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: US and Chinese archival data, as well as US 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 investors form mental frames at the stock and portfolio level and these frames combine to generate the PDDE.

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I. Introduction

There is perhaps no more robust trading phenomenon than the disposition effect, the observation that investors are more likely to sell an asset when it is at a gain than when it is at a loss (Shefrin and Statman, 1985). The disposition effect has been documented among US retail investors (Odean, 1998), foreign retail investors (Grinblatt and Keloharju, 2001; Frydman and Wang, 2020), institutional investors (Shapira and Venezia, 2001), homeowners (Genesove and Mayer, 2001), corporate executives (Heath, Huddart, and Lang, 1999), and in experimental settings (Frydman, Hartzmark, and Solomon, 2018; Weber and Camerer, 1998).

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 which 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) show that if an investor has prospect theory 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.

To illustrate the idea, consider an investor with three stocks: X_1, X_2, and X_3. The disposition effect says Pr(X_i is sold | X_i is at a gain) > Pr(X_i is sold | X_i is at a loss) for all . If the investor has preferences over each individual stock, then we would expect those three

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

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) dataset, 97,000 investors in a Chinese brokerage dataset, 2,300 US participants in an Amazon Mechanical Turk ("MTurk") trading-game experiment, or 800 experimental participants at a Chinese university, all the data 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 in the Barber and Odean dataset, we find that the probability 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 which portfolios are up in the Barber and Odean (2000) dataset.

Because it is well known that there is a disposition effect in the Barber and Odean dataset, 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

(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 which 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; Kruschke, 1992; Nosofsky, 1986). As Evers, Imas, and Kang (2022) 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 3 assets: Stock X, Stock Y, and a house. When considering focal Stock X, similarity would dictate that Stock Y is more likely to be placed in the same mental account as Stock X, and thus will be more influential to 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 by the same account as the focal stock generate a PDDE which is 21% larger than that of stocks held in the same household but a different account than the focal stock. This pattern is also robust when restricting to one-adult households, where the size of the effect is 28%.

Second, rather than measuring 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 US 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 US common stock, the PDDE shrinks as the source of the portfolio capital gain bears less resemblance to US common stocks. For example, the moderating effect of one unit of capital gains generated by other US 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 wanes.

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effect. We confirm this in both the US and Chin they frame at the total portfolio level. Each of their models can explain some well-known empirical patterns, and they conclude that a superior model of investor behavior would include both stock-level framing and broader forms of framing.[2] Our evidence here via the PDDE is that investors indeed frame at both the stock and portfolio level.

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

II. Data and Methodology

We begin with the large US discount broker dataset utilized by Barber and Odean (2000). The raw data include trading activity for roughly 78,000 households with roughly 158,000 accounts between January 1991 and November 1996. Following Odean (1998), we restrict our main analyses to the [illegible] 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 dataset and make several simplifying assumptions. First, we include only securities that are identified as common shares and appear in CRSP. Because prices in the discount brokerage dataset are not adjusted for splits and dividends, we rely on CRSP factor adjustments to account for these issues. Second, we remove any account-stocks with negative commissions since they may indicate a reverse transaction. Third, account-stocks that include short sa[illegible]

As with the US 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 is taken 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 account-days where investors hold only one stock, the resulting dataset contains 97,000 unique investors and 84,793,767 (account, stock, day) observations. We report summary statistics for this sample in Panel B of Table 1. Note that the Chinese investors trade much more frequently than US 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 US investors are between 0.2% and 0.4%.

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

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

where observations occur at the account ( ), stock ( ), and date ( ) level.[6] For every account-stock-day, $h_{i,j}(t)$ is investor 's probability of selling position on day conditional on not having sold prior to day , and $h_0(t)$ is the baseline hazard. Additionally, 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, $\exp(\beta_1)$, measures the ratio of the probability of selling a winning position versus the probability of selling a losing position. Many previous studies show

[6] We report our main results using the linear probability model in Tables A1 and A2 of the Internet Appendix.

that is positive and statistically significant, or $\exp(\beta_1)$ is significantly greater than 1, 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 the following equation:

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

Our additional variable, , is a dummy indicating whether or not the investor's stock portfolio is at a gain or a loss. We compute this variable by first summing up the gains/losses (in dollars) of the investor's positions in all of her stocks as of the given day.[7]

Our main coefficient of interest in equation (2) is , the coefficient of the interaction term, which represents the ratio difference in disposition effects for paper gain portfolios and paper loss portfolios. In equation (2), exp( ) measures the disposition effect for paper loss portfolios, and exp( ) 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 that of selling 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., Gervais and Odean, 2001; Ben-David, Birru, and Prokopenya, 2018), the difference between the probability of selling winners

[7] In Internet Appendix Table A3, we repeat our main analysis when the variable is defined without considering the performance of the stock associated with the given observation, i.e., when the portfolio gain is computed based on the performance of the of the investor's portfolio. The results are very similar.

