# The Portfolio-Driven Disposition Effect*

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July 17, 2018

**Abstract:** In simple univariate tests, we find no disposition effect for a stock if the remaining portfolio is at a gain. We find a large disposition effect only when the remaining portfolio is at a loss. The portfolio-driven disposition effect we document is not explained by extreme returns, portfolio rebalancing, simultaneous transactions, or investor sophistication/skill. The evidence suggests investors' utility comes from both paper gains and losses and realized gains and losses; and when their portfolio has paper losses, they compensate by realizing gains.

* We thank Nick Barberis, Justin Birru, and David Solomon for early feedback on our idea. We especially thank Terry Odean for sharing the individual trading data.

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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 stock investors (Odean, 1998), foreign retail investors (Grinblatt and Keloharju, 2001), institutional investors (Shapira and Venezia, 2001), homeowners (Genesove and Mayer, 2001), corporate executives (Heath, Huddart, and Lang, 1999), and in experimental settings (Frydman, Hartzmark, and Solomon, 2018).

Standard explanations for the disposition effect – such as tax considerations, portfolio rebalancing, and informed trading – have been proposed and dismissed (Odean, 1998), leaving explanations that rely on investor preferences such as prospect theory (Kahneman and Tversky, 1979). For example, Barberis and Xiong (2009) show that the disposition effect is most reliably generated in a model of prospect theory preferences over realized gains and losses.

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

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

The latter is precisely what we find in the data. In fact, when we examine the trading among the 78,000 households in the Barber and Odean (2000) dataset, we find no disposition effect for Stock X if the remaining portfolio is up. In this case, Stock X is just as likely to be liquidated at a paper gain as a paper loss. However, if the remaining portfolio is down, Stock X is more than twice as likely to be liquidated at a paper gain as a paper loss. Given how pervasive the disposition effect is, it is surprising to find that the disposition effect disappears among the 64% of observations in which portfolios are up in the Barber and Odean (2000) dataset.

We document this relationship between the performance of an investor's portfolio and her tendency to exhibit a disposition effect in both univariates and regressions with a host of fixed effects. We then consider some possible explanations for our finding.

One possibility is that we are simply capturing a manifestation of Hartzmark's (2015) attention-based finding that investors tend to sell their extreme positions, i.e., their best and worst performing stocks. We address this possibility by restricting our sample to only non-extreme stocks in an investor's portfolio, and we show that our results are strong in this sample, too.

We also consider the possibility that portfolio rebalancing drives our result; e.g., perhaps when one of an investor's stocks is up and the rest of her stocks are down, she partially liquidates her winning position because it now comprises a large share of her portfolio, and she uses the proceeds to invest in other stocks to rebalance her portfolio. Additional analysis casts doubt on this explanation: the portfolio-driven disposition effect is actually stronger when we restrict attention to complete (rather than partial) liquidations, and investors are *less* likely to reinvest their proceeds when they liquidate a winner and the rest of their portfolio is at a loss.

Another possibility is that portfolio gains proxy for skilled or sophisticated investors. However, when we consider investor proxies for sophistication – such as professional jobs or high income – we find the same results. We also find similar results when we consider portfolio gains generated entirely from stock-picking alpha, as identified from a DGTW characteristics-based model, or not. Because it doesn't seem to matter whether the portfolio gain was achieved via stock-picking alpha or not, this suggests our result is isn't being driven by portfolio gain as a statistical stand-in for investor skill.

Yet another possibility is that we are simply capturing framing tricks that investors use to maximize their realization utility. For example, perhaps investors are more willing to recognize a loss when their portfolio is at a gain because they are able to match the losing stock with a winning stock whose gain exceeds the losing stock's loss. By realizing both transactions simultaneously, the investor can mentally account for this dual transaction as a single realized gain. To ensure that this is not driving our results, we restrict our sample to days on which an investor sells just one stock. We find that our result is strong in this subsample, too.

The explanation that seems most consistent with the evidence is that investors derive utility from both paper gains and realized gains and that they take utility by realizing gains when they have disutility from unrealized losses.

According to standard expected utility theory, investors only derive utility from consumption, and a stock's return only affects an investor's utility through its effect on the investor's consumption. Because expected utility theory has difficulty explaining people's behavior in many settings, prospect theory was developed to argue that people derive utility over gains and losses rather than over absolute wealth levels (Kahneman and Tversky 1979; Kahneman and Tversky 1992). Economists who have incorporated prospect theory preferences into their models have assumed that investors derive utility from *paper* gains (Barberis and Huang, 2001; Barberis, Huang, and Santos, 2001; Barberis and Xiong, 2009) as well as *realized* gains (Barberis and Xiong, 2009; Barberis and Xiong, 2012; Henderson, 2012; Ingersoll and Jin, 2013).

Our evidence is consistent with investors deriving utility from *both* paper gains and realized gains. Regarding paper gains, when an investor's portfolio is performing well, the investor might derive utility from anticipating the increased future consumption she will have. Alternatively, the performance of an investor's portfolio might affect her utility in ways that are unrelated to her future consumption. For example, if an investor's portfolio is doing poorly, she might experience regret over her decision to participate in the market, or she might have lower self-esteem because of her poor choice of stocks (Barberis, Huang, and Santos, 2001). Regarding realized gains, investors receive a “burst” of utility at the moment that gains are realized (Barberis and Xiong, 2012; Henderson, 2012; Ingersoll and Jin, 2013; Frydman et. al., 2014).

If investors derive utility from both sources, we should expect an investor’s desire for a “burst” of realization utility to be inversely related to the level of utility the investor is deriving from her paper gains/losses. More specifically, when an investor’s overall portfolio is down, the investor will receive a lot of negative utility from the paper losses, so she should be especially likely to seek a burst of positive utility from realizing a paper gain to offset some of the negative utility she has received due to the poor performance of her portfolio. This could explain why we find such a strong disposition effect when an investors’ portfolio is down.

Following this intuition, we find that this condition – when the stock is at a gain and the portfolio is at a loss– is the one in which investors are most likely to keep their stock sale in cash. That is, in the case when their portfolio is down and they realize a gain, it is important to investors that the gain “stay” realized rather than creating a new mental account as in Frydman, Hartzmark and Solomon (2018). Conversely, when her portfolio is performing well, she receives positive utility from the paper gains, so she should feel less need for a burst of utility from realizing a gain. This could explain why we see little to no disposition effect when an investor’s portfolio sits at a gain.

The paper is organized as follows. We discuss our data and methodology in Section 2. In Section 3, we analyze the disposition effect and portfolio performance impacts, and in Section 4, we discuss alternate explanations. Section 5 concludes.

## II. Data and Methodology

We begin with the large discount broker dataset utilized by Barber and Odean (2000). The raw data include trading activity for 78,000 households with 158,000 accounts between January 1991 and November 1996.

The unit of observation is an account-stock-day triple. Given that we have approximately 104 thousand accounts that hold common stock, with an average of 3.5 stocks per account over the 1,497 trading days in our sample, we begin with approximately 545 million observations. Following Ben-David and Hirshleifer (2012), we filter the raw dataset and make several simplifying assumptions. First, we include only securities that are identified as common shares and appear in CRSP. Because prices in the discount brokerage dataset are not adjusted for splits and dividends, we rely on CRSP factor adjustments to account for these issues. Second, we remove any account-stocks with negative commissions since they may indicate a reverse transaction. Third, if a stock has at least one day with no active trading in the preceding 250 trading days, we remove it. Fourth, investor-stocks with any negative positions (either from short sales or from belonging to a position opened before the start of the sample period) are assumed to be liquidated at the time of turning negative to avoid any misrepresentation in the value-weighted average price (VWAP) of portfolio holdings. Fifth, for the purposes of computing the VWAP of an investor's portfolio of stocks, we begin including stocks the day *after* they've been purchased (because the data do not include intraday time stamps, the VWAP for the purchase day is ambiguous). Finally, since our primary area of interest is portfolio behavior, we keep only account-days with at least two common stock holdings. After applying these filters and rules, we are left with a dataset of 102,821,438 (account, stock, day) observations.

We also analyze a special subset of the dataset described above: only those daily observations where an account has a sale. We refer to this subsample as the "sale conditioned dataset." This filter is used in much of the disposition effect literature (Odean, 1998; Chang, Solomon, and Westerfield, 2016). Given how seldom an account makes a sale, this filter reduces the dataset to 1,403,572 observations.

