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The Portfolio-Driven Disposition Effect

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ABSTRACT

The disposition effect for a stock significantly weakens if the portfolio is at a gain, but is large when it is at a loss. We find this portfolio-driven disposition effect (PDDE) in four independent settings: U.S. and Chinese archival data, as well as U.S. and Chinese experiments. The PDDE is robust to a variety of controls in regression specifications and is not explained by extreme returns, portfolio rebalancing, tax considerations, or investor heterogeneity. Our evidence suggests that investors form mental frames at both the stock and the portfolio levels and that these frames combine to generate the PDDE.

THERE IS PERHAPS NO MORE robust trading phenomenon than the disposition effect, the pattern whereby 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 U.S. retail investors (Odean (1998)), foreign retail investors (Frydman and Wang (2020), Grinblatt and Keloharju (2001)), institutional investors (Shapira and Venezia (2001)), homeowners (Genesove and Mayer (2001)), and corporate executives (Heath, Huddart, and

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Lang (1999)), as well as in experimental settings (Weber and Camerer (1998), 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] Models that attempt to explain the disposition effect often have investors with preferences over some subset of their wealth such as an individual stock, which Thaler et al. (1997) call "narrow framing." For example, Barberis and Xiong (2009, 2012) and Ingersoll and Jin (2013) show that if an investor has preferences defined over realized stock-level gains and losses, she will predictably exhibit a disposition effect.

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 independently for each individual asset, or does it depend on the portfolio as a whole? In doing so, we ask the related question of whether investors have preferences over individual stocks, the portfolio as a whole, or both.

Consider an investor with three stocks: X_1, X_2, and X_3. The disposition effect says that $\Pr(X_i \text{ is sold} \mid X_i \text{ is at a gain}) > \Pr(X_i \text{ is sold} \mid X_i \text{ is at a loss})$ for all i. If the investor has preferences over each individual stock, then we would expect the three probabilistic statements to be independent of each other. However, if preferences depend in part on portfolio performance, then we would 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. Whether we examine 78,000 households in the Barber and Odean (2000) data set, 97,000 investors in a Chinese brokerage data set, 2,300 U.S. participants in an Amazon Mechanical Turk ("MTurk") trading game experiment, or 800 experimental participants at a Chinese university, the results consistently tell the same story: an investor's disposition effect is large when her portfolio is at a loss and significantly smaller when it is at a gain.

To illustrate the main finding, consider the probability of selling a given stock among the four possible (Stock, Portfolio) conditions: (Gain, Gain), (Gain, Loss), (Loss, Gain), and (Loss, Loss). When we calculate simple univariate statistics for each of these conditions in the Barber and Odean data set, we find that the probabilities of selling in the (Gain, Gain) and (Loss, Gain) conditions are nearly equal: in other words, there is almost no disposition effect when the portfolio is at a gain. Given how pervasive the disposition effect is, it is surprising to find that the disposition effect largely disappears among the 61% of observations in the Barber and Odean (2000) data set in which portfolios are up.

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

Because the existence of a disposition effect in the Barber and Odean data set is well-known, there must be a large effect among the remaining 39% of the data when portfolios are at a loss. This is precisely what we find: the probability of selling in the (Gain, Loss) condition is nearly twice as large as that of the (Loss, Loss) condition. We call this the *portfolio-driven disposition effect* (PDDE).

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 hazard regressions with a host of controls. Perhaps the cleanest way to see our findings is via a matched-sample analysis. More specifically, we compare selling decisions across investors made on the same day for the same stock that was also purchased on the same day. 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 portfolios. The results are very similar to those from the baseline analysis.

The PDDE is not a repackaging of earlier research on the disposition effect. Specifically, we show that it is distinct from the rank effect documented by Hartzmark (2015), and it is not explained by tax considerations, portfolio rebalancing, or investor heterogeneity in the disposition effect.

The evidence is most consistent with investors having at least two frames—one at the stock level and one at the portfolio level—when making their trading decisions. While prior research on the disposition effect has established narrow framing at the stock level, here we provide empirical evidence of an additional frame at the portfolio level that interacts with the stock-level frame, resulting in the PDDE. To do this, we exploit the fact that a focal asset's membership in a portfolio will be a function of how similar the other assets in the portfolio are. Similarity has long been thought to be a defining characteristic of how an individual creates her mental account (Goldstone (1994)). As Evers, Imas, and Kang (2022), Nosofsky (1986), Kruschke (1992) put it, "when outcomes are perceived to be similar, they are categorized together, assigned to the same mental account and evaluated jointly." Thus, when considering focal Stock X, if investors frame at the portfolio level, then we should expect a stronger PDDE when defining a portfolio with assets most similar to Stock X. For example, consider an investor that owns three assets—Stock X, Stock Y, and a house. When considering focal Stock X, similarity would predict that Stock Y is more likely to be placed in the same mental account as Stock X, and thus will be more influential for the trading decisions of Stock X than the house.

With this in mind, we perform two tests based on similarity. First, we exploit the fact that a single household can have multiple accounts from the same discount brokerage. Similarity would predict that two stocks in the same account are more likely to be considered in the same portfolio while two stocks from different accounts are less likely to be, even though all stocks in the brokerage accounts contribute to the household's wealth. We find evidence of PDDE moderation following dissimilarity: stocks held in the same account as the focal stock generate a PDDE that is 21% larger than that of stocks held by the same household but in a different account than the focal stock. This pattern is also robust to restricting attention to one-adult households, where the size of the effect is 28%.

Second, rather than measure the similarity of stocks across brokerage accounts within the same household, we exploit the characteristics of the individual assets within a single brokerage account. Specifically, we sort investors' assets into U.S. common stocks, foreign stocks, open-end mutual funds, options, and other stock-type securities (such as closed-end funds and preferred stock). When the focal stock is a U.S. common stock, the PDDE shrinks as the source of the portfolio capital gain bears less resemblance to U.S. common stocks. For example, the moderating effect of one unit of capital gains generated by other U.S. common stocks in the portfolio is 2.7 times as large as that of foreign stocks, 3.2 times as large as that of other stock-type securities, and 3.6 times as large as that of mutual funds. In other words, as a stock in the portfolio looks less similar to the focal stock, its contribution to the PDDE declines.

The PDDE has important downstream consequences for aggregate behavior, prices, and investor welfare. When aggregate market indices rise (fall), a greater fraction of investors will have portfolios at a gain (loss), and so the PDDE predicts aggregate countercyclicality in the disposition effect. We confirm this in both the U.S. and Chinese brokerage data: following a bull market, the disposition effect falls, but following a bear market, it rises. Our evidence supports the view that investors engage in more heuristic-like behavior in bad times (Mullainathan and Shafir (2013), Schilbach, Schofield, and Mullainathan (2016)).

Our evidence that investors frame at both the individual stock and portfolio level has the potential to explain stock return patterns that existing single-frame models of investor behavior have difficulty predicting. For example, Barberis and Huang (2001) develop two models of framing, one in which investors frame at the individual stock level and another in which they frame at the total portfolio level. Each of their models can explain some well-known empirical patterns. They conclude that a superior model of investor behavior would include both stock-level framing and broader forms of framing.[2] Our evidence on the PDDE indicates that investors do indeed frame at both the stock and the portfolio levels.

Our paper is organized as follows. We describe our data and methodology in Section I. In Section II, we introduce the PDDE and show that it is a robust phenomenon. In Section III, we show that the PDDE is not explained by prior research. Section IV provides direct evidence of a multiple-frame explanation for the PDDE. Section V concludes.

[2] "While individual stock accounting can potentially be a helpful way of thinking about the data, we emphasize that it is only a potential ingredient in an equilibrium model, and by no means a complete description of the facts. For one thing, we show that it underpredicts the correlation of stocks with each other, and argue that a model that combines individual stock accounting with broader forms of accounting is likely to be superior to a model that uses individual stock accounting alone" (Barberis and Huang (2001, p. 1250)).

I. Data and Methodology

A. Retail Brokerage Data

We begin with the large U.S. discount broker data set used 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 U.S. 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.

The unit of observation is an account-stock-day triple. Following Seru, Shumway, and Stoffman (2010), we count every purchase of a stock as the beginning of a new position, and a position ends on the date the investor first sells part or all of her holdings.[3] 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 potential observations. Following Ben-David and Hirshleifer (2012), we filter the raw data set and make several simplifying assumptions. First, we include only securities that are identified as common shares and appear in the Center for Research in Security Prices (CRSP). Because prices in the discount brokerage data set 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 correspond to a reverse transaction. Third, account-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 arise if investors purchased stocks before the start of our sample period. Finally, since our primary question of interest is the effect of portfolio performance on investor behavior, we only retain account-days with at least two common stock holdings. After applying these filters, we are left with a data set of 110,554,055 (account, stock, and day) observations. We report summary statistics in Panel A of Table I.

We have a similar brokerage data set from China that begins in 2000 and ends in 2009.[4] This data set comes from a brokerage company that has multiple branches throughout China and serves approximately half a million investors.

[3] We find similar results if we remove partial sales from our sample (i.e., do not consider partial sales as the "death" of a position).

[4] Similar to the Barber and Odean data, the Chinese data set contains three files: a trade file, a position file, and an investor demographic file. There are a few minor differences between the two samples. First, relative to the U.S. data, the Chinese sample contains more limited information on investor demographics—only age and gender are available. Second, the position file is at the daily frequency in the Chinese data set, so we do not have to build the account-stock-day triple observations based on the trade file like we do for the U.S. data. Third, we do not have to remove short-sale positions because short selling was not allowed in China during our sample period.

Table I

Summary Statistics

The table presents the summary statistics for the retail brokerage samples: the U.S. sample (Panel A) and the Chinese sample (Panel B). 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 one if the current price of a stock is higher than its purchase price after adjusting for splits and dividends, and zero otherwise. *Ret* is the holding-period return of an investor-stock-day. *Portfolio Gain* is a dummy variable that equals one if the portfolio is at a gain, and zero 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: The United States

	Mean				Median			
Gain	Yes	Yes	No	No	Yes	Yes	No	No
Portfolio Gain	Yes	No	Yes	No	Yes	No	Yes	No
Ret	0.488	0.214	−0.192	−0.270	0.264	0.117	−0.126	−0.210
Portfolio ret	0.326	−0.108	0.222	−0.180	0.209	−0.075	0.126	−0.138
Time owned	416	293	335	309	315	200	227	225
Volatility	0.025	0.029	0.031	0.035	0.021	0.024	0.027	0.031
Obs. (in millions)	47.03	11.86	20.56	31.09				
Sell obs.	112,959	47,713	40,819	58,392				
% Sell	0.240	0.402	0.199	0.188				

Panel B: China

	Mean				Median			
Gain	Yes	Yes	No	No	Yes	Yes	No	No
Portfolio Gain	Yes	No	Yes	No	Yes	No	Yes	No
Ret	0.194	0.096	−0.083	−0.293	0.081	0.045	−0.040	−0.237
Portfolio ret	0.150	−0.082	0.068	−0.211	0.079	−0.043	0.038	−0.175
Time owned	37	41	43	87	25	28	22	67
Volatility	0.041	0.039	0.044	0.038	0.036	0.035	0.037	0.034
Obs. (in millions)	13.48	8.64	5.37	57.31				
Sell obs.	1,177,794	565,688	271,024	1,053,502				
% Sell	8.736	6.547	5.051	1.838				

To make the analysis computationally feasible, we focus on a randomly selected 20% of the investors.[5]

As with the U.S. data, we restrict our analyses to common stocks and calculate holding-period returns after adjusting for stock splits and dividends. Information on stock prices and distribution comes from the China Stock Market and Accounting Research Database (CSMAR). After excluding positions for which we do not have information on the purchase price and excluding

[5] Specifically, we focus on investors with an account number ending with either 0 or 5.

account-days for which investors hold only one stock, the resulting data set contains 97,000 unique investors and 84,793,767 (account, stock, and day) observations. We report summary statistics for this sample in Panel B of Table I. Note that the Chinese investors trade much more frequently than the U.S. investors—their daily selling probability ranges from 1.8% to 8.7%, depending on the status of the focal stock and the portfolio, while these numbers for the U.S. investors are between 0.2% and 0.4%.