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 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]

III. The Portfolio-Driven Disposition Effect

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

[Insert Figure 1 Here]

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[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 later analyses, we check the robustness of our results by specifying various strata, and we find that our results are robust. Second, we are unable to cluster the standard errors across multiple dimensions. We cluster by account, and we find that clustering by account gives more conservative -values than clustering by stock or date.

We report this figure using the US (Panel A) and Chinese (Panel B) brokerage samples. This

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.

We estimate equation (2) on the US (Chinese) sample described in Section II using a Cox hazard model and report the results in Table 2 Panel A (Panel B). Column 1 shows the baseline results with no stratification. Columns 2-4 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: (− , −50%), ..., [−4%, −2%), [−2%, 0), [0, 2%), [2%, 4%), ..., [50%, +). Additionally, one might be concerned that the variables and are mechanically related; therefore in column 6, we consider an alternative definition for that excludes the focal stock when computing portfolio performance. We also consider other alternative definitions of such as the fraction of stocks in the portfolio that are at a gain. These results are similar to our main specification and are reported in Table A4 of the Internet Appendix.[9]

[Insert Table 2 Here]

Across all specifications, the coefficient on the interaction term (*) ranges from −0.58 to −0.86 in the US data and −0.15 to −0.44 in the Chinese data. These

[9] We also examine specifications with a standard set of controls following Ben-David and Hirshleifer (2012) and find very similar results. We report them in Internet Appendix Table A5.

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 of indicates a PGR/PLR ratio of 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 winning portfolio to 1.36 for a losing portfolio. Moreover, these estimates are highly statistically significant, with -stats 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 with this specification.

Next, we consider more continuous measures of the focal stock and the overall portfolio's performance. In Figure 2, we generate a heat map 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 the observations into 12-by-12 boxes by the focal stock's holding period returns and the 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 1 if there is sale (including partial sale) on day t+1, and 0 otherwise. We include dummy variables indicating each of the 144 combinations. The $(-\infty, -25\%]\times(-\infty, -25\%]$ group is

[10] In Internet Appendix Table A6, we provide additional robustness by analyzing at the household level instead of the account level and find very similar results.

the base case. All the regressions are stratified by account. Areas with more (less) selling depict a darker shade of red (blue). The median is white.[11]

[Insert Figure 2 Here]

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 US 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 US data and a reverse V-shape disposition effect in the Chinese data makes it less likely for us to find a PDDE in the US sample and more likely in the Chinese sample. To see why, consider the case where an investor exhibits a strong V-shape disposition effect (as in the US 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, i.e., she will exhibit a stronger disposition effect when her portfolio is at a gain. This works the PDDE. By the same logic, a reverse V-shape disposition effect works the PDDE. Consistent with this reasoning, including V-shape controls in Table 2 strengthens the PDDE in the US data 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 US and Chinese samples, indicating tha

Several observations emerge from Table 3. First, we find that the moderating effect of portfolio gain is similar across the different age and gender groups but is slightly larger for high (low) trading frequency investors in the US (Chinese) sample.[13] Second, the PDDE is larger for longer holding periods in both the US and Chinese samples. Finally, the moderating role of portfolio gain on the disposition effect remains strong across all subsamples, indicated by the significantly negative interaction coefficients ranging from −0.501 to −0.849 (t-stats range from −9.64 to −41.64) in the US sample and −0.274 to −0.606 (t-stats range from −47.66 to −91.48) in the Chinese sample.

