USC FBE FINANCE SEMINAR
presented by Sam Hartzmark
FRIDAY, Sept. 6, 2013
10:30 am – 12:00 pm, **Room: JKP-202**

The Worst, the Best, Ignoring All the Rest: The Rank Effect and Trading Behavior

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This Draft: August 31st, 2013

Abstract: In this paper, I document a new stylized fact about how investors trade assets in a portfolio setting. Specifically, investors are much more likely to sell the extreme winning and extreme losing position in a portfolio, even after controlling for a number of possibly confounding factors associated with extreme rank. The tendency to sell extreme positions is exhibited by both retail traders and mutual fund managers, and is large enough to induce significant price reversals in stocks of 40-160 basis points per month. I present evidence that this effect is related to extreme portfolio positions being more salient to investors.

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In classical finance models, such as Markowitz's (1952) mean variance framework, investors are assumed to trade stocks in order to form optimal portfolios. Behavioral finance has attacked a number of the assumptions of such models, for example investigating investors' limited cognitive ability to process signals, or their non-standard preferences over gains and losses. In doing so, behavioral finance has largely ignored the portfolio problem faced by investors, namely how do investors choose to combine multiple assets? Instead, traders are assumed to consider each stock in isolation, leading to stylized facts about trading such as the disposition effect (the tendency to sell gains more than losses) and overconfidence (trading too much). The current literature either models investors as performing difficult portfolio optimization, or as ignoring the portfolio problem in its entirety and simply considering each stock on its own. This leaves an unexplored middle ground of what investors may actually do in a portfolio setting that falls short of the assumptions of standard optimization.

In this paper, I explore one such aspect of the investor's portfolio choice problem. In particular, I document a new stylized fact about trading in a portfolio setting – investors are more likely to sell their best *and* worst positions, based on return from purchase price. I term this the rank effect. This effect is large and robust. It holds for traders of different sophistication levels, being exhibited by both retail traders and mutual fund managers. It survives controlling for a number of confounding factors that may cause a stock to have an extreme rank. The selling of extreme positions by mutual funds is sufficiently widespread to cause predictable returns.

Figure 1 illustrates the rank effect using individual trading records from a large retail brokerage. Each stock in an investor's portfolio is ranked using the return from purchase price. The graph shows the increase in probability of selling a given ranked stock versus a middle ranked stock (not ranked in the top two or bottom two returns) controlling for being at a gain, return from purchase price, holding period and volatility. The middle rank has the lowest probability of being sold and the probability of selling increases as rank moves to best (to the right) and moves to worst (to the left). The best or worst ranked stock is 14-18% more likely to be sold than a stock ranked in the middle of a portfolio.

I show that the rank effect survives after controlling for many possible confounding factors that are correlated with a stock's position in a portfolio. Rank might proxy for information or other stock characteristics used by investors to trade. To show that this does not drive the effect, I examine a sample of stocks that on the same day, are extreme ranked in one investor's portfolio, while not extreme ranked in another investor's portfolio. This analysis has the exact same set of information, such as recent returns, earnings announcement, analyst forecasts, etc., for both the extreme rank and non-extreme ranked stocks. In this sample, both individual investors and mutual funds are more likely to sell a stock that is at the extreme rank.

The rank effect also survives after controlling for each stock's return from purchase. This has been shown to affect trading, such as in the disposition effect (the tendency to sell gains more than losses). The rank effect is conceptually different, as it applies to extreme ranked winners *and* losers. After controlling for the return of the stock, the rank effect becomes stronger. I analyze portfolios where all stocks are at a gain and all stocks are at a loss and find a greater propensity to sell the best and worst ranked stocks. This evidence is inconsistent with rank simply proxying for the stock return from purchase.

The rank effect is also not explained by tax considerations. The effect is present every calendar month, meaning it is not driven by end of year tax selling of worst ranked positions. Furthermore, investors may have different incentives to sell extreme ranked stocks based on realized capital gains and losses. If an investor sells positions throughout a tax year resulting in a capital gain, realizing losses decreases the taxable portion of this gain. Under this explanation, traders at a capital gain within a tax year are more likely to realize their worst position and traders at a capital loss are more likely to realize their best. Empirically, investors exhibit the opposite behavior, offering further evidence that tax motivations do not drive the effect.

The analysis suggests that individual investors exhibit the rank effect because the extreme positions are salient and that the salience is due to their inclusion in an investor's consideration set. When faced with a complex problem, a person will often use a rough decision rule, known as a heuristic, to focus their attention on a specific, simpler portion of the decision, called a consideration set. In a portfolio context, an object that does not receive attention will not be traded, thus a salient position is more likely to both bought and sold. In addition to selling, individual investors are significantly more likely to buy more of the extreme ranked position.

To show rank induces salience, I examine an ordering that is orthogonal to economic variables, the ordering of stocks in a brokerage statement. Both the first and the last stock by alphabetical ticker order is more likely to be traded. Models of consideration sets suggest salience is driven by rank as well as the difference between the extreme return and the next closest return. Positions are more likely to be bought and sold as this difference increases.

Mutual funds trade significant portions of market value, thus heavy selling of extreme ranked stocks may impact market prices. Funds sell extreme ranked positions more heavily than middle ranked positions. Worst positions are sold the most heavily, and are 23.7% more likely to be completely liquidated compared to a middle position that is sold.

I develop a trading strategy to take advantage of the predictable price pressure induced by this heavy selling. Due to the delay in reporting and the inability to estimate the exact day of sale, the strategy does not focus on the initial price pressure, but rather on the subsequent reversal. To form tradable portfolios using publicly available information, stocks are ranked nearly a quarter after they were reported as held by the fund. An equal weighted portfolio long best ranked stocks is formed, as well as a portfolio long worst ranked stocks. The best ranked portfolio has a monthly alpha of 36 basis points and the worst ranked portfolio has a monthly alpha of 161 basis points. Weighting the portfolios towards stocks predicted to have higher selling pressure increases the alphas to as high as 65 basis points for best ranked and 222 basis points for worst ranked. Using Fama-Macbeth regressions, I find that dummies for best and worst ranked stocks have positive and significant coefficients after controlling for a number of other return predictors.

The broad explanation based on salience and consideration sets is not incorporated into standard explanations of rational investors or behavioral theories of trade constructed to examine the disposition effect. Explanations of the effect focus on decisions made versus homogenous reference points for each trader such as a zero return, the risk free rate, or stock specific expectations of performance. The rank of a stock in a portfolio is idiosyncratic to each trader and their portfolio. The theories of individual trade based on the disposition effect do not include this idiosyncratic component of decision making induced by the portfolio.

The rank effect provides evidence for a fundamental aspect of investor behavior – namely, that the evaluation given to any particular stock depends on what else the investor is holding. This fact may provide a micro-foundation for models that rely on disagreement across investors, such as those explaining the level of trading volume in the stock market (Stokey and Milgrom (1982)). In particular, investors may be acting differently towards the same piece of information about the same stock due to effect that *other* stocks in their portfolio (which are likely to differ, even for similar investors) have on the way they perceive the given information.

The remainder of the paper is structured as follows. Section 2 discusses the literature and develops hypothesis. Section 3 discusses the data. Section 4 empirically examines the rank effect. Section 5 presents the price impact of the rank effect. Section 6 presents further robustness based on tax and covariate balance. Section 7 concludes.

2. Literature Review and Hypothesis

2.1. Joint Evaluation within Portfolio

Many explanations of trade focus on decision making utilizing narrow framing (Barberis, Huang and Thaler (2006), Barberis and Huang (2001), Barberis and Xiong (2012), Ingersoll and Jin (2013)). Narrow framing occurs when decisions are made over specific portions of wealth, rather than broadly framed decisions such as over total wealth (Kahneman and Lovallo (1993)). For example, Barberis and Huang (2001) examine the impact on asset prices when investors narrowly frame on each stock separately, or over the performance of the portfolio as a whole.

Investors typically hold multiple stocks and have the stock's performance presented together in a brokerage statement. Behavioral economics provides evidence that individuals evaluate decisions differently if they are considered separately or jointly with other decisions (Bazerman, Loewenstein and White (1992), Hsee (1996), Hsee, Loewenstein, Blount and Bazerman (1999), Kahneman (2003), List (2002)). The rank of a return in a portfolio is only relevant to an investor that is comparing positions in their portfolio and not narrowly framing over individual stocks or their portfolio's aggregate performance. Thus the importance of rank after controlling for confounding factors shows investors compare the holdings in their portfolio against one another in a way that significantly impacts trade.

2.2. Salience

When faced with a large number of possibilities, individuals typically do not pay equal attention to each, but spend more time examining the most salient. According to Taylor and Thompson (1982), "salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments." The salience of extreme outcomes has been shown to be important in a finance setting when proxied by extreme returns (Barber and Odean (2008)), extreme abnormal trading volume (Gervais, Kaniel and Mingelgrin (2001); Barber and Odean (2008)), mentions in the news (Barber and Odean (2008)) and Google search volume (Da, Engelberg and Gao (2011)). These measures examine extremeness versus the market as a whole, which cannot explain the rank effect (see section 4.2).