B. Main Methodology

Following Feng and Seasholes (2005), Seru, Shumway, and Stoffman (2010), and Barber and Odean (2013), we estimate the disposition effect using a hazard model that takes the form

$$h_{i,j}(t) = h_0(t)\exp\{\beta_0 + \beta_1 Gain_{i,j,t-1} + \epsilon_{i,j,t}\}, \tag{1}$$

where observations occur at the account (i), stock (j), and date (t) level.[6] For every account-stock-day, $h_{i,j}(t)$ is investor i's probability of selling position j on day t conditional on not having sold prior to day t, and $h_0(t)$ is the baseline hazard. In addition, *Gain* is a dummy variable equal to one if the stock's return since purchase (price/VWAP−1) is strictly positive and zero otherwise. With this structure, the hazard ratio, exp(β_1), measures the ratio of the probability of selling a winning position versus the probability of selling a losing position. Many previous studies show that β_1 is positive and statistically significant, or exp(β_1) is significantly greater than one, suggesting that investors are more prone to liquidate winning positions than losing positions.

Our interest in this study is the relationship between the disposition effect and the performance of the investor's portfolio. We analyze this relationship by estimating

$$\begin{aligned} h_{i,j}(t) = h_0(t)\exp\{&\beta_0 + \beta_1 Gain_{i,j,t-1} + \beta_2 Portfolio\_Gain_{i,t-1} + \beta_3 Gain_{i,j,t-1} \\ &\times Portfolio\_Gain_{i,t-1} + \epsilon_{i,j,t}\}. \end{aligned} \tag{2}$$

The variable *Portfolio Gain* is a dummy indicating whether 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.[7]

Our main coefficient of interest in equation (2) is β_3, the coefficient on the interaction term, which represents the ratio difference in disposition effects for

[6] We report our main results using the linear probability model in Tables IA.I and IA.II of the Internet Appendix. The Internet Appendix may be found in the online version of this article.

[7] In Table IA.III, we repeat our main analysis when the *Portfolio Gain* variable is defined without considering the performance of the stock associated with the given observation, that is, when the portfolio gain is computed based on the performance of the *rest* of the investor's portfolio. In Table IA.IV, we repeat our main analysis when the *Portfolio Gain* variable is defined with alternative definitions using the number of winners and losers in a portfolio. The results are all very similar.

paper gain portfolios and paper loss portfolios. In equation (2), $\exp(\beta_1)$ measures the disposition effect for paper loss portfolios, while $\exp(\beta_1+\beta_3)$ measures the disposition effect for paper gain portfolios.

Compared to the linear probability model, which essentially estimates the disposition effect as the difference between the probability of selling winners and losers, the hazard model measures the disposition effect as the ratio of the two. This feature of the Cox (1972) proportional hazard model fits our research purpose particularly well: because investors typically increase trading activity after positive portfolio performance (e.g., Ben-David, Birru, and Prokopenya (2018), Gervais and Odean (2001)), the difference between the probability of selling winners and that of selling losers should mechanically change, while the ratio of the two should be immune to the change of turnover (Feng and Seasholes (2005)).

There are two ways to control for unobservable heterogeneity in the Cox proportional hazard model: fixed effects and stratification. The fixed-effects model assumes that the hazard rates between different groups are proportional, and it can be estimated by adding dummy variables to the right-hand side of equation (2). However, the shortcoming is that it is difficult to incorporate a large number of fixed effects because the maximum likelihood estimator can suffer from the incidental parameters problem (Lancaster (2000)). The stratification method avoids the incidental parameters problem, and it relaxes the proportional hazard rate assumption of the fixed-effect method and allows for different baseline hazards between the strata. In other words, with stratification, the baseline hazard function of $h_0(t)$ is allowed to vary across strata. Because of its flexibility, we use stratification to account for unobservable heterogeneity.[8]

II. The PDDE

A. Univariate Results

The PDDE can be illustrated by a simple figure.

We examine the U.S. and Chinese brokerage samples in Panels A and B, respectively. The univariate view of the PDDE is strong in both samples.

Consider the probability that an investor sells one of her holdings, plotted in the portion of Figure 1 labeled "All Portfolios." The disposition effect can be seen as the difference between the green (probability of selling a gain) and the red (probability of selling a loss) bars. The black bars (which represent all stocks) are included to show the weighted average. In Panel A, the unconditional probability of selling a given stock is approximately 0.24%. Adding the

[8] There are two limitations of the hazard model. First, the hazard model does not allow for multiple-dimensional stratification. For example, we cannot include investor strata and at the same time also date strata. In analyses below, we check the robustness of our results by specifying various strata and find that our results are robust. Second, we are unable to cluster standard errors across multiple dimensions. We cluster by account, and we find that clustering by account gives more conservative t-values than clustering by stock or date.

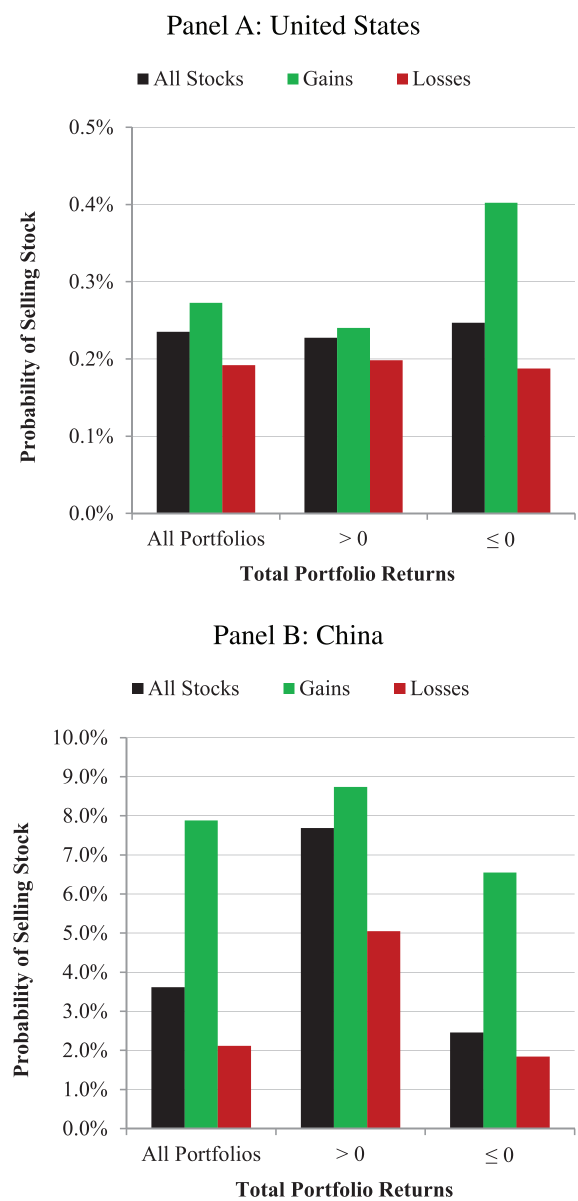

Figure 1. Probability of selling a stock based on its return and the return of the portfolio. In this figure, we show the probability of selling a stock (including partial sales) based on the stock's performance (gain vs. loss) from the date the investor purchased the stock and the performance of the investor's portfolio of stocks. In Panel A (Panel B), we show results using the U.S. (Chinese) brokerage sample described in Section I. The U.S. sample has 110,554,055 observations (53% stock gains, 47% stock losses; 61% total portfolio gains, 39% total portfolio losses). The Chinese sample has 84,796,020 observations (26% stock gains, 74% stock losses; 22% total portfolio gains, 78% total portfolio losses). We define gains (green bars) as strictly greater than zero while losses (red bars) include zeros.

condition that a given stock's return is positive (the green bar) increases the probability of an investor selling to 0.27%. The ratio (difference) in the probability of selling a gain versus a loss is approximately 1.42 (8 basis points). In other words, an investor is approximately 42% (0.27%/0.19% − 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: (i) the investor's portfolio is at a gain (the portion labeled "> 0"), and (ii) the investor's portfolio is at a loss (the portion labeled "≤ 0"). The PDDE refers to the fact that the disposition effect is much stronger in the scenario where the investor's portfolio is at a loss compared to when her portfolio is at a gain. In fact, in the U.S. sample, the disposition effect ratio (difference) decreases to approximately 1.21 (4 basis points) for gain portfolios. Conversely, the disposition effect grows substantially when the sample is restricted to observations for which the portfolio is at a paper loss, resulting in a disposition effect ratio (difference) of approximately 2.14 (21 basis points). These disposition effect ratios reveal that when an investor's portfolio is at a paper loss (gain), she is 114% (21%) more likely to sell a gain than a loss.

As we mention above, the investors in our Chinese sample trade much more frequently: the unconditional probability of selling a given stock is approximately 3.62%, which is more than 15 times the probability in the U.S. sample (Figure 1, Panel B). Nevertheless, the ratio (difference) in the probability of selling a gain versus a loss is approximately 3.73 (5.77%) for Chinese investors. In other words, an investor is approximately 273% (7.88%/2.11% − 1) more likely to sell a gain than a loss, indicating a strong disposition effect in the Chinese data. The PDDE is also strong in the Chinese sample: the disposition effect ratio (difference) decreases to approximately 1.73 (3.69%) for gain portfolios and grows to approximately 3.56 (4.71%) for loss portfolios. These disposition effect ratios reveal that when an investor's portfolio is at a paper loss (gain), she is 256% (73%) more likely to sell a gain than a loss.