In an ideal experiment, we would compare identical positions in a particular stock owned by identical investors, with the only difference being the investors' portfolio performance. By identical positions, we mean that both investors own the same stock, and they purchased the stock on the same day and at the same price. By identical investors, we mean investors who would make the same decisions when facing any economic scenario. Because of our large sample, we have identical positions; however, this ideal experiment is not feasible because we do not have identical investors. In this matching analysis, we approximate the ideal experiment by comparing identical positions owned by different investors. Specifically, we stratify by positions built on the same day and of the same stock in the regressions. By doing this matching, we keep the stock and purchase date the same and focus on the portfolio return variation across investors. We also only keep the observations where there are at least two investors within the same strata. The number of observations is 52.2% of the entire sample. We find that the coefficient of the interaction term is

[13] The t-stat on Female is reduced in the US sample because they 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.

negative and highly significant whether we stratify by account (−0.831, t-stat −38.90) or by stock*purchase date (−0.588, t-stat −34.13). We report these results in columns 1 and 2 of Table 4.

[Insert Table 4 Here]

With the stratification by positions built on the same day and of 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 the 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, and yet the PDDE effect is similar in magnitude, with interaction coefficients of (−0.838, t-stat −30.26) and (−0.550, t-stat −23.30) in columns 3 and 4, respectively. In the third specification, columns 5 and 6, we further exclude the positions that were constructed with multiple purchases, and we continue to find a strong PDDE.[14]

We repeat the above analyses for the Chinese sample.[15] The coefficient of the interaction term remains negative and highly significant.[16] The results are broadly similar across the six specifications. The relative magnitude of the and terms are similar to the baseline estimation in Table 2, which suggests that the PDDE is not driven by unobserved stock-level characteristics that are correlated with the portfolio's gain/loss status.

[14] 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.
[15] During our sample period, in the US, the tick size was one eighth of a dollar. 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.
[16] If we do not round the purchase price, the coefficient of the interaction term is −0.290 (t-stat −4.89) and −0.313 (t-stat −5.54) in column 4 and 6, respectively. The number of observations is 2,525,960 and 2,166,353, respectively. Both are significantly smaller than the analysis with the rounded price.

In the prior section, we compare the selling decision for the same stocks at the same point game. Across games, however, the probabilities are randomly reassigned. Second, the magnitude of the price increase or decrease is determined. Prices either change by $1, $3, or $5, each with equal probability. The magnitude of the price changes is independent of whether the price is increasing or decreasing.

Each round, subjects are shown a graph of each stock's price evolution up to that round.[18] Each game, subjects are endowed with 1,000 units of experimental cash that they can use to trade the fictitious stocks, and their compensation 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 randomly chosen. 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 5. In columns 1-3, column 1. The coefficient on 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 (=$e^{0.699-0.420}$). Additionally, we find that in the most controlled tests with return bracket FEs the interaction coefficient is −0.362 (t-stat −6.93) in the Chinese experimental sample, −0.421 (t-stat −10.71) in the MTurk sample, and −0.400 (t-stat −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 loss and can observe her differential tendency to exhibit the disposition effect.

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 a "disposition effect comovement."

To test this prediction, we calculate the level of the disposition effect across different investor groups quarter by quarter in both the US and Chinese samples. We stratify investors by gender, age, portfolio size (into ten equal-sized groups), and in the fourth test, randomly (into ten equal-sized groups). For each investor group in each quarter, we estimate the average disposition effect by running equation (1) using the investor-stock-day observations. Internet Appendix Figure A1 presents the results. The y-axis is the value of the disposition effect, and the x-axis is quarter. We see that investors with different gender, age, portfolio size, and other characteristics comove very closely over time in the level of the disposition effect.

Moreover, 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 Internet Appendix Table A10, we examine the relation between the quarterly average disposition effect across all the 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.[19] Moreover, when we compare the correlation across different horizons, we find that the negative correlation between the disposition effect and past market return peaks at eight quarters in the US sample and at three quarters in the Chinese sample. Interestingly, these horizons closely match investors' average holding periods in the two samples.[20] These coefficients are economically sizable. For example, in the US, 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).

[Insert Figure 3 Here]

Figure 3 presents the time series of the average disposition effect and the past market returns for the US and Chinese samples, with past market returns measured over the past eight (three) quarters for the US (China). The negative correlation between the disposition effect and past

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

[20] According to 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.

market return is evident. Thus, we document a systematic and cyclical component in one of the most robust behavioral patterns, the disposition effect.