**[Insert Table 1 Here]**

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

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

where observations occur at the account (i), stock (j), and date (t) level. For every account-stock-day, Sale is a dummy variable equal to one if a sale occurs (including partial sales) and zero otherwise. Additionally, Gain is a dummy variable equal to one if the stock's return (price / VWAP − 1) is strictly positive and zero otherwise. With this structure, the mean of the dependent variable, Sale, is the probability of selling a given position. Thus, $\beta_0$ (the constant) measures the probability of selling a stock whose return is less than or equal to zero, and $\beta_1$ measures the increase in probability of selling a given stock if that stock's return is strictly greater than zero. Recently, Chang, Solomon, and Westerfield (2016) as well as many others show that $\beta_1$ is positive and statistically significant.

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

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

where observations also occur at the account (i), stock (j), and date (t) level. We construct our additional variable, Portfolio_Gain, in the same manner as Gain except we use the return of the remaining holdings of the account on a given day. Note, that the stock of interest is always excluded in calculating the Portfolio_Gain variable.

Our main coefficient of interest in (2) is $\beta_3$ (the coefficient of the interaction term), which represents the difference in disposition effects for paper gain portfolios and paper loss portfolios.

In equation (2), $\beta_1$ represents the disposition effect for paper loss portfolios, and the sum of $\beta_1$ and $\beta_3$ represents the disposition effect for paper gain portfolios.

## III. The Portfolio-Driven Disposition Effect

The phenomenon that we document in this paper, which we refer to as "the portfolio-driven disposition effect," can be illustrated with a simple figure. Consider the probability that an investor sells one of her holdings. This is plotted in the portion of Figure 1 labeled "All Portfolios" for both the unconditional dataset (which does not condition on the investor making a sale on the given date) and the sale conditioned dataset.

**[Insert Figure 1 Here]**

The disposition effect can be seen visually as the difference between the green (the probability of selling a gain) and the red (the probability of selling a loss) bars. The black bars (which represent all stocks) are included to show the weighted average. The probability of selling a given stock is approximately 0.27% for the unconditional sample and 20% for the sale conditioned sample. Adding the condition that a given stock's return is positive (the green bar) increases that probability of an investor selling to 0.30% for the unconditional sample and 22% for the sale conditioned sample. The difference in the probability of selling a gain versus a loss is approximately 7 bps for the unconditional sample and 6% for the sale conditioned sample. In other words, an investor is approximately 32% (0.30%/0.23% − 1) more likely to sell a gain than a loss using the unconditional sample and approximately 37% (22%/16% − 1) more likely using the sale conditioned sample. This is the disposition effect.

To illustrate the portfolio-driven disposition effect, we reproduce these probabilities for two different scenarios: (i) the rest of the investor's portfolio is at a gain (the portion labeled "$>0$"), and (ii) the rest of her portfolio is at a loss (the portion labeled "$\leq 0$"). The portfolio-driven disposition effect refers to the fact that the disposition effect is concentrated in the scenario where the rest of her portfolio is at a loss; when the rest of her portfolio is at a gain, the disposition almost entirely disappears. In fact, the disposition effect decreases to approximately 0 bps using the unconditional sample and 1% using the sale conditioned sample. Thus, when the portfolio is at a paper gain, an investor is no more likely to sell a gain than a loss using the unconditional sample and only 7% more likely using the sale conditioned sample. Conversely, the disposition effect more than doubles when we restrict to observations in which the rest of the portfolio is at a paper loss to produce a disposition effect of approximately 22 bps using the unconditional sample and 17% using the sale conditioned sample. This means that when an investor's portfolio is at a paper loss, she is 103% more likely to sell a gain than a loss using the unconditional sample and 108% more likely using the sale conditioned sample.

Moreover, the probability of selling *gains* seems to drive the change in the disposition effect based on portfolio performance. While the probability of selling losses changes slightly when conditioning on the rest of the portfolio's performance, the probability of selling gains increases considerably (46% in the unconditional sample and 44% in the sale conditioned sample).

In the rest of the paper, we simply document that the portfolio-driven disposition effect is a robust phenomenon, we examine whether it can be explained by prior studies of the disposition effect, and we consider several possible explanations for the phenomenon.

Regarding robustness, we first consider the unconditional dataset, which does not restrict the sample based on whether or not the investor sold any shares of any stock on the given date. We estimate equation (2) on this sample and report the results in Table 2.

**[Insert Table 2 Here]**

Column 1 of Table 2 shows the baseline results with no fixed effects. Columns 2-4 add fixed effects controls for date, account, and stock, respectively. Finally, column 5 displays our most controlled specification with account, date, and stock fixed effects. Because investor sale decisions are likely correlated within account, within stock, and within date, we cluster our standard errors across all three of these dimensions following the procedure of Cameron, Gelbach, and Miller (2011).

Across all regressions in Table 2, the coefficient on the interaction term (Gain x Portfolio_Gain) ranges from −0.22% to −0.29% and is significant (t-stats between −22 and −24). These results suggest that the portfolio-driven disposition illustrated in Figure 1 is unlikely to be explained by unobservable investor, time, or stock characteristics that affect investors' propensity to sell shares of stock. Furthermore, the disposition effect is economically insignificant and at times statistically insignificant when the rest of the portfolio is at a paper gain. Recall the disposition effect when the rest of the portfolio is at a paper gain is measured by the sum of the coefficient from Gain and the coefficient on the interaction term (Gain x Portfolio_Gain). This sum for our base test (column 1) is 0.006%, and a linear restriction test which tests whether the sum of coefficients is zero fails to reject (p-value 0.48). The sum in column 2, which includes date fixed effects is -0.002% and the corresponding linear restriction test also fails to reject (p-value 0.83). Although the sum is statistically significant for columns 3-5, the economic significances are minimal with the largest effect in column 5, which has a sum of 0.084%. Even in this specification, the disposition effect is more than four times larger when the rest of an investor's portfolio is at a loss (0.365%) than when it is at a gain.

Many researchers who study the disposition effect restrict attention to days in which the investor sells shares of any stock in her portfolio. In Table 3, we restrict attention to such observations, and we run the same regressions that we reported in Table 2 on this subsample. We report these results in Table 3.

**[Insert Table 3 Here]**

While the magnitudes of the coefficients are larger due to the sale condition, the interaction coefficients remain negative (between −13% and −15%) and significant (t-stats between −26 and −30). In addition, the disposition effect for gain portfolios (measured as the sum of gain and the interaction coefficient) range from 1% - 3%. Although statistically significant, the economic significance of the disposition effect for gain portfolios is small compared to loss portfolios. In fact, even in our most controlled regression (column 5), the disposition effect is still more than five times larger when the rest of an investor's portfolio is at a loss (16.2%) than when it is at a gain (2.8%).

## IV. Explanations

### *A. Attention Effects?*

We first test whether extreme stocks drive the portfolio-driven disposition effect. Hartzmark (2015) finds that individual and mutual fund investors are more likely to sell their best and worst performing stock on a given sale day. Intuitively, these extreme stocks grab the investor's attention and, as a result, are sold more often. In our setting, the attention-grabbing hypothesis could predict some of our results, but not others. For example, if an investor has one stock that is a winner and the rest losers, then this stock is very likely to be sold under both the attention-grabbing hypothesis (it is an extreme stock) and the portfolio-driven disposition effect (investors are very likely to sell their winners when the rest of 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 portfolio-driven disposition effect because losers are just as likely to be sold as winners are when the remaining portfolio is at a gain. Nevertheless, in Table 4 we test the impact of extreme stocks on the portfolio-driven disposition effect by removing the best and worst stocks for every account-day and running the same regressions as in Table 2.

**[Insert Table 4 Here]**

Column 1 of Table 4 reports the base test (column 5 from Table 2). Column 2 restricts to only extreme observations, and column 3 removes extreme stock observations. It is worth noting that when an investor owns only two stocks, both are considered extreme. Because of this fact, column 3 inherently includes account-days in which at least three stocks are held. Still, the interaction coefficient on extreme observations is −0.29% (t-stat −23.36) and non-extremes is −0.29% (t-stat −15.91). While the statistical significance of the interaction term drops minimally when removing extreme observations, the economic significance remains unchanged. Similarly, the interaction coefficient remains statistically significant for these sub-samples in the sale conditioned sample as well. These results suggests that the rank effect (Hartzmark 2015) does not explain the portfolio-driven disposition effect.

### *B. Portfolio Rebalancing*

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

To test this, we define the dummy variable Full_Sale to equal one if the investor completely liquidates her position in a stock and zero otherwise. The probabilities of complete liquidations are graphed in Figure 2 for both samples.