The evidence supports an explanation of the rank effect based on consideration sets. Individuals often simplify choices with many options by using a simple rule to figure out which options to pay attention to. This is called forming a consideration set and the method used to form the consideration set is called a heuristic. There is a large literature in marketing on consideration sets and heuristics (see Hauser (2013) for an overview), as well as literatures examining costly information acquisition and consideration sets (Gabaix, Laibson, Moloche and Weinberg (2006)), how firms optimally respond to consumer's consideration sets (Ellison and Ellison (2009)) as well as models of how such heuristics impact asset prices (Gabaix (2013)).

To illustrate the intuition in a portfolio context using a simple example, consider an investor holding a portfolio of stocks that conducts time consuming research on a stock before deciding to trade. The investor does not want to research everything, so a heuristic is used to decrease the number of stocks to be researched. If the investor is using a heuristic of examine “good” and “bad” performing stocks where “good” and “bad” are based on the portfolio, the best and worst stocks will always be in the consideration set. The chance the 2nd best or worst stock enters into the choice set hinges on how different the investor perceives it from the best or worst. Thus rank combined with the difference in prices between the two most extreme positions predicts the rank effect in this case.

This simple example uses the heuristic of “good” or “bad” performing stocks within the portfolio, but investors most likely consider additional information to form their consideration sets. For example if a stock is in the news investors may be more likely to consider that stock. This paper emphasizes that investors utilize portfolio specific characteristics, but this does not mean that investors are not also incorporating other information into their trading decisions.

A salient position receives more attention so it is more likely to be traded. This means that it is more likely to be purchased or to be sold. A position that is not in a consideration set, receives no attention and is held, while a position that receiving attention can be held, sold or purchased.

In addition to models of consideration sets, other models of salience also predict a rank effect. Rank dependent utility models, such as cumulative prospect theory (Tversky and Kahneman (1992)), predict that rank ordering itself impacts attention and the best and the worst ranked positions are the most salient. Psychology has a long history examining rank, both describing its influence in a variety of situations and explicitly incorporating it into decision theory.[1] The intuition of rank dependent utility is that extreme ranks are salient, attention grabbing positions (Diecidue and Wakker (2001)).

Salience theory (Bordalo, Gennaioli, and Shleifer (2012)) predicts a rank effect, where the effect is based on the extremeness of a return versus a portfolio specific benchmark, such as

[1] For a thorough overview of the literature see (Diecidue and Wakker (2001), and Wakker (2010)).

the average return. Bordalo, Gennaioli, and Shleifer (2013) examine salience and asset prices, focusing on attention grabbing characteristics of stocks, such as positive skewness or safe assets chosen because they are "most different or salient relative to the average." A common market benchmark used in that paper is ruled out in section 4.2, but with a portfolio specific benchmark this theory predicts the rank effect.

2.3. Previous Studies of Portfolios

The empirical literature examining investors' portfolios generally focuses on portfolio composition rather than trading behavior. It finds that investors do not hold properly diversified portfolios (Odean 1998, Bernartzi and Thaler (2001), Goetzmann and Kumar (2008)), that the degree of diversification varies with investor characteristics (Goetzmann and Kumar (2008)) and that investors exhibit a preference for local or familiar stocks (Huberman (2001), Frieder and Subrahmanyam (2005)). There has been very little research examining how investors trade in a portfolio setting (Subrahmanyam (2008)).

3. Data and Summary Statistics

The analysis is based on two main datasets. The first is comprised of individual investors trading on their personal accounts. This data has the benefit of a large number of accounts with information on the exact day that trading occurs. The analysis is also conducted on mutual fund data. Funds control significantly more money that is traded by professional investors and the data offers a longer time series. Unfortunately, it is only available when a fund reports its holdings, not on the day a position is traded and may be subject to window dressing.

The individual investor data are the same as that used in Barber and Odean (2000), Strahilevitz, Odean and Barber (2011) and Ben-David and Hirshleifer (2012). It is comprised of retail investors from a large discount brokerage from January 1991 through November 1996. The dataset is comprised of two relevant parts. One is a file listing all trades, the date, price, quantity and position (though not the exact time). A second file contains an end of month listing of portfolios by accounts, with the equity in the portfolio, but no information on the initial purchase price. Thus it is impossible to calculate the return relative to the purchase price for positions that existed prior to the beginning of the trade file. To examine as complete a set of portfolios as possible, accounts that held positions in the first month of the position files are excluded (roughly 25% of accounts in the trade data).

For multiple trades within a day for the same trader of the same stock, the value weighted average price of all the trades is used as well as the net quantity traded. Because the time of trade is not observed, on days that a position is opened (purchased when previous holdings were 0) and a different position is closed the opened positions are not included in the analysis as it is uncertain whether they were a part of the portfolio at the time of sale. If a position is below 0 at the end of the day it is considered closed. Some trades have negative commissions which could indicate canceled trades (0.5% of observations). All observations of a stock with a negative commission for a given investor are dropped.[2] The reference price used to calculate returns is the purchase price. If a position is held and further shares are purchased the purchase price used is the value weighted average of the multiple purchase prices. Returns on both realized and paper gains and losses are calculated between the purchase price and the CRSP closing price on the day before the sell day. This keeps consistency between actual sales and paper gains and losses.[3] All prices are adjusted for splits and dividends.

[2] Results are robust to including these positions, or to a more complicated cleaning algorithm trying to explicitly match the two sides of a cancelled trade and keep the rest of the observations.
[3] The analysis is not materially different if the actual sale price is used on positions that are sold and the CRSP closing price used for those that are not, or if the closing price of the sell day instead of the day before is used.

Portfolios are examined each day that an investor sells at least a portion of an existing position (a sell day), or in section 4.4, each day an investor buys a position (a buy day). As the paper examines portfolio rank, investors must hold at least five stocks to be considered. This excludes 57% of account sell day observations, a significant number of accounts. It excludes a much smaller fraction of total value of holdings, about 20%. Days in which all positions are liquidated and nothing is purchased are excluded.

Table 1 Panel A shows summary statistics of the analysis data. After the filters are applied the analysis includes 11,524 unique accounts, 110,117 sell day by account observations with a sale, and 1,287,021 positions held on those days. On a sell day, on average 11.3% of positions in a portfolio are sold, of which 9% are completely closed.

The mutual fund analysis examines holdings data from Thompson-Reuters and fund price and volume information using CRSP and stock return information from CRSP. The Thompson-Reuters and CRSP files are merged using the Wharton Financial Institution Center number (WFICN). Holding period returns are calculated analogously to the investor data, but using report dates because sell dates are not known. To be included in the analysis at least 20 stocks must be held. The same filters as used in Frazzini (2006) are applied to the Thompson-Reuters data to exclude observations that appear to be errors.[4] The sample period studied is 1990-2011, though data beginning in 1980 is used to construct the history of prices.

Table 1 Panel B shows summary statistics for the mutual fund data. There are 4,730 funds holding 120 stocks on average. 38.9% of positions are at least partially sold between report dates and 15.1% of positions closed.

[4] Holdings are set to missing when: 1) the number of shares a fund holds is greater than the number of shares outstanding of that stock, 2) the value of a holding is greater than the fund's total asset value, 3) the value of the fund's reported holding is different from the CRSP value by more than 100%.

The paper mainly examines the decision to sell a stock, rather than trading generally. An investor is limited to selling stocks in their portfolio, while they can buy any stock in the market. An investor purchasing a stock will in practice consider a small subset of all the stocks in the market, but this subset is not known. Thus the set of possible positions to be sold is considerably smaller and better defined than the positions considered when buying a stock. Section 4.4 examines trading in general including the decision to buy more of a position already held.

4. The Rank Effect

4.1 Summary Statistic Results

Table 2 shows the rank effect, the tendency to sell the best and worst ranked stocks, without controls. All analyses requires an investor to hold at least five stocks in their portfolio, excluding stocks that were purchased that day and not held before (opened positions). The minimum number of stocks is set to five in order to allow dummy variables for the top two and bottom two positions, with all other positions in the omitted group. Only days where an investor sells at least one stock are examined, thus each observation is a stock (j) held by an investor (i) on a day (t) that the investor sells at least one stock.

Each row is the proportion of positions of the indicated rank that are sold. A stock is ranked best if it has the highest return from purchase price in the portfolio, and worst if it has the lowest. The rows marked best and worst are equal to:

$$Best = \frac{Best\ Sold}{Best\ Sold + Best\ Not\ Sold};\ Worst = \frac{Worst\ Sold}{Worst\ Sold + Worst\ Not\ Sold}$$

The measure is analogous to the proportion of gains (losses) realized analyzed in Odean (1998).

The rank effect can be seen examining the bottom portion of the table. Best – Middle is the difference between the best and middle ratio with the t-statistic, clustered by date and account, with the test that they are equal underneath. For individual investors a best ranked position is 14.4% more likely to be sold than a middle ranked position and a worst ranked position is 7.5% more likely to be sold, both with highly significant t-statistics. The mutual fund results are of a similar magnitude, but the worst ranked position is more likely to be realized than the best. For these funds a best ranked position is 11.9% more likely to be realized than a middle ranked position, and a worst ranked position is 19.1% more likely to be realized.