IV. Relationship to Prior Research

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

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 losers, then this stock is very likely to be sold under both the attention-grabbing hypothesis (it is an extreme stock) and the PDDE (investors are very likely to sell their winners when the portfolio is at a loss). However, if an investor has one stock that is a loser and the rest winners, this stock is very likely to be sold under the attention-grabbing hypothesis (because it is an extreme stock) but not the PDDE (because losers are nearly as likely to be sold as winners are when the remaining portfolio is at a gain).

[Insert Table 6 Here]

Nevertheless, in Table 6 we evaluate how the rank effect relates to our empirical results. Specifically, in column 1, we add indicator variables for the best performed and the worst performed stocks in an investor's portfolio. 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 2 both in terms of statistical significance and economic magnitude for the US (Panel A) and Chinese (Panel B) samples. These results suggest that the rank effect (Hartzmark, 2015) does not explain the PDDE.

the stock that is at a gain when the rest of the portfolio is at a loss. That is, we should expect the PDDE to disappear when we restrict attention to liquidations of stocks.

To test this, we adjust our specification to use a full liquidation dummy as the dependent variable, thus eliminating any variation from partial sales. In column 5 of Panel A and column 3 of Panel B of Table 6, we report the full liquidation results. For the US, we see that the interaction coefficient of −0.915 (t-stat −49.84) is still negative and significant well below the 1% level and nearly offsets the magnitude of the coefficient. For the Chinese sample, the interaction coefficient is −0.597 (t-stat −115.57) and is about two-thirds of the coefficient. Thus, portfolio rebalancing is an unlikely explanation for the PDDE.

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).[21] 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 the following two approaches. First, when calculating , 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.[22] Under this construction, the variation of is mainly driven by the performance of securities in the portfolio, and is unrelated to whether these positions are realized or not (and thus

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[21] We discuss the relation between investor sophistication and the PDDE in more detail in Internet Appendix Section A1. Internet Appendix Table A11 provides evidence that the estimation of PDDE does not vary across investor subsamples based on income levels and occupations.

[22] In Table A12 of the Internet Appendix, we show results using different horizons for adding realized gains/losses and find that the PDDE persists across all specifications.

the investor's tendency to exhibit a disposition effect). Table 7 columns 1 and 3 report results based on constructed this way.

[Insert Table 7 Here]

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 for his/her propensity to sell (the baseline hazard function) to differ across winning and losing positions.[23] As shown in Table 7 columns 1-3, under the alternative definition of and/or the more saturated stratification, the coefficient estimate on the interaction term between and 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 in both the US and Chinese samples. This observation suggests that investor heterogeneity in the disposition effect can only explain part of the PDDE.[24]

V. Multiple Frames

[23] Note that the estimation from this specification is likely to be conservative. Controlling for the individual heterogeneity in the disposition effect will mechanically lead to a negative autocorrelation of the disposition effect. To the extent that at is an inverse function of the disposition effect before , the account-gain stratification tends to underestimate the PDDE effect (e.g., a less negative coefficient on x). In Internet Appendix Table A13, we show that the results in the experimental samples are also robust to subject-gain stratification.

[24] Additionally, 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 III.G.

The prior section rejected explanations where the PDDE is a byproduct 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 which combine to generate the PDDE.[25]

Prior research on the disposition effect has established 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 a 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 their self-image of being someone who makes good decisions.[26] Conversely, if the investor's portfolio is at a gain, she can still convince herself

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

[26] 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

she is a good trader by paying attention to the portfolio-level frame, which suggests she is a good trader who makes good decisions.

In order to provide direct evidence of an additional frame at the portfolio level, 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; Kruschke, 1992; Nosofsky, 1986). As Evers, Imas, and Kang (2022) put it: "when outcomes are perceived to be similar, they are categorized together, assigned to the same mental account and evaluated jointly." If a portfolio-level frame drives the PDDE, similarity has a direct prediction: assets which are most similar to the focal stock (i.e., 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.

First, we exploit the fact that a single household can have multiple accounts from the US discount15-a sok-2.1 (l)6.4 (f)1.9 nthy.

where *Accou*

stock.[28] Moreover, the p-value testing the difference between β_3 and β_5 is less than 1%. When restricting 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.[29] Additionally, we reject the null that β_3 = β_5 at the 1% level.

