the disposition effect and the performance of the investor's portfolio. We analyze this relationship by estimating the following regression equation:

$$Sale_{i,j,t+1} = \beta_0 + \beta_1 Gain_{i,j,t} + \beta_2 Portfolio\_Gain_{i,t} + \beta_3 Gain_{i,j,t} \times Portfolio\_Gain_{i,t} + \epsilon_{i,j,t+1} \qquad (2)$$

where observations also occur at the account (i), stock (j), and date (t) level. Our additional variable, *Portfolio Gain*, is a dummy indicating whether or not the investor's stock portfolio is at a gain or a loss. We compute this variable by first summing up the gains/losses (in dollars) of the investor's positions in all of her stocks as of the given day. If the investor has a net gain in her holdings, *Portfolio Gain* takes the value of 1; otherwise, it is 0.

Our main coefficient of interest in (2) is β_3, the coefficient of the interaction term, which represents the difference in disposition effects for paper gain portfolios and paper loss portfolios. In equation (2), β_1 represents the disposition effect for paper loss portfolios, and the sum of β_1 and β_3 represents the disposition effect for paper gain portfolios.

III. The Portfolio-Driven Disposition Effect

A. Univariate Results

The phenomenon that we document in this paper, which we refer to as "the portfolio-driven disposition effect" (PDDE), can be illustrated with a simple figure.

[Insert Figure 1 Here]

We report these figures using two samples: (1) the full "unconditional" sample described in Section II and (2) the "sale-conditioned" subsample, consistent with many researchers who study the disposition effect that restrict attention to days in which the investor sells shares of any stock in her portfolio.[4] The unconditional sample has 118,269,397 observations, and the sale-conditioned sample has 1,482,590 observations, indicative of how seldom an account makes a sale. We also show two versions for each sample based on whether the stock of interest is included in portfolio holdings. We refer to the portfolio that includes (excludes) the stock of interest as "Total Portfolio" ("Rest of Portfolio").

[4] See Odean (1998) and Chang, Solomon, and Westerfield (2016) among others.

Consider the probability that an investor sells one of her holdings. This is plotted in the portion of Figure 1 labeled “All Portfolios.” The disposition effect can be seen visually as the difference between the green (the probability of selling a gain) and the red (the probability of selling a loss) bars. The black bars (which represent all stocks) are included to show the weighted average. In Panel A, the probability of selling a given stock is approximately 0.25%. Adding the condition that a given stock’s return is positive (the green bar) increases that probability of an investor selling to 0.29%. The difference in the probability of selling a gain versus a loss is approximately 8 bps. In other words, an investor is approximately 41% (0.29%/0.21% – 1) more likely to sell a gain than a loss. Similarly, in Panel B, the probability of selling a given stock is approximately 20%. The probability is much larger due to the sale condition, and yet similar patterns emerge. Adding the condition that a given stock’s return is positive (the green bar) increases that probability of an investor selling to 23%. The difference in the probability of selling a gain versus a loss is approximately 7%. In other words, an investor is approximately 45% (23%/16% – 1) more likely to sell a gain than a loss. This is the disposition effect.

To illustrate the PDDE, we reproduce these probabilities for two different scenarios: (1) the investor’s portfolio is at a gain (the portion labeled “>0”), and (2) the investor’s portfolio is at a loss (the portion labeled “≤ 0”). We report the figures using two definitions of portfolio performance: (left) excluding the stock of interest and (right) including the stock of interest. The PDDE refers to the fact that the disposition effect is concentrated in the scenario where her portfolio is at a loss; when her portfolio is at a gain, the disposition effect is minimal. In fact, in the unconditional sample, the disposition effect decreases to approximately 2 bps (5 bps) when excluding (including) the stock of interest from portfolio performance. Conversely, the disposition effect more than quadruples when comparing to observations in which the portfolio is at a paper loss, resulting in a disposition effect of approximately 21 bps (22 bps) excluding (including) the stock of interest. This means that when an investor’s portfolio excluding (including) the stock of interest is at a paper loss, she is 103% (107%) more likely to sell a gain than a loss. In Panel B, we note qualitatively similar results for the sale-conditioned sample, although the effect is somewhat stronger in the unconditional sample and when excluding the stock of interest.

Across all variations in Figure 1, the probability of selling gains seems to drive the change in the disposition effect based on portfolio performance. While the probability of selling losses changes slightly when conditioning on the rest of the portfolio's performance, the probability of selling gains increases considerably.[5]

In the rest of the paper, we simply document that the PDDE is a robust phenomenon, we examine whether it can be explained by prior studies of the disposition effect, and we consider implications and plausible explanations for the phenomenon.

B. Baseline Regressions

We estimate equation (2) and report the results in Table 2 using a host of fixed effects and four variations of regression methodologies.

[Insert Table 2 Here]

In Panel A, we run equation (2) on our sample described in Section II using a linear probability model. Column 1 of Table 2 shows the baseline results with no fixed effects. Columns 2-4 add fixed effects controls for account, date, and stock, respectively. Finally, column 5 displays our most controlled specification with account, date, and stock fixed effects. Because investors' selling decisions are likely correlated within account, within stock, and within date, we cluster our standard errors across all three of these dimensions following the procedure of Cameron, Gelbach, and Miller (2011).

[5] We will later show that when we control for unobservable investor, date, and stock characteristics, the PDDE is predominantly driven by the propensity to sell *losers*.

Across all specifications in Panel A of Table 2, the coefficient on the interaction term (*Gain x Portfolio Gain*) ranges from −0.17% to −0.21% and is statistically significant well below the 1% level (t-stats between −18 and −21). These results suggest that the PDDE illustrated in Figure 1 is unlikely to be explained by unobservable investor, time, or stock characteristics that affect investors' propensity to sell shares of stock. Furthermore, the disposition effect is economically insignificant when the portfolio is at a paper gain. Recall the disposition effect when the portfolio is at a paper gain is measured by the sum of the coefficient from *Gain* and the coefficient on the interaction term (*Gain x Portfolio Gain*). The economic significances are minimal across all specifications with the largest effect in column 5, which has a sum of 0.087%. Even in this specification, the disposition effect is more than three times larger when an investor's portfolio is at a loss (0.293%) than when it is at a gain.

In Panel B of Table 2, we consider alternative specifications.[6] Recall that our unit of observation is (account, stock, date). Clearly, the variables *Gain* and *Portfolio Gain* are mechanically related. In column 1, we therefore consider an alternative definition for *Portfolio Gain* by disregarding the gain/loss of the stock associated with the observation when computing an investor's portfolio gain.[7] Note that in this specification, *Portfolio Gain* now varies at the account, date, and stock level. Not only does the interaction coefficient remain negative and statistically significant, but it is more negative. Therefore, economic and statistical significance increase using this alternate definition.

Thus far, we have considered the performance of an investor's portfolio based on her current holdings. In other words, once an investor liquidates a stock that was at a $10,000 gain, this $10,000 gain is no longer factored into her portfolio's performance. This is consistent with the literature that typically assumes that selling a stock closes the mental account associated with

[6] In Table 2 Panel B, we show only the most controlled fixed effects specification of each alteration. However, we show additional variations in Appendix Tables A1, A2, A3, A4, and A5. The results are similar.
[7] For example, consider an account whose portfolio consists of three stocks: stock A, stock B, and stock C. For each observation associated with stock A, we compute *Portfolio Gain* by considering the gains/losses of stocks B and C, but not stock A. Similarly, for the observations associated with stock B, we compute *Portfolio Gain* by considering the gains/losses of stocks A and C, but not B.

this stock. Frydman, Hartzmark, and Solomon (2018) find that investors roll an account from one asset to another if they sell the original asset and buy another within a short period of time. We therefore also examine an alternative approach in which we consider the investor's past liquidated gains/losses for some specified period of time when measuring the performance of her portfolio. We follow this approach in column 2. In column 2, we include all of an investor's liquidations in the past year (in addition to her current holdings) when computing her portfolio gain. The interaction coefficient remains negative and highly statistically significant.[8] The fact that the interaction coefficient remains negative and statistically significant is important, because it suggests that we are not simply capturing a selection effect whereby investors who exhibit a disposition effect mechanically have a poor portfolio performance, because they hold onto their losing positions rather than liquidating them.

In column 3, we add several control variables and return bracket fixed effects. The control variables are chosen and calculated following Ben-David and Hirshleifer (2012). The return bracket fixed effects are used to control the V-shaped relation between holding returns and selling probability as documented by Ben-David and Hirshleifer (2012). Specifically, we split all the observations by holding period return into 52 brackets: (-∞, -50%), ⋯, [-4%, -2%), [-2%, 0), [0, 2%), [2%, 4%), ⋯, [50%, -∞). Again, we document the PDDE is robust.

In column 4, we run the same regression as Panel A column 5 on the sale-conditioned subsample. While the magnitudes of the coefficients are larger due to the sale condition, the interaction coefficient remain negative at -8.67% and significant (t-stat -21.1).

Finally, we estimate a Cox proportional hazard model with time-varying covariates instead of the linear probability model in all other specifications. The main difference between the linear probability model and the hazard model is that the linear probability model implicitly defines the

[8] In Appendix Table A3, we include the liquidations in the past 1, 3, 6, 12, and 24 months. The interaction coefficient remains negative and statistically significant at the 1% level for all specifications. We also note that the interaction coefficient declines (in absolute value) monotonically as we move further back in time when maintaining past liquidating gains/losses.

disposition effect as the difference between the propensity to sell winners (PGR) and losers (PLR). In contrast, the hazard regression defines the disposition effect as the ratio between PGR and PLR. We follow Seru, Shumway, and Stoffman (2010) in counting every purchase of a stock as the beginning of a new position, and we assume a position ends on the date the investor first sells part or all of his holdings. Specifically, we estimate

$$h_{i,j,t+1} = \phi \quad exp\{\beta_1 Gain_{i,j,t} + \beta_2 Portfolio\_Gain_{i,t} + \beta_3 Gain_{i,j,t} \times Portfolio\_Gain_{i,t} + \gamma X\} \qquad (3)$$

where the hazard rate, $h_{i,j,t}$, is investor i's probability of selling position j at time t conditional on not selling the position by time t-1, and ϕ is the baseline hazard. The Cox proportional hazard model does not impose any structure on the baseline hazard, and Cox's (1972) partial likelihood approach allows us to estimate the coefficients without estimating the baseline hazard. The β_1 coefficient in the above specification provides a measure of the disposition effect when an investor's portfolio is at a loss—a positive value of β_1 indicates a greater willingness to sell winners relative to losers. The expression $\exp(\beta_1)$, the hazard ratio, captures the ratio between the probability of selling winners and the probability of selling losers when the investor's portfolio is at a loss. The expression $\exp(\beta_3)$ captures the moderating effect of portfolio gain on the disposition effect measured based on the ratio.

We report the results from the hazard regression described above in column 5. We use the original definition of *Portfolio Gain*, which includes the gain/loss of the stock associated with the observation. Similar to the other columns, we stratify by account. The stratified analysis is similar to the fixed effect analysis in the linear probability model. However, we do not include 3-way stratification tests due to computational limitations of the hazard model. The coefficient on *Gain* is 1.018, which indicates that, when portfolio is at a loss, investors are $e^{1.018} \approx 2.77$ times more likely to sell a winning stock compared to a losing stock. The coefficient of the interaction is −0.761, which indicates that, when portfolio is at a gain, investors are $e^{1.018-0.761} \approx 1.29$ times more likely to sell a winning stock compared to a losing stock. This outcome is consistent with our previous results using the linear probability model, confirming that the disposition effect is significantly weaker when the portfolio is at a gain.

C. Matching Analysis

In an ideal experiment, we would compare identical positions in a particular stock owned by identical investors, with the only difference being the investors' portfolio performance. By identical positions, we mean that both have the same stock, on the same day, and were purchased on the same day and at the same price. By identical investors, we mean investors who would make the same decisions when facing any economic scenario. Because of our large sample, we have identical positions; however, this ideal experiment is not feasible because we do not have identical investors. In this matching analysis, we approximate the ideal experiment by comparing identical positions owned by different investors after controlling for investor fixed effects. Specifically, we add stock×day×time–owned triple–way fixed effects into the regressions. By doing this matching, we keep the stock, day, and the holding period the same and focus on the portfolio return variation across investors. We also only keep the stock-day-time–owned observations when there are at least two investors for the same combination. The number of observations is around 37.8% of the entire sample. We find that the coefficient of the interaction term is negative and highly significant without account fixed effects (-0.056%, t-stat -9.6) and even more so with account fixed effects (−0.144%, t-stat 20.9). We report these results in columns 1a and 1b of Table 3.

[Insert Table 3 Here]

With the inclusion of stock×day×time–owned fixed effects, investors' holding returns only vary because they may have purchased the stocks at different prices within the same day. Thus, the variation in purchase price is already very small by construction. In the second specification, columns 2a and 2b, we further require that the holding period returns are exactly the same by adding stock×day×time–owned×purchase price quadruple-way fixed effects. Relative to the first specification, this filter reduces the sample by around two thirds, and yet the PDDE strengthens in both instances to -0.101% (t-stat -10.7) without account fixed effects and -0.174% (t-stat -15.1) with account fixed effects. In the third specification, columns 3a and 3b, we further exclude the observations in which the position was built up with multiple purchases. The second and the third specifications have a similar number of observations and coefficients values because most of the positions are built up with one single purchase.

The results are very similar across the three specifications. The magnitude of the interaction term is only slightly smaller compared to the baseline estimation in Table 2 (Panel A), which suggests that the baseline results are not significantly driven by the fact that stock-level characteristics could be different conditional on whether the portfolio is at a gain versus at a loss.

D. The Impact of the Magnitude of Portfolio Returns

In Table 4, we investigate the effect of the levels of portfolio returns. Specifically, we sort all the observations based on the magnitude of portfolio returns into ten brackets symmetrically arranged around zero: small returns between 0% and 5% (or between -5% and 0%), and all the way to large returns higher than 25% (or below -25%). We create ten dummy variables indicating each of these portfolio return brackets, and we interact each of them with the stock-level *Gain* dummy. The stock-level *Gain* dummy is perfectly collinear with the ten interaction terms and therefore is omitted. The coefficients of these interaction terms estimate the disposition effect for observations that fall into each of the portfolio return brackets.