**[Insert Figure 2 Here]**

Far from disappearing, the portfolio-driven disposition effect is even *stronger* when we restrict attention to complete liquidations. Not only does the disposition effect disappear when the remaining portfolio is positive—it actually *reverses*. In both samples, the probability of selling a loss is greater than selling a gain when the remaining portfolio is at a gain. Consequently, the disposition effect when the remaining portfolio is at a loss is more than triple the size of the disposition effect for all portfolios.

Next, we turn to multivariate analysis to see whether portfolio rebalancing explains the portfolio-driven disposition effect. Similar to Tables 2 and 3, we consider five specifications with variations of fixed effects for the unconditional sample (Panel A) and the sale conditioned sample (Panel B); the only difference is that we now use Full_Sale as our dependent variable. Across all specifications, the interaction coefficient is negative and statistically significant. Moreover, the economic magnitude is large and actually offsets the coefficient on Gain in four of the ten specifications. Even in column 5 of both panels, the interaction coefficient is 82% (unconditional) and 90% (sale conditioned) of the gain coefficient in absolute value. This means that most of the disposition effect is eliminated when the remaining portfolio is at a gain when controlling for unobservable investor, time, or stock characteristics that affect investors' propensity to sell shares of stock.

Our univariate and multivariate analysis suggests that the portfolio-driven disposition effect is actually stronger when we restrict attention to complete liquidations. Thus, we conclude that portfolio rebalancing is an unlikely explanation for the portfolio-driven disposition effect.

**[Insert Table 5 Here]**

### *C. Mental Accounting Tricks using Simultaneous Liquidations?*

Another possible explanation for the portfolio-driven disposition effect is that investors might simultaneously realize losses and gains in order to cushion the blow of realizing the loss. For example, suppose an investor liquidates a losing position at the same time that she liquidates a winning position. If the gains of the winning position exceed the loss from the losing position, she can mentally account for these two transactions as a single realized gain. When an investor's portfolio is performing well, she can more easily find a winning position that dominates any of her losing positions, and hence, she might be more likely to realize one of her losses when her portfolio is performing well.

To address this possibility, we first examine whether there is any evidence that investors actually seek to simultaneously realize gains and losses. To do this, we need a model to predict how often we should observe investors simultaneously liquidating two losses, two gains, and one gain and one loss (conditional on them liquidating two positions). Consider an investor who has N stocks in her portfolio, and $N_G$ are at a gain while $N_L = N - N_G$ are at a loss. Suppose that she liquidates exactly two stocks on a given day. If she randomly picks two stocks to liquidate, it is straightforward to verify that

$$\Pr(\textit{sell two gains}) = \frac{\binom{N_G}{2}}{\binom{N}{2}} = \frac{N_G(N_G-1)}{N(N-1)} \tag{3}$$

$$\Pr(\textit{sell one gain and one loss}) = \frac{N_G N_L}{\binom{N}{2}} = \frac{2N_G N_L}{N(N-1)} \tag{4}$$

$$\Pr(\textit{sell two losses}) \quad = \quad \frac{\binom{N_L}{2}}{\binom{N}{2}} \quad = \quad \frac{N_L(N_L-1)}{N(N-1)} \tag{5}$$

where $\binom{x}{y}$ ("x choose y") is the binomial coefficient representing the number of subsets of size y that exist given a set of size x. Of course, we know a priori that this model is not entirely valid, because the disposition effect implies that investors should be more likely to liquidate two gains than two losses. Hence, the disposition effect implies that our model should overestimate the likelihood that investors simultaneously liquidate two losses.

Having established a baseline prediction for the probability of an investor liquidating two gains, two losses, or one gain and one loss, we can test whether investors are disproportionately likely to simultaneously recognize a gain and loss by comparing the empirical frequencies with the model's predictions. For each instance when an investor liquidates exactly two stocks on a given day, we calculate the model's residual for each of the three possibilities according to (3)-(5). For example, suppose the model predicts (conditional on an investor liquidating two positions) that it is 50% likely that the investor will liquidate two gains, 40% likely she will liquidate one gain and one loss, and 10% likely that she will liquidate two losses. If in reality the investor liquidates two gains, then the model's residual for the "liquidate two gains" scenario is 0.5, while the model's residuals for the "liquidate one gain and one loss" and "liquidate two losses" are $-0.4$ and $-0.1$, respectively. We report average residuals and their t-stats (clustered by account using Rogers (1993) standard errors) in Table 6. The average residual of the "sell one gain and one loss" is $-0.15$, which is highly significant (t=-41.41). This suggests that investors are not disproportionately likely to simultaneously liquidate gains and losses in order to soften the blow of realizing losses.

**[Insert Table 6 Here]**

Even though our evidence in Table 6 suggests that investors are not disproportionately likely to simultaneously realize gains and losses, it is possible that other forms of mental accounting tricks using simultaneous liquidations can explain the portfolio-driven disposition effect. To address this, we run our baseline regression on the sample of investor-dates where the investor only sells shares of one stock. We find that the portfolio-driven disposition effect (i.e., negative and significant coefficient of the interaction Gain*Portfolio_Gain) is similar in magnitude in this subsample as it is in the entire sample, suggesting that the portfolio-driven disposition effect is not driven by mental accounting tricks relying on simultaneous liquidations. These regressions are reported in Table 7.

**[Insert Table 7 Here]**

### *D. Unobserved Skill?*

Grinblatt, Keloharju, and Linnainmaa (2012) analyze data on Finnish investors and document that high IQ investors are superior stock pickers and they exhibit less of a disposition effect. Hence, it's possible that high IQ investors (who do not exhibit a disposition effect and are superior traders) likely have portfolios at a gain, and low IQ investors (who are prone to the disposition effect and are inferior traders) likely have portfolios at a loss. In other words, it is possible that we are simply documenting a consequence of Grinblatt, Keloharju, and Linnainmaa's (2012) finding. We address this possibility in two ways. First, we use proxies for investor sophistication that have been used by prior researchers to see if our results differ across investor sophistication. Second, we identify situations in which an investor's portfolio gain is more likely to be driven by skill than luck, and we compare the disposition effect in these two scenarios. If investor IQ drives our results, then there should be little disposition effect in scenarios where the portfolio is performing well due to stock-picking skill but a much stronger disposition effect when the portfolio is performing well due to luck.

The trading data we use have several demographics characteristics available for a sub-sample of investors. We follow Dhar and Zhu (2006) in using employment and income as proxies for investor sophistication. Like them, we classify employment as either professional ("professional/technical" or "administrative/managerial") or non-professional ("white collar/clerical," "blue collar/craftsman," or "service/sale"). Additionally, we follow them in categorizing annual income as high if their income is at least $100,000 and low if it is no more than $40,000. Dhar and Zhu (2006) document that investor sophistication is negatively correlated with the disposition effect, so we test whether the portfolio-driven disposition effect holds for both samples, or if it disappears when we separate investors based on their level of sophistication.

Table 8, Panel A shows tests of the four sub-samples of sophistication-related proxies: non-professional, professional, low income, and high income. Columns 1 and 4 confirm the Dhar and Zhu (2006) result without fixed effect controls. Indeed, the disposition effect is higher for non-professional (0.097%, t-stat 7.12) versus professional (0.086%, t-stat 8.11) investors, as well as low-income (0.095%, t-stat 8.48) versus high-income (0.076%, t-stat 7.09) investors. Columns 2 and 4 add account, stock, and date fixed effects controls and show the same pattern. In columns 3 and 6, we estimate equation (2) to determine the impact of these proxies on the portfolio-driven disposition effect. Here, we actually find that the portfolio's impact on the disposition effect, as denoted by the interaction coefficient, is actually economically and statistically stronger among professional (−0.29%, t-stat −14.33) versus non-professional (−0.26%, t-stat −9.06) investors. Therefore, this measure of sophistication does not seem to have any impact on our result. Additionally, the portfolio-driven disposition effect is almost identical among low-income (−0.30%, t-stat −14.39) and high-income (−0.29%, t-stat −12.88) investors. From these results, we conclude that our findings are not explained by the patterns documented by Dhar and Zhu (2006).