B. Baseline Regressions

We estimate equation (2) on the U.S. (Chinese) sample described in Section I using a Cox hazard model and report the results in Table II, Panel A (Panel B). Column (1) shows the baseline results with no stratification. Columns (2) to (4) add stratification by date, stock, and account, respectively. In column (5), we control for the V-shaped disposition effect (Ben-David and Hirshleifer (2012)) by including 52 return bracket indicators for the focal stock's return: $(-\infty, -50\%)$, ..., $[-4\%, -2\%)$, $[-2\%, 0)$, $[0, 2\%)$, $[2\%, 4\%)$, ..., $[50\%, +\infty)$. In addition, one might be concerned that the variables *Gain* and *Portfolio Gain* are mechanically related, and thus, in column (6), we consider an alternative definition for *Portfolio Gain* that excludes the focal stock when computing portfolio performance. We also consider other alternative definitions of *Portfolio Gain* such as the fraction of stocks in the portfolio that are at a gain. The

Table II
Baseline Regressions

The table reports the baseline Cox proportional hazard regression estimation for equation (2). Panel A (Panel B) shows results using the U.S. (Chinese) sample. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) on day $t + 1$, and zero otherwise. *Gain* is a dummy variable that equals one if a stock in an investor's portfolio has a positive return since purchase at day t, and zero otherwise. *Portfolio Gain* is a dummy variable that equals one if an investor's portfolio has a positive paper gain at day t, and zero otherwise. We stratify the baseline hazard function by date, stock, and account in columns (2), (3), and (4), respectively. In column (5), we control for the V-shaped disposition effect (Ben-David and Hirshleifer (2012)) by including 52 return bracket indicators for the focal stock's return: $(-\infty, -50\%)$, ..., $[-4\%, -2\%)$, $[-2\%, 0)$, $[0, 2\%)$, $[2\%, 4\%)$, ..., $[50\%, -\infty)$. Column (6) reports results using an alternative definition of *Portfolio Gain*; in that specification, portfolio return is measured without incorporating the return of the stock associated with the given observation. Standard errors are clustered by account. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: The United States

	(1)	(2)	(3)	(4)	(5)	Rest of Portfolio Return (6)
Gain	0.833***	0.835***	0.909***	0.970***		1.018***
	(65.69)	(66.95)	(69.03)	(65.33)		(69.02)
Portfolio Gain	0.172***	0.136***	0.194***	0.716***	0.704***	0.453***
	(11.89)	(9.14)	(13.99)	(50.77)	(49.33)	(34.87)
Gain × *Portfolio Gain*	−0.584***	−0.616***	−0.583***	−0.809***	−0.863***	−0.761***
	(−37.71)	(−39.79)	(−37.78)	(−45.28)	(−48.30)	(−43.75)
Stratified by date	No	Yes	No	No	No	No
Stratified by stock	No	No	Yes	No	No	No
Stratified by account	No	No	No	Yes	Yes	Yes
Return bracket FE	No	No	No	No	Yes	No
Pseudo-R^2	0.003	0.007	0.008	0.023	0.026	0.021
Obs.	110,554,055	110,554,055	110,554,055	110,554,055	110,554,055	110,554,055

(*Continued*)

Table II—*Continued*

Panel B: China						
	(1)	(2)	(3)	(4)	(5)	Rest of Portfolio Return (6)
Gain	0.626***	0.600***	0.618***	0.748***		0.725***
	(132.45)	(131.53)	(134.14)	(152.01)		(159.73)
Portfolio Gain	0.362***	0.269***	0.362***	0.463***	0.188***	0.410***
	(63.45)	(44.26)	(67.56)	(112.55)	(50.21)	(111.98)
Gain × *Portfolio Gain*	−0.259***	−0.187***	−0.258***	−0.441***	−0.146***	−0.291***
	(−42.54)	(−29.24)	(−44.87)	(−93.68)	(−32.64)	(−67.80)
Stratified by date	No	Yes	No	No	No	No
Stratified by stock	No	No	Yes	No	No	No
Stratified by account	No	No	No	Yes	Yes	Yes
Return bracket FE	No	No	No	No	Yes	No
Pseudo-R^2	0.004	0.004	0.007	0.013	0.013	0.014
Obs.	84,793,767	84,793,767	84,793,767	84,793,767	84,793,767	84,793,767

results, reported in Table A4 of the Internet Appendix, are similar to those for our main specification.[9]

Across all specifications, the coefficient on the interaction term (*Gain*Portfolio Gain*) ranges from −0.58 to −0.86 in the U.S. data and from −0.15 to −0.44 in the Chinese data. These coefficients indicate significant declines in the disposition effect when the portfolio is at a gain relative to when the portfolio is at a loss. For example, in our preferred specification with account stratification (column (4)), the coefficient on *Gain* indicates the ratio of proportion of gains realized (PGR) to proportion of losses realized (PLR) is 2.64 (= $e^{0.970}$) when the portfolio is at a loss. When the portfolio is at a gain, PGR/PLR decreases to 1.17 (= $e^{0.970-0.809}$). In the same specification of the Chinese data, PGR/PLR decreases from 2.11 for a losing portfolio to 1.36 for a winning portfolio. Moreover, these estimates are highly statistically significant, with t-statistics all greater than 29. Taken together, 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.[10] Given that the account stratification gives a significantly better model fit (as reflected by the pseudo R^2) than stock or date stratification, we use it as our preferred stratification and report most of the remaining analyses using this specification.

C. The Magnitude of the Focal Stock and Portfolio Returns

Next, we consider more continuous measures of the focal stock and the overall portfolio's performance. In Figure 2, we display a heatmap of hazard regression coefficients indicating relative selling probabilities as a function of the performance of the focal stock and the total portfolio. Specifically, we sort all observations into 12-by-12 boxes by the focal stock's holding-period returns and total portfolio returns. Rows indicate different portfolio return brackets, and columns indicate different stock return brackets. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) on day $t + 1$, and zero otherwise. We include dummy variables indicating each of the 144 combinations. The $(-\infty, -25\%] \times (-\infty, -25\%]$ group is the base case.[11] All of the regressions are stratified by account. Areas with more (less) selling are depicted by a darker shade of red (blue). The median is white.[12]

[9] We also examine specifications with a standard set of controls following Ben-David and Hirshleifer (2012). We find very similar results. See Table IA.V.

[10] In Table IA.VI, we analyze at the household level instead of the account level. We find very similar results.

[11] In a linear regression, coefficients on dummy variables that span a set of categories should be interpreted as a difference relative to the omitted group. Similarly, in hazard regressions, estimated coefficients on group dummies should be interpreted relative to the base case. For example, the coefficient on the $(-\infty,-25\%]\text{x}(-25\%, -20\%]$ group is 0.10, indicating that this group's hazard is 10.5% (i.e., exp(0.10) − 1) higher than the base case.

[12] In Table IA.VII, we provide heatmap examples of how a binary stock-level disposition effect (Panel A), a binary "portfolio-level disposition effect" whereby investors are more likely to sell a

Panel A: United States

Portfolio return \ Focal stock return	(-∞,-25%]	(-25%,-20%]	(-20%,-15%]	(-15%,-10%]	(-10%,-5%]	(-5%,0]	(0,5%]	(5%,10%]	(10%,15%]	(15%,20%]	(20%,25%]	(25%,+∞)
(-∞,-25%]	0.00	0.10	0.19	0.18	0.18	0.34	0.90	1.24	1.40	1.46	1.70	1.54
(-25%,-20%]	0.35	-0.24	0.07	0.21	0.22	0.36	0.91	1.38	1.49	1.71	1.78	1.74
(-20%,-15%]	0.43	0.27	-0.11	0.27	0.21	0.41	0.96	1.32	1.66	1.70	1.65	1.77
(-15%,-10%]	0.58	0.42	0.37	0.02	0.28	0.39	0.99	1.37	1.47	1.67	1.59	1.73
(-10%,-5%]	0.70	0.62	0.49	0.43	0.15	0.42	1.01	1.34	1.51	1.71	1.74	1.77
(-5%,0]	1.02	0.89	0.82	0.72	0.56	0.38	0.95	1.32	1.49	1.62	1.66	1.75
(0,5%]	1.22	1.09	1.10	0.96	0.84	0.66	0.83	1.26	1.43	1.55	1.62	1.73
(5%,10%]	1.37	1.38	1.31	1.22	1.03	0.82	0.99	0.98	1.35	1.48	1.52	1.69
(10%,15%]	1.47	1.38	1.38	1.29	1.15	0.93	1.08	1.18	0.97	1.46	1.55	1.68
(15%,20%]	1.57	1.52	1.49	1.27	1.18	1.01	1.13	1.19	1.27	0.86	1.45	1.61
(20%,25%]	1.56	1.46	1.44	1.40	1.22	1.13	1.13	1.20	1.26	1.34	0.76	1.59
(25%,+∞)	1.71	1.68	1.62	1.45	1.44	1.21	1.24	1.24	1.27	1.28	1.29	1.29

Panel B: China

Portfolio return \ Focal stock return	(-∞,-25%]	(-25%,-20%]	(-20%,-15%]	(-15%,-10%]	(-10%,-5%]	(-5%,0]	(0,5%]	(5%,10%]	(10%,15%]	(15%,20%]	(20%,25%]	(25%,+∞)
(-∞,-25%]	0.00	0.30	0.38	0.47	0.67	1.04	1.53	1.58	1.51	1.37	1.31	1.02
(-25%,-20%]	0.23	0.30	0.50	0.61	0.78	1.10	1.53	1.65	1.59	1.43	1.42	1.19
(-20%,-15%]	0.25	0.37	0.45	0.63	0.82	1.11	1.54	1.64	1.58	1.53	1.31	1.10
(-15%,-10%]	0.29	0.37	0.48	0.58	0.84	1.13	1.54	1.62	1.54	1.44	1.37	1.16
(-10%,-5%]	0.32	0.48	0.49	0.65	0.86	1.16	1.54	1.62	1.52	1.50	1.46	1.07
(-5%,0]	0.55	0.64	0.74	0.78	1.03	1.27	1.61	1.66	1.60	1.43	1.41	1.04
(0,5%]	0.86	0.92	0.90	0.98	1.17	1.41	1.61	1.64	1.57	1.45	1.31	1.03
(5%,10%]	1.00	1.02	1.06	1.09	1.28	1.39	1.69	1.57	1.56	1.48	1.36	1.14
(10%,15%]	1.14	1.08	1.14	1.19	1.42	1.38	1.68	1.69	1.44	1.46	1.41	1.20
(15%,20%]	1.24	1.04	1.21	1.20	1.36	1.39	1.69	1.68	1.62	1.29	1.41	1.24
(20%,25%]	1.03	1.16	1.10	1.15	1.44	1.39	1.68	1.70	1.63	1.54	1.19	1.23
(25%,+∞)	0.95	1.06	1.15	1.14	1.37	1.39	1.69	1.66	1.57	1.50	1.43	1.14

Figure 2. Nonbinary measures of the focal stock and portfolio returns. We sort the sample into 12 × 12 boxes by the focal stock's holding-period return and total portfolio return, defining an indicator variable for each box. This figure reports the Cox hazard regression coefficients for these 144 indicator variables. Rows indicate different portfolio return brackets; columns indicate different focal stock return brackets. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) on day $t+1$, and zero otherwise. The $(-\infty, -25\%] \times (-\infty, -25\%]$ group is the base case. Regressions are stratified by account. Areas with more (less) selling are depicted by a darker shade of red (blue). The median is white.

The disposition effect can be observed in Figure 2 by noting that the right half of the two panels tends to be red, which indicates elevated selling activity, while the left half tends to be blue, which indicates reduced selling activity. Interestingly, the specific pattern of the disposition effect diverges across the two samples—there is a V-shaped selling schedule in the U.S. sample (as documented by Ben-David and Hirshleifer (2012)), whereas the Chinese sample has a reverse V-shape with elevated selling activity near zero.

The presence of a V-shaped disposition effect in the U.S. data and a reverse V-shape disposition effect in the Chinese data makes it less likely for us to find a PDDE in the U.S. sample and more likely in the Chinese sample. To see why, consider the case in which an investor exhibits a strong V-shaped disposition effect (as in the U.S. data). If her portfolio is at a gain, she is more likely to sell her individual stock gains because they are likely to be extreme gains, that is, she will exhibit a stronger disposition effect when her portfolio is at a gain. This works *against* the PDDE. By the same logic, a reverse V-shaped disposition effect works *for* the PDDE. Consistent with this reasoning, including V-shaped controls in Table II strengthens the PDDE in the U.S. data

stock when the total portfolio is at a gain irrespective of the performance of the individual stock (Panel B), and a binary PDDE (Panel C) would materialize in isolation.

and weakens it in the Chinese data. Nevertheless, the PDDE remains strong in both samples.