[Insert Table 4 Here]

Table 4 presents the results using no fixed effects (column 1) and 3-way (account, stock, and date) fixed effects (column 2). In all the specifications, we control for portfolio return bracket fixed effects, but their coefficients are not reported. The decreasing pattern of the coefficients is evident in the results. For column 1, it is 0.184% when the portfolio return is lower than -25%, but it is only −0.011% when the portfolio return is more than 25%. Interestingly, the decreasing relationship has a hockey-stick pattern in both columns: it is almost flat when portfolio return is below -5% and only starts to decrease materially when portfolio return is higher than -5%. These results expand on the binary portfolio performance tests to show the expected negative relation between the level of portfolio returns and the disposition effect.

E. Subsample Analysis

We examine how the PDDE varies with individual demographics and portfolio characteristics. For investor characteristics, we study age and gender, and for portfolio characteristics, we examine trading frequency and holding period. For each characteristic, we group all observations into subsamples and conduct regression analyses using the same structure as was done in column 5 of Table 2, Panel A.

[Insert Table 5 Here]

Investors are grouped into three age groups: 1 to 40, 41 to 55, and greater than 55; 40 and 55 are the roughly the first and the third quartile of the age distribution. Trading frequency is calculated as the unconditional selling propensity of an investor over the whole sample period. We sort all the investors into two trading frequency groups. Following Ben-David and Hirshleifer (2012), we split all observations into three groups based on prior holding period (days): 1 to 20, 21 to 250, and greater than 250. Because not all demographic information is available on all investors, the combination of all the subsamples is sometimes smaller than the whole sample.

Several observations emerge from the results in Table 5. First, the moderating role of portfolio gain on the disposition effect is prevalent across all subsamples. Second, the moderating effect of portfolio gain is similar across different age and gender groups. Finally, the magnitude of the interaction coefficient is larger when the prior holding period is shorter and among high trading frequency investors.

F. Aggregate Implications

The PDDE has natural aggregate implications. Although conventional wisdom suggests that the disposition effect is idiosyncratic and specific to each individual investor, the moderating role of portfolio performance can generate aggregate and cyclical effects because the performance of individual portfolios is commonly driven by the overall market. Therefore, one implication of our documented trading pattern, the PDDE, is that all investors tend to exhibit the disposition effect around similar points in time, or in other words, there should be a "disposition effect comovement." To test this prediction, we calculate the level of the disposition effect across different investor groups quarter by quarter both in the US and a Chinese sample.[9]

We stratify investors by gender, age, portfolio size (into ten equal-sized groups), and in the fourth test, randomly (into ten equal-sized groups). For each investor group in each quarter, we estimate the average disposition effect by running equation (1) using the investor-stock-day observations.

[9] The Chinese data set contains similar information as the US data set and is also similar to the Chinese data set used in other studies (Feng and Seasholes, 2004, 2005; Frydman and Wang, 2019). The data originate from a brokerage company that has multiple branches throughout China and serves approximately half a million investors. We use the daily trade file and daily position file to construct a holding sample containing an observation for each investor-stock-day the same as we did with the US trade data. However, our Chinese data spans a more recent period from January 2000 to December 2009. Additionally, we do not have to remove short sale positions since short selling was not allowed in China during our sample period. Due to computational capacity limitations, we randomly selected 20% of the investors. After applying this procedure, we have 97,000 unique investors, 8 million sales, and nearly 83 million investor-stock-day observations. In Appendix Table A6, we show the PDDE is robust to this Chinese sample as well, providing external validity.

Figure 2 presents the results. The y-axis is the value of the disposition effect, and the x-axis is quarter. We see that investors with different gender, age, portfolio size, and other characteristics comove very closely over time in the level of disposition effect.

[Insert Figure 2 Here]

Moreover, our documented trading pattern not only implies the comovement across investors, but it also predicts that this comovement (the time-series variation of the disposition effect) should be related to past market performance. After a bull market, most investors should be facing portfolio gains, and therefore, the average disposition effect would be weak. In contrast, a bear market would lead to portfolio losses for most investors, and the average disposition effect would be strong.

[Insert Table 6 Here]

In Table 6, we calculate the simple correlation between the quarterly average disposition effect across all the investors and various horizons of past market returns. We find the quarterly average disposition effect is negatively correlated with the past market return at all horizons in both samples, except when the past market return is measured over the previous quarter in the US sample. More interestingly, when we compare the correlation across different horizons, we find that the negative correlation between the disposition effect and past market return peaks at six quarters in the US sample and at two quarters in the Chinese sample. These numbers match surprisingly well with the average holding horizon of investors in the two samples, respectively. The average market turnover during our sample periods is 65% (implying an average holding period of six quarters) in the United States and 200% (implying an average holding period of two quarters) in China.

Figure 3 presents the time series of the average disposition effect and the past market returns for the US and Chinese sample, with past market returns measured over the past six quarters for the US and over two quarters for China. The negative correlation between the disposition effect and past market return is evident. With the caveat that the time series is short and the test is in no way to exclude other possible omitted factors, these findings are consistent with our documented trading pattern.

[Insert Figure 3 Here]

The vast literature on investor behavioral biases mostly focuses on the individual level and suggests that people may make mistakes in response to signals that are specific to themselves. If these biases are idiosyncratic and can be averaged out across investors, these mistakes would have little relevance in generating aggregate asset pricing effects. Here we document a systematic and cyclical component in one of the most robust behavioral patterns, the disposition effect. The clustering of behavioral biases, especially when related to market conditions, may be important in understanding how investor behavior affects asset pricing.

IV. Relationship to Prior Research on the Disposition Effect

In this section, we examine whether the PDDE we document is simply a manifestation of prior empirical research concerning the disposition effect.

A. The Rank Effect

We first test whether extreme stocks drive the PDDE. Hartzmark (2015) finds that individual and mutual fund investors are more likely to sell their best and worst performing stocks on a given sale day. Intuitively, these extreme stocks grab the investor's attention and, as a result, are sold more often. In our setting, the attention-grabbing hypothesis could predict some of our results, but not others. For example, if an investor has one stock that is a winner and the rest losers, then this stock is very likely to be sold under both the attention-grabbing hypothesis (it is an extreme stock) and the PDDE (investors are very likely to sell their winners when the portfolio is at a loss). However, if an investor has one stock that is a loser and the rest winners, this stock is very likely to be sold under the attention-grabbing hypothesis because it is an extreme stock, but not the PDDE because losers are just as likely to be sold as winners are when the remaining portfolio is at a gain.

Nevertheless, in Table 7 we evaluate how the rank effect affects our empirical results. Specifically, in column 1 we add fixed effects indicating each of the 15 stocks with the best performance and the 15 stocks with the worst performance in an investor's portfolio, following Hartzmark (2015). We also require that an investor's portfolio contains at least five stocks. When the number of stocks in one's portfolio is less than 15, we just create as many rank fixed effects as possible. The interaction coefficient remains highly statistically significant after we control for the rank fixed effects.

[Insert Table 7 Here]

Column 2 restricts to only extreme observations (the best and worst holding for an account on a given date), and column 3 removes extreme stock observations. Not only are the interaction coefficients in both subsamples negative and highly significant, but also the effect is actually *stronger* for non-extreme stocks. In addition to the non-extreme observations having a stronger interaction coefficient of -0.224% (t-stat -24.7) vs -0.170% (t-stat -17.5) for extreme observations, the disposition effect *reverses* for paper gain portfolios of non-extreme holdings. This fact is illustrated by the observation that the interaction coefficient of -0.224% more than offsets the

Gain coefficient of 0.190% (t-stat 16.1).[10] These results suggest that the rank effect (Hartzmark, 2015) does not explain the PDDE.

B. Tax Incentives

Although tax-loss selling cannot explain why there is a disposition effect on average, Odean (1998) reports that the disposition effect reverses in December and attributes this fact to tax-loss selling.[11] Additionally, we conduct our analyses in the US tax-exempt accounts. Columns 4 and 5 of Table 7 report the regression results splitting the US sample by tax-exempt and taxable accounts, respectively. Although the PDDE is stronger for taxable accounts, the PDDE exists in this tax-exempt account sample significantly with an interaction coefficient of -0.119% (t-stat -11.1). This outcome suggests that tax-loss selling cannot explain the PDDE.

C. Portfolio Rebalancing

Although Odean (1998) provides evidence that portfolio rebalancing does not explain the disposition effect, it is possible that portfolio rebalancing causes the PDDE that we document. For example, suppose all but one of an investor's stocks are at a loss. It is likely that the lone stock that is trading at a gain comprises a disproportionately large percentage of the investor's portfolio due to its gains and the rest of the stocks' losses. The investor might therefore want to liquidate some of her holdings in the stock that is at a gain in order to rebalance her portfolio. According to this explanation, we should expect investors to *partially* (not completely) liquidate their positions in the stock that is at a gain when the rest of the portfolio is at a loss. That is, we should expect the PDDE to disappear when we restrict attention to *complete* liquidations of stocks.

To test this, we adjust our specification to use a full liquidation dummy as the dependent variable, thus eliminating any variation from partial sales. In column 6 of Table 7, we report the

[10] Recall, the disposition effect for paper loss portfolios is the *Gain* coefficient, while the disposition effect for paper gain portfolios is simply the sum of the *Gain* coefficient and the interaction term.
[11] However, tax-loss selling cannot explain our findings based on the Chinese sample (Appendix Table A6) where the capital gains are not taxed.

full liquidation results. We see that the interaction coefficient of -0.214% (t-stat -22.3) is still negative and significant well below the 1% level and is nearly 80% of the magnitude of the *Gain* coefficient (in absolute value). This means that most of the disposition effect is eliminated when the remaining portfolio is at a gain when controlling for unobservable investor, time, and stock characteristics after removing partial liquidations from the dependent variable, i.e., the PDDE is very strong. Thus, portfolio rebalancing is an unlikely explanation for the PDDE.

D. Unobserved Sophistication/Skill

Grinblatt, Keloharju, and Linnainmaa (2012) analyze data on Finnish investors and document that high IQ investors are superior stock pickers and they exhibit less of a disposition effect. Hence, it's possible that high IQ investors (who do not exhibit a disposition effect and are superior traders) likely have portfolios at a gain, and low IQ investors (who are prone to the disposition effect and are inferior traders) likely have portfolios at a loss. In other words, it is possible that we are simply documenting a consequence of Grinblatt, Keloharju, and Linnainmaa's (2012) finding. We address this possibility in two ways. First, we use proxies for investor sophistication that have been used by prior researchers to see if our results differ across investor sophistication. Second, we decompose an investor's portfolio return into that which is driven by skill and luck, and we compare the moderating effecting of portfolio performance in each of these categories. If investor IQ drives our results, then the PDDE should be concentrated entirely within the portfolio return driven by luck while the portfolio return driven by skill should exhibit no moderating effect.

The trading data we use have several demographics characteristics available for a sub-sample of investors. We follow Dhar and Zhu (2006) in defining an investor's level of sophistication using income groups and occupation groups. Specifically, we classify investors with an annual income lower than $40,000 into the low-income category, investors with annual income between $40,000 and $100,000 into the medium-income category, and investors with an annual income more than $100,000 into the high-income category. We classify individuals as working in "professional" occupations if they report working in "professional/technical" or "managerial/administrative" positions. We classify individuals as working in "nonprofessional" occupations if they report working in "white collar/clerical," "blue collar/craftsman," or "service/sales." Dhar and Zhu (2006) document that investor sophistication is negatively correlated with the disposition effect, so we test whether the PDDE holds for all subsamples of investors, or if it disappears when we separate investors based on their level of sophistication.

Table 7, columns 7 – 11, report our results on five sub-samples based on sophistication-related proxies: non-professional, professional, low income, medium income, and high income. In columns 7 and 8, we find that the portfolio's impact on the disposition effect, as denoted by the interaction coefficient, is nearly identical among professional (−0.188%, t-stat −12.7) versus non-professional (−0.191%, t-stat −11.3) investors. Therefore, this measure of sophistication does not seem to have any impact on our result. Additionally, in columns 9, 10, and 11 we observe respectively that the PDDE is nearly identical among low-income (−0.192%, t-stat −10.2), medium income (-0.204%, t-stat -13.8), and high-income (−0.200%, t-stat −11.7) investors. From these results, we conclude that our findings are not explained by the patterns documented by Dhar and Zhu (2006).

Our final approach is to decompose an investor's portfolio return based on their Daniel, Grinblatt, Titman, and Wermers (DGTW) performance.[12] More specifically, we decompose each investor's portfolio return into two components, one that is determined based on each stock's characteristic (size, book-to-market, and momentum), and the other based on the stock's performance relative to its matched portfolio (where the matching is done on size, book-to-market, and momentum). The idea is that while highly skilled investors might be able to pick stocks that perform well relative to the stock's matched portfolio, it is unlikely that individual investors can predict the future performance of the market, HML, SMB, and MOM factors. By

[12] See Daniel, Grinblatt, Titman, and Wermers (1997).

comparing the effect among instances in which positive portfolio performance is driven by luck versus skill, we can examine the likelihood that *Portfolio Gain* is simply proxying for investor skill.

We match each stock-date to one of the 125 (5 x 5 x 5) DGTW member groups for each year using the benchmarks available on Russ Wermers' website.[13] Since the DGTW member groups are created on June 30 of each year, we match all account-stock observations in July-December to the same year and all account-stock observations in January-June to the previous year's member group. With some abuse of terminology, we separate each account-stock-date's return into "alpha" and "beta," where beta represents the return (rather than a factor loading) of the corresponding DGTW portfolio and alpha equals the stock's return minus the matched portfolio. It trivially follows that any stock's cumulative return since the investor purchased it is simply the sum of its alpha and beta.

To separate portfolio return based on alpha and beta performance, we sum all the capital gains within both categories and divide by the cost basis of the investor's overall portfolio. This procedure generates portfolio-level *Alpha* and *Beta* return variables for each account-date and ensures the sum of *Alpha* and *Beta* is equal to the overall portfolio return. Intuitively, it follows that *Alpha* (*Beta)* is the return for the investor's portfolio that is driven by DGTW alpha (beta), or skill (luck).

Column 12 of Table 7 tests whether *Portfolio Gain* is simply a proxy for skill using DGTW performance benchmarks. By interacting *Gain* with *Alpha* and *Beta* independently, we can determine if the PDDE (negative, significant coefficient on *Gain***Portfolio Gain*) is driven primarily by one of the two categories that proxy for skill and luck. Although we observe the interaction with *Beta* is more negative (-0.789%, t-stat -14.41), the interaction of *Gain* and Alpha is still negative and statistically significant well below the 1% level (-0.460%, t-stat -15.54).[14] In

[13] The DGTW benchmarks are available via
http://terpconnect.umd.edu/~wermers/ftpsite/Dgtw/coverpage.htm.
[14] It is worth noting that for this specification, the coefficients are not directly comparable in economic magnitudes to other columns since we use continuous return variables for *Alpha* and *Beta* while *Portfolio Gain* is a dummy variable in other columns.

terms of economic magnitudes, a 10% increase in the portfolio return driven by DGTW alpha (beta) decreases the disposition effect by approximately 11% (19%). The moderating effect of portfolio performance on the disposition effect is present in both *Alpha* and *Beta* categories. If *Portfolio Gain* was simply a representation of investor skill, we would have seen the interaction of *Gain* and *Alpha* as non-negative. Therefore, we conclude that *Portfolio Gain* is not simply a proxy for investor skill.