In the prior section, we measured the similarity of stocks across accounts within the same household. Here we exploit the characteristics of the individual assets within a single brokerage account. For example, two US common stocks are more similar to each other than one US 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 US stocks in the same way.[30] To conduct the asset-class similarity analysis, we make some necessary modifications to our baseline model. We revise the model in equation (2) to the following:

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

[28] 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% ($1 - e^{\beta_5} = 1 - e^{-1.364}$).

[29] 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 this number for return generated by stocks in other accounts is 68.5% ($1 - e^{\beta_5} = 1 - e^{-1.156}$).

[30] We examine these predictions using the US data because we do not have trading data on other securities in the Chinese dataset. To this point, we have only analyzed the US common stock holdings of investors in the US sample, but now we expand their portfolios to analyze the influence of returns from other asset classes.

where

[Insert Table 9 Here]

In Table 9, we decompose the overall portfolio return and compare capital gains from US common stocks against those from the other four categories one by one. We observe that the moderating effect of the US 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 US 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 US 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.[35] Additionally, we reject the null that β_3 = β_5 at the 1% level. The moderating effect of other US common stock is 3 to 4 times as large as those of mutual funds and options; in fact, 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.

Together, the PDDE is increasing in both asset and account similarity. These results provide evidence that investors not only frame at a stock level but also at a portfolio level, and the combination of these two frames generates the PDDE.

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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.

[35] Column 1 shows that, a one-unit increase in portfolio return generated by other US 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 US 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% ($1 - e^{\beta_5}$=$1 - e^{-1.155}$).

VI. Conclusion

The disposition effect is a stock-level phenomenon. But individuals rarely hold single stocks; they often hold portfolios. The purpose of this paper has been to answer the question: does the stock-level disposition effect depend on the portfolios they hold? We find a consistent answer among four independent settings: 78,000 US households in a large discount brokerage, 97,000 investors in a Chinese brokerage, 2,300 US participants in an Amazon Mechanical Turk ("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 portfolio-driven disposition effect is robust to a variety of controls and does not seem to be a repackaging of previously documented research concerning the disposition effect. However, we find direct evidence that the PDDE is a byproduct of investors using an additional frame – at the portfolio level – when making investment decisions. In doing so, the PDDE 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), and they sometimes frame across trades (Frydman, Hartzmark, and Solomon, 2018). Our evidence suggests investors frame at multiple levels—the stock level and portfolio level— when making