This analysis aggregates all individuals into a single measure, thus it may mask heterogeneity across investors in their tendency to realize extreme positions. The same trader could be more likely to sell both best and worst ranked positions, or it could be that a fraction of traders sell only best positions, with another fraction more likely to sell worst. Figure 2 graphs the joint density of the probability of closing out best and worst positions for each investor and fund with at least five trading days in the data. The x-axis is the investor specific proportion of best positions realized, while the y-axis is the corresponding proportion of worst positions. The darker the red of a cell, the more density it has, and the darker the blue a cell, the lower the density. If half of the investors sold only best ranked positions, and half sold only worst, the bottom right and top left corners would be dark red. For both types of traders these are the areas with the lowest density. The correlation of these measures is positive, 0.37 for individual investors and 0.41 for mutual funds. Thus traders tend to sell both best and worst ranked stocks.

4.2 Controlling For Information

Most rational theories posit that investors trade to rebalance their portfolio, or after they update their beliefs changing the composition of the optimal portfolio. Simple rebalancing is ruled out given the pattern of the rank effect. If beliefs are held constant, a best ranked stock has increased from its optimal portfolio weight and a worst ranked stock has decreased. To rebalance, the best ranked stock is sold and the worst ranked stock is purchased. The effect for worst ranked stocks rules out simple rebalancing as an explanation for the rank effect.

Rank could be proxying for stock specific information. To examine this possibility, I limit the analysis to stocks that on the same day are extreme ranked in one investor's portfolio, but not extreme ranked in another investor's portfolio. Thus the analysis is conducted on a group of extreme ranked stocks and non-extreme ranked stocks that have the identical information set and differ only in portfolio rank across investors. If investors update their beliefs without regard to a stock's rank, there will be no rank effect in this sample.

Table 3 examines the rank effect for this subsample. The "All" column includes the observations in the subsample aggregated together. Thus the "Best" row of the "All" column is the proportion of best ranked stocks that are sold. The "Not Best" row is the proportion sold that are not best. The difference row is the difference between these two values. It is thus the propensity for an investor to sell a best ranked stock relative to the propensity of another investor to sell the identical stock, but the stock was not the best ranked.

Examining the difference row for individual investors and mutual funds, extreme ranked stocks are more likely to be sold than the same set of stocks in a portfolio where they are not extreme ranked. Individual investors are 8.5% more likely to sell a best ranked stock than the same stock that is not best ranked, and are 5.2% more likely to sell a worst ranked stock than the same stock that is not worst ranked. Mutual funds are 8.4% more likely to sell a best ranked stock and 15% more likely to sell a worst ranked stock.

The "By Stock" column examines the difference between each stock by day pair and then calculates the average, so that common differences in selling probability for each stock day pair is removed before aggregation. The difference row for best ranked stocks is:

$$Difference = \frac{1}{(\#\ Pairs)} \sum_{t=1}^{T} \sum_{j=1}^{J} \left(Sell_{j,t}^{Best} - Sell_{j,t}^{Not\ Best} \right)$$

Where *t* indexes each day and *j* indexes each stock. An equivalent measure is calculated for worst ranked stocks. If more than one investor holds the same stock with the same rank (e.g. two investors hold stock *j* on sell day *t* and both are best ranked) the average over the sell dummy for those investors is taken before differencing. The results are similar to the "All" column, with large and significant values for individual investors and mutual funds.

I also consider the question of whether the rank effect can be driven by investor expectations of means, variance, or covariances. Table 3 casts doubt on this explanation, nonetheless, I directly test the effect in Appendix A and Appendix B explicitly controlling for a stock's mean, variance and covariance. These proxies do not materially impact the magnitude or significance of the rank effect.

4.3 Controlling For Explanations Based on Past Performance

One of the largest literatures on trading behavior focuses on the disposition effect. Coined by Shefrin and Statman (1985), the disposition effect refers to investor's predilection for closing out positions at a gain relative to a loss. Odean (1998) examines data from a large US discount brokerage and finds evidence consistent with the disposition effect. The effect is a robust empirical result that has been found in a variety of settings.[5]

The disposition effect is based on a stock's performance from the time it was purchased. As a consequence, it relies on investor-specific reference points, and the analysis in section 4.2, which holds constant public information, does not preclude the disposition effect from being a contributing factor. The rank effect of selling gains based on their portfolio order differs from the

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[5] Settings include individual investors (Odean 1998, Feng and Seasholes (2005), Kaustia (2010)), mutual fund managers (Wermers (2003), Frazzini (2006)), futures traders (Locke and Mann (2005)) and prediction markets (Hartzmark and Solomon (2012)). Kaustia (2010) provides a recent review of the disposition effect literature.

standard disposition effect, which simply discusses gains and losses overall. Nonetheless, the sharpest distinction between the rank effect and disposition effect is the tendency for investors to sell their most extreme-ranked *losing* positions, which the disposition effect claims they should hold on to. Finding that the worst ranked position (typically a loss) is the second most likely stock (for investors) or the most likely stock (for mutual funds) to be sold makes it unlikely that simply controlling for a gain or a loss can account for the rank effect.

Table 4 repeats the summary statistics analysis of Table 2, restricting the sample to portfolios where all positions are at a gain and all positions are at a loss. While this is not a random sample of traders, it is a clean test of the disposition effect because within each trader's portfolio there is no variation in whether each asset is at a gain or a loss. This sample still exhibits the rank effect. Traders with all positions at a gain are 5.8% more likely to sell their worst stock and 7.7% more likely to sell their best compared to a middle stock. Traders with all positions at a loss are 3.5% more likely to sell their worst and 10.4% more likely to sell their best stock compared to a middle ranked position.

While the disposition effect is often described purely in terms of gains and losses, the magnitude of the gain and loss impacts trade as well (Ben-David and Hirshleifer (2012)).[6] Empirically, investors are more likely to sell a position as it becomes a larger gain, or a larger loss. Investors trading on the magnitude of past returns could drive the rank effect as portfolio rank is best with the biggest gain and worst with the biggest loss.

Return levels are controlled for to show that rank, not return levels, is responsible for the effect. Using logit regressions, a dummy variable *sell*, equal to one if a stock is sold and zero

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[6] Meng (2012) analyzes the same data and finds investors are less likely to sell larger returns. In unreported results I find the difference in sign between the Ben-David and Hirschleir and Meng is the inclusion of holding day controls. Exclusion of holding day variables does not materially change the rank results.

otherwise, is regressed on variables for rank and a number of controls.[7] Equation 1 shows the controls which are taken from Ben-David and Hirshleifer (2012): [8]

$$\begin{aligned} sell = {} & \beta(Rank\ Variables) + \gamma_1(Return * Gain) + \gamma_2(Return * Loss) + \gamma_3(Gain) \\ & + \gamma_4\left(Return * Gain * \sqrt{Holding\ Days}\right) + \gamma_5\left(Return * Loss * \sqrt{Holding\ Days}\right) \\ & + \gamma_6\left(\sqrt{Holding\ Days}\right) + \gamma_7(Gain * Variance) + \gamma_8(Loss * Variance) \end{aligned} \quad (1)$$

Rank Variables represents the various measures of the rank effect. To control for the likelihood of closing out a gain versus a loss I include a dummy variable equal to one if the position has a positive return relative to the purchase price (*Gain*). To control for an increasing probability of sale in returns I include variables for the return from purchase price interacted with a dummy for a positive return relative to the purchase price (*Gain*Return*), and a separate variable of the return interacted with a dummy for non-positive return from the purchase price (*Loss*Return*). Including these variables allows for the probability of sale to increase in absolute value and to have a different slope in the positive and negative domain.[9]

Mechanical effects due to holding period and volatility are also controlled for. All else equal, a stock held for a longer time is more likely to achieve a higher rank. To control for the number of days a position is held from purchase and sell date, the square root of the days $\left(\sqrt{Holding\ Days}\right)$ and interactions with the gain and return (*Gain*Return**$\sqrt{Holding\ Days}$) and loss dummy by return *Loss*Return**$\sqrt{Holding\ Days}$) are included. A stock with a higher variance is more likely to achieve a best rank or a worst rank. To control for this effect, the

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[7] Similar results are obtained utilizing probit, or linear probability models.
[8] This paper's focus is slightly different than Ben-David and Hirchleifer (2012), so the variables have been modified for conciseness. I have omitted log(buy price), included zero returns in the *Loss* dummy instead of a separate dummy and included only one variable for holding days. The results are robust to using the original specification.
[9] Appendix C contains robustness checks of these specifications and shows that the results are robust to examining subsets of portfolio size, days between trade and allowing for non-linear patterns in the level of returns.

variance over the previous year, is interacted with the gain dummy (*Gain*Variance*) and loss dummy (*Loss*Variance*).[10] All results are presented as marginal effects.

Table 5 column [1] presents the regression for individual investors, with no rank variables and only the controls. The propensity to sell bigger gains and larger losses is apparent as the *Gain*Return* coefficient is positive and significant, while the *Loss*Return* dummy is negative and significant. Further, the *Gain* dummy is positive and significant indicating a higher likelihood of selling gains rather than losses, even with the controls. Without controlling for rank, investors are more likely to sell a gain than a loss, and also more likely to sell both gains and losses as their returns become larger in absolute value.

Columns [2] and [3] add dummy variables to examine the rank effect. Column [2] adds dummy variables for the highest return in the portfolio (*Best*) and the lowest (*Worst*). The best ranked stock is 14.3% more likely to be sold and the worst ranked stock (*Worst*) is 10.4% more likely to be sold, both with large t-statistics. Including the two dummy variables for return levels, the *Loss*Return* and *Gain*Return* coefficients are 0 and the *Gain* dummy decreases. In this specification, the propensity to sell stocks with higher returns can be explained as an increased propensity to realize extreme ranked positions.