As we move down each panel of Figure 2 (indicating improved portfolio performance), we see that the relative probability of selling losers (the left half of each panel) increases significantly. Conversely, the performance of the portfolio has a much weaker effect on the propensity to sell a winning stock (the right half of each panel). This pattern arises in both the U.S. and Chinese samples, indicating that when we control for unobserved heterogeneity across accounts, the PDDE appears to be driven by the effect of portfolio returns on the propensity to sell losing positions.

D. Subsample Analysis

We next examine how the PDDE varies with individual and portfolio characteristics. For each characteristic, we group all of the observations into subsamples and estimate the regression model from column (4) of Table II on various subsamples. We report all subsample tests in the U.S. (Panel A) and Chinese (Panel B) brokerage samples. Because not all demographic information is available for all investors, the combination of all subsamples is sometimes smaller than the full sample. For investor characteristics, we study age, gender, and trading frequency. Investors are grouped into three age groups: 1 to 40, 41 to 55, and greater than 55. In the United States, these three groups roughly correspond to the first quartile, quartiles 2 to 3, and quartile 4, respectively. In the Chinese sample, these three groups roughly correspond to quintiles 1 to 2, quintiles 3 to 4, and quintile 5, respectively.[13] Trading frequency is calculated as the unconditional selling propensity of an investor over the full-sample period. We sort all the investors into two trading-frequency groups: those above and below the median. For portfolio characteristics, we test the impact of the holding period on the PDDE. To employ the hazard model described in Section I.B, we must include all observations from the start of the holding period until a maximum number of days. We report two variations of the maximum holding period, 20 and 250 days.

Several observations emerge from Table III. First, we find that the moderating effect of portfolio gains is similar across the different age and gender groups but is slightly larger for high- (low-) trading-frequency investors in the U.S. (Chinese) sample.[14] Second, the PDDE is larger for longer holding periods in both the U.S. and Chinese samples. Finally, the moderating role of portfolio gains on the disposition effect remains strong across all subsamples, as indicated by the significantly negative interaction coefficients ranging from −0.501 to −0.849 (t-statistics from −9.64 to −41.64) in the U.S. sample and −0.274 to −0.606 (t-statistics from −47.66 to −91.48) in the Chinese sample.

[13] In the Chinese sample, age 40 is the 39$^{\text{th}}$ percentile, and age 55 is the 79$^{\text{th}}$ percentile.

[14] The t-statistic on Female is reduced in the U.S. sample because women make up only about 10% of the observations. The gender distribution is significantly more balanced in the Chinese sample, with females representing roughly 54% of the observations. Regardless, the economic magnitudes of the interaction coefficients are similar in both samples.

Table III

Subsample Analysis

The table reports results from Table II, column (4), regression using different subsamples based on the investor's age, gender, trading frequency (above vs. below median), and focal stock-holding period, respectively. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) on day $t + 1$, and zero otherwise. *Gain* is a dummy variable that equals one if a stock in an investor's portfolio has a positive return since purchase at day t, and zero otherwise. *Portfolio Gain* is a dummy variable that equals one if an investor's portfolio has a positive paper gain, and zero otherwise. All standard errors are clustered by account. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: The United States

	Age			Gender		Trading Frequency		Holding Period	
	1 to 40	41 to 55	>55	Female	Male	Low	High	1 to 20	to 250
Gain	1.140***	1.069***	0.890***	0.934***	1.012***	0.763***	0.988***	0.853***	0.990***
	(32.84)	(33.67)	(41.39)	(15.63)	(49.44)	(23.67)	(62.60)	(31.85)	(59.89)
Portfolio Gain	0.652***	0.752***	0.704***	0.676***	0.732***	0.794***	0.703***	0.459***	0.690***
	(17.98)	(23.01)	(35.91)	(9.37)	(36.87)	(23.75)	(46.24)	(17.86)	(43.27)
Gain × *Portfolio Gain*	−0.716***	−0.849***	−0.799***	−0.697***	−0.829***	−0.710***	−0.809***	−0.501***	−0.772***
	(−16.16)	(−22.13)	(−31.44)	(−9.64)	(−33.87)	(−18.36)	(−41.64)	(−16.31)	(−38.43)
Stratified by account	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.038	0.029	0.018	0.022	0.026	0.016	0.023	0.017	0.023
Obs.	12,524,750	23,819,060	59,511,195	6,226,295	55,641,482	60,205,982	50,348,073	6,765,147	54,493,253

(*Continued*)

Table III—*Continued*

Panel B: China									
	Age			Gender		Trading Frequency		Holding Period	
	1 to 40	41 to 55	>55	Female	Male	Low	High	1 to 20	1 to 250
Gain	0.739***	0.769***	0.728***	0.812***	0.699***	1.199***	0.588***	0.572***	0.721***
	(99.81)	(113.74)	(74.12)	(128.57)	(97.78)	(176.96)	(116.03)	(119.45)	(149.13)
Portfolio Gain	0.488***	0.474***	0.433***	0.482***	0.456***	0.676***	0.396***	0.317***	0.448***
	(67.53)	(77.80)	(54.16)	(83.06)	(76.72)	(86.91)	(84.94)	(78.71)	(111.80)
Gain × *Portfolio Gain*	−0.472***	−0.446***	−0.415***	−0.460***	−0.433***	−0.606***	−0.365***	−0.274***	−0.420***
	(−56.79)	(−62.16)	(−47.66)	(−70.80)	(−58.54)	(−71.30)	(−69.63)	(−60.16)	(−91.48)
Stratified by account	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.014	0.014	0.012	0.016	0.012	0.039	0.008	0.008	0.013
Obs.	18,114,248	35,762,807	30,916,712	40,733,457	35,283,000	54,211,615	30,582,152	21,422,788	62,911,421

E. 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 investors own the same stock and purchased the stock on the same day at the same price. By identical investors, we mean investors would make the same decisions when facing a given 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 our matching analysis, we approximate the ideal experiment by comparing identical positions owned by different investors. Specifically, we stratify by positions built on the same day with the same stock in the regressions. By doing so, we keep the stock and purchase date the same and focus on the portfolio return variation across investors. We also only keep the observations for which there are at least two investors within the same strata. The number of observations represents 52.2% of the full sample. In columns (1) and (2) of Table IV, we find that the coefficient on the interaction term is negative and highly significant whether we stratify by account (−0.831, *t*-statistic −38.90) or by stock*purchase date (−0.588, *t*-statistic −34.13).

With the stratification by positions built on the same day using the same stock, there is not much variation in purchase price within a stratum because we consider purchases of the same stock on the same day. Nevertheless, in a second specification, we further require the exact same purchase price in the stratification. Relative to the first specification, this filter reduces the sample by around half, but the PDDE is similar in magnitude, with interaction coefficients of −0.838 (*t*-statistic −30.26) and −0.550 (*t*-statistic −23.30) in columns (3) and (4), respectively. In a third specification, reported in columns (5) and (6), we further exclude positions that were constructed with multiple purchases. We continue to find a strong PDDE.[15]

We repeat the above analyses for the Chinese sample.[16] The coefficient of the interaction term remains negative and highly significant.[17] The results are broadly similar across the six specifications. The relative magnitude of the *Gain* and *Gain*Portfolio Gain* terms are similar to the baseline estimation in Table II, which suggests that the PDDE is not driven by unobserved stock-level characteristics that are correlated with the portfolio's gain/loss status.

[15] In other words, in this last specification, we only consider (investor-stock-purchase date) triples such that the investor liquidates some of her position in the stock before purchasing any more shares of the stock.

[16] During our sample period, in the United States, the tick size was one-eighth of a dollar, whereas in China the tick size was one cent RMB. To be consistent, in the Chinese data we round the purchase prices to the nearest eighth and require that the rounded purchase price be the same.

[17] If we do not round the purchase price, the coefficient on the interaction term is −0.290 (*t*-statistic −4.89) and −0.313 (*t*-statistic −5.54) in columns (4) and (6), respectively. The number of observations is 2,525,960 and 2,166,353, respectively.

Table IV

Matching Sample Analysis

The table reports regression results of the matching analysis. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) on day $t + 1$, and zero otherwise. *Gain* is a dummy variable that equals one if a stock in an investor's portfolio has a positive return since purchase at day t, and zero otherwise. *Portfolio Gain* is a dummy variable that equals one if an investor's portfolio has a positive paper gain, and zero otherwise. In columns (1) and (2), we focus on the instances in which there are at least two positions built on the same day using the same stock. In columns (3) and (4), we further require that the purchase price is the same for the U.S. sample (Panel A). In the Chinese sample (Panel B), we round the purchase price to the nearest eighth and require that the rounded purchase prices are the same. In columns (5) and (6), we further require that the positions are acquired in one purchase, that is, we only consider investor-stock-purchase date triples such that the investor liquidates some of her position in the stock before purchasing any more shares of the stock. In columns (1), (3), and (5), we stratify by account, and in columns (2), (4), and (6), we stratify by position built on the same day and of the same stock. Standard errors are clustered by account. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: The United States

	(1)	(2)	(3)	(4)	(5)	(6)
Gain	0.999***	0.641***	1.003***	0.615***	0.952***	0.328***
	(57.14)	(31.89)	(45.58)	(17.82)	(37.72)	(6.63)
Portfolio Gain	0.704***	0.084***	0.718***	0.115***	0.681***	0.120***
	(42.18)	(5.79)	(31.82)	(6.40)	(25.32)	(5.83)
Gain × *Portfolio Gain*	−0.831***	−0.588***	−0.838***	−0.550***	−0.797***	−0.559***
	(−38.90)	(−34.13)	(−30.26)	(−23.30)	(−24.81)	(−20.78)
Stratification	Account	Positions in same stock with same purchase date	Account	Positions in same stock with same purchase date and price	Account	Positions in same stock with same purchase date and price; requiring one purchase
Pseudo-R^2	0.027	0.008	0.032	0.006	0.030	0.171
Obs.	57,680,893	57,680,893	29,807,432	29,807,432	21,457,460	21,457,460

(*Continued*)

Table IV—*Continued*

Panel B: China						
	(1)	(2)	(3)	(4)	(5)	(6)
Gain	0.845***	0.451***	0.845***	0.250***	0.896***	0.273***
	(164.36)	(10.86)	(164.36)	(53.32)	(182.59)	(54.87)
Portfolio Gain	0.553***	0.233***	0.553***	0.266***	0.589***	0.284***
	(127.39)	(29.20)	(127.39)	(56.11)	(129.69)	(56.41)
Gain × *Portfolio Gain*	-0.510***	−0.296***	−0.510***	−0.178***	−0.537***	−0.205***
	(−102.02)	(−18.78)	(−102.02)	(−32.69)	(−102.83)	(−35.70)
Stratification	Account	Positions in same stock with same purchase date	Account	Positions in same stock with same purchase date and price	Account	Positions in same stock with same purchase date and price; requiring one purchase
Pseudo-R^2	0.017	0.000	0.017	0.002	0.021	0.002
Obs.	67,679,549	67,679,549	43,802,363	43,802,363	37,317,624	37,317,624

F. Experimental Settings

In the prior section, we compare the selling decision for the same stocks at the same point in time across investors whose portfolios are at a gain and a loss. While this is as close to ideal in the archival setting as possible, we can come even closer to the ideal setting in an experiment in which we can do several things that are not possible in an archival setting: (i) have the same trader on the same day be faced with a portfolio gain and a portfolio loss and observe her differential behavior across these conditions, (ii) inform each trader of the stock data-generating process to minimize differences in information across traders, and (iii) control the display of information to traders.