**[Insert Table 8 Here]**

Investor sophistication is different than investor skill, and so our final approach is to decompose an investor's portfolio return based on their Daniel, Grinblatt, Titman, and Wermers (DGTW) performance.[1] More specifically, we decompose each investor's portfolio return into two components, one that is determined based on each stock's characteristic (size, book-to-market, and momentum), and the other based on the stock's performance relative to its matched portfolio (where the matching is done on size, book-to-market, and momentum). The idea is that while highly skilled investors might be able to pick stocks that perform well relative to the stock's matched portfolio, it is unlikely that individual investors can predict the future performance of the market, HML, SMB, and MOM factors. By comparing the disposition effect among investors whose positive portfolio performance is driven by luck versus skill, we can examine the likelihood that portfolio gain is simply proxying for investor skill.

We match each stock-date to one of the 125 (5 x 5 x 5) DGTW member groups for each year using the benchmarks available on Russ Wermers' website.[2] Since the DGTW member groups are created on June 30 of each year, we match all account-stock observations in July-December to the same year and all account-stock observations in January-June to the previous year's member group. With some abuse of notation, we separate each account-stock-date's return into "alpha" and "beta," where beta represents the return (rather than a factor loading) of the corresponding DGTW portfolio and alpha equals the stock's return minus the matched portfolio. It trivially follows that any stock's cumulative return since the investor purchased it is simply the sum of its alpha and beta.

[1] See Daniel, Grinblatt, Titman, and Wermers (1997).
[2] The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

We define a variable, "Alpha," to identify observations in which portfolio gain is driven by skill versus luck. Therefore, Alpha is defined as 1 if portfolio gain is generated only due to positive DGTW alpha (i.e., alpha > 0, beta ≤ 0) and 0 if portfolio gain is generated only due to positive DGTW beta (i.e., alpha ≤ 0, beta > 0). For all other observations, Alpha is defined as missing. Due to ambiguity, we omit the instances when both alpha and beta drive portfolio gain (alpha > 0, beta > 0).

Table 8, Panel B tests whether portfolio gain is simply a proxy for skill using DGTW performance benchmarks. Column 1 shows the disposition effect for all observations with a DGTW identifier in which Portfolio_Gain equals 1 using no fixed effects controls (-0.002%, t-stat -0.27). This column shows our main result: in simple univariate tests, the disposition effect disappears when the return of an investor's remaining holdings are strictly greater than zero. Column 2 adds account, stock, and date fixed effects controls (0.082%, t-stat 11.12). Column 3 then shows the same test as column 2 with the restriction that the investor's portfolio gain is entirely driven by skill (Alpha = 1 ), whereas Column 4 reports the results with the restriction that the investor's portfolio gain is entirely driven by luck (Alpha = 0). Here, we see little impact to the disposition effect when the portfolio gain is driven by superior stock picking versus luck. If portfolio gain were simply proxying for unobserved investor skill, then we would have expected to see a much smaller disposition effect once we conditioned on portfolio gains that appeared to be the result of stock-picking alpha.  In fact, the Gain coefficient remains unchanged at 0.00082 (t-stat 4.80). Column 5 tests the difference between the coefficients reported in columns 3 and 4. We add the Alpha dummy variable as well as an interaction term (Gain*Alpha) to the regression equation. Thus, we interpret the coefficient of the interaction term as the difference in disposition effects between skilled investors and lucky investors. This coefficient is both economically and statistically insignificant (0.009%, t-stat 0.73).  This suggests that portfolio gain is not simply proxying for investor skill because we see little difference in disposition effect when the source of the gain as coming from stock-picking skill or not.

In Table 9, we conduct the same tests as in Table 8, except we run them on the sale conditioned sample instead. These tests produce the same qualitative results.

**[Insert Table 9 Here]**

*E. Utility over both Paper Gains/Losses and Realized Gains/Losses?*

According to standard expected utility theory, investors only derive utility from consumption. According to this view, a stock's return only affects an investor's utility through its effect on the investor's consumption. This standard theory has had difficulty explaining people's behavior in many settings, and an alternative theory (prospect theory) was developed that posits that people derive utility over gains and losses rather than over absolute wealth levels (Kahneman and Tversky 1979; Kahneman and Tversky 1992). Prospect theory is silent on whether people derive utility from paper gains or realized gains, and some models have been built on the assumption that investors derive utility from paper gains/losses, while others have been built on the assumption that they derive utility from realized gains/losses.[3] Frydman et al (2014) conduct experiments of trade in an asset market, and they measure subjects' brain activity using functional magnetic resonance imaging. They find evidence that subjects' brains exhibit activity consistent with them receiving pleasure upon learning that their positions have increased in value, and they find that the effect is much stronger when subjects actually realize their gains, which is consistent with the predictions of realization utility.

This leads to another possible explanation for the portfolio-driven disposition effect: that investors derive utility from *both* paper (i.e., unrealized) gains/losses and realized gains/losses.

[3] Because transaction costs are generally small, especially at discount brokerages, the distinction between paper gains/losses and realized gains/losses should be irrelevant, because investors can easily convert their paper gains/losses to realized gains/losses without incurring any significant costs. However, economists have argued that realized losses are more painful than paper losses (Thaler, 1999), and they have shown that investors' risk tolerance is differentially affected by paper losses and realized losses (Imas, 2016). In other words, investors do seem to distinguish between paper gains/losses and realized gains/losses, even though it is unclear why.

The idea is the following. When an investor's portfolio is at a gain, she has received a lot of positive utility from the paper gains. The positive utility causes her to feel psychologically strong and hence more willing to realize a loss and take the resulting realization (dis)utility. Hence, there is less of a disposition effect in this scenario as she is willing to realize her losses. Conversely, if her portfolio is loss, she has received a lot of negative utility from the paper losses, which leaves her feeling psychologically fragile. In this scenario, she is loath to experience additional disutility by realizing a loss; rather, she is likely to realize a gain in order to reduce her disutility from her paper losses. It follows that there is a strong disposition effect when her portfolio is down.

To develop a testable prediction of this explanation, we consider what investors do once they sell their stock: do they keep it in cash or do they reinvest it in a different stock? Frydman, Hartzmark, and Solomon (2018) provide strong evidence that people do not "close" their mental accounts when they liquidate a stock and reinvest the proceeds into a new stock; rather, they continue to use the amount they invested in the initial stock as a reference point when deciding whether or not to liquidate their position in the new stock. According to this view, investors should be less likely to receive a burst of realization utility whenever they sell shares at a gain and reinvest the proceeds into a new position; rather, the bursts of realization utility should occur when investors realize a gain and "close" the mental account by not reinvesting the proceeds into a new stock. Hence, if our results are driven by investors receiving utility over both paper gains/losses and realized gains/losses, then we should expect investors to be unlikely to invest in a different stock whenever they sell a stock at a gain and their portfolio is at a loss; keeping their mental account open in this way would prevent them from receiving the burst of positive realization utility from realizing the gain.[4]

[4] In contrast, if portfolio rebalancing (discussed in Section IV.B) explains the portfolio-driven disposition effect, we should expect investors to be more likely to reinvest when they sell a stock at a gain and the rest of their portfolio is at a loss.

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

We report the results of this test in Table 10.

**[Insert Table 10 Here]**

The variable "Loss_Gain" takes the value of one if the stock sold is at a loss and the remaining portfolio is at a gain. The same naming convention follows for the other independent variables. The variable "Gain_Loss" is omitted. Thus, each coefficient is interpreted as the difference in reinvestment probability from the case in which the stock is at a gain and the remaining portfolio is at a loss.

In Table 10, because all coefficients are positive and statistically significant well below the 1% level, investors selling a gain when the rest of their portfolio is at a loss are most likely to keep those gains in cash over the next two trading days. These results are consistent with the idea that investors are eager to realize gains whenever their portfolio is at a loss, and when they do so, they refrain from reinvesting the proceeds because they want to close the mental account (and lock in the realized gain).

## V. Conclusion

We document a new stylized fact which we term the portfolio-driven disposition effect: the disposition effect is concentrated in scenarios which the investor's remaining portfolio is performing poorly. When an investor's portfolio is performing well, the disposition effect is almost non-existent. The effect is robust to a wide variety of controls. We explored several possible explanations for the effect, and the one that is most consistent with the data is that investors derive utility from both paper gains/losses and realized gains/losses. When an investor has disutility from unrealized losses, she takes utility by realizing gains.

One way to think about our finding is that investors treat unrealized gains like an in-the-money "utility option" that they can exercise at a time which is most valuable to them, i.e. when they are experiencing disutility somewhere else. While our study focuses on individual stocks in a portfolio, of interest is the generality of this phenomenon. For example, does an investor's choice to sell stocks or bonds depend on her unrealized gains or losses in another asset class such as housing? Or could it also depend on disutility from non-financial sources such as health or well-being? We find these questions of interest for future research.