V. Possible Explanations

The PDDE reveals that investors do not engage in pure narrow framing; rather, the performance of the rest of an investor's portfolio affects her decision to sell a particular stock. In this section, we propose two possible reasons for this PDDE. Our goal here is not to adjudicate which explanation, if either, generates the PDDE we document. Instead, we simply present possible models of investor preferences which we believe are intuitive and could generate this strong, portfolio-level effect we find in the data.

In the two subsections below, we describe the intuition behind each model. A more formal representation of these models, each presented in a common framework based on Barberis and Xiong (2009), can be found in the appendix.

A. Hedonic Mental Accounting

Mental accounting, a term coined by Thaler (1985, 1999), refers to the heuristics that people use to break complex financial decision-making into smaller, more manageable parts, with outcomes in one account being evaluated jointly, while outcomes in different accounts are evaluated separately. Regarding how mental accounts are formed, Thaler (1985, 1999) further proposes that, when faced with multiple outcomes and a situation involving a combination of the outcomes, investors may combine outcomes in a way that gives them the highest utility value.

In the context of the disposition effect, we know that people are reluctant to sell losing stocks, possibly due to prospect theory, realization utility, or cognitive dissonance. If an investor's portfolio has gone up, he or she can choose to evaluate gains and losses at the *portfolio level* and frame the action of selling losers as realizing part of the *overall gain*. For example, if an investor's portfolio is up and she liquidates a losing position, she can frame this as liquidating part of her (winning) portfolio rather than framing it as liquidating her (losing) position in the individual stock. In contrast, if her portfolio is at a loss, it is difficult for her to frame liquidating a loss as liquidating a gain: whether she views it as an individual stock or part of the larger portfolio, she is forced to acknowledge that she is liquidating a losing position. Therefore, within the context of the disposition effect, hedonic mental accounting predicts that the disposition effect should be weaker when the portfolio is at a gain. In the appendix, we consider a model similar to Barberis and Xiong (2009) except that it allows an investor to strategically choose how to frame her liquidations, either at the stock-level or the portfolio-level. We show that this typically generates a PDDE under standard parameters of the model.

If the PDDE is driven by the hedonic mental accounting mechanism described above, then the PDDE should become weaker when it is more difficult for the investor to group the position in the individual stock with other securities in her portfolio. For example, it is relatively easy to group US domestic stocks and foreign stocks together and convince oneself that both are stocks. It is less plausible for an investor to group individual stocks with closed-end mutual funds, and it is even harder to group individual stocks together with open-end mutual funds.[15]

Thus far, we have restricted attention to US stocks when analyzing the PDDE because US stock transactions compose the majority of investor trading in the data. In addition, we have daily price data that enable us to calculate returns every day. For other asset classes, investors do not trade as frequently, and prices are not available at a daily frequency for our sample period.

[15] Closed-end funds trade similar to stocks, while most open-end mutual funds do not trade on the open market and can only be bought or redeemed at the daily closing price.

Nevertheless, to test our hedonic mental accounting story, we examine how the performance of other asset classes moderates the disposition effect, and we compare this with the moderating effect of the performance of the investor's portfolio of individual stocks.

To conduct the analyses, we first make several necessary modifications to our baseline model. We revise the model in equation (2) to the following:

$$\begin{aligned} Sell_{i,j,m+1} = {} & \alpha + \beta_1 Gain_{i,j,m} + \beta_2 PortfolioRet_{i,m}^{CommonStock-j} \\ & + \beta_3 Gain_{i,j,m} \times PortfolioRet_{i,m}^{CommonStock-j} + \beta_4^{Category} PortfolioRet_{i,m}^{Category} \\ & + \beta_5^{Category} Gain_{i,j,m} \times PortfolioRet_{i,m}^{Category} + \varepsilon_{i,j,m+1}, \qquad (4) \end{aligned}$$

where m indexes month. $PortfolioRet_{i,m}^{CommonStock-j}$ is the portfolio return from the US common stock portfolio other than the focal stock j. $PortfolioRet_{i,m}^{Category}$ is the portfolio return from another category of asset classes. β_3, as in equation (2), measures the moderating effect of stock portfolio performance on the disposition effect, and $\beta_5{}^{Category}$ captures the moderating effect of portfolio gains that originates from other asset classes.

Aside from the addition of the interaction term between portfolio gains from other asset classes and the stock-level *Gain*, equation (4) contains three major differences from equation (2). First, the unit of analysis is investor-stock-month rather than investor-stock-day because daily prices for many asset classes are not available during the sample period. Second, portfolio return variables are defined as continuous variables rather than dummies, which allow us to decompose and compare returns contributed by each asset category. Third, we exclude the focal stock j in calculating the portfolio return of US common stocks. This specification aims to avoid the mechanical correlation between stock j's return and the return of the total stock portfolio when stock j is included. These modifications allow us to make fair comparisons between the magnitudes of β_3 and $\beta_5^{Category}$.

We follow Chang, Solomon, and Westerfield (2016) in calculating gains and losses for securities in each asset class at a monthly frequency. We use both the trade file and the position file, and we delete the observations where the holdings in the positions file cannot be matched with those inferred by trading records in the trades file. Purchase price is calculated as the volume-weighted average prices using the trades file. We then evaluate gains and losses for each security at each month end. Unlike common stocks, for which we have complementary price information from the CRSP data set (as in our main analysis), daily prices for many asset classes are not available during the sample period. Instead, we obtain a monthly snapshot of security prices as long as a security is held by at least one investor in the data set. To ensure fair comparison, we use monthly price information in the position file for securities in all asset classes including US common stocks. This approach yields 3.75 million investor-security-month level observations.

The brokerage firm that provides our data classifies all the asset classes into three general categories: stock-related securities, open-end mutual funds, and options. We follow Chang, Solomon, and Westerfield (2016) in excluding money market funds. Our final sample consists of 22 asset classes.[16] We further classify stock-related securities into US common stocks, foreign stocks (mainly Canadian stocks and ADRs), and other stock-type securities (mainly closed-end mutual funds, master limited partnership, and preferred stocks).[17] Appendix Table A7 presents details for the classification.

At each month end, we add up the capital gains within each category and normalize them by the sum of the cost basis of all securities in the portfolio. In this way, the sum of the five category returns is equal to the overall portfolio return. Moreover, capital gains accumulated by securities

[16] Many of the money market funds have a price that is fixed at some value such as one dollar per share, and hence there are very few observable gains and losses.

[17] These asset classes are indicated with the code "ST" in the Position Readme file (the data manual), but they are neither US common stocks nor foreign stocks. We stick to this letter code to avoid discretion in classification. These asset classes generally trade similar to stocks. Warrants are classified as "ST". We could also categorize warrants into the group of options, but given the very small number of observations (7,492), it would not have a discernable impact on our analysis. See Table A7 and A8 in the Appendix for more details on the categorization and summary statistics.

across categories are comparable because, given an investor-month, both β_3 and $\beta_5^{Category}$ capture the marginal effect of the same dollar amount of portfolio returns.

To conduct our analysis, we require that an investor holds at least two common stocks as well as securities in other asset classes in the given month. This final sample consists of 738,910 observations.[18]

[Insert Table 8 Here]

We first check the robustness of our main results in this sample by considering all the securities in defining overall portfolio returns. The results are reported in Panel A of Table 8. In columns 1 - 5, we analyze the moderating effect of an investor's overall portfolio return on the disposition effect. These models differ in terms of the choices of fixed effects—with no fixed effects, with account fixed effects, with month fixed effects, with stock fixed effects, and with all three. In columns 6 – 10, we exclude the focal stock j in calculating portfolio returns. Similar to our main results, in all specifications in this monthly sample, the overall portfolio return has a highly significant negative coefficient, which suggests that the disposition effect on trading a single stock becomes weaker as the overall portfolio return becomes more positive.

We then decompose the overall portfolio return into capital gains originating from the five categories and compare their moderating effects. We pit capital gains from US common stocks against those from the other four categories one by one. To be included in the regression, an investor in a given month needs to hold at least two common stocks and at least one security in the asset category being examined.

[18] We do not repeat this exercise on other asset classes for several reasons. First, our regression design requires that the investor holds at least two securities in the asset class in question as well as securities in other asset classes, which greatly reduces the number of observations available. Second, Chang, Solomon, and Westerfield (2016) show that in many delegated assets, the disposition effect reverses or disappears.

We report the results in Panel B of Table 8. For each asset category, we run five specifications similar to Panel A. A few observations emerge. First, the moderating effect of US common stock portfolio (excluding the focal stock) is highly statistically significant across all the models, and the coefficients all have a similar magnitude. Second, the moderating effect of capital gains generated by other asset categories is smaller than that of US common stocks, as indicated by the smaller coefficients (in terms of the absolute value) of the second interaction term in the regressions.

The third, and perhaps most interesting, observation is that the magnitude of the coefficient of the interaction term decreases, both in magnitude and in statistical significance, as the asset category becomes less similar to US common stocks. Taking the average estimation across the five specifications, the moderating effect of one unit of capital gains generated by other US common stocks in the portfolio is 1.9 times as large as that of foreign stocks, 2.8 times as large as that of other stock-type securities, and 3.6 times as large as that of mutual funds. The moderating effect of capital gains generated by options is estimated to have the opposite sign, but the coefficients are all statistically insignificant.

The findings show that investors treat capital gains differently depending on the source of their capital gains. These results support the hedonic mental accounting hypothesis.

While our interpretation is compelling, it is obviously difficult, if not impossible, to directly observe people editing their mental accounts when their portfolio has gone up or down. US common stocks and mutual funds differ in delegation, trading methods, and other dimensions. These differences might explain to a certain extent why capital gains from them are not fully fungible. However, US common stocks and foreign stocks are remarkably similar, as the majority of foreign stocks in our sample are Canadian stocks and ADRs, which are mostly listed and traded in the US. The moderating effect of US common stock portfolio is twice as large as that of foreign stocks, and this magnitude raises a challenge for alternative explanations. Our findings suggest that, although money should be fungible, it might not be fungible in investors' minds.

B. Utility over both Paper Gains/Losses and Realized Gains/Losses

The second model we consider is one in which investors have preferences over *both* realized and unrealized gains and losses. Frydman et al. (2014) conduct experiments of trade in an asset market, and they measure subjects' brain activity using functional magnetic resonance imaging. They find evidence that subjects' brains exhibit activity consistent with them (1) receiving pleasure upon learning that their positions have increased in value, and (2) experiencing extra pleasure when gains are realized. This is consistent with the idea that investors receive utility from both unrealized and realized gains/losses, with realizations producing enhanced effects.

The interaction between preferences over realized and unrealized gains/losses naturally generates a PDDE. The idea is the following: when an investor's portfolio is at a gain, she has received a lot of positive utility from the paper gains. The positive utility causes her to feel psychologically strong and hence more willing to realize a loss and take the resulting realization (dis)utility. Hence, there is less of a disposition effect in this scenario as she is willing to realize her losses. Conversely, if her portfolio is at a loss, she has received a lot of negative utility from the paper losses, which leaves her psychologically fragile. In this scenario, she is loath to experience additional disutility by realizing a loss; rather, she is likely to realize a gain in order to reduce her disutility from her paper losses. It follows that there is a strong disposition effect when her portfolio is down. We formalize this intuition in the appendix with a model that considers both the realization utility in Barberis and Xiong (2009) as well as utility from unrealized gains/losses.

To develop a testable prediction of this explanation, we consider what investors do once they sell their stock: do they keep it in cash or do they reinvest it in a different stock? Frydman, Hartzmark, and Solomon (2018) provide strong evidence that people do not "close" their mental accounts when they liquidate a stock and reinvest the proceeds into a new stock; rather, they continue to use the amount they invested in the initial stock as a reference point when deciding whether or not to liquidate their position in the new stock. According to this view, investors should be less likely to receive a burst of realization utility whenever they sell shares at a gain and reinvest the proceeds into a new position; rather, the bursts of realization utility should occur when investors realize a gain and "close" the mental account by not reinvesting the proceeds into a new stock. Hence, if our results are driven by investors receiving utility over both paper gains/losses and realized gains/losses, then we should expect investors to be unlikely to invest in a different stock whenever they sell a stock at a gain and their portfolio is at a loss; keeping their mental account open in this way would prevent them from receiving the burst of positive realization utility from realizing the gain.[19]

To test this, we take the sample of account-days in which the investor sells exactly one stock. Our dependent variable is a dummy for whether or not she purchases shares of a different stock (*Reinvest Dummy*). Our independent variables of interest are the four dummies representing the possible scenarios for whether the stock that she sold was at a gain or a loss and whether her portfolio was at a gain or a loss at the time she sold the stock. We predict that investors should be unlikely to reinvest whenever the stock that they sold was at a gain and their portfolio was at a loss.

We report the results of this test in Table 9.

[Insert Table 9 Here]

The variable *Loss_Gain* takes the value of one if the stock sold is at a loss and the portfolio is at a gain. The same naming convention follows for the other independent variables. The variable

[19] In contrast, if portfolio rebalancing (discussed in Section IV.C) explains the PDDE, we should expect investors to be more likely to reinvest when they sell a stock at a gain and the portfolio is at a loss.

Gain_Loss is omitted. Thus, each coefficient is interpreted as the difference in reinvestment probability from the case in which the stock is at a gain and the portfolio is at a loss.

In Table 9, almost all coefficients are positive and statistically significant below the 1% level. With the exception of the *Gain_Gain* scenario, investors are consistently more likely to reinvest their proceeds versus the *Gain_Loss* scenario. These results are consistent with the idea that investors are eager to realize gains and more likely to hold on to that positive utility than when they sell losses. Once we include account fixed effects in columns 2 and 5, we note that even the *Gain_Gain* scenario becomes positive and statistically significant, indicating that investors are even more likely to keep the cash from their sale and *not* reinvest whenever their portfolio is at a loss (the *Gain_Loss* scenario). We interpret this as investors refraining from reinvesting the proceeds because they want to close the mental account and lock in the realized gain.