We employ a trading game that is similar to Weber and Camerer (1998). We recruited subjects from two pools: undergraduate students from a Chinese university and volunteer workers ("MTurkers") from "MTurk." We required subjects to pass a quiz administered prior to the trading game, and we collected trading data from 766 and 2,377 subjects in the Chinese university and MTurk samples, respectively.[18] There are four fictitious stocks, labeled A, B, C, and D, whose prices evolve randomly. Each trading game lasts 12 rounds. In the first two rounds, subjects simply observe the stock prices and are not able to trade. In Rounds 3 through 12, subjects can use their experimental cash to purchase shares of stocks using a "Buy" button, and if they own shares of a stock, they can sell shares of the stock using a "Sell" button. Each subject plays this 12-round stock trading game a total of four times. Subjects are not allowed to borrow cash or short sell.

Stock prices evolve each round according to the following two independent processes. First, whether a stock's price will increase or decrease is determined randomly. One of the stocks is randomly chosen to have a 65% chance each round of having its price increasing, while the other three stocks are randomly assigned corresponding probabilities of 55%, 45%, and 35%. The probabilities of increases or decreases are different for each stock and do not change between rounds within a game. Across games, however, the probabilities are randomly reassigned. Second, the magnitude of the price increase or decrease is determined. Prices change by \$1, \$3, or \$5, each with equal probability. The magnitude of the price change is independent of whether the price increases or decreases.

Each round, subjects are shown a graph of each stock's price evolution up to that round.[19] Each game, subjects are endowed with 1,000 units of experimental cash that they can use to trade the fictitious stocks, and their compensation

[18] We administered the quiz to 1,295 Chinese university students and 9,600 people from MTurk. Of these, a total of 811 (62.6%) and 2,537 (26.4%) Chinese university and MTurk subjects passed the quiz and played the trading game. Due to a server failure, we do not have complete trading data for some of these subjects, leaving us with a final sample of 766 and 2,377 subjects in the Chinese university and MTurk samples. Thus, our pooled sample of MTurk and Chinese university students consists of 3,143 subjects. The Internet Appendix includes prequiz introductory information, quiz questions, and experimental treatment descriptions.

[19] We discuss additional details about the display of portfolio performance in Internet Appendix Section II.

Table V
The PDDE in Two Experimental Settings

The table reports results for the hazard regressions shown in equation (2) on the experimental samples. The samples consist of all subject-round-stock triples such that the subject owns shares of the given stock and at least one other stock entering the given round. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) of the fictitious stock in the given round, and zero otherwise. *Portfolio Gain* is a dummy variable that equals one if a subject's portfolio has a positive paper gain, and zero otherwise. In column (1), the sample consists of Chinese university students. Columns (2) and (3) report the results for the MTurk sample and the pooled sample consisting of all subjects (Chinese and MTurk), respectively. In all columns, we stratify by subject. In columns (4) to (6), we repeat these regressions controlling for the V-shaped disposition effect (Ben-David and Hirshleifer (2012)) by including 52 return bracket indicators for the focal stock's return: $(-\infty, -50\%)$, …, $[-4\%, -2\%)$, $[-2\%, 0)$, $[0, 2\%)$, $[2\%, 4\%)$, …, $[50\%, -\infty)$. Standard errors are clustered by subject. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Gain	0.699***	0.491***	0.559***			
	(11.13)	(10.63)	(15.03)			
Portfolio Gain	0.614***	0.447***	0.503***	0.574***	0.476***	0.512***
	(13.50)	(13.94)	(19.12)	(13.47)	(15.38)	(20.32)
Gain × *Portfolio Gain*	−0.420***	−0.402***	−0.406***	−0.362***	−0.421***	−0.400***
	(−7.26)	(−9.49)	(−11.89)	(−6.93)	(−10.71)	(−12.74)
Sample	Chinese	Mturk	Pooled	Chinese	MTurk	Pooled
Stratified by subject	Yes	Yes	Yes	Yes	Yes	Yes
Return bracket FE	No	No	No	Yes	Yes	Yes
Pseudo-R^2	0.024	0.010	0.014	0.013	0.004	0.016
Obs.	52,903	162,810	215,713	52,903	162,810	215,713

depends on the total value of their assets (stock plus experimental cash) at the end of the experiment. Specifically, subjects are paid a 1 RMB ($0.25) show-up fee in the Chinese university (MTurk) sample plus a bonus that is based on their performance during one of the four trading games, which is chosen randomly. The average pay for the subjects was 20.93 RMB and $3.25 in the Chinese and MTurk samples, respectively.

We begin by estimating our baseline hazard regression model in Table V. In columns (1) to (3), we stratify by subject, and in columns (4) to (6), we also add controls for the V-shaped disposition effect (Ben-David and Hirshleifer (2012)) by including the same return bracket fixed effects from column (5) of Table II. We report the estimates for the Chinese sample in columns (1) and (4), the MTurk sample in columns (2) and (5), and the pooled sample consisting of all subjects in columns (3) and (6).

The positive coefficients on *Gain* in columns (1) to (3) demonstrate a strong disposition effect in our experimental settings. As in the previous tables, we look for a PDDE by examining the interaction of *Gain* and *Portfolio Gain*. In each specification, we find that the coefficient on the interaction is negative and statistically significant, consistent with subjects exhibiting a PDDE. For example, consider the coefficients of 0.699 on *Gain* and −0.420 on *Gain*Portfolio*

Gain in column (1). The coefficient on *Gain* indicates a PGR/PLR ratio of 2.01 (= $e^{0.699}$) when the portfolio is at a loss. When the portfolio is at a gain, PGR/PLR decreases to 1.32 (= $e^{0.699-0.420}$). In addition, we find that in the most controlled tests with return bracket fixed effects, the interaction coefficient is -0.362 (t-statistic -6.93) in the Chinese experimental sample, -0.421 (t-statistic -10.71) in the MTurk sample, and -0.400 (t-statistic -12.74) in the pooled sample. Together, these results provide evidence that the PDDE holds in this well-controlled environment where we observe the same person on the same day exposed to both a portfolio gain and a portfolio loss and hence can observe her differential tendency to exhibit the disposition effect.

G. 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 the PDDE is that all investors tend to exhibit the disposition effect around similar points in time, or in other words, there should be comovement in the disposition effect.

To test this prediction, we calculate the level of the disposition effect across different investor groups quarter by quarter in both the U.S. and Chinese samples. We stratify investors by gender, age, and portfolio size (into 10 equal-sized groups). In the fourth test, we stratify investors randomly into 10 equal-sized groups. For each investor group in each quarter, we estimate the average disposition effect by running equation (1) using investor-stock-day observations. Internet Appendix Figure IA.1 presents the results. The y-axis corresponds to the value of the disposition effect, and the x-axis to the quarter. We find that investors with different gender, age, portfolio size, and other characteristics comove very closely over time in the level of the disposition effect.

The PDDE also predicts that the time-series variation of the disposition effect should be related to past market performance: after a bull market, most investors' portfolios will be at a gain, and therefore the PDDE implies that they should exhibit a weaker disposition effect. In contrast, a bear market should lead to portfolio losses for most investors, and thus a strong disposition effect among investors. In Table IA.X, we examine the relation between the quarterly average disposition effect across all investors and various horizons of past market returns in a univariate regression framework. We find that the quarterly average disposition effect is negatively correlated with past market returns at almost all horizons in both samples.[20] Moreover, when we compare the correlation across different horizons, we find that the negative correlation between the disposition effect and past market returns peaks at eight quarters in the

[20] Bernard, Loos, and Weber (2022) find similar patterns using individual investor trading data from Germany.

U.S. sample and at three quarters in the Chinese sample. Interestingly, these horizons closely match investors' average holding periods in the two samples.[21] These coefficients are economically sizable. For example, in the United States, a one-standard-deviation (13.1%) change in the cumulative market return over the past eight quarters ($R_{t-8,t-1}$) is associated with a 0.083 decrease of the disposition effect, which is 18% of the average of the quarterly disposition effect (0.455). In China, a one-standard-deviation (41.6%) change in $R_{t-3,t-1}$ (the cumulative market return over the past three quarters) is associated with a 0.112 decrease of the disposition effect, which is 17% of the average of the quarterly disposition effect (0.667).

Figure 3 presents the time series of the average disposition effect and past market returns for the U.S. and Chinese samples, with past market returns measured over the past eight (three) quarters for the United States (China). The negative correlation between the disposition effect and past market returns is evident.[22] We therefore document a systematic and cyclical component in one of the most robust behavioral patterns, the disposition effect.

III. Relationship to Prior Research

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

A. The Rank Effect

We first test whether extreme stocks drive the PDDE. Hartzmark (2015) finds that retail and mutual fund investors are more likely to sell their best- and worst-performing stocks. 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 are 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 are 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 nearly as likely to be sold as winners are when the remaining portfolio is at a gain).

Nevertheless, in Table VI we evaluate how the rank effect relates to our empirical results. Specifically, in column (1), we add indicator variables for

[21] According to the World Bank, the average market turnover during our sample periods is 65% (implying an average holding period of six quarters) in the United States and 195% (implying an average holding period of two quarters) in China.

[22] We also investigate whether the PDDE is different in boom and bust periods in Table IA.XI. We find no difference in the PDDE between boom and bust periods in the United States and a slightly stronger PDDE during bust periods in China.