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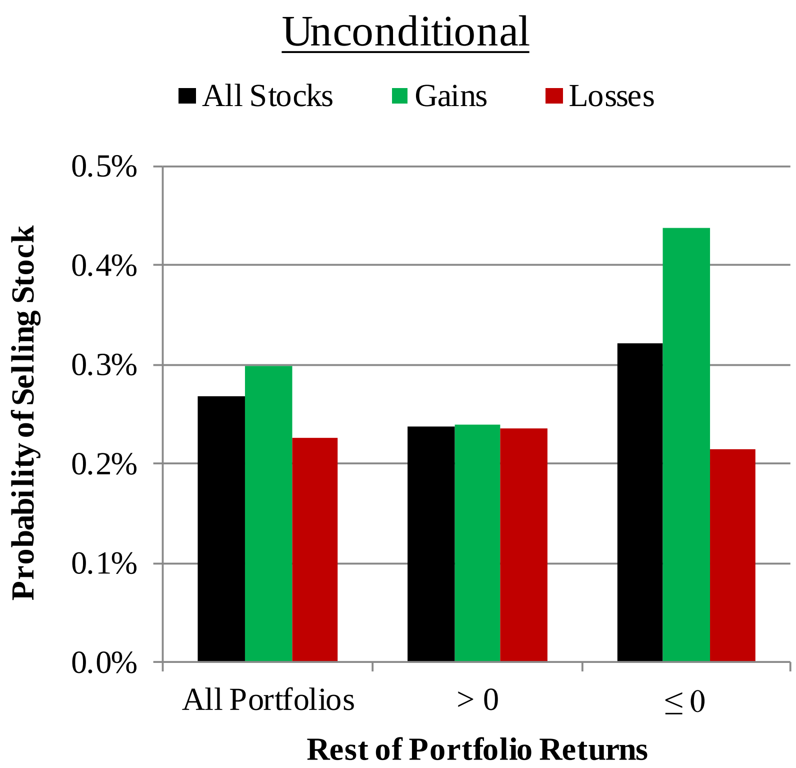
**Figure 1: Probability of Selling a Stock Based on its Return and the Return of the Rest of the Portfolio**

We report the probability of selling a stock (including partial sales) based on the stock's performance (gain versus loss) from the date the investor purchased the stock and the performance of the rest of the investor's portfolio (excluding the stock under consideration). We report the unconditional probabilities (left) and conditioning on a sale taking place (right). The unconditional results have 102,821,438 observations (57% stock gains, 43% stock losses; 64% portfolio gains, 36% portfolio losses). The conditional results have 1,403,572 observations (56% stock gains, 44% stock losses; 64% portfolio gains, 36% portfolio losses). We define gains as strictly greater than zero while losses include zeros.



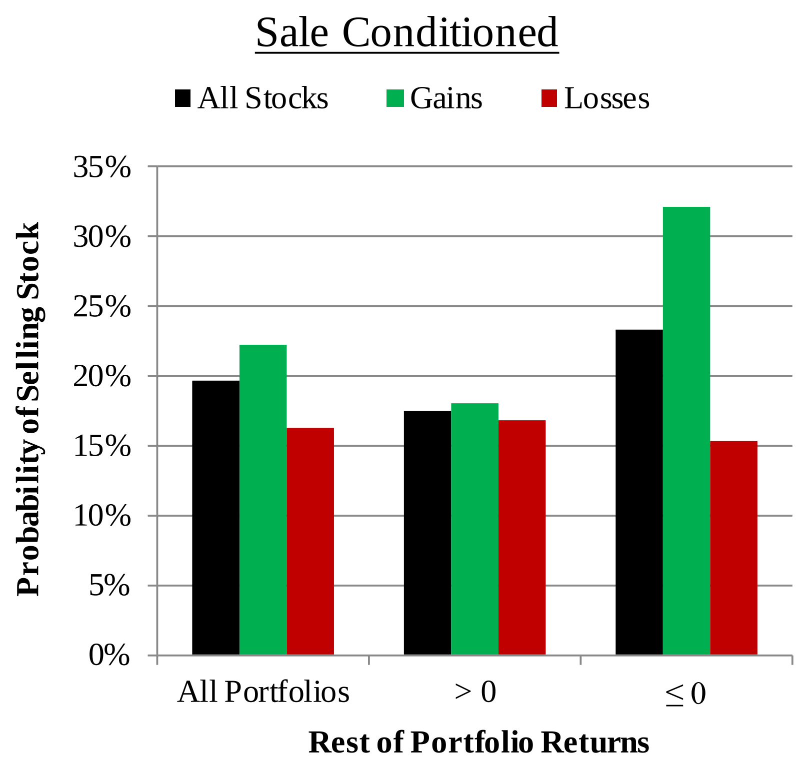
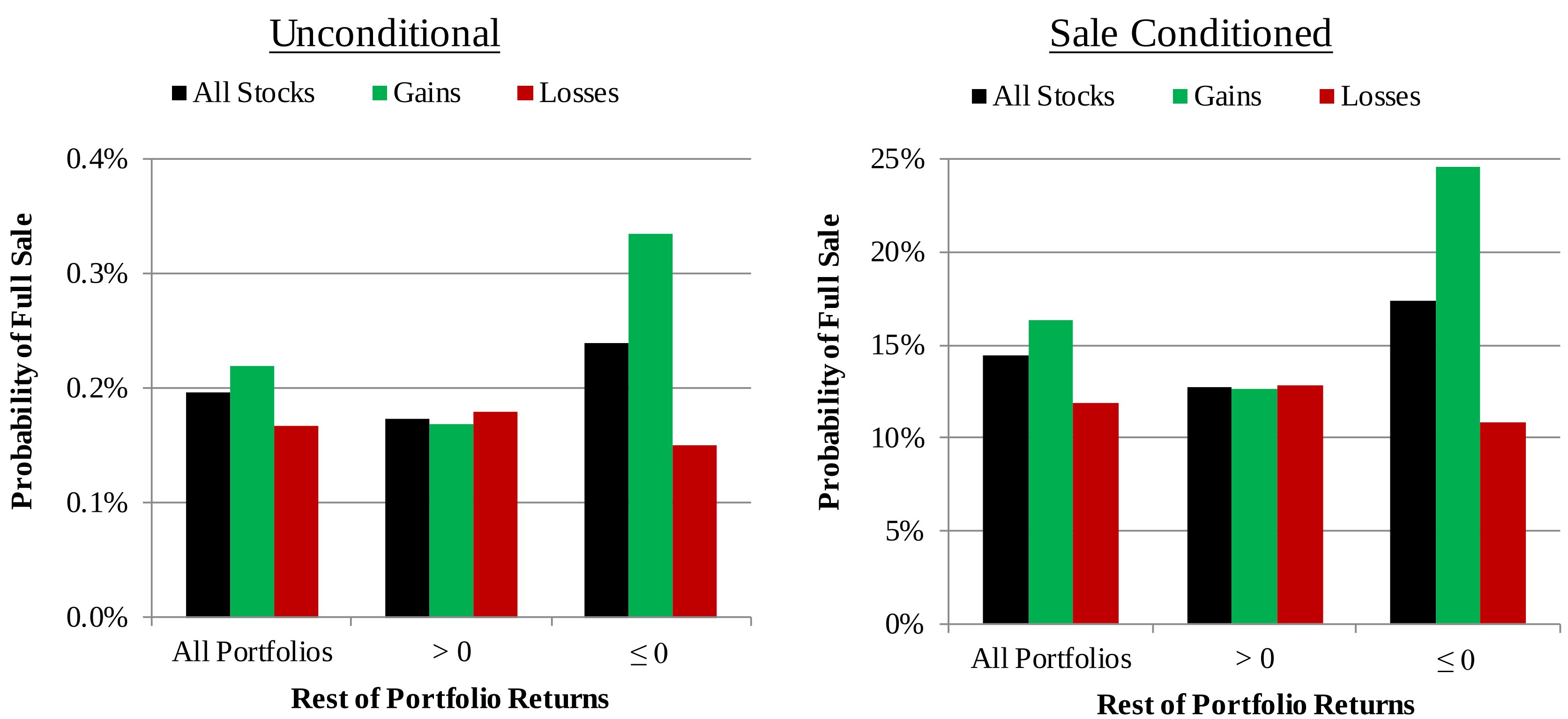



**Figure 2: Probability of a Complete Liquidation Based on its Return and the Return of the Rest of the Portfolio**

We report the same graphs as in Figure 1 except that here we analyze only full sales, or complete liquidations, instead of including partial sales. These graphs show the probability of a complete liquidation based on the stock's performance (gain versus loss) from the date the investor purchased the stock and the performance of the rest of the investor's portfolio (excluding the stock under consideration). We report the unconditional probabilities (left) and conditioning on a sale taking place (right). The unconditional results have 102,821,438 observations (57% stock gains, 43% stock losses; 64% portfolio gains, 36% portfolio losses). The conditional results have 1,403,572 observations (56% stock gains, 44% stock losses; 64% portfolio gains, 36% portfolio losses). We define gains as strictly greater than zero while losses include zeros.