VI. Conclusion

The disposition effect is a stock-level phenomenon. But individuals rarely hold single stocks; they often hold portfolios. The purpose of this paper has been to answer the question: does the stock-level disposition effect depend on the portfolios they hold? Considering the totality of evidence in both U.S. and Chinese data, the answer appears to be "yes" and in a particular way: the disposition effect seems to be stronger (weaker) when a portfolio is at a loss (gain).

This portfolio-driven disposition effect is robust to a variety of controls and does not seem to be a repackaging of previously documented research concerning the disposition effect. However, it is consistent with investors who engage in hedonic mental accounting or have preferences over both realized and unrealized gains and losses.

The PDDE we document has aggregate implications. Specifically, it predicts that the average disposition effect across all investors will be stronger after market downturns than market booms which we and others (Bernard, Loos, and Weber, 2018) find empirical support for. These findings suggest that there is a systematic and cyclical pattern in one of the most robust behavioral phenomena, the disposition effect. The dynamics of behavioral biases, especially when it is related to market conditions, can be an important component in understanding how investor behavior affects asset pricing. We leave this possibility for future research.

References

Barber, B. and T. Odean, 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance* 55, 773–806.

Barberis, N. and M. Huang, 2001, Mental Accounting, Loss Aversion, and Individual Stock Returns, *Journal of Finance* 56, 1247-1292.

Barberis, N., M. Huang, and T. Santos, 2001, Prospect Theory and Asset Prices, *Quarterly Journal of Economics* 116, 1-53.

Barberis, N. and W. Xiong, 2009, What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation, *Journal of Finance* 64, 751–784.

Barberis, N. and W. Xiong, 2012, Realization Utility, *Journal of Financial Economics* 104, 251–271.

Ben-David, I. and D. Hirshleifer, 2012, Are Investors Really Reluctant to Realize Their Losses? Trading Responses to Past Returns and the Disposition Effect, *Review of Financial Studies* 25, 2485–2532.

Bernard, S., B. Loos, and M. Weber, 2018, The Disposition Effect in Boom and Bust Markets, *working paper*.

Birru, J., 2015, Confusion of Confusions: A Test of the Disposition Effect and Momentum, *Review of Financial Stu*dies 28, 1849–1873.

Cameron, A. C., J. B. Gelbach, and D. L. Miller, 2011, Robust Inference with Multiway Clustering, Journal of Business and Economic Statistics 29, 238–249.

Chang, T., D.H. Solomon, and M. M. Westerfield, 2016, Looking for Someone to Blame: Delegation, Cognitive Dissonance, and the Disposition Effect, *Journal of Finance* 71, 267–302.

Cox, D. R., 1972, Regression Models and Life Tables, *Journal of the Royal Statistical Society B* 34, 187-220.

Dhar, R. and N. Zhu, 2006, Up Close and Personal: Investor Sophistication and the Disposition Effect, *Management Science* 52, 726–740.

Daniel K., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035–1058.

Feng, L. and M. Seasholes, 2004, Correlated Trading and Location, *Journal of Finance* 59, 2117-2144.

Feng, L. and M. Seasholes, 2005, Do Investors Sophistication and Trading Experience Eliminate Behavioral Biases in Finance Markets? *Review of Finance* 9, 305-351.

Festinger, L., 1957, *A Theory of Cognitive Dissonance* (Stanford University Press, Sanford, CA).

Frydman, C., N. Barberis, C. Camerer, P. Bossaerts, and A. Rangel, 2014, Using Neural Data to Test a Theory of Investor Behavior: An Application to Realization Utility, *Journal of Finance* 69, 907-946.

Frydman, C., S. Hartzmark, and D. Solomon, 2018, Rolling Mental Accounts, *Review of Financial Studies* 31, 362-397.

Frydman, C. and B. Wang, 2019, The Impact of Salience on Investor Behavior: Evidence from a Natural Experiment, *Journal of Finance* forthcoming.

Genesove, D. and C. Mayer, 2001, Loss Aversion and Seller Behavior: Evidence from the Housing Market, *Quarterly Journal of Economics* 116, 1233–1260.

Grinblatt, M. and M. Keloharju, 2001, What Makes Investors Trade?, *Journal of Finance* 56, 589–616.

Grinblatt, M., M. Keloharju, and J. Linnainmaa, 2012, IQ, Trading Behavior, and Trading Performance, *Journal of Financial Economics* 104, 339-362.

Hartzmark, S., 2015, The Worst, the Best, Ignoring All the Rest: The Rank Effect and Trading Behavior, *Review of Financial Studies* 28, 1024-1059.

Hastings, J. and J. Shapiro, 2018, How Are SNAP Benefits Spent? Evidence from a Retail Panel, *American Economic Review* 108, 3493-3540.

Heath, C., S. Huddart, and M. Lang, 1999, Psychological Factors and Stock Option Exercise, *Quarterly Journal of Economics* 114, 601-627.

Henderson, V., 2012, Prospect Theory, Liquidation, and the Disposition Effect, *Management Science* 58, 445-460.

Ingersoll, J., and L. Jin, 2013, Realization Utility with Reference-Dependent Preferences, *Review of Financial Studies* 26, 723-767.

Odean, T., 1998, Are Investors Reluctant to Realize Their Losses?, *Journal of Finance* 53, 1775–1798.

Seru, A., T. Shumway, and N. Stoffman, 2010, Learning by Trading, *Review of Financial Studies* 23, 705-739.

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

Shefrin, H. and M. Statman, 1985, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, *Journal of Finance* 40, 777–790.

Thaler, R., 1985, Mental Accounting and Consumer Choice, *Marketing Science* 4, 199-214.

Thaler, R., 1999, Mental Accounting Matters, *Journal of Behavioral Decision Making* 12, 183-206.

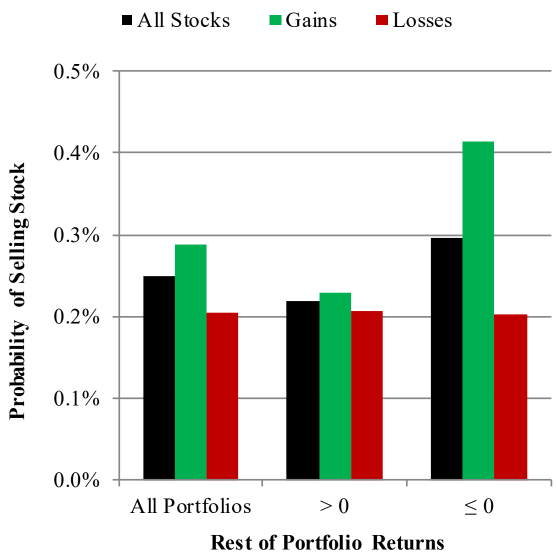
Tversky, A. and D. Kahneman, 1981, The framing of decisions and the psychology of choice, *Science* 211: 453-458.

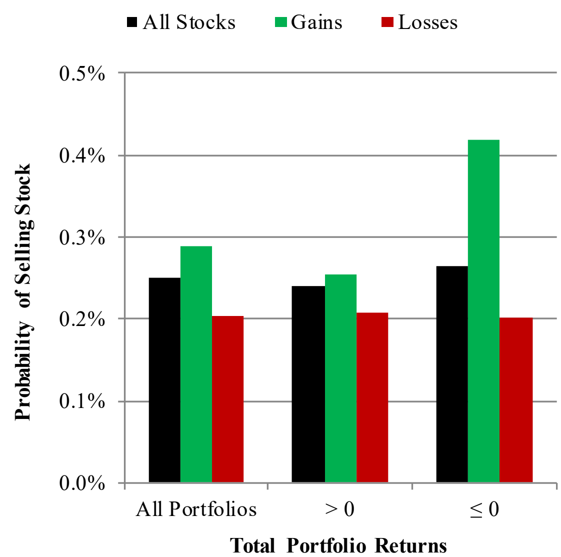
Wermers, R., 2004, Is Money Really "Smart"? New Evidence on the Relation Between Mutual Fund flows, Manager Behavior, and Performance Persistence, Available at SSRN: https://ssrn.com/abstract=414420 or http://dx.doi.org/10.2139/ssrn.414420.

Figure 1. Probability of selling a stock based on its return and the return of the portfolio

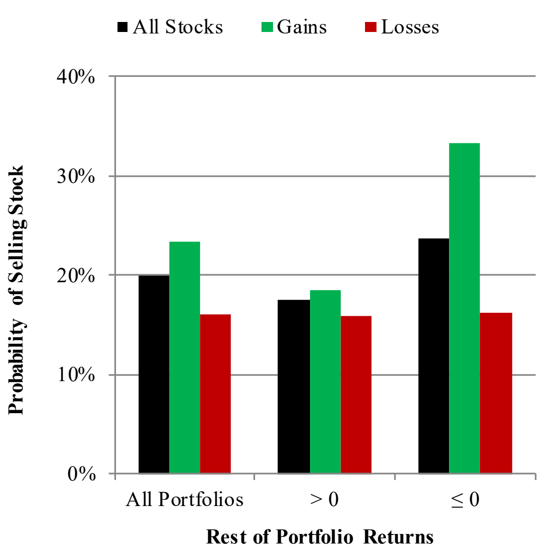
We report the probability of selling a stock (including partial sales) based on the stock's performance (gain versus loss) from the date the investor purchased the stock and the performance of the investor's portfolio of stocks. For each panel, we report two version: (left) conditioning on the rest of the portfolio performance (excluding the stock of interest) and (right) conditioning on total portfolio performance (including the stock of interest). In Panel A, we report the results using the full unconditional sample described in Section II. The results have 118,269,397 observations (54% stock gains, 46% stock losses; 60% rest of portfolio gains, 40% rest of portfolio losses; 61% total portfolio gains, 39% total portfolio losses). In Panel B, we report the results using only the account-date pairs in which at least one sale takes place (i.e. the "sale-conditioned" sample). The results have 1,482,590 observations (53% stock gains, 47% stock losses; 60% rest of portfolio gains, 40% rest of portfolio losses; 61% total portfolio gains, 39% total portfolio losses). We define gains (green bars) as strictly greater than zero while losses (red bars) include zeros.

Panel A. Unconditional Sample





Panel B. Sale-Conditioned Sample



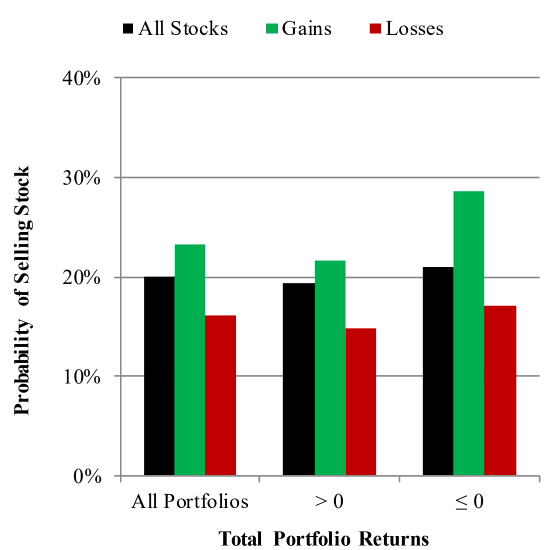
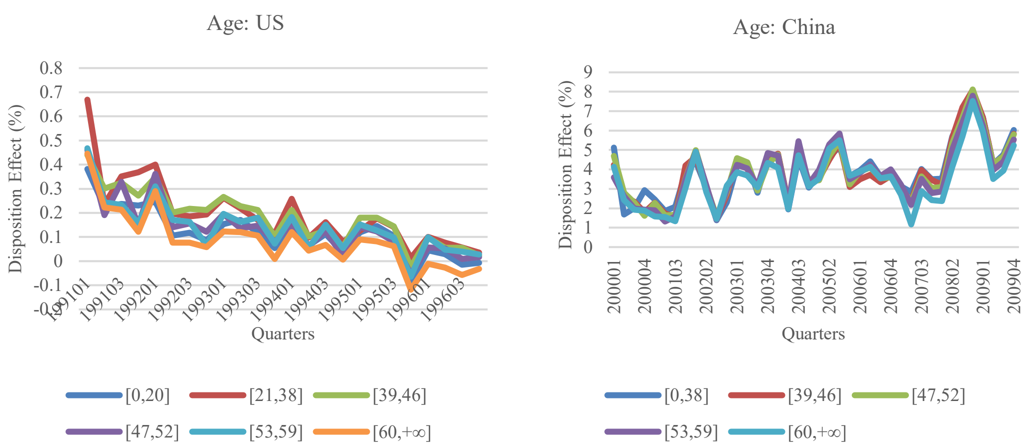


Figure 2. Comovement of the disposition effect

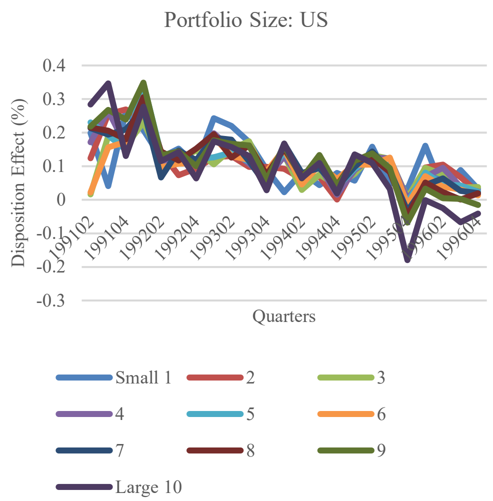
This figure presents the comovement of the disposition effect across different groups of investors: by gender (Panel A), by age (Panel B), by portfolio size (Panel C), and by random grouping (Panel D). The y-axis is the average disposition effect within each group of investors and quarter. The x-axis is quarter.