Table VI
Alternative Mechanisms

The table examines whether alternative mechanisms can explain our main finding. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) on day $t+1$, and zero otherwise. *Gain* is a dummy variable that equals one if a stock in an investor's portfolio has a positive return since purchase at day t, and zero otherwise. *Portfolio Gain* is a dummy variable that equals one if an investor's portfolio has a positive paper gain, and zero otherwise. Following Hartzmark (2015), in Panel A, column (1), we add indicator variables for the best- and worst-performing stocks in an investor's portfolio, and in column (2), we include rank indicator variables for the 15 best and 15 worst performing stocks. In columns (3) and (4), we run the test within tax-exempt accounts and taxable accounts, respectively. In column (5), the dependent variable is defined differently: it is equal to one for full liquidations and zero otherwise. For Panel B, we replicate our analysis in the Chinese sample when possible; the tax incentive columns are omitted because there is no capital gain tax in China during our sample period. All of the models are estimated using the Cox proportional hazard model, and the baseline hazard is stratified by account. Standard errors are clustered by account. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: The United States

	Rank Effect?		Tax Incentives?		Rebalancing?
	FE	Extreme	Tax-Exempt	Taxable	Full Liquidation
	(1)	(2)	(3)	(4)	(5)
Gain	0.956***	0.831***	0.933***	0.981***	1.008***
	(62.36)	(58.70)	(36.42)	(55.43)	(65.86)
Portfolio Gain	0.729***	0.747***	0.732***	0.709***	0.776***
	(50.73)	(51.01)	(27.48)	(42.82)	(53.43)
Gain × *Portfolio Gain*	−0.819***	−0.768***	−0.700***	−0.845***	−0.915***
	(−45.43)	(−42.64)	(−21.93)	(−39.99)	(−49.84)
Stratified by account	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.023	0.026	0.025	0.022	0.023
Obs.	110,554,055	110,554,055	32,467,052	78,046,422	118,269,397

Panel B: China

	Rank Effect?		Rebalancing?
	FE	Extreme	Full Liquidation
	(1)	(2)	(3)
Gain	0.740***	0.774***	0.896***
	(143.82)	(149.67)	(185.17)
Portfolio Gain	0.474***	0.469***	0.608***
	(112.18)	(105.91)	(132.46)
Gain × *Portfolio Gain*	−0.449***	−0.459***	−0.597***
	(−94.65)	(−97.98)	(−115.57)
Stratified by account	Yes	Yes	Yes
Pseudo-R^2	0.013	0.014	0.019
Obs.	84,793,767	84,793,767	101,123,567

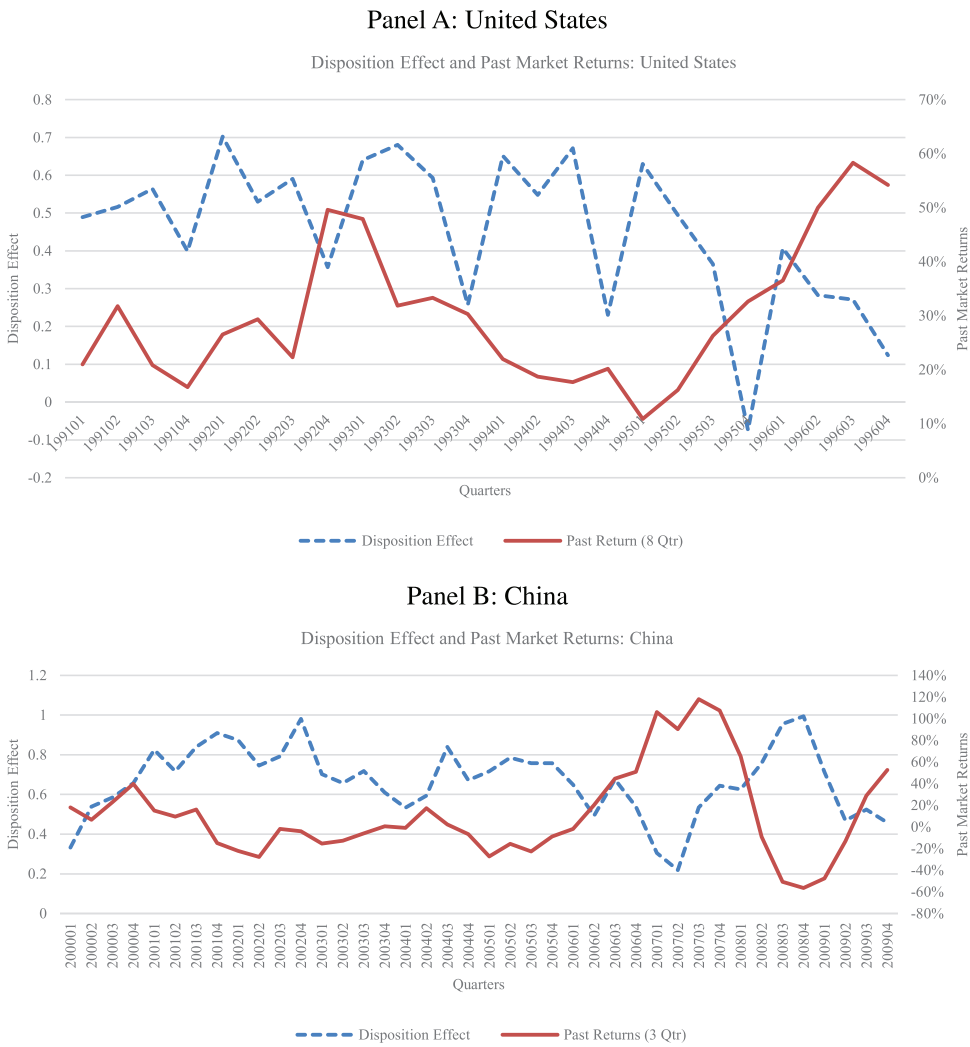

Figure 3. The disposition effect and past market returns. This figure presents the time series of past market returns and the disposition effect across all investors. We estimate the quarterly disposition effect by estimating the coefficients of the interaction terms between the *Gain* dummy and quarterly dummies in a Cox hazard regression model. Panel A plots the U.S. sample results, where the past market return is measured over the past eight quarters. Panel B plots the Chinese sample results, where the past market return is measured over the past three quarters. The left side of the y-axis is the disposition effect. The right side of the y-axis is the past market return. The x-axis is the quarter. (Color figure can be viewed at wileyonlinelibrary.com)

the best-performing and the worst-performing stocks in an investor's portfolio, and in column (2), we add indicator variables for 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). The interaction coefficient is very similar to the baseline regression in column (4) of Table II in terms of both statistical significance and economic magnitude for the U.S. (Panel A) and Chinese (Panel B) samples. These results suggest that the rank effect (Hartzmark (2015)) does not explain the PDDE.

B. Tax Incentives

Because Odean (1998) finds that the disposition effect is time-varying due to tax motivations, we consider the possibility that the PDDE could be explained by such considerations. To do so, we conduct our analyses separately within U.S. tax-exempt accounts. Columns (3) and (4) of Table VI, Panel A report the regression results splitting the U.S. sample by tax-exempt and taxable accounts, respectively. Although the PDDE is slightly stronger for taxable accounts, the PDDE is strong among tax-exempt accounts with an interaction coefficient of −0.700 (t-statistic −21.93). Furthermore, tax-loss selling cannot explain the PDDE in the Chinese sample, where capital gains are not taxed. These findings suggest that tax considerations do not 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. For example, suppose all but one of an investor's stocks is at a loss. The lone stock that is trading at a gain may comprise a disproportionately large percentage of the investor's portfolio due to its gains and the rest of the stocks' losses. The investor may 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* (but not completely) liquidate their positions in the stock that is at a gain when the rest of the portfolio is at a loss, while we should expect the PDDE to disappear when we restrict attention to *complete* liquidations of stocks.

To test this prediction, we adjust our specification to use a full liquidation dummy as the dependent variable, thus eliminating any variation from partial sales. In column (5) of Panel A and column (3) of Panel B of Table VI, we report the full liquidation results. For the United States, we see that the interaction coefficient of −0.915 (t-statistic −49.84) is still negative and significant well below the 1% level and nearly offsets the magnitude of the *Gain* coefficient. For the Chinese sample, the interaction coefficient is −0.597 (t-statistic −115.57) and is about two-thirds of the *Gain* coefficient. Thus, portfolio rebalancing is an unlikely explanation for the PDDE.

D. Investor Heterogeneity of the Disposition Effect

Another possibility is that the PDDE is explained by heterogeneity of the disposition effect across investors, which may stem from various sources such as investor IQ (Grinblatt, Keloharju, and Linnainmaa (2012)).[23] Specifically, people who have a strong disposition effect tend to sell winners in their portfolio and keep losers. Therefore, individuals with a strong disposition effect are more likely to have a (paper) portfolio loss compared to individuals with a weak disposition effect, a pattern that might confound our findings.

To address this concern, we employ two approaches. First, when calculating *Portfolio Gain*, instead of restricting attention to the paper gain/loss of currently held positions, we add back previously realized gains/losses in the past one year as if they were not realized.[24] Under this construction, the variation in *Portfolio Gain* is driven mainly by the performance of securities in the portfolio, and is unrelated to whether these positions are realized or not (and thus the investor's tendency to exhibit a disposition effect). Table VII columns (1) and (3) report results based on *Portfolio Gain* constructed this way.

Second, we control for heterogeneity in the disposition effect across investors by stratifying the baseline hazard function at the account-gain level in columns (2) and (3) instead of the account level as in column (1). This specification is designed to control for the variation in the disposition effect across investors. That is, for each account, we explicitly allow his or her propensity to sell (the baseline hazard function) to differ across winning and losing positions.[25] As shown in Table VII, columns (1) to (3), under the alternative definition of *Portfolio Gain* and/or the more saturated stratification, the coefficient estimate on the interaction term between *Gain* and *Portfolio Gain* remains significantly negative. Note that since we have subsumed the baseline, account-specific disposition effect under these specifications, the magnitude of the coefficient on the interaction term is not directly comparable across columns, as it reflects a proportional change relative to the baseline case. However, within each column, the magnitude of the coefficient on the interaction term is similar to that on *Portfolio Gain* in both the U.S. and Chinese samples. This observation suggests that investor heterogeneity in the disposition effect can explain only part of the PDDE.[26]

[23] We discuss the relation between investor sophistication and the PDDE in more detail in Internet Appendix Section I. Table IA.XII provides evidence that the estimation of PDDE does not vary across investor subsamples based on income levels and occupations.

[24] In Table IA.XIII, we show results using different horizons for adding realized gains/losses and find that the PDDE persists across all specifications.

[25] Note that the estimation from this specification is likely to be conservative. Controlling for individual heterogeneity in the disposition effect will mechanically lead to a negative autocorrelation of the disposition effect. To the extent that *Portfolio Gain* at t is an inverse function of the disposition effect before t, the account-gain stratification tends to underestimate the PDDE effect (e.g., a less negative coefficient on *Gain* × *Portfolio Gain*). In Table IA.XIV, we show that the results in the experimental samples are also robust to subject-gain stratification.

[26] In addition, investor heterogeneity in the disposition effect cannot explain the correlation between the disposition effect and past market returns, or the comovement in the disposition effect across different investor types, which we document in Section II.G.