## Table 1: Individual Investor Summary Statistics

This table presents summary statistics for the two datasets created from the individual trading data from January 1991 to November 1996 (Barber and Odean, 2000). Panel A represents all account-stock-days in which a position is held while Panel B adds the condition that a sale occurred on a given account-day. We define gains as strictly greater than zero while losses include zeros.

| **PANEL A: Unconditional Data** | | | | Stock Returns | | | | Portfolio Returns | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Sell Obs | % Sell | Mean | 10% | Median | 90% | Mean | 10% | Median | 90% |
| **All Account-Stock-Dates** | **132,884,090** | **358,300** | **0.27%** | **0.15** | **-0.34** | **0.04** | **0.68** | | | | |
| with 1 stock | 30,062,652 | 82,610 | 0.27% | 0.12 | -0.38 | 0.02 | 0.62 | | | | |
| Stock at a Gain | 15,735,356 | 54,512 | 0.35% | 0.43 | 0.03 | 0.21 | 1.00 | | | | |
| Stock at a Loss | 14,327,296 | 27,951 | 0.20% | -0.23 | -0.53 | -0.17 | -0.02 | | | | |
| with 2+ stocks | 102,821,438 | 275,690 | 0.27% | 0.16 | -0.32 | 0.04 | 0.70 | 0.15 | -0.20 | 0.07 | 0.55 |
| Stock at a Gain | 59,083,007 | 176,610 | 0.30% | 0.44 | 0.03 | 0.23 | 1.02 | 0.19 | -0.16 | 0.10 | 0.62 |
| Stock at a Loss | 43,738,431 | 99,080 | 0.23% | -0.21 | -0.50 | -0.15 | -0.02 | 0.09 | -0.25 | 0.03 | 0.46 |
| Portoflio at a Gain | 66,043,740 | 157,388 | 0.24% | 0.22 | -0.28 | 0.08 | 0.80 | 0.32 | 0.03 | 0.19 | 0.72 |
| Portfolio at a Loss | 36,777,698 | 118,302 | 0.32% | 0.06 | -0.38 | -0.01 | 0.48 | -0.16 | -0.37 | -0.11 | -0.02 |
| Accounts | 75,111 | | | | | | | | | | |
| Account-Days | 57,475,343 | | | | | | | | | | |

| **PANEL B: Sale Conditioned Data** | | | | Stock Returns | | | | Portfolio Returns | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Sell Obs | % Sell | Mean | 10% | Median | 90% | Mean | 10% | Median | 90% |
| **All Account-Stock-Dates** | **1,530,216** | **358,300** | **23%** | **0.12** | **-0.28** | **0.03** | **0.54** | | | | |
| with 1 stock | 126,644 | 82,610 | 65% | 0.10 | -0.28 | 0.04 | 0.48 | | | | |
| Stock at a Gain | 76,219 | 54,512 | 72% | 0.32 | 0.03 | 0.15 | 0.70 | | | | |
| Stock at a Loss | 50,425 | 27,951 | 55% | -0.22 | -0.48 | -0.13 | -0.01 | | | | |
| with 2+ stocks | 1,403,572 | 275,690 | 20% | 0.12 | -0.29 | 0.03 | 0.55 | 0.09 | -0.17 | 0.06 | 0.42 |
| Stock at a Gain | 792,877 | 176,610 | 22% | 0.37 | 0.03 | 0.17 | 0.84 | 0.11 | -0.14 | 0.08 | 0.46 |
| Stock at a Loss | 610,695 | 99,080 | 16% | -0.19 | -0.45 | -0.12 | -0.01 | 0.06 | -0.20 | 0.02 | 0.36 |
| Portoflio at a Gain | 896,260 | 157,388 | 18% | 0.18 | -0.25 | 0.06 | 0.64 | 0.30 | 0.03 | 0.15 | 0.54 |
| Portfolio at a Loss | 507,312 | 118,302 | 23% | 0.03 | -0.34 | 0.00 | 0.35 | -0.27 | -0.33 | -0.09 | -0.01 |
| Accounts | 52,151 | | | | | | | | | | |
| Account-Days | 305,925 | | | | | | | | | | |

**Table 2: Probability of Selling a Stock Based on its Return and the Return of the Rest of the Portfolio (Regressions on the Unconditional Sample)**

We report the results of various regressions on the sample of 102,821,438 account-stock-day triples such that the account owns shares of at least two different common stocks on the given day. After controlling for account, stock, day fixed effects, the sample has 102,821,233 observations. Our dependent variable, "Sale", is a dummy variable representing whether the investor sold any shares of the given stock on the given date. The variable "Gain" represents whether the investor's position in the stock is at a gain on the given date. Similarly, "Portfolio_Gain" represents whether the rest of the investor's portfolio (excluding the stock under consideration) is at a gain on the given date. We report cluster-robust t-stats in parentheses. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011).

| Dependent Variable: Sale | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Gain | 0.00226*** | 0.00218*** | 0.00348*** | 0.00270*** | 0.00365*** |
| | (17.31) | (17.17) | (22.80) | (20.91) | (23.52) |
| Portfolio_Gain | 0.00022*** | 0.00011** | 0.00187*** | 0.00030*** | 0.00173*** |
| | (4.13) | (2.17) | (19.92) | (5.97) | (19.13) |
| Gain * Portfolio_Gain | -0.00220*** | -0.00220*** | -0.00288*** | -0.00218*** | -0.00281*** |
| | (-22.94) | (-22.80) | (-22.72) | (-23.60) | (-22.68) |
| Observations | 102,821,233 | 102,821,233 | 102,821,233 | 102,821,233 | 102,821,233 |
| R-squared | 0.000 | 0.001 | 0.012 | 0.001 | 0.012 |
| Date FE | No | Yes | No | No | Yes |
| Account FE | No | No | Yes | No | Yes |
| Stock FE | No | No | No | Yes | Yes |
| Clustering (Date, Account, Stock) | Yes | Yes | Yes | Yes | Yes |

**Table 3: Probability of Selling a Stock Based on its Return and the Return of the Rest of the Portfolio (Regressions on the Sale Conditioned Sample)**

We report the same analysis as Table 2 with the condition that we only include account-days in which a sale occurred. This restriction reduces our sample to 1,403,572 account-stock-day triples. After controlling for account, stock, day fixed effects, the sample has 1,397,274 observations. We report cluster-robust t-stats in parentheses. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011).

| Dependent Variable: Sale | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Gain | 0.166*** | 0.165*** | 0.152*** | 0.178*** | 0.162*** |
| | (29.38) | (29.54) | (31.29) | (33.15) | (34.40) |
| Portfolio_Gain | 0.015*** | 0.020*** | 0.062*** | 0.0216*** | 0.067*** |
| | (2.76) | (3.94) | (18.87) | (4.88) | (21.73) |
| Gain * Portfolio_Gain | -0.154*** | -0.152*** | -0.135*** | -0.151*** | -0.134*** |
| | (-26.23) | (-26.52) | (-28.37) | (-28.24) | (-29.92) |
| Observations | 1,397,274 | 1,397,274 | 1,397,274 | 1,397,274 | 1,397,274 |
| R-squared | 0.021 | 0.029 | 0.153 | 0.044 | 0.173 |
| Date FE | No | Yes | No | No | Yes |
| Account FE | No | No | Yes | No | Yes |
| Stock FE | No | No | No | Yes | Yes |
| Clustering (Date, Account, Stock) | Yes | Yes | Yes | Yes | Yes |