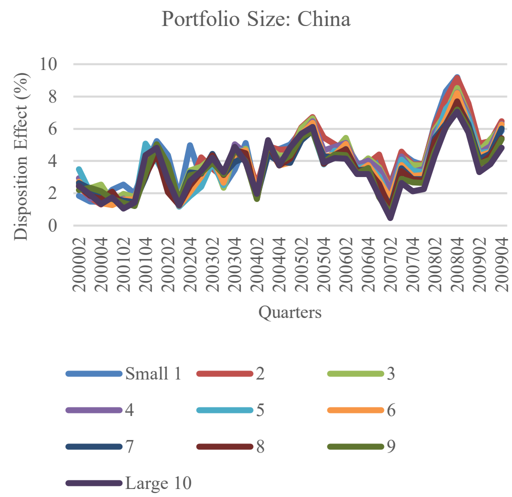
Panel A. by gender

Panel B. by age

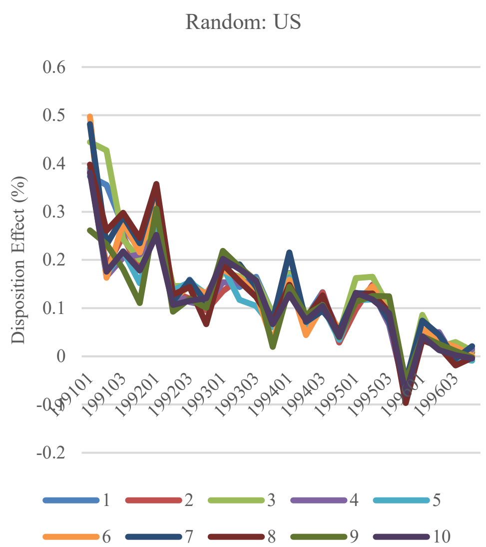


Panel C. by portfolio size





Panel D. random



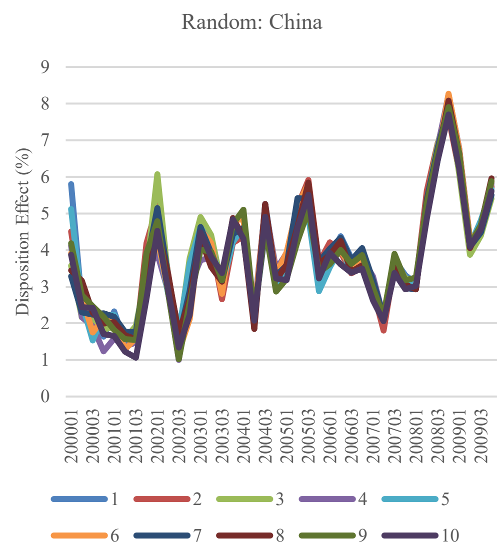
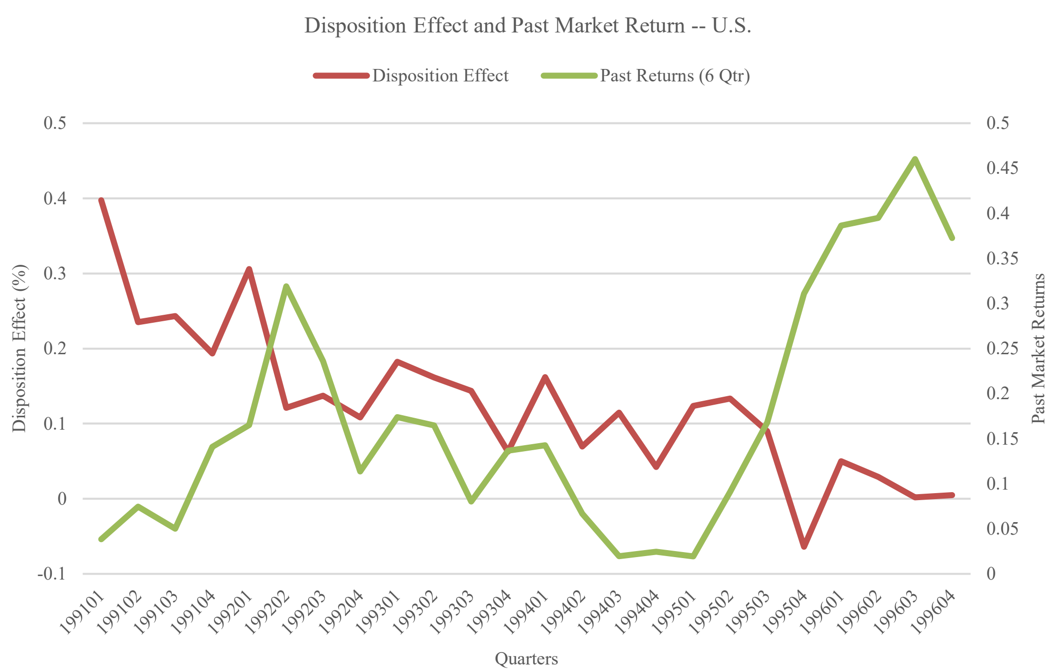


Figure 3. The disposition effect and past market return

This figure presents the time series of the disposition effect across all the investors and the past market returns. The first panel shows the US sample results, in which past market return is measured over the past six quarters. The second panel shows the China sample results, where past market return is measured over the past two quarters. The left-side of the y-axis is the disposition effect. The right-side of the y-axis the market returns. The x-axis is quarter.

Panel A. United States



Panel B. China

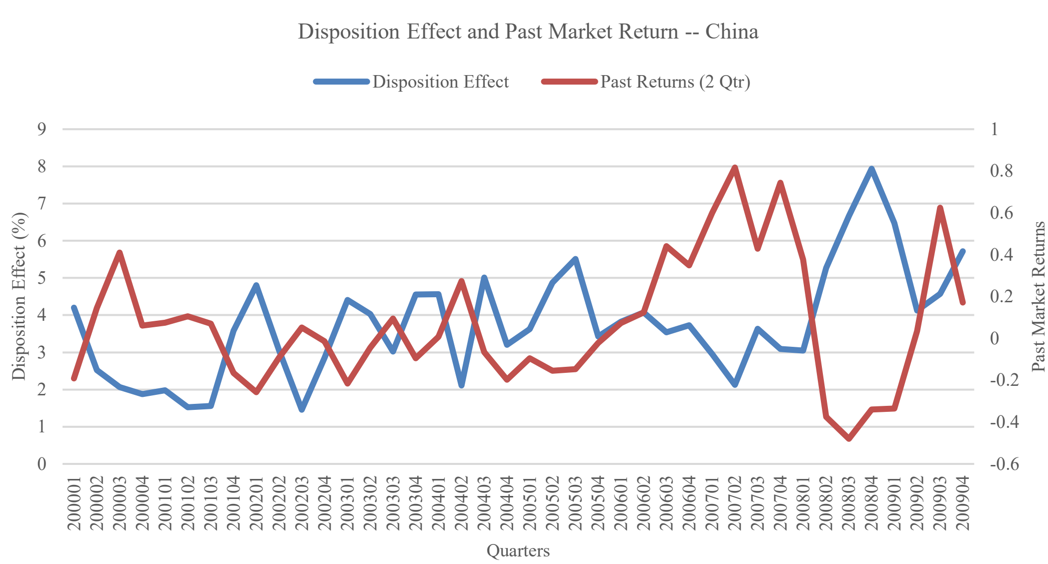


Table 1. Summary Statistics

This table presents the summary statistics for our sample. We group all observations into four categories by the values of *Gain* and *Portfolio Gain*. For each group, we report the mean and median for a few portfolio and stock characteristics. *Gain* is a dummy variable that equals 1 if the current price of a stock is higher than its purchase price after adjusting for splits and dividends, and 0 otherwise. *Ret* is the holding period return of an investor-stock-day. *Portfolio Gain* is a dummy variable that equals 1 if the portfolio is at a gain, and 0 otherwise. *Portfolio return* is calculated as the total dollar gains/losses across all stocks held by an investor at the end of day *t*, divided by the total purchase costs of these stocks. *Time owned* is the number of trading days since purchase. *Volatility* is the standard deviation of daily returns, calculated using the 250 days prior to the purchase. The last three rows report the number of observations (in millions), the number of sell observations, and the daily propensity to sell.

Panel A. with two or more stocks

	Mean				Median			
Gain	Yes	Yes	No	No	Yes	Yes	No	No
Portfolio Gain	Yes	No	Yes	No	Yes	No	Yes	No
Ret	0.526	0.240	-0.195	-0.273	0.277	0.125	-0.129	-0.214
Portfolio ret	0.333	-0.112	0.225	-0.182	0.213	-0.078	0.127	-0.140
Time owned	432	315	347	318	335	220	239	234
Volatility	0.026	0.029	0.031	0.035	0.022	0.025	0.027	0.031
Obs. (in millions)	50.74	13.05	21.64	32.84				
Sell Obs.	129,625	54,666	45,014	66,562				
% Sell	0.255	0.419	0.208	0.203				

Panel B. with one stock

	Mean		Median	
Gain	Yes	No	Yes	No
Portfolio Gain	NA	NA	NA	NA
Ret	0.445	-0.254	0.218	-0.189
Portfolio ret	NA	NA	NA	NA
Time owned	399	346	291	253
Volatility	0.027	0.033	0.023	0.029
Obs. (in millions)	15.41	15.96		
Sell Obs.	42,891	22,713		
% Sell	0.278	0.142		

Table 2. Baseline regressions

This table reports the results for the baseline regressions, as shown in equation (2). The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive paper gain, and 0 otherwise. Panel A employs linear probability model on the unconditional full sample. Panel B reports results using other specifications. In column (1), portfolio return is measured without considering the stock of interest. In column (2), besides tracking the unrealized portfolio gain at a given time point, we add capital gains realized in the past year as the overall portfolio return. In column (3), we control Sqrt(Time Owned), Log(Buy price), Volatility$^-$, Volatility$^+$, and return bracket fixed effects. Specifically, we split all the observations by holding period return into 50 brackets: (-∞, -50%), …, [-4%, -2%), [-2%, 0), [0, 2%), [2%, 4%), …, [50%, -∞). Column (4) restricts the sample to trading days that investors actually sell, and the coefficients are estimated using a linear probability model as specified in Odean (1998). Column (5) reports the hazard regression results. All coefficients are multiplied by 100. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Linear probability model

	(1)	(2)	(3)	(4)	(5)
Gain	0.216***	0.277***	0.214***	0.249***	0.293***
	(17.49)	(22.32)	(17.44)	(22.30)	(24.15)
Portfolio Gain	0.007	0.184***	0.000	0.018***	0.177***
	(1.55)	(20.86)	(0.07)	(4.22)	(21.99)
Gain*Portfolio Gain	-0.170***	-0.202***	-0.173***	-0.171***	-0.206***
	(-18.16)	(-19.85)	(-18.82)	(-18.79)	(-20.66)
Account FE	No	Yes	No	No	Yes
Date FE	No	No	Yes	No	Yes
Stock FE	No	No	No	Yes	Yes
Adj-R^2	0.000	0.011	0.001	0.001	0.012
Obs.	118,155,489	118,155,489	118,155,489	118,155,489	118,155,489

Panel B. Other specifications

	(1)	(2)	(3)	(4)	(5)
	rest of portfolio return	realized gains + paper gains	control for size of return	sale-conditioned sample	hazard model
Gain	0.328***	0.252***	0.120***	14.169***	1.018***
	(26.26)	(24.80)	(7.66)	(31.34)	(69.02)
Portfolio Gain	0.177***	0.129***	0.175***	2.350***	0.453***
	(23.49)	(21.47)	(22.72)	(9.25)	(34.87)
Gain*Portfolio Gain	-0.240***	-0.122***	-0.213***	-8.670***	-0.761***
	(-24.45)	(-17.71)	(-22.13)	(-21.08)	(-43.75)
Account FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	No
Stock FE	Yes	Yes	Yes	Yes	No
Adj-R^2	0.012	0.012	0.012	0.137	0.021
Obs.	118,155,489	118,155,489	118,135,228	1,479,983	110,554,055

Table 3. Matching sample analysis

This table reports the regression results of the matching analysis. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive paper gain, and 0 otherwise. In all the specifications, we add stock×day×time-owned fixed effects. In specification 1, we focus on the instances in which there are at least two observations for each stock×day×time-owned. In specification 2, we further require that the purchase price is the same. In specification 3, we further require that the positions were built up in one purchase. In columns (1b), (2b), and 3(b), we add account fixed effects. All coefficients are multiplied by 100. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
	same stock, same day, same time owned		same stock, same day, same time owned, same buy price		same stock, same day, same time owned, same buy price, one purchase	
Portfolio Gain	-0.042***	0.121***	-0.006	0.120***	-0.006	0.115***
	(-9.86)	(23.93)	(-1.09)	(15.40)	(-1.02)	(13.27)
Gain×Portfolio Gain	-0.056***	-0.144***	-0.101***	-0.174***	-0.103***	-0.163***
	(-9.58)	(-20.92)	(-10.69)	(-15.14)	(-10.14)	(-13.10)
Stock×day×time-owned FE	Yes	Yes	Yes	Yes	Yes	Yes
Account FE	No	Yes	No	Yes	No	Yes
Adj-R^2	0.055	0.068	0.162	0.183	0.171	0.195
Obs.	44,621,163	44,620,321	15,516,423	15,515,464	13,582,233	13,581,438

Table 4. The magnitude of portfolio returns

This table analyzes the disposition effect for different ranges of portfolio returns. We categorize portfolio returns into 10 groups and interact each of them with the Gain dummy. The dependent variable is a dummy variable that equals 1 if there is a sale (including partial sale) on day t+1, and 0 otherwise. Gain is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. Ranges of portfolio returns are indicated in the brackets. We also add the portfolio return bracket fixed effects.

	(1)	(2)
	Whole sample	Whole sample
Gain*(-∞, -25%)	0.184***	0.268***
	(13.06)	(18.54)
Gain*(-25%, -15%)	0.230***	0.321***
	(15.31)	(21.33)
Gain*(-15%, -10%)	0.206***	0.297***
	(15.29)	(21.17)
Gain*(-10%, -5%)	0.208***	0.298***
	(15.35)	(21.48)
Gain*(-5%, 0)	0.164***	0.238***
	(13.11)	(21.56)
Gain*(0, 5%)	0.177***	0.170***
	(14.71)	(19.96)
Gain*(5%, 10%)	0.130***	0.116***
	(11.06)	(15.14)
Gain*(10%, 15%)	0.104***	0.096***
	(9.54)	(13.40)
Gain*(15%, 25%)	0.061***	0.062***
	(6.60)	(9.98)
Gain*(25%, +∞)	-0.011	0.014**
	(-1.29)	(2.35)
Account FE	No	Yes
Date FE	No	Yes
Stock FE	No	Yes
Adj-R^2	0.000	0.012
Obs.	118,156,395	118,155,489

Table 5. Subsample analysis

This table reports the results in different subsamples, classified according to age, gender, trading frequency, and holding period, respectively. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive paper gain, and 0 otherwise. All coefficients are multiplied by 100. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Age			Gender		Trading Frequency		Holding period		
	1 to 40	41 to 55	>55	Female	Male	Low	High	1 to 20	21-250	>250
Gain	0.368***	0.316***	0.266***	0.242***	0.304***	0.046***	0.478***	0.799***	0.374***	0.114***
	(15.54)	(17.73)	(19.43)	(10.83)	(21.40)	(18.15)	(27.58)	(16.96)	(29.53)	(20.68)
Portfolio Gain	0.188***	0.176***	0.167***	0.141***	0.179***	0.033***	0.264***	0.379***	0.232***	0.085***
	(15.08)	(17.25)	(19.00)	(9.66)	(20.41)	(15.18)	(24.28)	(15.18)	(25.75)	(17.53)
Gain*Portfolio Gain	-0.203***	-0.207***	-0.198***	-0.130***	-0.207***	-0.026***	-0.311***	-0.513***	-0.264***	-0.077***
	(-9.63)	(-13.53)	(-15.96)	(-6.57)	(-17.46)	(-12.42)	(-20.21)	(-12.12)	(-24.25)	(-16.68)
Account FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.013	0.012	0.011	0.013	0.011	0.001	0.012	0.038	0.009	0.005
Obs.	13,457,088	25,463,703	63,473,068	6,654,721	59,492,437	62,089,688	56,065,798	6,792,633	49,293,469	62,068,963

Table 6. Correlation between the disposition effect and past market returns

This table reports the pairwise correlation coefficients between past market returns and the average disposition effect across all investors in quarter *t*, either in the US data set or the Chinese data set. We estimate the disposition effect by calculating the difference between the propensity to sell winners and the propensity to sell losers across all the investor-stock-day observations quarter by quarter.