Table VII

Investor Heterogeneity in the Disposition Effect

The table reports Cox proportional hazard regression results for specifications that take into account potential investor heterogeneity in the disposition effect. The dependent variable is a dummy variable that equals one if there is sale (including partial sale) on day $t + 1$, and zero otherwise. *Gain* is a dummy variable that equals one if a stock in an investor's portfolio has a positive return since purchase at day t, and zero otherwise. *Portfolio Gain* is a dummy variable that equals one if an investor's portfolio has a positive paper gain, and zero otherwise. In column (2), portfolio performance is defined in the same way as the baseline specification, in which we only consider unrealized gains/losses. Columns (1) and (3) employ an alternative definition of portfolio performance: besides paper gains/losses of currently held securities, we also add back previously realized gains/losses in the past one year. In all specifications, we control for the V-shaped disposition effect (Ben-David and Hirshleifer (2012)) by including 52 return bracket indicators for the focal stock's return: $(-\infty, -50\%)$, …, $[-4\%, -2\%)$, $[-2\%, 0)$, $[0, 2\%)$, $[2\%, 4\%)$, …, $[50\%, +\infty)$. We stratify the baseline hazard function by account in column (1) and by account-gain in columns (2) and (3). Standard errors are clustered by account. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: The United States

	Paper Gains + Realized Gains (1)	Paper Gains (2)	Paper Gains + Realized Gains (3)
Portfolio Gain	0.511***	0.226***	0.437***
	(36.05)	(15.72)	(28.55)
Gain × *Portfolio Gain*	−0.447***	−0.126***	−0.360***
	(−25.43)	(−8.06)	(−21.50)
Stratified by account	Yes	No	No
Stratified by account-gain	No	Yes	Yes
Return bracket FE	Yes	Yes	Yes
Pseudo-R^2	0.022	0.009	0.010
Obs.	110,554,055	110,554,055	110,554,055

Panel B: China

	Paper Gains + Realized Gains (1)	Paper Gains (2)	Paper Gains + Realized Gains (3)
Portfolio Gain	0.152***	0.162***	0.160***
	(21.04)	(41.16)	(32.46)
Gain × *Portfolio Gain*	−0.131***	−0.150***	−0.134***
	(−27.67)	(−30.49)	(−27.26)
Stratified by account	Yes	No	No
Stratified by account-gain	No	Yes	Yes
Return bracket FE	Yes	Yes	Yes
Pseudo-R^2	0.012	0.011	0.011
Obs.	84,793,767	84,793,767	84,793,767

IV. Multiple Frames

The prior section rejects explanations whereby the PDDE is a by-product of various possible mechanisms, such as the rank effect or investor heterogeneity of the disposition effect. In this section, we present evidence that investors have multiple frames that combine to generate the PDDE.[27]

Prior research on the disposition effect has establishes narrow framing at the stock level, among stocks within a portfolio (Hartzmark (2015)), and even framing across trades (Frydman, Hartzmark, and Solomon (2018)). Here, we present evidence that investors simultaneously use two separate frames—one at the stock level and one at the portfolio level—when making decisions, resulting in the PDDE. There are several ways that multiple frames could generate the PDDE. For example, investors might engage in hedonic mental accounting (Thaler (1985)), which posits that people frame their decisions in the way that makes them feel best. Specifically, by framing the sale of a losing stock as a liquidation of (part of) the larger portfolio, the investor can mentally account for the liquidation of a loss as a gain, but this is only possible when the portfolio is at a gain. Another possibility is cognitive dissonance, which has been proposed as a mechanism for the disposition effect (Chang, Solomon, and Westerfield (2016)). An investor who simultaneously frames at both the individual stock level and the portfolio level should be especially prone to exhibit the disposition effect when her portfolio is at a loss; in this case, both frames (stock and portfolio) suggest that the investor made bad decisions, and liquidating a loss in this scenario should be particularly difficult to reconcile with one's self-image of a good decision-maker.[28] Conversely, if the investor's portfolio is at a gain, she can still convince herself she is a good trader by paying attention to the portfolio-level frame, which suggests she is a good trader who makes good decisions.

To provide direct evidence of an additional frame at the portfolio level, we use the fact that a focal asset's membership in a portfolio will be determined based on how similar the other assets in the portfolio are. Similarity has been extensively documented as a defining characteristic of how individuals create mental accounts (Evers, Imas, and Kang (2022), Goldstone (1994), Nosofsky (1986), Kruschke (1992)). If a portfolio-level frame drives the PDDE, similarity

[27] The idea that investors have multiple frames is consistent with the contemporaneous theoretical work of Dai, Qin, and Wang (2023).

[28] As Chang, Solomon, and Westerfield (2016) explain, "[I]nvestors feel a cognitive dissonance discomfort when faced with 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. While all losses cause such dissonance, realized losses create a greater level of discomfort than paper losses: when the loss exists only on paper the investor is able to partly resolve the dissonance by convincing themselves that the loss is only a temporary setback. This reduces the blow to their self-image of being someone who makes good decisions. When the loss is realized, it becomes permanent, which makes it harder for the investor to avoid the view that buying the share may have been a mistake. Cognitive dissonance provides the basis for an overall reluctance to realize losses, and thus generates a wedge relative to the investor's propensity to realize gains (where no such dissonance discomfort exists)."

has a direct prediction: assets that are most similar to the focal stock, that is, most likely to be in the same mental account as the focal stock, should have the greatest contribution to the PDDE. With this in mind, we perform two tests based on similarity.

A. Evidence from Account Similarity

First, we exploit the fact that a single household can have multiple accounts from the U.S. discount brokerage. Two stocks in the same account are more likely to be considered in the same portfolio than two stocks in different accounts, even though all stocks in the multiple accounts contribute to the household's wealth. We decompose the household return into those stocks in the same account as the focal stock and those stocks held in different accounts in the same household as the focal stock by revising equation (2) as follows:

$$
\begin{aligned}
h_{i,j}(t) = h_0(t)\exp\{&\beta_0 + \beta_1 Gain_{i,j,\mathrm{t}-1} + \beta_2 AccountPortfolioRet_{i,\mathrm{t}-1}^{all-j} \\
&+ \beta_3 Gain_{i,j,\mathrm{t}-1} \times AccountPortfolioRet_{i,\mathrm{t}-1}^{all-j} \\
&+ \beta_4 HouseholdPortfolioRet_{i,\mathrm{t}-1}^{all-Account} + \beta_5 Gain_{i,j,t-1} \\
&\times HouseholdPortfolioRet_{i,\mathrm{t}-1}^{all-Account} + \varepsilon_{i,j,t}\},
\end{aligned} \tag{3}
$$

where $AccountPortfolioRet_{i,\mathrm{t}-1}^{all-j}$ is the return from the other stocks in the same account as focal stock j, and $HouseholdPortfolioRet_{i,\mathrm{t}-1}^{all-Account}$ is the return from all household stocks excluding the stocks in the same account as focal stock j. We define return variables as continuous variables rather than dummies in order to decompose the remaining returns of a household into $AccountPortfolioRet_{i,\mathrm{t}-1}^{all-j}$ and $HouseholdPortfolioRet_{i,\mathrm{t}-1}^{all-Account}$. Thus, β_3 measures the moderating effect of stock portfolio performance on the disposition effect from performance in the same account as the focal stock, while β_5 captures the moderating effect of household gains that originate from other accounts. To decompose household returns, we sum the capital gains within each account and normalize them by the sum of the cost basis of the entire household. Therefore, the sum of the account returns within a household is equal to the overall household return. Moreover, capital gains accumulated across accounts are comparable because both β_3 and β_5 capture the marginal effect of the same dollar amount of household returns. For these tests, we require a household to have at least two accounts. The final sample has approximately 50 million account-stock-date observations.[29]

In Table VIII, we decompose the household return into those stocks in the same account as the focal stock and those stocks held in different accounts. Consistent with the prediction of a portfolio-level frame, the PDDE moderates following dissimilarity. Specifically, column (1) shows that stocks held by the

[29] In Table IA.XV, we verify that the PDDE holds when a household's portfolio is constructed using all assets in all accounts within the household.

Table VIII

The Impact of Portfolio Performance from Other Household Accounts

The table reports regressions on the comparison of the focal account (the account in which the focal stock resides) portfolio and other accounts within the same household. The dependent variable is a dummy variable that equals one if there is any sale (including partial sale) from the end of month t to the end of month $t+1$, and zero otherwise. *Gain* is a dummy variable that equals one if a stock in an investor's portfolio has a positive return since purchase at day t, and zero otherwise. $AccountPortfolioRet^{all\text{-}j}$ is a continuous variable that measures the return for the focal account after excluding the focal stock j, and $HouseholdPortfolioRet^{all\text{-}Account}$ is the continuous household return after excluding the entire focal account. In column (2), we restrict the sample to only those households with one adult. To decompose household returns, all returns of subsets of the household are calculated by summing the capital gains within that subset and normalizing them by the cost basis of the entire household. The sum of all account returns within a household is therefore equal to the overall household return. We run Cox proportional hazard regressions with account stratification. Standard errors are clustered by account. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	All (1)	One Adult (2)
Gain	0.685***	0.667***
	(37.49)	(13.05)
$AccountPortfolioRet^{all\text{-}j}$	1.943***	1.822***
	(22.37)	(9.66)
$Gain \times AccountPortfolioRet^{all\text{-}j}$	−2.302***	−2.088***
	(−20.74)	(−9.69)
$HouseholdPortfolioRet^{all\text{-}Account}$	1.059***	1.049***
	(7.95)	(3.76)
$Gain \times HouseholdPortfolioRet^{all\text{-}Account}$	−1.364***	−1.156***
	(−11.79)	(−4.84)
Stratified by account	Yes	Yes
Testing $\beta_3 = \beta_5$, p-value	0.00	0.01
Pseudo-R^2	0.0230	0.0234
Obs.	49,923,314	4,010,386

same account as the focal stock generate a PDDE that is 21% (90.0%/74.4% − 1) larger than that of stocks held in the same household but a different account than the focal stock.[30] Moreover, the p-value testing the difference between β_3 and β_5 is less than 1%. When restricting attention to one-adult households, the effect of dissimilarity grows: other holdings in the focal account have a 28% (87.6%/68.5% − 1) larger PDDE compared to that of holdings in different accounts of the same household.[31] In addition, we reject the null that $\beta_3 = \beta_5$ at the 1% level.

[30] As shown in column (1), a one-unit increase in portfolio return generated by other stocks in the same account leads to a 90.0% ($1 - e^{\beta_3} = 1 - e^{-2.302}$) decrease in the disposition effect, while this number for a portfolio return generated by stocks in other accounts is 74.4% ($1 - e^{\beta_5} = 1 - e^{-1.364}$).

[31] For one-adult households, as shown in column (2), a one-unit increase in portfolio return generated by other stocks in the same account leads to a 87.6% ($1 - e^{\beta_3} = 1 - e^{-2.088}$) decrease in the disposition effect, while a one-unit increase in portfolio return generated by stocks in other accounts is 68.5% ($1 - e^{\beta_5} = 1 - e^{-1.156}$).

B. Evidence from Asset Similarity

In the prior section, we measure the similarity of stocks across accounts within the same household. Here, we exploit characteristics of the individual assets within a single brokerage account. For example, two U.S. common stocks are more similar to each other than one U.S. common stock and one mutual fund in the same brokerage account.

Specifically, we explore whether portfolio gains from different asset classes affect the disposition effect of U.S. stocks in the same way.[32] To conduct the asset-class similarity analysis, we revise our baseline model in equation (2) to

$$\begin{aligned} h_{i,j}(m) = h_0(m)\exp\{\beta_0 + \ & \beta_1 Gain_{i,j,m-1} + \beta_2 PortfolioRet_{i,m-1}^{CommonStock-j} \\ & + \beta_3 Gain_{i,j,m-1} \times PortfolioRet_{i,m-1}^{CommonStock-j} + \beta_4 PortfolioRet_{i,m-1}^{Category} \\ & + \beta_5 Gain_{i,j,m-1} \times PortfolioRet_{i,m-1}^{Category} + \varepsilon_{i,j,m}\}, \end{aligned} \tag{4}$$

where m indicates time and is now monthly because daily prices are not available for many asset classes during the sample period, $PortfolioRet_{i,m-1}^{CommonStock-j}$ is account i's portfolio return from the U.S. common stock, excluding the focal stock j,[33] and $PortfolioRet_{i,m-1}^{Category}$ is account i's portfolio return from another category of asset classes. As in equation (2), β_3 measures the moderating effect of U.S. common stock portfolio performance on the disposition effect, and β_5 captures the moderating effect of the portfolio return from a different asset-class category. We sort investors' assets into U.S. common stocks, foreign stocks (mainly Canadian stocks and American Depository Receipts), open-end mutual funds, options, and other stock-type securities (mainly closed-end mutual funds, master limited partnerships, and preferred stocks).[34] Consistent with the analysis in the prior section, we calculate all asset-class returns by summing the capital gains within that asset class and normalizing them by the cost basis of the entire portfolio so that the sum of all asset-class returns is equal to the overall portfolio return. We follow Chang, Solomon, and Westerfield (2016) in calculating gains and losses for securities in each asset class at a monthly frequency.[35] To ensure a fair comparison, we use monthly price information in the positions file for securities in all asset classes, including U.S.