## Table 4: Extreme versus Non-Extreme Stocks in the Investor's Portfolio

We report the same regression as column 5 of Tables 2 and 3 with various sample restrictions. We identify a stock as "extreme" if its cumulative return since it was purchased is the best or worst in the given investor's portfolio. Columns 1-3 report regressions on our unconditional sample, whereas Columns 4-6 report regressions on the sale conditioned sample. Columns 1 and 4 are the base case reported in column 5 of Tables 2 and 3. Columns 2 and 5 report regression coefficients when the sample is restricted to the extreme stocks in the investor's portfolio, while Columns 3 and 6 restrict attention to the non-extreme stocks in the investor's portfolio. We report cluster-robust t-stats in parentheses. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). All regressions control for date, account, and stock fixed effects.

| | Unconditional Sample | | | Sale Conditioned Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dependent Variable: Sale | Base | Extreme | Non-Extreme | Base | Extreme | Non-Extreme |
| Gain | 0.00365*** | 0.00400*** | 0.00351*** | 0.162*** | 0.241*** | 0.096*** |
| | (23.52) | (24.77) | (17.19) | (34.40) | (38.10) | (21.25) |
| Portfolio_Gain | 0.00173*** | 0.00196*** | 0.00147*** | 0.067*** | 0.084*** | 0.040*** |
| | (19.13) | (18.94) | (14.45) | (21.73) | (20.51) | (14.21) |
| Gain * Portfolio_Gain | -0.00281*** | -0.00286*** | -0.00290*** | -0.134*** | -0.178*** | -0.069*** |
| | (-22.68) | (-23.36) | (-15.91) | (-29.92) | (-35.10) | (-14.99) |
| Observations | 102,821,233 | 54,896,360 | 47,924,494 | 1,397,274 | 412,860 | 979,596 |
| R-squared | 0.012 | 0.014 | 0.014 | 0.173 | 0.246 | 0.104 |
| Date FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Account FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustering (Date, Account, Stock) | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 5: Probability of a Complete Liquidation Based on its Return and the Return of the Rest of the Portfolio (Unconditional and Sale Conditioned Regressions)

We report the same analysis as Tables 2 and 3 except with "Full_Sale" as the dependent variable instead of "Sale". We define "Full_Sale" to be equal to one if an entire position is sold and zero otherwise. This definition does not identify partial sales like the original "Sale" variable. Thus, Full_Sale only identifies complete liquidations. We report cluster-robust t-stats in parentheses. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011).

**Panel A: Unconditional**

| Dependent Variable: Full_Sale | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Gain | 0.00184*** | 0.00179*** | 0.00282*** | 0.00218*** | 0.00298*** |
| | (17.22) | (17.13) | (22.96) | (21.11) | (24.06) |
| Portfolio_Gain | 0.00028*** | 0.00023*** | 0.00161*** | 0.00034*** | 0.00152*** |
| | (7.06) | (5.86) | (20.43) | (9.03) | (19.60) |
| Gain * Portfolio_Gain | -0.00194*** | -0.00193*** | -0.00252*** | -0.00193*** | -0.00245*** |
| | (-23.16) | (-23.04) | (-23.33) | (-23.99) | (-23.25) |
| Observations | 102,821,233 | 102,821,233 | 102,821,233 | 102,821,233 | 102,821,233 |
| R-squared | 0.000 | 0.001 | 0.007 | 0.001 | 0.008 |
| Date FE | No | Yes | No | No | Yes |
| Account FE | No | No | Yes | No | Yes |
| Stock FE | No | No | No | Yes | Yes |
| Clustering (Date, Account, Stock) | Yes | Yes | Yes | Yes | Yes |

**Panel B: Sale Conditioned**

| Dependent Variable: Full_Sale | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Gain | 0.134*** | 0.133*** | 0.123*** | 0.144*** | 0.133*** |
| | (27.70) | (27.90) | (29.31) | (31.76) | (33.05) |
| Portfolio_Gain | 0.020*** | 0.025*** | 0.058*** | 0.024*** | 0.063*** |
| | (4.73) | (6.31) | (19.84) | (7.04) | (22.12) |
| Gain * Portfolio_Gain | -0.136*** | -0.134*** | -0.121*** | -0.133*** | -0.120*** |
| | (-27.31) | (-27.65) | (-29.11) | (-29.21) | (-30.50) |
| Observations | 1,397,274 | 1,397,274 | 1,397,274 | 1,397,274 | 1,397,274 |
| R-squared | 0.017 | 0.027 | 0.153 | 0.036 | 0.172 |
| Date FE | No | Yes | No | No | Yes |
| Account FE | No | No | Yes | No | Yes |
| Stock FE | No | No | No | Yes | Yes |
| Clustering (Date, Account, Stock) | Yes | Yes | Yes | Yes | Yes |

## Table 6: Two Sell Residuals – A Test of Simultaneous Selling Independence

We report the average residuals according to the simple model described in (3)-(5). The sample is restricted to account-days in which the investor owns at least three stocks and sells exactly two stocks. We calculate predicted probabilities that an investor sells two gains, one gain and one loss, or two losses based on (3)-(5). Next, we define residuals as the dummy for whether the investor actually sold two gains (or 1 gain and 1 loss, or 2 losses) minus the predicted probability of that event. Finally, we average those residuals across all observations. If an investor's choice is truly independent, then all residuals should be insignificant from zero. We report cluster-robust t-stats. All standard errors are clustered by account, following the procedure of Rogers (1993).

| | Residual Statistics | | |
|---|---|---|---|
| Two Sell Scenarios | Mean | t-stat | Observations |
| Sell 2 Gains | 0.120*** | 24.69 | 21,595 |
| Sell 1 Gain and 1 Loss | -0.150*** | -41.41 | 21,595 |
| Sell 2 Losses | 0.030*** | 7.60 | 21,595 |

## Table 7: Non-Simultaneous Sales

We report the same regression as column 5 of Tables 2 and 3 with various sample restrictions. Columns 1 and 2 report regressions on the unconditional sample, while columns 3 and 4 report regressions on the sale conditioned sample. Columns 1 and 3 restrict attention to account-days in which the investor makes at most one sale transaction on the given date, while Columns 2 and 4 restrict attention to account-days in which the investor makes at most one sale transaction in the five day window centered on the given date. We report cluster-robust t-stats in parentheses. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011). All regressions control for date, account, and stock fixed effects.

| | Unconditional Sample | | Sale Conditioned Sample | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable: Sale | ≤1 Trans | ≤1Trans, 5 day window | ≤1 Trans | ≤1Trans, 5 day window |
| Gain | 0.00287*** | 0.00232*** | 0.174*** | 0.186*** |
| | (26.12) | (27.24) | (40.20) | (43.09) |
| Portfolio_Gain | 0.00132*** | 0.00105*** | 0.072*** | 0.080*** |
| | (21.14) | (21.11) | (24.22) | (25.50) |
| Gain * Portfolio_Gain | -0.00206*** | -0.00166*** | -0.134*** | -0.144*** |
| | (-25.08) | (-26.53) | (-34.95) | (-37.46) |
| Observations | 102,302,932 | 101,850,656 | 978,805 | 782,659 |
| R-squared | 0.006 | 0.005 | 0.186 | 0.192 |
| Date FE | Yes | Yes | Yes | Yes |
| Account FE | Yes | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes | Yes |
| Clustering (Date, Account, Stock) | Yes | Yes | Yes | Yes |

## Table 8: Sophisticated/Skilled Investors? (Unconditional Sample)

Panel A reports tests split by non-professional, professional, low-income and high-income investors. We define these sub-samples consistent with Dhar and Zhu (2006). Professional investors include those classified as "professional/technical" or "administrative/managerial". Non-professional investors include those classified as "white collar/clerical," "blue collar/craftsman," or "service/sale". High-income investors have an annual income of at least $100,000. Low-income investors have an annual income no greater than $40,000. Panel B, columns 1 and 2 report the disposition effect when Portfolio_Gain equals 1 on all observations with a DGTW identifier. Columns 3 and 4 report the same test as column 2 for the sub-samples in which Alpha equals 1 and 0, respectively. Alpha is defined as 1 if portfolio gain is generated only due to positive DGTW alpha (alpha > 0, beta ≤ 0), 0 if portfolio gain is generated only due to positive DGTW beta (alpha ≤ 0, beta > 0), and missing otherwise. In Column 5, the interaction term tests the difference between the coefficients reported in Columns 3 and 4. We report cluster-robust t-stats in parentheses. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011).