Column [3] includes dummies for the *Best* and *Worst* ranked stocks as well as *2nd Best* and *2nd Worst* ranked stocks. Each of these variables is large and positive. Coefficients on *Best* and *Worst* are larger than the simple summary stats after controlling for these competing effects. Compared to the Table 2 difference columns, *Best* increased from 14.4% without controls to 18.6% with controls and *Worst* increased from 7.5% to 14.1%. Rather than explaining the rank effect, the inclusion of disposition effect controls makes the rank effect larger. Further, examining the adjusted R^2 presented below columns [1] and [3] there is an increase from 0.014

[10] The variance is calculated over the preceding 250 trading days, if there are at least 50 non-missing observations.

to 0.048. While this R^2 indicates much more is needed to fully explain trading behavior, including controls for the rank effect increases the explanatory power more than threefold.

Examining columns [4] through [6] yields similar patterns for mutual funds. In column [6] the coefficient on *Best* is 10.6% and the coefficient on *Worst* is 14.6%, both are highly significant. Thus, the *Best* and *Worst* coefficients for the funds are large and highly significant, with a similar magnitude to those of the individual investors.

In Table 2, the two most likely positions to be sold for individual investors are best and 2^{nd} best, while for the mutual funds it is worst and second worst. After including controls, it is best and worst for both types of investors. The asymmetry remains in the ordering of best and worst, where best is more likely to be sold for investors, and worst is more likely to be sold for funds, but the importance of being the highest, or lowest return becomes clear with the addition of the controls.

As an additional control for the disposition effect, Table 6 again limits the analysis to the subsample where all positions in a portfolio are at a gain or a loss. In all specifications the rank variables are positive and significant after including the controls in Equation 1 (with the positive and negative dummies omitted).

Section 4.2 examines if rank proxyies for common information, while section 4.3 examines whether trading based on past returns can explain the rank effect. Table 7 rules out both possibilities simultaneously, utilizing regressions with controls for past performance, on the sample of stocks that are extreme ranked and non-extreme ranked on the same day.

For this sample the rank effect is still a major determinant of trading behavior. For individual investors, best ranked positions are 14.3% more likely to be sold than not best ranked positions, and worst ranked positions are 8.4% more likely to be sold than not worst ranked. For mutual funds best ranked positions are 8.5% more likely to be sold, and worst ranked positions are 12.6% more likely to be sold.

Further robustness of the rank effect is examined in section 6. Section 6.1 shows that tax based trade doe not account for the rank effect, and section 6.2 shows that a lack of covariate balance does not drive the results of section 4.3.

4.4 Salience

The salience of extreme outcomes offers a possible explanation for the rank effect. Section 2 developed four testable predictions based on salience examined in this section:

1) A salient position is more likely to be traded, both bought and sold
2) *Rank Extremeness:* Rank dependent utility models (such as Tversky and Kahneman (1992)) predict that the best and worst returns are the most salient.
3) *Average Extremeness:* Models such as Bordalo, Gennaioli, and Shleifer (2012) predict a position becomes more salient as it becomes more extreme relative to the portfolio benchmark, such as the average holding return in the portfolio.
4) *Outlier Extremeness:* Certain models of consideration sets predict that a position is more salient when it is best or worst ranked and also as it becomes more extreme versus the next closest return in the portfolio.

The first prediction is common to each model considered, while the last three examine mechanisms predicted by the theories that make a position more salient. This section examines each prediction empirically. The evidence strongly supports the salience hypothesis and that rank is a determinant of salience. In addition to rank, outlier extremeness is important, supporting models based on consideration sets.

If salience accounts for the rank effect, investors will be more likely to sell, but also more likely to buy more of a stock with the best or worst return. Investors decide to buy more of a given stock far less frequently than they decide to sell a position, as only about 3.3% of purchases are of positions already held. Table 8 column [1] presents summary statistic results similar to the difference rows in Table 2. A best ranked position is 0.5% more likely to be realized than a middle position and a worst ranked is 3.5% more likely to be. Table 8 columns

[2] and [3] presents the same specification as Equation 1, but uses a dummy *buy*, equal to one if additional shares of a position are purchased, as the dependent variable. Examining the top two rows, investors are more likely to purchase more shares of the best and worst ranked positions, with a best coefficient of 1.5% and a worst coefficient of 2.1%. While small in magnitude, these coefficients suggest that best and worst positions are roughly 50% to 80% more likely to be sold than the baseline middle probability of 2.6%.

The second prediction, from rank dependent utility, is that ordering induces salience. The rank of a stock is correlated with other economically meaningful variables, making clean identification of salience difficult. To test if investors are framing on their portfolio and that ordering itself is important, ideally investors would see stocks presented in an order uncorrelated with economic outcomes.

While brokerage statements do not present stocks in a random order, they do typically order stocks alphabetically by ticker symbol.[11] Ticker order is unlikely to exhibit significant correlation with economic variables of interest. Table 9 shows that the first and last ticker in the portfolio is more likely to be purchased and sold. The table presents the regressions of *sell* or *buy* on a dummy variable for the first and last ticker in the portfolio, along with ticker by day fixed effects.[12] The fixed effects mean that the regression is identified based on variation from stocks that are first or last in one portfolio and not first or last in another portfolio on the same day. Column [1] and [4] limits the data to the first and second ticker by alphabetical order. The first ticker is 1.8% more likely to be sold than the second ticker and 0.5% more likely to be purchased. Column [2] and [5] limits the sample to the last and second to last ticker. The last ticker is 2.6% more likely to be sold than the second to last and 0.6% more like to be purchased.

[11] Unfortunately I do not have example brokerage statements that are associated with this dataset. Alphabetical ticker ordering is assumed. Similar results are obtained using company names instead of ticker symbol.
[12] Similar results are obtained using only ticker fixed effects or adding the controls listed in Equation 1.

When the entire sample is considered in columns [3] and [6] the first ticker is 5.7% more likely to be sold than a middle ticker and 1.5% more likely to be purchase. The last ticker is 6.2% more likely to be sold and 1.7% more likely to be purchased. The unconditional probability of sale is 11.3% and of purchase is 3.3%. Thus the economically meaningless, but salient, extreme tickers by alphabetical order have a meaningful impact on the probability that a position is sold.

Table 10 examines what aspect of extremeness is behind the rank effect. Rank extremeness is proxied using rank dummies. Two variables are utilized as possible benchmarks to capture average extremeness from prediction 3. The first is the difference of the return from the portfolio's average return, scaled by the standard deviation of portfolio returns ((*Return-Avg Return)/SD Portfolio*). The second is to examine the difference from the median return in the portfolio (*Return-Med Return*).[13] Outlier extremeness from prediction 4, based on the intuition of consideration sets, examines the difference between the best and second best return (*Best Return - 2nd Best Return*) and the worst and second worst return (*Worst Return - 2nd Worst Return*).

Table 10 presents the results for regressions of sell on the extremeness variables and the controls in Equation 1. Appendix D presents the analogous results for buying. Examining columns [1], [2] and [3], each of the variables on its own is associated with more selling. Columns [4] through [6] add dummy variables for the top two and bottom two positions. The return minus average return variables change signs and the return minus median return variables become smaller and insignificant. Thus average extremeness does not explain the rank effect after controlling for rank. The variables for outlier extremeness decrease, but remain economically meaningful and significant. Thus both rank and extreme differences retain explanatory power, consistent with the models of consideration sets.

[13] Similar results are obtained if the mean return measure is not scaled by the standard deviation or the median is scaled by the standard deviation or interacting either variable with *Best* or *Worst*.

This section focuses on individual investors rather than mutual funds. Rank dependent trade is important for mutual funds as well, but it is not clear if the behavior reflects the preferences of the funds themselves, or the perceived preferences of their customers. Managers could be exhibiting a similar bias to investors, or they could think that clients are evaluating them using rank and engage in window dressing (Solomon, Soltes and Sosyura (2012)). Section 5 shows funds liquidate worst ranked stocks at a much higher rate than other positions. This could represent fund manager preferences, but it is also consistent with window dressing. Stocks that are liquidated before a report date are not present in the next report. Managers may hope that liquidating the position obfuscates the poor performance.

5. Price Effects

The rank effect has a large impact on trading behavior, does rank induced selling to impact the market price? Given heavy selling and downward sloping demand, selling pressure from rank based trade will impact market returns. Using the mutual fund data, a trading strategy is constructed to exploit this predictable impact on prices.

Before examining the price effects, I examine the selling intensity of mutual funds. Mutual funds are much more likely to sell only a portion of a position compared to the individual investors. A position that is sold more intensely will experience greater rank based selling pressure, and larger associated price effects. Table 11 shows that mutual funds sell a larger proportion of best and worst ranked positions, and are more likely to liquidate entire positions for both best and worst ranked positions. Selling is more intense for worst ranked stocks compared to best ranked stocks. The Fraction Sold columns present linear regressions, with the fraction of a position sold on the left hand side. The All column includes all holdings regardless of whether they are sold, and the Sell Only column includes only positions where some fraction of a holding is sold. Best ranked positions have 7.8% more of their position sold compared to all stocks, or 2.3% versus only stocks that are sold. Worst ranked stocks have a significantly larger fraction sold of 17.5% more versus all other stocks and 14.1% versus other stocks that are sold.