[32] We examine these predictions using the U.S. data because we do not have trading data on other securities in the Chinese data set. Thus far, we have only analyzed the U.S. common stock holdings of investors in the U.S. sample, but now we expand their portfolios to analyze the influence of returns from other asset classes.

[33] $PortfolioRet_{i,m-1}^{CommonStock-j}$ consists of the same set of stocks as $AccountPortfolioRet_{i,t-1}^{all-j}$.

[34] See Table IA.XVI for a detailed description of each asset category.

[35] Specifically, we use both the trade file and the position file, and we delete observations for which 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 price using the trades file. We evaluate the gains and losses for each security at the end of each month. We obtain a monthly snapshot of security prices as long as a security is held by at least one investor in the data. We exclude money market funds because many have a price that is fixed and therefore have very few observable gains and losses.

common stocks. This procedure yields 3.75 million account-stock-month observations. To conduct our analysis, we require that an investor holds at least two common stocks as well as a security in any of the other asset classes in a given month. This final sample consists of approximately 0.7 million observations.[36] Table IA.XVII verifies that the PDDE holds in this sample.

In Table IX, we decompose the overall portfolio return and compare capital gains from U.S. common stocks against those from the other four categories one by one. We observe that the moderating effect of the U.S. common stock portfolio (excluding the focal stock) is highly statistically significant across all of the specifications. Furthermore, the moderating effect of capital gains generated by other asset categories is significantly smaller than that of U.S. common stocks, as indicated by the smaller magnitude of β_5 compared to β_3. Economically speaking, the moderating effect of one unit of capital gains generated by other U.S. common stocks in the portfolio is 25% (83.0%/66.5% − 1) larger than that of foreign stocks and 24% (84.9%/68.5% − 1) larger than that of other stock-type securities.[37] In addition, we reject the null that $\beta_3 = \beta_5$ at the 1% level. The moderating effect of other U.S. common stock is three to four times as large as those of mutual funds and options, and the estimations of the latter two are not statistically significant. These findings provide additional evidence of a portfolio-level frame: when assets are similar and therefore more likely to be in the same mental account as the focal stock, those assets generate a stronger PDDE than assets that are dissimilar.

Taken together, the results suggest that the PDDE is increasing in both asset and account similarity. In particular, the results indicate that investors frame not only at the stock level but also at the portfolio level, with the combination of these two frames generating the PDDE.

V. Conclusion

The disposition effect is a stock-level phenomenon. But individuals rarely hold single stocks—they often hold portfolios. The purpose of this paper is to answer the question: does the stock-level disposition effect depend on the portfolios they hold? We find a consistent answer among four independent settings: 78,000 U.S. households in a large discount brokerage, 97,000 investors in a

[36] We analyze the disposition effect only among U.S. common stocks (i.e., other asset classes are never the focal asset) for two reasons. First, Chang, Solomon, and Westerfield (2016) show that in many delegated assets (such as mutual funds), the disposition effect actually reverses or disappears. Second, our regression design would require that the investor hold at least two securities in the given asset class in addition to securities in other asset classes, which greatly reduces the number of observations available.

[37] Column (1) shows that a one-unit increase in portfolio return generated by other U.S. common stocks leads to an 83.0% ($1 - e^{\beta_3} = 1 - e^{-1.770}$) decrease in the disposition effect, while this number for a portfolio return generated by foreign stocks is 66.5% ($1 - e^{\beta_5} = 1 - e^{-1.093}$). Column (2) shows that a one-unit increase in portfolio return generated by other U.S. common stocks leads to a 84.9% ($1 - e^{\beta_3} = 1 - e^{-1.888}$) decrease in the disposition effect, while this number for a portfolio return generated by other stock-type securities is 68.5% ($1 - e^{\beta_5} = 1 - e^{-1.155}$).

Table IX

The Impact of Portfolio Performance from Various Asset Classes

The table reports regression results on various asset classes of the overall portfolio performance. Assets are classified into five categories: U.S. common stocks, foreign stocks, other stock-type securities, mutual funds, and options. Internet Appendix Table IA.XVI presents details for the asset classifications. $PortfolioRet^{Category}$ is a continuous variable that measures the account's portfolio return for securities in a given category. Performance of securities is calculated following Chang, Solomon, and Westerfield (2016). The dependent variable is a dummy variable that equals one if there is any sale (including partial sale) from the end of month t to the end of month $t+1$, and zero otherwise. *Gain* is a dummy variable that equals one if the stock in question has a positive return since purchase at month end t, and zero otherwise. $PortfolioRet^{US\ common\ stock\text{-}j}$ is the portfolio return for all U.S. common stock after excluding the focal stock j. To decompose portfolio returns, all returns of subsets of the portfolio are calculated by summing the capital gains within that subset and normalizing them by the cost basis of the entire portfolio (from all asset classes). The sum of all asset-class returns is therefore equal to the overall portfolio return. We run Cox proportional hazard regressions with account stratification. Standard errors are clustered by account. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Category =	Foreign Stocks (1)	Other Stock-Type Securities (2)	Mutual Funds (3)	Options (4)
Gain	0.356***	0.395***	0.247***	0.303***
	(19.06)	(16.98)	(8.28)	(6.46)
$PortfolioRet^{US\ common\ stock\text{-}j}$	1.364***	1.505***	1.382***	0.209
	(10.45)	(7.95)	(5.24)	(0.71)
$Gain \times PortfolioRet^{US\ common\ stock\text{-}j}$	−1.770***	−1.888***	−1.879***	−0.839*
	(−12.66)	(−9.67)	(−6.59)	(−1.86)
$PortfolioRet^{Category}$	0.822***	0.325	1.498**	0.675
	(3.88)	(0.82)	(2.07)	(1.37)
$Gain \times PortfolioRet^{Category}$	−1.093***	−1.155***	−0.223	0.203
	(−5.13)	(−3.32)	(−0.31)	(−0.60)
Stratified by account	Yes	Yes	Yes	Yes
Testing $\beta_3 = \beta_5$, p-value	0.01	0.01	0.03	0.29
Pseudo-R^2	0.007	0.008	0.004	0.005
Obs.	461,961	307,688	124,336	26,363

Chinese brokerage, 2,300 U.S. participants in an "MTurk" trading game experiment, and 800 experimental participants at a Chinese university. In each of these settings, an investor's disposition effect is large when her portfolio is at a loss and significantly smaller when it is at a gain.

This PDDE is robust to a variety of controls and does not seem to be a repackaging of previously documented research concerning the disposition effect. However, we find direct evidence that the PDDE is a by-product of investors using an additional, portfolio-level frame when making investment decisions. The PDDE therefore contributes to our understanding of how people frame financial decisions. Originally, researchers assumed that investors use fairly static and fixed frames, but recent research suggests that framing is more fluid and nuanced: sometimes individuals engage in relative evaluation within a portfolio (Hartzmark (2015)), while sometimes they frame across trades (Frydman, Hartzmark, and Solomon (2018)). Our evidence suggests that investors frame at multiple levels—the stock level and the portfolio level—when making trading decisions.

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REFERENCES

Barber, Brad, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

Barber, Brad, and Terrance Odean, 2013, The behavior of individual investors, *Handbook of the Economics of Finance* 2, 1533–1570.

Barberis, Nicholas, and Ming Huang, 2001, Mental accounting, loss aversion, and individual stock returns, *Journal of Finance* 56, 1247–1292.

Barberis, Nicholas, and Wei Xiong, 2009, What drives the disposition effect? An analysis of a long-standing preference-based explanation, *Journal of Finance* 64, 751–784.

Barberis, Nicholas, and Wei Xiong, 2012, Realization utility, *Journal of Financial Economics* 104, 251–271.

Ben-David, Itzhak, Justin Birru, and Viktor Prokopenya, 2018, Uninformative feedback and risk taking, *Review of Finance* 22, 2009–2036.

Ben-David, Itzhak, and David 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, Sabine, Benjamin Loos, and Martin Weber, 2022, The disposition effect in boom and bust markets, Working paper.

Chang, Tom, David Solomon, and Mark 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.

Dai, Min, Cong Qin, and Neng Wang, 2023, Dynamic trading with realization utility, Working paper.

Evers, Ellen, Alex Imas, and Christy Kang, 2022, On the role of similarity in mental accounting and hedonic editing, *Phychological Review* 129, 777–789.

Feng, Lei, and Mark Seasholes, 2005, Do investors sophistication and trading experience eliminate behavioral biases in finance markets? *Review of Finance* 9, 305–351.

Frydman, Cary, Samuel Hartzmark, and David Solomon, 2018, Rolling mental accounts, *Review of Financial Studies* 31, 362–397.

Frydman, Cary, and Baolian Wang, 2020, The impact of salience on investor behavior: Evidence from a natural experiment, *Journal of Finance* 75, 229–276.

Genesove, David, and Christopher Mayer, 2001, Loss aversion and seller behavior: Evidence from the housing market, *Quarterly Journal of Economics* 116, 1233–1260.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1–27.

Goldstone, Robert, 1994, The role of similarity in categorization: Providing a groundwork. *Cognition* 52, 125–157.

Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade? *Journal of Finance* 56, 589–616.

Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa, 2012, IQ, trading behavior, and trading performance, *Journal of Financial Economics* 104, 339–362.

Hartzmark, Samuel, 2015, The worst, the best, ignoring all the rest: The rank effect and trading behavior, *Review of Financial Studies* 28, 1024–1059.

Heath, Chip, Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise, *Quarterly Journal of Economics* 114, 601–627.

Ingersoll, Jonathan, and Lawrence Jin, 2013, Realization utility with reference-dependent preferences, *Review of Financial Studies* 26, 723–767.

Kruschke, John, 1992, ALCOVE: An exemplar-based connectionist model of category learning, *Psychological Review*, 99, 22–44.

Lancaster, Tony, 2000, The incidental parameter problem since 1948, *Journal of Econometrics* 95, 391–413.

Mullainathan, Sendhil, and Eldar Shafir, 2013, *Scarcity: Why Having Too Little Means So Much* (Times Books, New York, NY).

Nosofsky, Robert, 1986, Attention, similarity, and the identification categorization relationship, *Journal of Experimental Psychology: General* 115, 39–57.

Odean, Terrance, 1998, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775–1798.

Schilbach, Frank, Heather Schofield, and Sendhil Mullainathan, 2016, The psychological lives of the poor, *American Economic Review* 106, 435–440.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by trading, *Review of Financial Studies* 23, 705–739.

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

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777–790.

Thaler, Richard, 1985, Mental accounting and consumer choice, *Marketing Science* 4, 199–214.

Thaler, Richard, Amos Tversky, Daniel Kahneman, and Alan Schwartz, 1997, The effect of myopia and loss aversion on risk taking: An experimental test, *Quarterly Journal of Economics* 112, 647–661.

Weber, Martin, and Colin Camerer, 1998, The disposition effect in securities trading: An experimental analysis, *Journal of Economic Behavior and Organization* 33, 167–184.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.