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

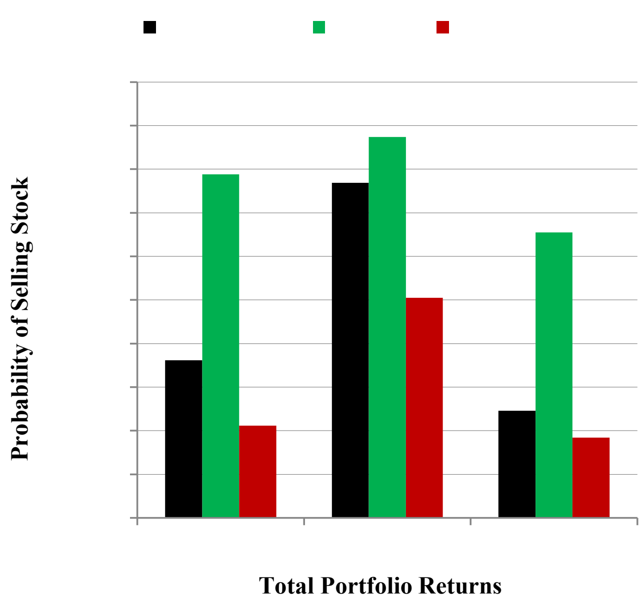

Figure 2. Non-binary measures of the focal stock and portfolio returns

t

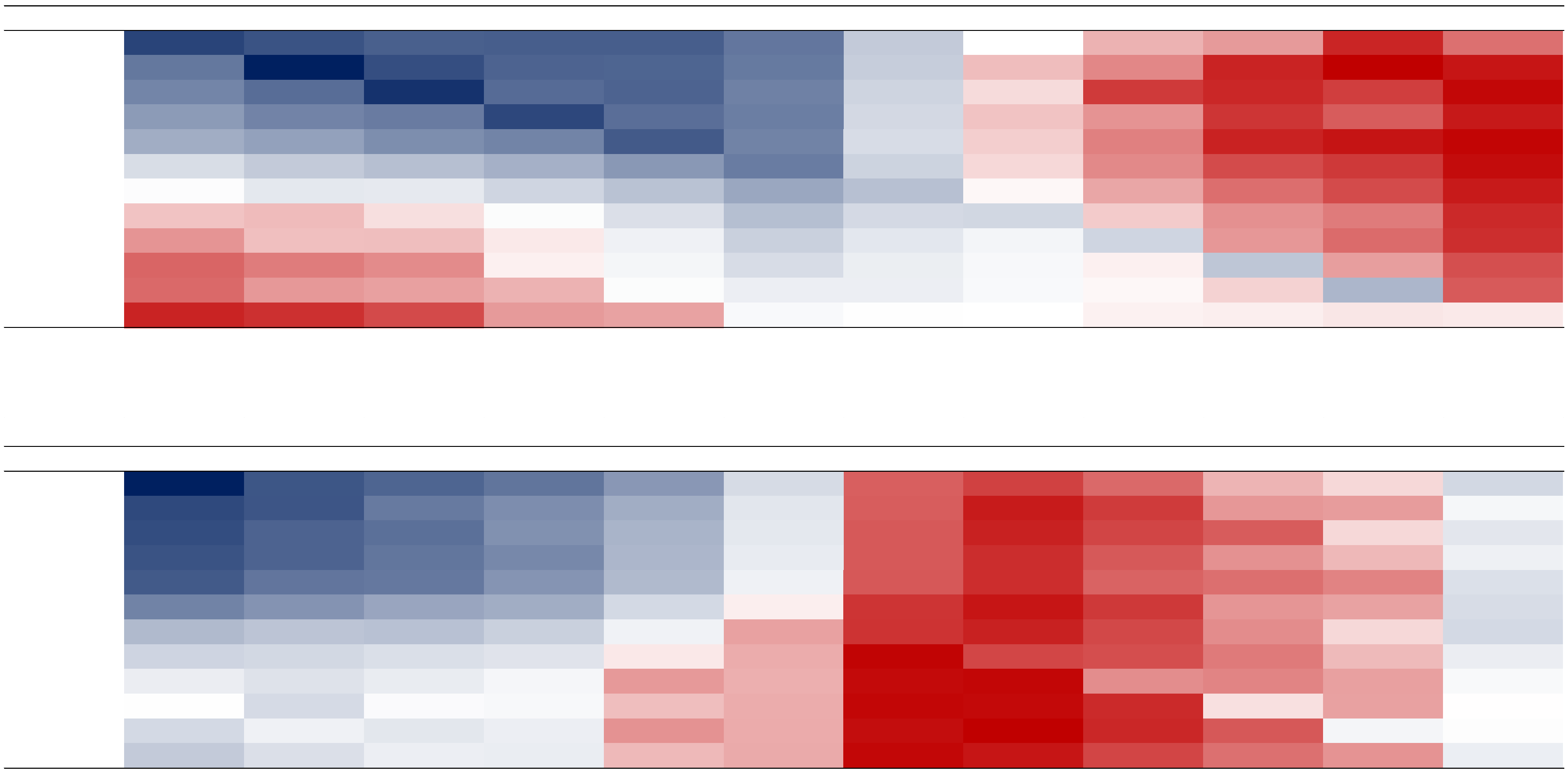

Table 1. Summary statistics

Gain

Portfolio Gain

Gain

Ret

Portfolio Gain

Portfolio

return

t

Time owned

Volatility

Table 2. Baseline regressions

t *Gain*
t *Portfolio Gain*
t

Portfolio Gain

[redacted]

Table 4. Matching sample analysis

t *Gain*
t *Portfolio Gain*

Table 5. The PDDE in two experimental settings

	Portfolio Gain

Table 6. Alternative mechanisms

Gain

Portfolio Gain

[redacted]		

	[redacted]

[redacted]

[redacted]

Table 7. Investor heterogeneity in the disposition effect

Gain

Portfolio Gain

Table 8. The impact of portfolio performance from other household accounts

t

$t+1$ *Gain*

$AccountPortfolioRet^{all\text{-}j}_{Account}$ j $HouseholdPortfolioRet^{all\text{-}}$

Table 9. The impact of portfolio performance from various asset classes

$PortfolioRet^{Category}$

t $t+1$ $Gain$

t $PortfolioRet^{US\ common\ stock\text{-}j}$ j