Best and worst ranked stocks are also more likely to be completely liquidated than other positions. The Liquidate column presents marginal effects from a logit regression similar to Equation 1, where instead of a sell dummy, a dummy equal to one if a position is completely liquidated is on the left hand side. Best ranked stocks are 3.8% more likely to be liquidated than all other positions, and 0.1% more likely to be liquidated versus other stocks that are sold. The worst ranked stock has a larger effect where it is 12.7% more likely to be liquidated than all other positions and 23.7% more likely to be liquidated than other positions that are sold. Thus worst ranked stocks should receive the most price pressure and exhibit larger price effects as they are sold the most intensely.

The analysis shows that mutual funds sell extreme ranked positions before the next report date and they sell these positions more heavily. The trading strategy focuses on the reversal subsequent to the sale, rather than the initial price pressure for two reasons. First, the mutual fund data does not report precisely when a position is sold. Second, as discussed in Schwarz and Potter (2012), there is a lag from the date that a fund holds a portfolio of positions and the date the information becomes public. By law a fund has 60 days to report the information to their shareholders, and must make it publicly available 10 days after this report. Schwarz and Potter show that the information is public within 71 days for almost all observations, but that it is typically not available much earlier. Thus an implementable strategy must be based on information at least 71 days after the report date.

To capture returns from the reversals, portfolios are formed in the following manner. All holdings reported in a given month, denoted month *M*, are examined ten trading days into month *M+3*. This is more than 70 trading days past the report day and almost a full quarter from the report date in most cases. All stocks that are ranked best in at least one fund from purchase price to ten trading days into month *M*+3 are put into an equal weighted portfolio as are all stocks ranked worst. These portfolios are held from the 11th trading day of month *M*+3 until the 10th trading day of month *M*+4.

For example, if a fund reports its holdings on March 25, 2006, the stocks in that fund are ranked on their returns between the purchase price and June 14, 2006, 81 days after the report. Based on these ranks, portfolios are formed the next trading day and held until July 17, 2006. All holdings from all of the funds reporting in March, 2006 are ranked from purchase price to June 14, 2006. Thus the equal weighted portfolio from June to July will be based on each fund that reports in March.

The stocks in the best portfolio will generally have done well recently and the stocks in the worst portfolio will have done poorly. Thus both portfolios are impacted by momentum (Jegadeesh and Titman (1993)) and one month reversals (De Bondt and Thaler (1985)) although in opposite directions. If momentum is responsible for the returns in these portfolios then the best ranked stocks should have positive returns while the worst should be negative. Similarly, if one month reversals (De Bondt and Thaler (1985)) are responsible for the returns, the best ranked stocks will have negative returns while the worst ranked will have positive returns. To control for the two effects I include a momentum factor (UMD) and a short term reversal factor (ST_REV).

Table 12 presents CAPM, Fama-French three factor, four factor and five factor regressions (including a one month reversal factor) for the best and worst ranked portfolios.

Examining the worst portfolio, the CAPM and three factor models have insignificant alpha coefficients. The surprise is not the insignificance, but rather the fact that it is not significantly negative, as in general the worst ranked portfolio will be a negative momentum portfolio. After including a momentum factor the alpha becomes 137 basis points and significant with a t-statistic of nearly five. It loads heavily and inversely on the momentum factor. Adding the short term reversal factor yields an alpha of 161 basis points.

The best ranked portfolio has a positive and significant alpha for both the CAPM and three factor alpha, as it is in general a positive momentum portfolio. After including the momentum factor, the alpha decreases and becomes insignificant. This portfolio will in general also be a high one month reversal portfolio, indicating it should have a low return the month after ranking. After including controls for a short term reversal factor the alpha is 36 basis points and is significant with a t-statistic of 1.98. The worst ranked portfolio has a higher alpha than the best ranked, consistent with the Table 11 finding that worst ranked stocks are sold more intensely.

These equal weighted portfolios can be refined to put more weight on stocks predicted to experience greater selling pressure. Table 13 examines the price effects in the four and five factor regressions using two such weighting schemes. First, portfolios are weighted by the number of funds holding the stock at an extreme rank. The worst ranked portfolio has a four factor alpha of 182 basis points with a t-statistic of 4.57, which decreases to 163 with a t-statistic of 3.57 after including the short term reversal factor. The number-of-funds-weighted best-ranked portfolio has insignificant abnormal returns in the four-factor model, but increases to 65 basis points with a t-statistic of 2.39 after the short term reversal factor is added.

The second weighting scheme weights the portfolios based on the fraction of a stock's market cap that is extreme ranked. Stocks with a higher proportion of their market cap sold are more likely to experience greater price pressure. Worst ranked positions have a four factor alpha of 211 basis points with a t-statistic of 4.10 and an alpha of 222 basis points with a t-statistic of 3.75 after the short term reversal factor is added. Best ranked stocks have an insignificant alpha of 21 basis points before the short term reversal factor is added, which increases to 42 basis points with a t-statistic of 2.15 with the short term reversal factor.

Table 14 uses Fama-Macbeth regressions (Fama and Macbeth (1973)) to control for additional factors in the cross section. Regressions are run on the same monthly time periods (from 11 trading days into a month until ten trading days into the next month). Column [1] presents the results from the regression including only dummy variables for being the best or worst ranked position. The coefficients are positive, but significant only for the worst portfolio. Column [2] adds controls for momentum, one month reversals, market capitalization, and book to market (calculated as in Fama and French (1992)). The coefficients on *Best* and *Worst* are now significant with *Best* having a coefficient of 0.003 and a t-statistic of 2.04 and *Worst* having a coefficient of 0.007 and a t-statistic of 2.64.

Next controls are included for three anomalies that rank may proxy for, the earnings announcement premium (Beaver (1968); Frazzini and Lamont (2007)), the Gervais, Kaniel and Mingelgrin (2001) high-volume return premium and the dividend month premium (Hartzmark and Solomn (2013)). Earnings are controlled for by a dummy variable equal to one if the stock has an earnings announcement during the period. The high-volume return premium is controlled for using a dummy equal to one if the ranking day was in the top five of the previous fifty trading days of that stock's volume or in the bottom five. Predicted dividend is a dummy equal to one if the company paid a dividend 3, 6, 9 or 12 months ago, where month is defined from 11 trading days into the current month until 10 trading days into the next month. After adding these controls, the coefficients on best and worst increase in both point estimate and significance.

6. Rank Effect Robustness

6.1 Tax Based Explanations

Tax incentives may induce trade in such a way that rank proxyies for tax based trade. US tax law creates time varying incentives to sell positions throughout the year, especially for losses (Constantinides (1984)). Tax related selling of losses could be an important factor for rank. Figure 3 repeats the specification from Table 5 column [2] separately for each calendar month. It graphs the coefficients on Best and Worst along with their 95% confidence intervals as dotted lines. There is a seasonal pattern where loses are more likely to be realized in November and December. The reverse pattern is apparent for the best positions which are most likely to be sold in January. Even though the coefficients exhibit seasonality, the effect in each month for both Best and Worst is large.

In addition, selling might occur to mitigate the overall size of a taxable gain or loss in a tax year. If an individual realizes a net capital gain during a tax year they can realize losses to offset this gain and minimize taxes. Similarly, if an investor realizes a net capital loss in a tax year, they can sell positions at a gain with less of a tax consequence. Best ranked stocks could be proxying for selling positions at a gain to offset losses, and worst ranked stocks could be proxying for investors selling losses to offset capital gains. If such tax based trading is responsible for the rank effect, when an investor has realized a net gain in a tax year, the investor will be more likely to sell their worst ranked stocks. Similarly, if they have realized a net loss, they will be more likely to sell their best ranked position.

Table 15 allows for different effects based on whether an investor has realized a net capital gain or loss in a tax year. *Capital Gain* is a dummy variable equal to one if the sum of profits from all realized positions in the tax year is greater than zero. *Capital Loss* is defined analogously, but for non-positive total realizations.

The opposite pattern to this tax hypothesis is present, suggesting that tax based selling is not responsible for the rank effect. The coefficient on *Capital Gain*Best* is larger than the coefficient on *Capital Loss*Best*. Further, the coefficient on *Capital Loss*Worst* is larger than the coefficient on *Capital Gain*Worst*. This is the opposite pattern of the tax hypothesis.

6.2 Covariate Balance

If the data lacks the requisite covariate balance, logit regression may not identify the effect of becoming extreme ranked. This lack of balance can increase model dependence and bias the estimation of the effect of being extreme ranked (for example Abadie and Imbens (2007) and Ho, Imai, King and Stuart (2007)). There is a large mass of high return values that are ranked best with very few positions at those levels not ranked best (and vice versa for worst ranked positions). This could lead to improper inference that rank is responsible for the pattern, when it is a spurious relation due to model dependence and a sample where the treatment group (best or worst rank) is not balanced with the control group (not ranked best or worst).