**Panel A: Sophistication Proxies (Income and Employment)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: Sale | | Non-Professional | | | Professional | |
| Gain | 0.00097*** | 0.00230*** | 0.00385*** | 0.00086*** | 0.00206*** | 0.00385*** |
| | (7.12) | (10.83) | (11.93) | (8.11) | (15.19) | (16.46) |
| Portfolio_Gain | | | 0.00152*** | | | 0.00170*** |
| | | | (8.13) | | | (12.75) |
| Gain * Portfolio_Gain | | | -0.00258*** | | | -0.00287*** |
| | | | (-9.06) | | | (-14.33) |
| Observations | 3,828,938 | 3,828,914 | 3,828,914 | 20,205,445 | 20,205,403 | 20,205,403 |
| R-squared | 0.000 | 0.015 | 0.015 | 0.000 | 0.011 | 0.012 |
| Stock FE | No | Yes | Yes | No | Yes | Yes |
| Date FE | No | Yes | Yes | No | Yes | Yes |
| Account FE | No | Yes | Yes | No | Yes | Yes |
| Clustering (Account, Stock, Date) | Yes | Yes | Yes | Yes | Yes | Yes |

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: Sale | | Low Income | | | High Income | |
| Gain | 0.00095*** | 0.00216*** | 0.00398*** | 0.00076*** | 0.00198*** | 0.00381*** |
| | (8.48) | (15.78) | (17.03) | (7.09) | (14.36) | (15.19) |
| Portfolio_Gain | | | 0.00177*** | | | 0.00169*** |
| | | | (13.73) | | | (11.23) |
| Gain * Portfolio_Gain | | | -0.00296*** | | | -0.00290*** |
| | | | (-14.39) | | | (-12.88) |
| Observations | 27,406,365 | 27,406,299 | 27,406,299 | 15,732,390 | 15,732,363 | 15,732,363 |
| R-squared | 0.000 | 0.013 | 0.013 | 0.000 | 0.012 | 0.012 |
| Stock FE | No | Yes | Yes | No | Yes | Yes |
| Date FE | No | Yes | Yes | No | Yes | Yes |
| Account FE | No | Yes | Yes | No | Yes | Yes |
| Clustering (Account, Stock, Date) | Yes | Yes | Yes | Yes | Yes | Yes |

**Panel B: DGTW Breakout**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: Sale | Portfolio_Gain = 1 | | Alpha = 1 | Alpha = 0 | |
| Gain | -0.00002 | 0.00082*** | 0.00082*** | 0.00098*** | 0.00095*** |
| | (-0.27) | (11.12) | (4.80) | (11.94) | (11.80) |
| Alpha | | | | | -0.00010 |
| | | | | | (-1.02) |
| Gain * Alpha | | | | | 0.00009 |
| | | | | | (0.73) |
| Observations | 57,452,336 | 57,451,975 | 1,874,931 | 29,662,510 | 31,540,073 |
| R-squared | 0.000 | 0.012 | 0.065 | 0.012 | 0.012 |
| Stock FE | No | Yes | Yes | Yes | Yes |
| Date FE | No | Yes | Yes | Yes | Yes |
| Account FE | No | Yes | Yes | Yes | Yes |
| Clustering (Account, Stock, Date) | Yes | Yes | Yes | Yes | Yes |

# Table 9: Sophisticated/Skilled Investors? (Sale Conditioned Sample)

This table reports the same tests as Table 8 for the sale conditioned sample. Panel A reports tests split by non-professional, professional, low-income and high-income investors. We define these sub-samples consistent with Dhar and Zhu (2006). Professional investors include those classified as "professional/technical" or "administrative/managerial". Non-professional investors include those classified as "white collar/clerical," "blue collar/craftsman," or "service/sale". High-income investors have an annual income of at least $100,000. Low-income investors have an annual income no greater than $40,000. Panel B, columns 1 and 2 report the disposition effect when Portfolio_Gain equals 1 on all observations with a DGTW identifier. Columns 3 and 4 report the same test as column 2 for the sub-samples in which Alpha equals 1 and 0, respectively. Alpha is defined as 1 if portfolio gain is generated only due to positive DGTW alpha (alpha > 0, beta ≤ 0), 0 if portfolio gain is generated only due to positive DGTW beta (alpha ≤ 0, beta > 0), and missing otherwise. In Column 5, the interaction term tests the difference between the coefficients reported in Columns 3 and 4. We report cluster-robust t-stats in parentheses. All standard errors are clustered by account, day, and stock, following the procedure of Cameron, Gelbach, and Miller (2011).

**Panel A: Sophistication Proxies (Employment and Income)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: Sale | Non-Professional | | | Professional | | |
| Gain | 0.099*** | 0.130*** | 0.224*** | 0.071*** | 0.092*** | 0.177*** |
| | (7.20) | (9.65) | (14.39) | (7.89) | (13.03) | (17.46) |
| Portfolio_Gain | | | 0.085*** | | | 0.070*** |
| | | | (8.54) | | | (11.23) |
| Gain * Portfolio_Gain | | | -0.157*** | | | -0.138*** |
| | | | (-10.40) | | | (-13.89) |
| Observations | 38,934 | 38,340 | 38,340 | 258,803 | 257,304 | 257,304 |
| R-squared | 0.013 | 0.243 | 0.249 | 0.008 | 0.187 | 0.193 |
| Stock FE | No | Yes | Yes | No | Yes | Yes |
| Date FE | No | Yes | Yes | No | Yes | Yes |
| Account FE | No | Yes | Yes | No | Yes | Yes |
| Clustering (Account, Stock, Date) | Yes | Yes | Yes | Yes | Yes | Yes |

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: Sale | Low Income | | | High Income | | |
| Gain | 0.073*** | 0.089*** | 0.171*** | 0.071*** | 0.094*** | 0.177*** |
| | (8.90) | (14.39) | (22.41) | (8.42) | (13.57) | (15.92) |
| Portfolio_Gain | | | 0.065*** | | | 0.071*** |
| | | | (13.39) | | | (10.39) |
| Gain * Portfolio_Gain | | | -0.135*** | | | -0.139*** |
| | | | (-17.93) | | | (-12.52) |
| Observations | 387,379 | 385,437 | 385,437 | 194,119 | 192,992 | 192,992 |
| R-squared | 0.008 | 0.180 | 0.186 | 0.007 | 0.182 | 0.188 |
| Stock FE | No | Yes | Yes | No | Yes | Yes |
| Date FE | No | Yes | Yes | No | Yes | Yes |
| Account FE | No | Yes | Yes | No | Yes | Yes |
| Clustering (Account, Stock, Date) | Yes | Yes | Yes | Yes | Yes | Yes |

**Panel B: DGTW Breakout**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable: Sale | Portfolio_Gain = 1 | | Alpha = 1 | Alpha = 0 | |
| Gain | 0.009** | 0.026*** | 0.019** | 0.042*** | 0.041*** |
| | (2.13) | (7.82) | (1.96) | (11.62) | (11.64) |
| Alpha | | | | | -0.036*** |
| | | | | | (-5.74) |
| Gain * Alpha | | | | | -0.007 |
| | | | | | (-0.84) |
| Observations | 766,758 | 760,430 | 20,415 | 397,441 | 420,945 |
| R-squared | 0.000 | 0.164 | 0.363 | 0.133 | 0.132 |
| Stock FE | No | Yes | Yes | Yes | Yes |
| Date FE | No | Yes | Yes | Yes | Yes |
| Account FE | No | Yes | Yes | Yes | Yes |
| Clustering (Account, Stock, Date) | Yes | Yes | Yes | Yes | Yes |

## Table 10: Reinvestment Probabilities within 2 Days of Sale

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

| Dependent Variable: Reinvest Dummy | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Loss_Gain | 0.104*** | 0.102*** | 0.062*** | 0.102*** | 0.056*** |
| | (14.73) | (15.20) | (14.38) | (15.41) | (13.08) |
| Loss_Loss | 0.070*** | 0.075*** | 0.018*** | 0.071*** | 0.025*** |
| | (12.55) | (14.35) | (4.29) | (13.43) | (6.25) |
| Gain_Gain | 0.028*** | 0.019*** | 0.028*** | 0.026*** | 0.016*** |
| | (5.19) | (3.56) | (8.14) | (4.96) | (4.83) |
| Constant | 0.344*** | | | | |
| Observations | 189,623 | 189,623 | 189,623 | 189,623 | 189,623 |
| R-squared | 0.006 | 0.024 | 0.293 | 0.029 | 0.320 |
| Date FE | No | Yes | No | No | Yes |
| Account FE | No | No | Yes | No | Yes |
| Stock FE | No | No | No | Yes | Yes |
| Clustering (Date, Account, Stock) | Yes | Yes | Yes | Yes | Yes |