	US	China
R_{t-1}	0.201	-0.469
$R_{t-2,t-1}$	-0.177	**-0.538**
$R_{t-3,t-1}$	-0.321	-0.467
$R_{t-4,t-1}$	-0.367	-0.449
$R_{t-5,t-1}$	-0.438	-0.434
$R_{t-6,t-1}$	**-0.540**	-0.371
$R_{t-7,t-1}$	-0.424	-0.319
$R_{t-8,t-1}$	-0.380	-0.262

Table 7. Alternative mechanisms

This table tests whether alternative mechanisms can explain our main finding. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive paper gain, and 0 otherwise. In Column (1), we add fixed effects indicating each of the 15 stocks with the best performance and the 15 stocks with the worst performance in an investor's portfolio, following Hartzmark (2015). In column (2), we only include the two extremely performed stocks: the best and the worst. In column (3), we remove the two extremely performed stocks. In columns (4) and (5), we run the test within tax-exempt accounts and taxable accounts, respectively. In column (6), the dependent variable is defined differently: it is equal to 1 for full liquidation and 0 otherwise. Partial sales are treated as 0. In Columns (7) - (11), we separate our sample by income levels and occupations, and we follow the specifications in Dhar and Zhu (2006). Column (12) tests if the PDDE is simply capturing the reduced disposition effect of skilled investors. We remove *Portfolio Gain* and replace the equation with *Alpha* and *Beta. Alpha (Beta)* is the continuous portfolio return generated by DGTW alpha (beta). All regressions include 3-way fixed effects for accounts, dates, and stocks as in previous tables. All coefficients are multiplied by 100. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Rank effect?		Tax incentives?		Rebalancing?			Investor sophistication?			Skilled?
	FE	Extreme	Non-Extreme	Tax-exempt	Taxable	Full	Professional			Income		DGTW
						Liquidation	No	Yes	Low	Medium	High	Portfolios
Gain	0.281***	0.215***	0.190***	0.226***	0.321***	0.269***	0.277***	0.287***	0.299***	0.310***	0.293***	0.421***
	(24.94)	(16.37)	(16.13)	(18.24)	(22.61)	(24.48)	(14.62)	(16.42)	(14.53)	(18.06)	(15.15)	(14.46)
Portfolio Gain	0.205***	0.006	0.063***	0.152***	0.186***	0.168***	0.165***	0.173***	0.170***	0.177***	0.178***	
	(25.67)	(1.48)	(8.89)	(17.25)	(20.90)	(22.35)	(14.61)	(15.94)	(13.62)	(17.67)	(15.49)	
Gain*Port Gain	-0.242***	-0.170***	-0.224***	-0.119***	-0.241***	-0.214***	-0.191***	-0.188***	-0.192***	-0.204***	-0.200***	
	(-24.11)	(-17.51)	(-24.74)	(-11.09)	(-19.77)	(-22.30)	(-11.29)	(-12.69)	(-10.24)	(-13.76)	(-11.72)	
Alpha												0.477***
												(16.61)
Beta												0.589***
												(15.07)
Gain*Alpha												-0.460***
												(-15.54)
Gain*Beta												-0.789***
												(-14.41)
3-way FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.012	0	0	0.013	0.011	0.01	0.01	0.01	0.013	0.012	0.011	0.022
Obs.	118,155,489	48,120,020	70,036,375	34,187,143	84,012,032	118,155,489	14,542,803	22,723,360	11,645,002	35,271,671	19,763,613	84,847,045

Table 8. The impact of overall portfolio performance and its components from various asset classes

This table reports the results on the moderating effect of the overall portfolio performance (Panel A) and various components of the overall portfolio performance (Panel B). The unit of analysis is investor-stock-month. Performance of securities are calculated following Chang, Solomon, and Westerfield (2016). The dependent variable is a dummy variable that equals 1 if there is any sale (including partial sale) from the end of month t to the end of month $t+1$, and 0 otherwise. *Gain* is a dummy variable that equals 1 if the stock in question has a positive return since purchase at month end t, and 0 otherwise. $PortfolioRet^{all}$ is a continuous variable that equals the sum of capital gains for all securities in the portfolio divided by the sum of cost basis for each of the security. $PortfolioRet^{all\text{-}j}$ is portfolio return after excluding the focal stock j. In Panel B, assets are classified into five categories: US common stocks, foreign stocks, other stock-type securities, mutual funds, and options. $PortfolioRet^{Category}$ is a continuous variable that equals the sum of capital gains for securities in a given category divided by the sum of cost basis for all securities in the portfolio. Different models differ in choices of fixed effects. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Overall portfolio performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gain	0.032***	0.036***	0.031***	0.035***	0.036***	0.030***	0.041***	0.029***	0.034***	0.039***
	(9.59)	(11.47)	(9.54)	(11.01)	(12.46)	(8.19)	(11.46)	(8.61)	(9.67)	(12.84)
$PortfolioRet^{all}$	0.043***	0.135***	0.029***	0.052***	0.124***					
	(3.88)	(8.82)	(3.22)	(4.52)	(10.88)					
Gain* $PortfolioRet^{all}$	-0.165***	-0.105***	-0.135***	-0.151***	-0.096***					
	(-15.68)	(-8.98)	(-10.62)	(-14.43)	(-7.88)					
$PortfolioRet^{all\text{-}j}$						0.021*	0.126***	0.007	0.029**	0.108***
						(1.77)	(8.88)	(0.76)	(2.46)	(10.56)
Gain* $PortfolioRet^{all\text{-}j}$						-0.157***	-0.145***	-0.132***	-0.138***	-0.132***
						(-15.44)	(-13.62)	(-11.43)	(-13.83)	(-11.01)
Account FEs	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Month FEs	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Stock FEs	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Obs.	738,910	738,910	738,910	738,516	738,486	738,910	738,910	738,910	738,516	738,486
Adj-R^2	0.004	0.130	0.017	0.044	0.152	0.004	0.130	0.018	0.043	0.152

Panel B. Different asset classes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Category =	Foreign Stocks					Other Stock-type Securities				
Gain	0.029***	0.039***	0.028***	0.032***	0.038***	0.032***	0.042***	0.030***	0.036***	0.041***
	(7.94)	(10.77)	(8.01)	(9.23)	(11.76)	(8.25)	(11.04)	(8.44)	(10.21)	(12.59)
$PortfolioRet^{US\ common\ stock\text{-}j}$	0.019	0.135***	0.011	0.029**	0.114***	-0.008	0.150***	-0.016	0.013	0.130***
	(1.28)	(8.09)	(0.81)	(2.08)	(8.37)	(-0.48)	(7.51)	(-0.94)	(0.72)	(7.82)
$Gain \times PortfolioRet^{US\ common\ stock\text{-}j}$	-0.181***	-0.165***	-0.156***	-0.163***	-0.153***	-0.206***	-0.185***	-0.174***	-0.190***	-0.174***
	(-12.62)	(-10.86)	(-9.66)	(-12.33)	(-9.51)	(-11.63)	(-10.22)	(-9.14)	(-10.74)	(-8.92)
$PortfolioRet^{Category}$	0.049**	0.096***	0.010	0.042**	0.079***	0.075**	0.037	0.032	0.028	0.071*
	(2.44)	(4.46)	(0.57)	(2.53)	(4.77)	(2.07)	(0.76)	(0.99)	(0.86)	(1.94)
$Gain \times PortfolioRet^{Category}$	-0.096***	-0.092***	-0.089***	-0.069***	-0.079***	-0.072*	-0.098**	-0.063	-0.025	-0.077*
	(-4.37)	(-4.70)	(-4.11)	(-3.96)	(-4.20)	(-1.89)	(-2.35)	(-1.65)	(-0.69)	(-1.94)
Account FEs	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Month FEs	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Stock Fes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Obs.	480,647	480,647	480,647	480,238	480,213	319,644	319,644	319,644	319,273	319,248
Adj-R^2	0.004	0.129	0.016	0.049	0.154	0.005	0.119	0.018	0.055	0.151

Panel B. Different asset classes (Cont'd)

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Category =			Mutual Funds					Options		
Gain	0.025***	0.032***	0.022***	0.030***	0.032***	0.054***	0.063***	0.054***	0.056***	0.059***
	(5.27)	(6.73)	(4.97)	(6.25)	(7.59)	(5.52)	(7.30)	(6.32)	(5.72)	(6.64)
$PortfolioRet^{US\ common\ stock\text{-}j}$	0.050*	0.152***	0.049**	0.052*	0.131***	-0.022	0.063	-0.012	-0.026	0.005
	(1.82)	(4.99)	(2.23)	(1.92)	(5.98)	(-0.40)	(1.61)	(-0.26)	(-0.54)	(0.10)
$Gain \times PortfolioRet^{US\ common\ stock\text{-}j}$	-0.228***	-0.173***	-0.188***	-0.181***	-0.137***	-0.209***	-0.157**	-0.182***	-0.128**	-0.098
	(-8.39)	(-7.10)	(-6.59)	(-7.56)	(-5.69)	(-2.98)	(-2.60)	(-2.73)	(-2.28)	(-1.61)
$PortfolioRet^{Category}$	-0.056	0.276***	-0.117*	0.037	0.230***	-0.063	0.120	-0.093	-0.052	0.057
	(-0.78)	(3.05)	(-1.97)	(0.54)	(3.04)	(-0.71)	(1.56)	(-1.28)	(-0.81)	(0.92)
$Gain \times PortfolioRet^{Category}$	-0.045	-0.077	-0.018	-0.079	-0.034	0.079	0.038	0.045	0.087	0.052
	(-0.65)	(-1.10)	(-0.26)	(-1.15)	(-0.49)	(0.91)	(0.56)	(0.64)	(1.16)	(0.81)
Account FEs	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Month FEs	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Stock FEs	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Obs.	128,437	128,437	128,437	128,007	127,974	27,857	27,857	27,857	27,286	27,226
$Adj\text{-}R^2$	0.003	0.160	0.022	0.076	0.207	0.006	0.199	0.038	0.137	0.286

Table 9. Reinvestment probabilities

We report the difference in probabilities of reinvesting cash from a sale based on stock and portfolio performance. The dependent variable is *Reinvest Dummy* which takes the value of one if the investor makes a stock purchase different from the stock that was sold within two days of the original sale and zero otherwise. The variable *Loss_Gain* is one if the stock sold is at a loss and the portfolio is at a gain. The same convention follows for the other independent variables. The variable *Gain_Loss* is omitted. Thus, the coefficients are interpreted as the difference in probability from the *Gain_Loss* scenario. We restrict attention to account-days in which exactly one sale occurs to avoid ambiguity. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011).

Dependent Variable: Reinvest Dummy

	(1)	(2)	(3)	(4)	(5)
Loss_Gain	0.096***	0.087***	0.089***	0.095***	0.076***
	(13.08)	(18.71)	(12.34)	(13.51)	(16.24)
Loss_Loss	0.072***	0.045***	0.077***	0.078***	0.053***
	(12.31)	(11.01)	(13.87)	(14.10)	(13.10)
Gain_Gain	0.009	0.042***	-0.004	0.009	0.030***
	(1.40)	(11.31)	(-0.68)	(1.46)	(8.00)
Account FE	No	Yes	No	No	Yes
Date FE	No	No	Yes	No	Yes
Stock FE	No	No	No	Yes	Yes
R-squared	0.006	0.299	0.023	0.038	0.333
Observations	197,496	197,496	197,496	197,496	197,496

Appendix

"The Portfolio-Driven Disposition Effect"
Li An, Joseph Engelberg, Matthew Henriksson, Baolian Wang, and Jared Williams

Table A1. Linear probability model, portfolio return is measured without considering the stock of interest

This table is the same as Panel A of Table 2, except that portfolio return is measured without considering the stock of interest. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive return, and 0 otherwise. All coefficients are multiplied by 100. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Gain	0.204***	0.322***	0.196***	0.237***	0.328***
	(17.33)	(24.99)	(17.31)	(22.61)	(26.26)
Portfolio Gain	0.019***	0.192***	0.009**	0.028***	0.177***
	(4.16)	(23.53)	(2.12)	(6.71)	(23.49)
Gain*Portfolio Gain	-0.183***	-0.247***	-0.181***	-0.180***	-0.240***
	(-23.26)	(-24.75)	(-23.20)	(-24.11)	(-24.45)
Account FE	No	Yes	No	No	Yes
Date FE	No	No	Yes	No	Yes
Stock FE	No	No	No	Yes	Yes
Adj-R^2	0.000	0.011	0.001	0.001	0.012
Obs.	118,155,489	118,155,489	118,155,489	118,155,489	118,155,489

Table A2. Linear probability model, more control variables

This table is the same as Panel A of Table 2, except that we add more control variables. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive return, and 0 otherwise. Sqrt(Time Owned) is the square root of the number of days since purchase. Log(Buy price) is the logged purchase price (in dollars). Volatility^{-} (Volatility^{+}) is the stock volatility calculated using daily returns using the 250 days prior to the purchase if the return since purchase is negative (positive), zero otherwise. In the last two columns, we control for return bracket fixed effects. Specifically, we split all the observations by holding period return into 50 brackets: (-∞, -50%),…,[-4%, -2%), [-2%, 0), [0, 2%), [2%, 4%), …,[50%, -∞). All coefficients are multiplied by 100. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Gain	0.293***	0.302***	0.192***	0.228***	0.120***
	(24.19)	(24.29)	(12.60)	(19.94)	(7.66)
Portfolio Gain	0.174***	0.176***	0.173***	0.180***	0.175***
	(22.13)	(22.03)	(21.75)	(22.84)	(22.72)
Gain* Portfolio Gain	-0.200***	-0.206***	-0.198***	-0.219***	-0.213***
	(-20.81)	(-20.79)	(-19.86)	(-22.80)	(-22.13)
Sqrt(Time Owned)	-0.003***				-0.003***
	(-6.60)				(-9.42)
Log(Buy price)		0.046***			0.045***
		(7.14)			(5.97)
Volatility^{-}			-2.270***		-1.463***
			(-8.08)		(-6.11)
Volatility^{+}			1.005***		1.922***
			(3.88)		(5.94)
Account FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Return Bracket FE	No	No	No	Yes	Yes
Adj-R^2	0.012	0.012	0.012	0.012	0.012
Obs.	118,155,489	118,155,431	118,135,286	118,155,489	118,135,228

Table A3. Past realized gains

This table reports robustness checks. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive return, and 0 otherwise. In Panel A and B, besides tracking the unrealized portfolio gain at a given time point, we add back capital gains realized in a given past horizon as the overall portfolio return, dating back from 1 month to 2 years. Panel A controls for no fixed effects, and Panel B controls for account, day, stock fixed effects.