To identify the effect of becoming best or worst rank, I utilize entropy balancing (Hainmueller (2012)). To my knowledge this is the first paper to employ entropy balancing in a finance setting. Entropy balancing offers a number of advantages over methods such as nearest neighbor matching, propensity score matching or propensity score weighting. These indirectly attempt to achieve covariate balance using an estimated probability of treatment from the covariates of interest. They match on this probability and not on the covariates themselves.

Entropy balancing directly achieves covariate balancing by matching moments of the covariates between the treatment and control group. It weights to achieve this balance while keeping the weights as close to the original values as possible.

Table 16 presents the results. Entropy balancing is for binary treatments, thus best and worst variables are examined separately. The first column labeled "Unweighted" contains:

$$Best = \frac{\#Best\ Sold}{\#Best} - \frac{\#Not\ Best\ Sold}{\#Not\ Best}\ ;\ Worst = \frac{\#Worst\ Sold}{\#Worst} - \frac{\#Not\ Worst\ Sold}{\#Not\ Worst}$$

The first column contains similar, though slightly smaller numbers to the difference columns in Table 2. The magnitude is smaller as the comparison groups now contains extreme ranked positions (i.e. *Not Best* contains worst ranked stocks) and the 2^{nd} best and 2^{nd} worst positions making the comparison group mean slightly higher than the middle benchmark.

The second column contains these values utilizing the weights from entropy balancing. The balancing is conducted on return, square root of holding days, variance and the interaction of the return and holding days. The balancing is conducted separately for each day which indirectly controls for changes over time of the effect of the covariates. To make sure there is enough data for balancing, in the investor data I exclude days in the bottom quartile of observations per day (777 observations). Taking the *Best-Not Best* row in the Entropy Balanced column as an example, the *Best* proportion sold has a *Not Best* proportion sold subtracted from it where the weighted average sample comprising *Not Best* has the same average return, number of holding days, interaction term and variance each day as the data that comprise *Best*.

The 2^{nd} column labeled "Entropy" shows that after entropy balancing, the rank effect increases and remains highly significant for both individual investors and mutual funds. For individual investors, the values of 12.2% for best and 8.1% for worst are both slightly smaller than the coefficients with simple controls in the logit. For funds, the values of 10.7% for best and

15.8% for worst are of a similar magnitude to the previous coefficients. Entropy balancing estimates the population average treatment effect of being an extreme rank, suggesting the logit results are not driven by a lack of covariate bias.

The daily entropy balancing allows for each day to be analyzed separately. Figure 4 graphs the mean difference of the entropy balanced sample separately for each day. The x-axis indicates the daily entropy balanced mean for Best-Not Best and Worst-Not Worst, with the dotted red line indicating a 0 difference. The y-axis graphs the number of days with that difference. These figures underscore the robustness of the effect, as almost every observation with significance has a positive mean, indicating that looking at each day separately the extreme ranked positions are more likely to be sold.

Examining the investor charts, for most of the days (740 of 774 for Best and 728 of 774 for Worst) extreme ranked stocks were more likely to be sold, indicated by a positive value on the x-axis. For best ranked stocks, 554 of the days have a positive and significant difference (the red bars), while only 1 day has a negative and significant difference (the purple bar). For worst ranked positions, 365 days have a positive and significant difference, while no day has a negative and significant difference.

The bottom two figures present the results for mutual funds, showing a similar, strong effect. In 182 of the 200 report days, best ranked positions are more likely to be sold, and in 190 of the days worst ranked positions are more likely to be sold. For best ranked, 103 days are positive and significant, while no days are negative and significant. For worst ranked, 155 days are positive and significant while only two are negative and significant.

7. Conclusion

This paper documents a new stylized fact, the rank effect. Best and worst ranked positions are more likely to be sold compared to positions in the middle of the portfolio. This effect is present in both individual investors and mutual funds, and is robust to a variety of controls for common information, past returns, tax motivations and model dependence. The rank effect is associated with heavy selling of extreme positions by mutual funds which induces predictable price reversals of 40 to 160 basis points per month.

This paper illustrates that investors do not examine each stock in isolation, but trade in a portfolio context based on the performance of a stock compared to other holdings in their portfolio. While investors are not forming optimal portfolios, the portfolio remains a relevant and important component to trading behavior.

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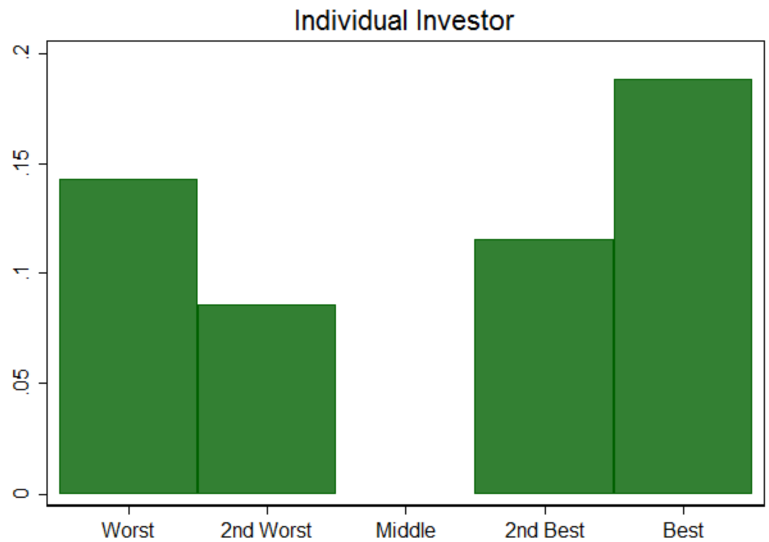
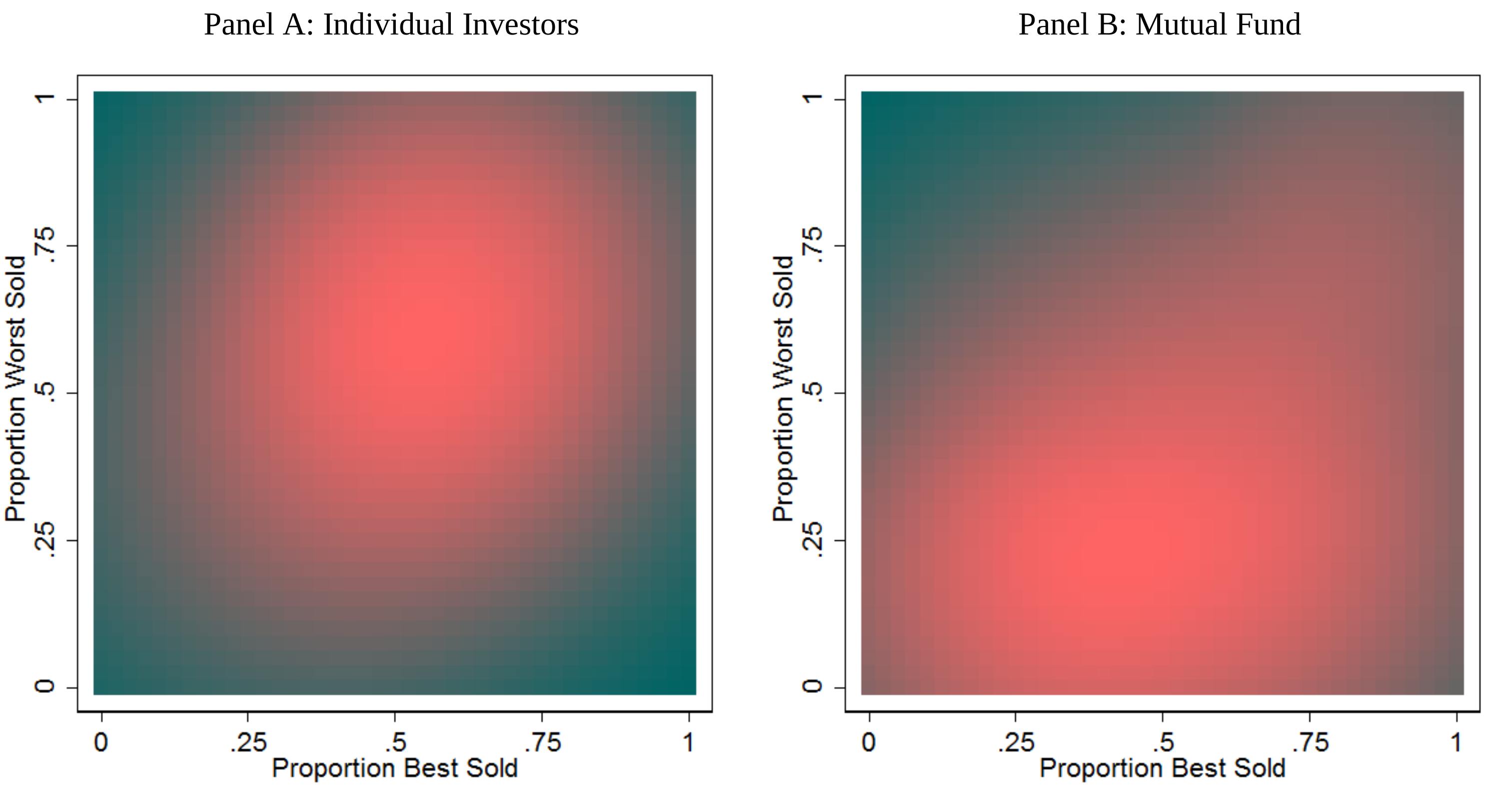
Figure 1 - Increased Probability of Sale Given Portfolio Rank versus Middle Rank



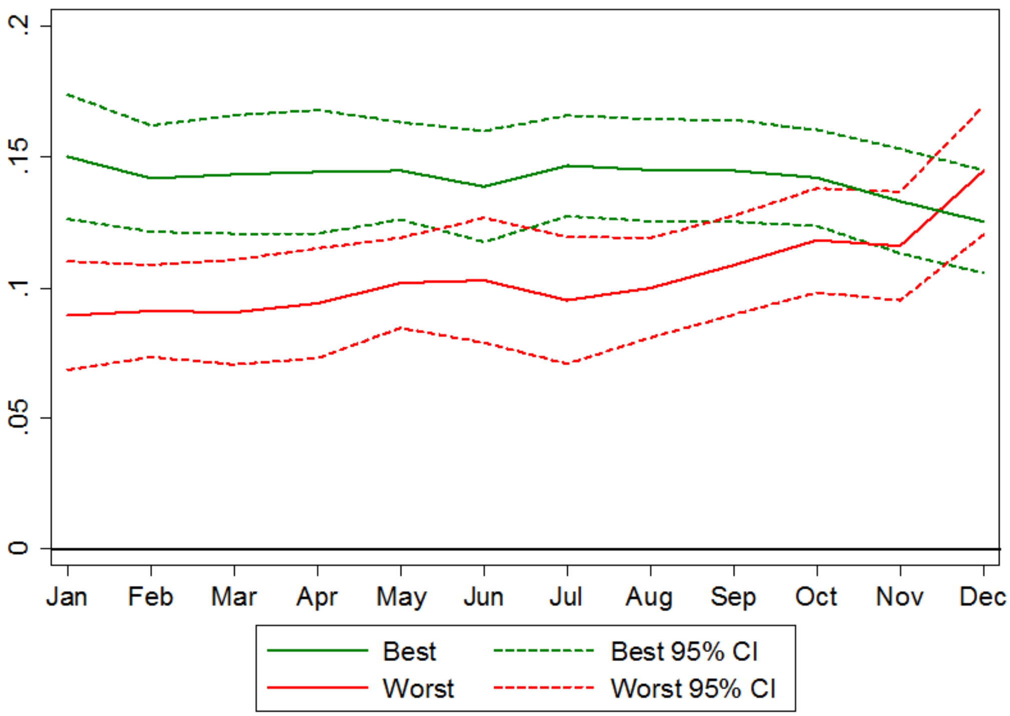
This figure contains individual trading data from January 1991 through November 1996. Portfolio rank is defined from the return if the position is sold relative to the purchase price. All variables use the Middle Rank as the comparison group. Each bar is the marginal effect from a logit regression including the controls from Equation 1, namely: *Gain, Return* Gain, Return* Loss, Return*√Holding Days*Gain, Return*√Holding Days*Loss, Variance *Gain, Variance *Loss,* and √*Holding Days* .

Figure 2 - Heterogeneity of Rank Based Selling



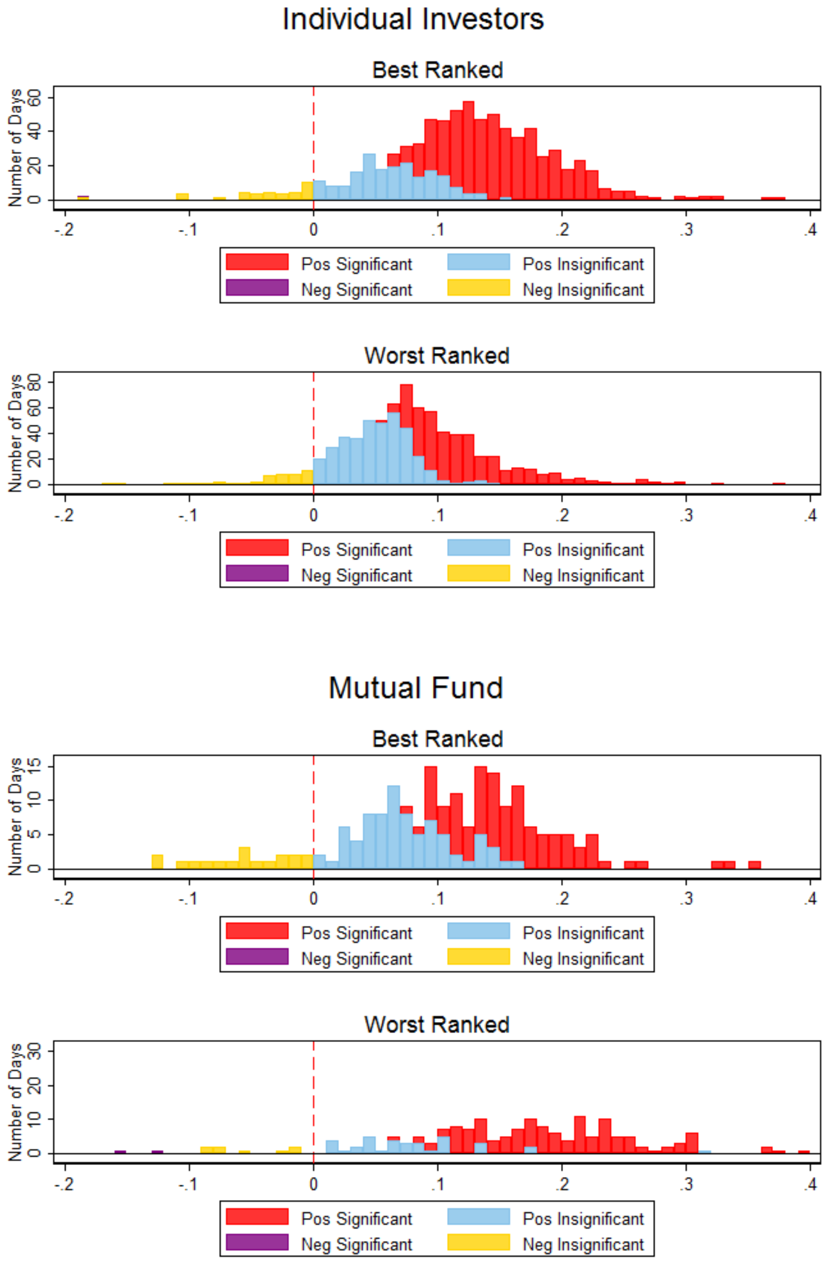
These figures present the joint density between the proportion worst realized and the proportion best realized for investors and fund managers that have at least five sell days, or report days in the data. A darker red corresponds to a higher the density, while a darker blue corresponds to less density. Investor data covers January 1991 to November 1996 and mutual fund data covers January 1990 to December 2011.

Figure 3 - Seasonality of Individual Investor Rank Effects



Marginal effect from logit regression as specified in Table 5 column [2]. Regressions are run separately for each calendar month. Best is the coefficient on the dummy variable for the highest return and worst is the coefficient from the dummy variable for the lowest ranked return. The dotted line is the upper and lower bound of the 95% confidence interval. This figure contains individual trading data from January 1991 through November 1996.

Figure 4 – Daily Rank Effect after Entropy Balancing



This table presents the entropy balanced regression coefficients from daily regressions of a dummy variable equal to 1 if a stock is sold regressed on a dummy variable for best (worst) versus not best (worst). Each day the sample is entropy balanced and these weights are used in the regression. Pos indicates a coefficient greater than 0 and Neg signifies a coefficient less than or equal to 0. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. A stock is considered best (worst) if the stock has the highest (lowest) return in the portfolio. Investor data covers January 1991 to November 1996 and mutual fund data covers January 1990 to December 2011. Standard errors are clustered by account or fund and indicated significance is at the 5% level.

Table 1 – Summary Statistics

Panel A: Investor

	Observations	Mean	Std. Dev.	Minimum	25th Pctile	Median	75th Pctile	Maximum
#Accounts	11,524							
#Sell Days	110,117							
Proportion Sold	1,287,021	0.113						
Proportion Closed	1,287,021	0.090						
Portfolio Size	110,117	11.688	14.938	5	6	8	13	463
Holding Days	1,287,021	352.919	387.853	1	70	204	505	2,148

Panel B: Mutual Fund

	Observations	Mean	Std. Dev.	Minimum	25th Pctile	Median	75th Pctile	Maximum
#Funds	4,730							
#Sell Days	129,415							
Proportion Sold	15,604,501	0.389						
Proportion Closed	15,604,501	0.151						
Portfolio Size	129,415	120.577	224.437	20	40	61	103	3,282
Holding Days	15,604,501	946.622	1056.988	11	243	548	1,277	11,048

This table presents summary statistics. Panel A presents information on investors from January 1991 to November 1996. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day their position is opened or on days when all stocks are liquidated. Panel B is based on mutual fund data from January 1990 to June 2010. Dates examined are report dates. A fund must hold at least 20 CRSP merged securities to be included in the analysis.