Panel A. without any fixed effects

	(1) 1 month	(2) 3 months	(3) 6 months	(4) 1 year	(5) 2 years
Gain	0.240***	0.228***	0.218***	0.201***	0.185***
	(19.11)	(18.88)	(18.77)	(18.34)	(17.39)
Portfolio Gain	0.017***	0.033***	0.047***	0.056***	0.059***
	(3.70)	(7.33)	(10.14)	(12.00)	(12.33)
Gain*Portfolio Gain	-0.204***	-0.197***	-0.188***	-0.168***	-0.146***
	(-20.64)	(-20.50)	(-20.37)	(-19.62)	(-18.09)
Account FE	No	No	No	No	No
Date FE	No	No	No	No	No
Stock FE	No	No	No	No	No
Adj-R^2	0.000	0.000	0.000	0.000	0.000
Obs.	118,156,395	118,156,395	118,156,395	118,156,395	118,156,395

Panel B. with all fixed effects

	(1) 1 month	(2) 3 months	(3) 6 months	(4) 1 year	(5) 2 years
Gain	0.311***	0.291***	0.274***	0.252***	0.233***
	(25.43)	(25.32)	(25.11)	(24.80)	(23.81)
Portfolio Gain	0.156***	0.149***	0.142***	0.129***	0.113***
	(20.83)	(21.61)	(22.15)	(21.47)	(19.68)
Gain*Portfolio Gain	-0.224***	-0.190***	-0.160***	-0.122***	-0.088***
	(-22.82)	(-22.13)	(-20.71)	(-17.71)	(-13.39)
Account FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.012	0.012	0.012	0.012	0.012
Obs.	118,155,489	118,155,489	118,155,489	118,155,489	118,155,489

Table A4. Hazard regression (Cox proportional hazard model)

This table is the same as Panel A of Table 2, except that the model is estimated based on Cox proportional hazard model. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive return, and 0 otherwise. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Gain	0.804***	1.018***	0.773***	0.882***
	(72.48)	(69.02)	(69.98)	(74.09)
Portfolio Gain	0.000	0.453***	-0.055***	0.030**
	(0.04)	(34.87)	(-3.92)	(2.30)
Gain*Portfolio Gain	-0.557***	-0.761***	-0.568***	-0.558***
	(-42.65)	(-43.75)	(-43.38)	(-42.27)
Stratified by accounts	No	Yes	No	No
Stratified by dates	No	No	Yes	No
Stratified by stocks	No	No	No	Yes
Adj-R^2	0.004	0.021	0.009	0.010
Obs.	110,554,055	110,554,055	110,554,055	110,444,711

Table A5. Sale conditioned sample, linear probability model (Odean (1998) specification)

This table is the same as Panel A of Table 2, except that the sample restricts to trading days that investors actually sell. The dependent variable is a dummy variable that equals 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive return, and 0 otherwise. All coefficients are multiplied by 100. Standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Gain	11.534***	13.619***	11.689***	12.552***	14.169***
	(21.90)	(27.38)	(22.17)	(26.25)	(31.34)
Portfolio Gain	-2.286***	1.901***	-1.851***	-1.579***	2.350***
	(-3.34)	(6.85)	(-3.00)	(-3.40)	(9.25)
Gain*Portfolio Gain	-4.771***	-8.482***	-4.969***	-5.115***	-8.670***
	(-9.76)	(-18.32)	(-10.16)	(-11.41)	(-21.08)
Account FE	No	Yes	No	No	Yes
Date FE	No	No	Yes	No	Yes
Stock FE	No	No	No	Yes	Yes
Adj-R^2	0.012	0.117	0.018	0.037	0.137
Obs.	1,479,983	1,479,983	1,479,983	1,479,983	1,479,983

Table A6. External validity: The Chinese sample

This table repeats our main empirical exercise in a Chinese sample. The data come from a large Chinese brokerage firm, which covers 97,000 investors and ranges from 2000 to 2009. The dependent variable is a dummy variable that equals 1 if a sale (including partial sale) occurs on day t+1, and 0 otherwise. *Gain* is a dummy variable that equals 1 if a stock in an investor's portfolio has a positive return since purchase at day t, and 0 otherwise. *Portfolio Gain* is a dummy variable that equals 1 if an investor's portfolio has a positive paper gain, and 0 otherwise. All coefficients are multiplied by 100. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Gain	4.162***	3.924***	3.741***	4.080***	3.452***
	(61.19)	(64.30)	(53.91)	(61.88)	(60.67)
Portfolio Gain	2.700***	2.316***	1.828***	2.629***	1.406***
	(38.30)	(41.61)	(26.50)	(39.33)	(36.15)
Gain*Portfolio Gain	-0.829***	-0.697***	-0.748***	-0.768***	-0.631***
	(-10.63)	(-11.46)	(-10.65)	(-9.86)	(-11.83)
Account FE	No	Yes	No	No	Yes
Date FE	No	No	Yes	No	Yes
Stock FE	No	No	No	Yes	Yes
Adj-R^2	0.018	0.053	0.024	0.020	0.059
Obs.	82,591,087	82,591,087	82,591,087	82,591,087	82,591,087

Table A7. Asset class categorization

This table provides detailed information for asset class categorization. *Product Code*, *Security*, and *Product Code 2* are the raw information in the Position Readme file provided by the broker, while *Category* shows our classification based on the similarity of each asset class to US common stocks. *#obs* reports the count of investor-security-month level observations for each asset class and category.

Product	Security	Product	Category	# obs	Category #
COM	US Company Shares	ST	US common stocks	2,882,	2,882,167
FGC	Foreign (Canadian)	ST	Foreign Stocks	107,25	
FGO	Foreign (Ordinaries)	ST	Foreign Stocks	29,436	288,221
ADR	ADR	ST	Foreign Stocks	151,53	
WAR	Warrants	ST	Other Stock-Type	7,492	
RET	Real Estate Trust	ST	Other Stock-Type	748	
UNI	Units	ST	Other Stock-Type	1,087	
CPR	Convertible Preferred	ST	Other Stock-Type	13,970	234,742
CEM	Closed-End Mutual	ST	Other Stock-Type	158,69	
MLP	Master Limited	ST	Other Stock-Type	33,749	
PRE	Preferred Stock	ST	Other Stock-Type	19,004	
MFS	Mutual Funds (In-	MF	Mutual Funds	26,100	
MPL	Marketplace Load	MO	Mutual Funds	1,135	
MPB	Marketplace Load	MO	Mutual Funds	237	
MFB	Bond Mutual Funds	MO	Mutual Funds	10,965	
MFF	One Source Bond	MS	Mutual Funds	29,238	319,693
MFA	One Source Equity	MS	Mutual Funds	203,71	
PFF	Ex One Source Bond	MO	Mutual Funds	1,214	
MFC	Equity Mutual Funds	MO	Mutual Funds	43,192	
PFA	Ex One Source Equity	MO	Mutual Funds	3,893	
OEQ	Option Equity	OP	Options	24,201	28,436
OIN	Options Index	OP	Options	4,235	

Table A8. Summary statistics: portfolio returns generated by various asset classes

This table provides summary statistics for portfolio returns that are formed over different asset classes. *PortfolioRet* indicates the overall portfolio return, while *PortfolioRet*^{Category} denotes the capital gains from an asset category divided by the sum of cost base for all securities in the portfolio. The samples correspond to those in Table 5, and the observations are at investor-month-stock level (the stock refers the focal stock in question).

	N (investor-month-stock)	N (investors)	Mean	Sd	Min	P10	P25	P50	P75	P90	Max
Panel A. holding at least two US common stocks as well as securities in any other asset classes (the sample corresponding to Table 4 Panel A)											
PortfolioRet	738,910	11,100	0.000	0.159	-0.694	-0.193	-0.088	0.000	0.085	0.188	0.716
PortfolioRet$^{\text{US Common Stock}}$	738,910	11,100	0.000	0.140	-0.381	-0.165	-0.073	-0.001	0.069	0.162	0.461
PortfolioRet$^{\text{US Common Stock -j}}$	738,910	11,100	0.001	0.116	-0.316	-0.134	-0.059	-0.001	0.056	0.135	0.388
PortfolioRet$^{\text{Non US Common Stock}}$	738,910	11,100	0.000	0.061	-0.385	-0.060	-0.020	0.000	0.020	0.060	0.438
Panel B. holding at least two US common stocks as well as foreign stocks (the sample corresponding to Table 4, Panel B, Columns (1)-(5))											
PortfolioRet$^{\text{US Common Stock -j}}$	480,647	6,733	-0.001	0.117	-0.316	-0.140	-0.062	-0.002	0.057	0.136	0.388
PortfolioRet$^{\text{Foreign Stock}}$	480,647	6,733	-0.003	0.062	-0.226	-0.064	-0.021	-0.001	0.015	0.054	0.240
Panel C. holding at least two US common stocks as well as other stock-type securities (the sample corresponding to Table 4, Panel B, Columns (6)-(10))											
PortfolioRet$^{\text{US Common Stock -j}}$	319,644	4,395	0.007	0.106	-0.316	-0.113	-0.048	0.002	0.055	0.130	0.388
PortfolioRet$^{\text{Other Stock-Type Sec}}$	319,644	4,395	-0.002	0.041	-0.174	-0.039	-0.013	0.000	0.011	0.034	0.136
Panel D. holding at least two US common stocks as well as mutual funds (the sample corresponding to Table 4, Panel B, Columns (11)-(15))											
PortfolioRet$^{\text{US Common Stock -j}}$	128,437	3,271	0.003	0.100	-0.316	-0.109	-0.042	0.002	0.048	0.112	0.388
PortfolioRet$^{\text{Mutual Funds}}$	128,437	3,271	0.016	0.035	-0.059	-0.012	-0.001	0.006	0.025	0.059	0.167
Panel E. holding at least two US common stocks as well as options (the sample corresponding to Table 4, Panel B, Columns (16)-(20))											
PortfolioRet$^{\text{US Common Stock -j}}$	27,857	1,100	-0.003	0.110	-0.316	-0.138	-0.056	-0.001	0.051	0.127	0.388
PortfolioRet$^{\text{Options}}$	27,857	1,100	-0.004	0.063	-0.228	-0.064	-0.020	-0.003	0.009	0.044	0.253

B. Online Appendix

"The Portfolio-Driven Disposition Effect"
Li An, Joseph Engelberg, Matthew Henriksson, Baolian Wang, and Jared Williams

General Framework

We consider a simple framework with two stocks that is based on Barberis and Xiong's (2009) single asset framework. We depart from Barberis and Xiong (2009) in that we only consider complete liquidations (as opposed to partial liquidations), and we do not force the investor to liquidate her positions at the terminal date. There are two risky assets, A and B, whose returns are i.i.d. across stocks and across time. There is also a risk-free asset (numeraire), whose return is normalized to 0. There are two periods and three dates: $t = 0$, $t = 1$, and $t = 2$.

There is a single investor who is endowed with an equal-weighted portfolio consisting of A and B at $t = 0$.[1]

At $t = 1$, the investor can choose to (fully) liquidate either of her positions, and if she chooses to liquidate a position, she can either keep the proceeds in the numeraire, or she can put (all) the proceeds back into the same stock. Liquidating a position and reinvesting it in the stock has no effect on the investor's $t = 2$ wealth, but it does affect her paper gains and losses at $t = 2$, because we assume that investors close their mental accounts whenever they completely liquidate a position in a stock.[2] Without loss of generality, we normalize the value of her holdings in the equal-weighted portfolio so that the value of her $t = 0$ holding in A and B are each worth 1 unit. Let A_t and B_t denote 1 plus the return of stock A and 1 plus the return of stock B in period t, respectively, so that the investor's portfolio is worth $A_1 + B_1$ at $t = 1$, and $A_1A_2 + B_1B_2$ at $t = 2$.

Let Γ_A and Γ_B denote the investor's $t = 2$ paper gain/loss in stocks A and B, respectively. Then,

$$\Gamma_A \equiv \begin{cases} A_1A_2 - A_1 & \text{if the investor liquidates A and reinvests at } t = 1 \\ A_1A_2 - 1 & \text{if the investor does not liquidate A at } t = 1 \end{cases}. \tag{B.1}$$

Let Γ_B be defined analogously:

$$\Gamma_B \equiv \begin{cases} B_1B_2 - B_1 & \text{if the investor liquidates B and reinvests at } t = 1 \\ B_1B_2 - 1 & \text{if the investor does not liquidate B at } t = 1 \end{cases}, \tag{B.2}$$

and let $\Gamma_p \equiv \Gamma_A + \Gamma_B$ denote the investor's portfolio-level paper gain/loss at $t = 2$.

We consider two models of investor preferences. In our hedonic mental accounting (HMA) model, the investor receives utility when positions are liquidated, and she strategically chooses the way she mentally accounts for the liquidation of a single stock. More

[1] For the parameter values that we will analyze, the investor will prefer to invest in stock at $t = 0$ rather than holding the numeraire.

[2] This is equivalent to assuming that there are four stocks (A, B, C, and D) whose returns are i.i.d. across stocks and across time, and if the investor liquidates stock A (B), she can either keep the proceeds in cash or invest it in stock C (D). The key assumption is that when a stock is liquidated and the proceeds are reinvested, the mental account is closed. However, it is worth noting that Frydman, Solomon, and Hartzmark (2018) provide evidence that investors often keep their mental accounts open in such transactions.

specifically, she chooses between narrow framing (i.e., disregarding the performance of the rest of her portfolio) and broad framing (i.e., considering the liquidation as being part of her overall portfolio). She chooses the form of mental framing that maximizes her expected utility. In our model of utility over paper and realized gains (UPRG), the investor receives utility over both paper gains/losses and realized gains/losses. Following Frydman et al (2014), we assume that investors receive larger "bursts" of utility/disutility upon realizing a gain/loss than upon simply having a paper gain/loss.

In both models, the investor's total utility, U is simply the sum of her utility at $t = 1$ and $t = 2$:

$$U \equiv U_1 + U_2. \tag{B.3}$$

In the following sections, we will specify how U_1 and U_2 are defined in the two models.

Hedonic Mental Accounting (HMA)

Suppose that at $t = 1$, the investor sells her position in A and reinvests it. She has two options for how she can mentally frame this transaction: she can *narrowly frame* the transaction and mentally record it as realizing a gain of $A_1 - 1$, or she can *broadly frame* the transaction and mentally record it as liquidating the proportion $\frac{A_1}{A_1+B_1}$ of her entire portfolio, which is at a gain of $A_1 + B_1 - 2$. In our HMA model, we assume that she will mentally account for the transaction in the way that is most favorable for her:

$$U_1 \quad = \quad \max\left\{v(A_1 - 1), v\left(\frac{A_1}{A_1 + B_1}(A_1 + B_1 - 2)\right)\right\}, \tag{B.4}$$

where $v(\cdot)$ is a prospect theory utility function. The other cases are analogous, so that her $t = 1$ utility is given by

$$U_1 \equiv \begin{cases} \max\left\{v(A_1 - 1), v\left(\frac{A_1}{A_1+B_1}(A_1 + B_1 - 2)\right)\right\} & \text{if she sells A and not B at } t = 1 \\ \max\left\{v(B_1 - 1), v\left(\frac{B_1}{A_1+B_1}(A_1 + B_1 - 2)\right)\right\} & \text{if she sells B and not A at } t = 1 \\ \max\left\{v(A_1 - 1) + v(B_1 - 1), v\left(A_1 + B_1 - 2\right)\right\} & \text{if she sells A and B at } t = 1 \\ 0 & \text{if she doesn't trade at } t = 1 \end{cases} \tag{B.5}$$

Note that we will restrict attention to parameter values where the investor will prefer to reinvest any proceeds that she receives from a $t = 1$ liquidation as opposed to keeping the proceeds in the numeraire.

At $t = 2$, the investor again has four options: she can liquidate A, she can liquidate B, she can liquidate both stocks, or she can choose not to trade. Thus, recalling (B.1)-(B.2) and the definition of Γ_p, her $t = 2$ utility is given by

$$U_2 \equiv \begin{cases} \max\left\{v(\Gamma_A), v\left(\frac{A_1A_2}{A_1A_2+B_1B_2}\Gamma_p\right)\right\} & \text{if she sells A and not B at } t = 2 \\ \max\left\{v(\Gamma_B), v\left(\frac{B_1B_2}{A_1A_2+B_1B_2}\Gamma_p\right)\right\} & \text{if she sells B and not A at } t = 2 \\ \max\left\{v(\Gamma_A) + v(\Gamma_B), v\left(\Gamma_p\right)\right\} & \text{if she sells A and B at } t = 2 \\ 0 & \text{if she doesn't trade} \end{cases}. \tag{B.6}$$

Since at $t = 2$, she will choose the action that maximizes her total utility, it follows that U_2 can be expressed,

$$U_2 = \max\left\{v(\Gamma_A), v\left(\frac{A_1A_2}{A_1A_2 + B_1B_2}\Gamma_p\right), v(\Gamma_B), v\left(\frac{B_1B_2}{A_1A_2 + B_1B_2}\Gamma_p\right), v(\Gamma_A) + v(\Gamma_B), v\left(\Gamma_p\right), 0\right\}. \tag{B.7}$$

Regarding the investor's decision at $t = 1$, after observing the $t = 1$ returns A_1 and B_1, the investor will choose the action (sell A, sell B, sell A and B, or sell nothing) that maximizes her expected total utility, i.e., she will choose the action that maximizes

$$U = U_1 + \mathbf{E}[U_2 \mid A_1, B_1, \text{ and her } t = 1 \text{ action}]. \tag{B.8}$$

Utility over Paper and Realized Gains (UPGR)

In this model, the investor derives utility over both paper gains/losses and realized gains/losses. Consistent with experimental evidence (e.g., Frydman et al., 2014), we assume that investors derive larger bursts of utility from realized gains/losses than from paper gains/losses.

Formally, suppose that in a given period t, an investor's position in A is at a gain of G_A, and her position in B is at a gain of G_B.[3] Then we assume that her utility in a given period is given by

$$U_t = v\Big(G_A\left(1 + \kappa \times \mathbf{1}_{\{\text{She sells A}\}}\right) + G_B\left(1 + \kappa \times \mathbf{1}_{\{\text{She sells B}\}}\right)\Big). \tag{B.9}$$

The parameter κ represents how much more utility the investor receives from realized gains/losses vis-a-vis paper gains/losses. $\kappa = 0$ corresponds to investors perceiving the gains/losses equally. Hence, our assumption that investors derive more utility from realized gains/losses than from paper gains/losses corresponds to $\kappa > 0$.

First, consider the investor's action at $t = 2$. Her gains in A and B at $t = 2$ are given by Γ_A and Γ_B, which are defined in (B.1)-(B.2). Since $\kappa > 0$, it trivially follows that at $t = 2$, an investor will liquidate her position in a stock if, and only if, that position is at a gain. In other words, U_2 is given by

$$U_2 = v\Big(\Gamma_A\left(1 + \kappa \times \mathbf{1}_{\{\Gamma_A > 0\}}\right) + \Gamma_B\left(1 + \kappa \times \mathbf{1}_{\{\Gamma_B > 0\}}\right)\Big). \tag{B.10}$$

Now, consider her $t = 1$ action. Her $t = 1$ gains in A and B are given by $A_1 - 1$ and $B_1 - 1$, respectively, so her $t = 1$ utility, U_1, is given by plugging these expressions into (B.9). After observing the $t = 1$ returns A_1 and B_1, the investor will choose the action (sell A, sell B, sell A and B, or sell nothing) that maximizes her expected total utility, i.e., she will choose the action that maximizes

$$U = U_1 + \mathbf{E}[U_2 \mid A_1, B_1, \text{ and her } t = 1 \text{ action}]. \tag{B.11}$$

[3] Negative values of G_A and G_B correspond to losses in A and B, respectively.

The Disposition Effect and the Portfolio-Driven Disposition Effect

Let Δ be defined as

$$\begin{aligned}\Delta &= \mathbf{Pr}(\text{Sell a stock at } t=1 \mid \text{stock is at a gain}) \\ &\quad -\mathbf{Pr}(\text{Sell a stock at } t=1 \mid \text{stock is at a loss}).\end{aligned} \tag{B.12}$$

We say that there is a *disposition effect* (DE) if $\Delta > 0$.

Let $\Delta_\uparrow$ and $\Delta_\downarrow$ denote the values of Δ conditional on the portfolio being at a gain and a loss, respectively. Formally, let $\Delta_\uparrow$ and $\Delta_\downarrow$ be defined as:

$$\begin{aligned}\Delta_\uparrow &= \mathbf{Pr}(\text{Sell a stock at } t=1 \mid \text{stock is at a gain, portfolio is at a gain}) \\ &\quad -\mathbf{Pr}(\text{Sell a stock at } t=1 \mid \text{stock is at a loss, portfolio is at a gain})\end{aligned} \tag{B.13}$$

$$\begin{aligned}\Delta_\downarrow &= \mathbf{Pr}(\text{Sell a stock at } t=1 \mid \text{stock is at a gain, portfolio is at a loss}) \\ &\quad -\mathbf{Pr}(\text{Sell a stock at } t=1 \mid \text{stock is at a loss, portfolio is at a loss}).\end{aligned} \tag{B.14}$$

We say that there is a *portfolio-driven disposition effect* (PDDE) if $\Delta_\downarrow > \Delta_\uparrow$.

Numerical Analysis

We numerically examine our models' predictions regarding the PDDE and the DE for a wide range of parameter values. We let the returns for each stock be independently distributed uniformly over the region $[\underline{R}, \overline{R}]$, i.e., $A_t \sim U[1+\underline{R}, 1+\overline{R}]$ and $B_t \sim U[1+\underline{R}, 1+\overline{R}]$, $t = 1, 2$.[4] We consider $(\underline{R}, \overline{R})$ values of $(-0.5, 0.7)$, $(-0.5, 0.6)$, $(-0.1, 0.3)$, and $(-0.1, 0.2)$. Note that these expected returns are either 5% or 10%, and the variance of returns are large in the first two specifications and small in the latter two specifications.

Next, consider the utility function, $v(\cdot)$. We consider the loss aversion preferences,

$$v(x) \equiv \begin{cases} \lambda_G x & \text{if } x \geq 0 \\ \lambda_L x & \text{if } x < 0 \end{cases}. \tag{B.15}$$

We let λ_L take the values 1, 1.5, and 2, and we let λ_G take the values 0.4, 0.6, 0.8, and 1. We exclude the case where $(\lambda_L, \lambda_G) = (1, 1)$ because such an investor does not exhibit loss aversion.[5] Thus, we consider 11 distinct values of (λ_L, λ_G).

We examine the investor's optimal decision at $t = 1$ given her $t = 1$ information for each of the values of A_1 and B_1. We consider return realizations for A_1, A_2, B_1, and B_2 that span the return regions and differ by 2.5%. In other words, for the $(\underline{R}, \overline{R}) = (-0.5, 0.7)$ case, we let A_1, A_2, B_1, and B_2 take the values $\{0.5, 0.525, \ldots, 1.675, 1.7\}$, and we consider the four-dimensional cartesian product consisting of all possible realizations of (A_1, A_2, B_1, B_2) given these ranges of values. We can then determine whether the investor exhibits a disposition effect and a portfolio-driven disposition effect for the given set of parameter values, $(\underline{R}, \overline{R}, \lambda_L, \lambda_G)$. Specifically, for each set of parameter values, we compute Δ, $\Delta_\uparrow$, and $\Delta_\downarrow$, which are defined in (B.12)-(B.14), and determine whether there is a DE and a PDDE for the given set of parameter values.

[4] Recall that we assume that the stocks' returns are i.i.d. across stocks and across time.

[5] The investor exhibits loss aversion if and only if $\lambda_L > \lambda_G$.

Recall that we have two models of investor behavior: HMA and UPRG. Moreover, the UPRG model requires an additional parameter, κ. In our numerical analysis, we consider the behavior in the UPRG model for $\kappa \in \{2, 3, 4\}$. In the analysis below, for each of the four distributions for the stock returns, and for each of the four specifications of investor behavior (HMA, UPRG with $\kappa = 2$, UPRG with $\kappa = 3$, and UPRG with $\kappa = 4$), we report the number of values of λ_L and λ_G (out of the 11 combinations that we consider) that generate a PDDE, a DE, and both a PDDE and a DE.

Portfolio-Driven Disposition Effect (PDDE)

Both the HMA and the UPRG model reliably predict a PDDE, as shown in the table below. To interpret the table, consider the uppermost cell in the HMA column. The "11/11" reflects the fact that HMA predicts a PDDE for all 11 combinations of (λ_L, λ_G) that we consider whenever returns are distributed uniformly over the interval $[-0.5, 0.6]$. Note that in the HMA model, a PDDE is predicted for all return distributions and for all combinations of (λ_L, λ_G). Similarly, the UPRG gain model almost always predicts a PDDE. There is only one return distribution (the top row) and one value of κ ($\kappa = 4$) that does not predict a PDDE for all 11 combinations of (λ_L, λ_G), but even there, a PDDE is predicted for 10 of the 11 values of (λ_L, λ_G).

		UPRG		
Return Distribution	HMA	$\kappa = 2$	$\kappa = 3$	$\kappa = 4$
$U(-.5, +.6)$	11/11	11/11	11/11	10/11
$U(-.5, +.7)$	11/11	11/11	11/11	11/11
$U(-.1, +.2)$	11/11	11/11	11/11	11/11
$U(-.1, +.3)$	11/11	11/11	11/11	11/11

Disposition Effect (DE)

Next, we conduct an analysis comparable to the PDDE analysis above, except here, we consider the disposition effect.

		UPRG		
Return Distribution	HMA	$\kappa = 2$	$\kappa = 3$	$\kappa = 4$
$U(-.5, +.6)$	11/11	9/11	11/11	11/11
$U(-.5, +.7)$	11/11	0/11	11/11	11/11
$U(-.1, +.2)$	0/11	0/11	11/11	11/11
$U(-.1, +.3)$	0/11	0/11	0/11	11/11

The HMA model predicts a disposition effect as long as the probability of a stock being at a loss is somewhat comparable to the probability of a stock being at a gain, e.g., the first two rows of the table above. However, HMA does not predict a disposition effect when returns are almost always positive, as in the bottom two rows. An HMA investor who owns two stocks, one of which is at a small loss and the other is at a larger gain, will choose to sell the loser and keep the winner. An HMA investor will mentally account for this transaction as liquidating part of their winning portfolio. When returns have low variance and are almost always positive, they find themselves in this position often, reversing the DE.

The UPRG model predicts a disposition effect as long as the realization utility is sufficiently larger than the paper gain utility, i.e., when κ is relatively large ($\kappa > 2$). When κ is small ($\kappa \leq 2$), a UPRG investor would rather hold on to her paper gains and receive paper gain utility from this gain over two periods rather than receiving the realization utility now and replacing it with a new stock that will have a greater probability of being at a loss at $t = 2$.

PDDE and DE

Finally, we report the frequency at which the models simultaneously predict both a DE and a PDDE. It is apparent from the table below that both of the models can often predict both a DE and a PDDE.

		UPRG		
Return Distribution	HMA	$\kappa = 2$	$\kappa = 3$	$\kappa = 4$
$U(-.5, +.6)$	11/11	9/11	11/11	10/11
$U(-.5, +.7)$	11/11	0/11	11/11	11/11
$U(-.1, +.2)$	0/11	0/11	11/11	11/11
$U(-.1, +.3)$	0/11	0/11	0/11	11/11