Table 2 – Proportion of Positions Realized by Rank

	Individual Investor	Mutual Fund
All Ranks	0.114	0.389
Worst	0.157	0.576
2nd Worst	0.135	0.529
Middle	0.082	0.384
2nd Best	0.185	0.487
Best	0.227	0.503
Worst-Middle	0.075	0.191
	(14.73)	(20.97)
Best-Middle	0.144	0.119
	(27.79)	(15.36)
Observations	1,287,460	15,604,501

This table presents summary statistics of the ratios of stocks that are sold in the indicated group divided by all stocks in that group. Each row is the fraction of the group that was sold. The last four rows present the difference between the indicated groups with a t-statistic (clustered by date and account) on the null hypothesis that the difference is 0 in parenthesis. Only days where a stock is sold and an investor holds at least 5 stocks are included in the sample. Stocks are not included on the day the position is opened or on days when all stocks are liquidated. Individual investor data covers January 1991 to November 1996. Mutual fund data covers January 1990 to June 2010. Dates examined are report dates. A fund must hold at least 20 CRSP merged securities to be included in the analysis.

Table 3 – The Rank Effect for Stocks that on the Same Day are Extreme Ranked in a Portfolio and Not Extreme Ranked in a Different Portfolio

Panel A: Individual Investors

	All	By Stock		All	By Stock
Best	0.206		Worst	0.172	
	64,275			51,112	
Not Best	0.122		Not Worst	0.120	
	145,987			109,475	
Difference	0.085	0.092	Difference	0.052	0.056
	(20.91)	(42.45)		(11.70)	(22.76)
N	210,262	46,770	*N*	160,587	37,128

Panel B: Mutual Funds

	All	By Stock		All	By Stock
Best	0.503		Worst	0.575	
	128,106			125,322	
Not Best	0.419		Not Worst	0.426	
	3,357,306			2,057,957	
Difference	0.084	0.074	Difference	0.150	0.126
	(16.93)	(25.45)		(19.47)	(30.64)
N	3,485,412	48,079	*N*	2,183,279	46,260

This table presents the proportion of best (worst) positions sold in the "Best" ("Worst") row, the not best (worst) in the "Not Best" ("Worst") row and the difference in the difference row. The "All" column calculates this proportion for all stocks and takes the difference. The "By Stock" column takes each pair of stocks and subtracts dummy variables equal to one if the position is sold. If the same stocks is held by multiple investors at the sane rank an average of the sell dummy is taken before differencing. To be included in this table the same stock on the same day must be ranked best (worst) for at least one investor and not best (worst) for at least one investor. For the investor data only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. Data covers January 1991 to November 1996. For the mutual fund data is analyzed on report dates and funds hold at least 20 stocks. Data covers January 1990 to December 2011. The top number is the difference, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account for the investors and date and WFICN for the mutual fund data.

Table 4 – Proportion of Positions Realized by Rank when All Positions are at a Gain or a Loss

	All Gain	All Loss
All Ranks	0.190	0.211
Worst	0.215	0.214
2nd Worst	0.193	0.197
Middle	0.156	0.179
2nd Best	0.210	0.226
Best	0.234	0.283
Worst-Middle	0.058	0.035
	(5.97)	(2.40)
Best-Middle	0.077	0.104
	(8.04)	(6.24)
Observations	24,089	9,133

This table presents summary statistics of the ratios of stocks that are sold in the indicated group divided by all stocks in that group. The All Gain column contains observations where all positions in that portfolio are trading at a positive return from purchase price. The All Loss column contains observations where all positions in that portfolio are trading at a non-positive return from purchase price. Each row is the fraction of the group that was sold. The last four rows present the difference between the indicated groups with a t-statistic (clustered by date and account) on the null hypothesis that the difference is 0 in parenthesis. Only days where a stock is sold and an investor holds at least 5 stocks are included in the sample. Stocks are not included on the day the position is opened or on days when all stocks are liquidated. Data covers January 1991 to November 1996.

Table 5 –Rank Effect with Controls for Past Performance

	Investor			Mutual Fund		
	[1]	[2]	[3]	[4]	[5]	[6]
Best		0.143	0.186		0.099	0.106
		(21.36)	(22.21)		(11.16)	(11.44)
Worst		0.104	0.141		0.142	0.146
		(16.20)	(18.25)		(11.28)	(11.29)
2nd Best			0.114			0.093
			(17.61)			(11.92)
2nd Worst			0.085			0.105
			(15.58)			(9.63)
Return*Gain	0.046	0.001	-0.015	0.035	0.026	0.019
	(5.44)	(0.20)	(-2.15)	(7.05)	(4.82)	(3.56)
Return*Loss	-0.105	-0.001	0.036	-0.272	-0.245	-0.228
	(-5.59)	(-0.03)	(2.04)	(-12.56)	(-11.41)	(-10.57)
Gain	0.036	0.029	0.026	-0.013	-0.014	-0.014
	(11.25)	(10.10)	(9.97)	(-3.95)	(-4.22)	(-4.26)
Return*Gain	-0.002	-0.001	-0.001	0.000	0.000	0.000
*√Holding Days	(-5.89)	(-4.00)	(-2.97)	(-4.66)	(-3.70)	(-3.09)
Return*Loss	0.003	0.002	0.001	0.008	0.007	0.007
*√Holding Days	(3.57)	(2.27)	(1.23)	(11.16)	(11.16)	(11.13)
Variance *Gain	2.415	1.818	1.602	5.127	5.243	5.274
	(3.57)	(3.46)	(3.62)	(1.91)	(1.96)	(1.98)
Variance *Loss	-1.817	-1.777	-1.625	-2.495	-2.287	-2.031
	(-2.95)	(-3.26)	(-3.32)	(-1.96)	(-1.94)	(-1.84)
√Holding Days	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-12.81)	(-13.42)	(-14.09)	(-5.31)	(-5.28)	(-5.28)
Observations	1,282,114	1,282,114	1282114	15,790,486	15,790,486	15,790,486
Adjusted R^2	0.014	0.034	0.048	0.006	0.006	0.007

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio and 2^{nd} Best (2^{nd} Worst) is a dummy for the second highest (lowest) return. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the return since purchase price, Data covers January 1991 to November 1996. The top number is the marginal effect, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account for the investors and date and WFICN for the mutual fund data. Mutual fund data are from January 1990 to June 2010. Dates examined are report dates. A fund must hold at least 20 CRSP merged securities to be included in the analysis.

Table 6 – Rank Effect with Controls for Past Performance When All Positions in a Portfolio are at a Gain or Loss

	All Gain	All Loss
Best	0.111	0.086
	(7.84)	(4.72)
Worst	0.067	0.062
	(5.75)	(3.38)
2nd Best	0.074	0.038
	(6.93)	(2.39)
2nd Worst	0.046	0.031
	(4.56)	(2.04)
Return	0.013	-0.076
	(0.41)	(-1.26)
Return*√Holding Days	-0.001	0.009
	(-1.06)	(2.75)
Variance	11.425	-4.342
	(2.72)	(-3.48)
√Holding Days	-0.001	0.000
	(-2.61)	(0.27)
Observations	24,004	9,081
Adjusted R^2	0.014	0.011

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. The All Gain column includes investor day observations where all positions in a portfolio have positive returns and All Loss contains observations where all holdings are non-positive returns. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio and 2nd Best (2nd Worst) is a dummy for the second highest (lowest) return. Return is the return since purchase price, Data covers January 1991 to November 1996. The top number is the marginal effect, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account. Mutual fund data are from January 1990 to June 2010. Dates examined are report dates. A fund must hold at least 20 CRSP merged securities to be included in the analysis.

Table 7 - Rank Effect with Controls for Stocks that on the Same Day Are Extreme Ranked in a Portfolio and Not Extreme Ranked in another Portfolio

	Individual Investor		Mutual Fund	
	Best	Worst	Best	Worst
Rank	0.143	0.084	0.085	0.126
	(13.89)	(17.40)	(12.20)	(13.23)
Return*Gain	0.040	0.097	0.005	0.006
	(2.15)	(4.84)	(1.58)	(1.42)
Return*Loss	-0.099	-0.099	-0.079	-0.116
	(-4.06)	(-4.06)	(-4.14)	(-6.96)
Gain	0.035	0.035	-0.026	-0.024
	(7.91)	(7.91)	(-6.20)	(-6.74)
Additional Controls	X	X	X	X
Observations	160,587	160,587	3,485,412	2,183,279
Adjusted R^2	0.019	0.019	0.002	0.009

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. To be included in this table the same stock on the same day must be ranked best (worst) for at least one investor and not best (worst) for at least one investor. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio and 2^{nd} Best (2^{nd} Worst) is a dummy for the second highest (lowest) return. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the return since purchase price. Additional controls are *Gain, Return* Gain, Return* Loss, Return*√Holding Days*Gain, Return*√Holding Days*Loss, Variance *Gain, Variance *Loss*, and *√Holding Days*. Investor data covers January 1991 to November 1996. Mutual fund data are from January 1990 to June 2010. Dates examined are report dates. A fund must hold at least 20 CRSP merged securities to be included in the analysis. The top number is the marginal effect, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account for the investors and date and WFICN for the mutual fund data.

Table 8 – Rank Effect for Buying

	Summary Statistics	Regression	
	[1]	[2]	[3]
Best	0.005	0.015	0.020
	(2.01)	(6.54)	(6.92)
Worst	0.035	0.021	0.030
	(14.26)	(10.74)	(10.74)
2nd Best	0.009		0.017
	(3.72)		(6.96)
2nd Worst	0.030		0.021
	(12.79)		(9.46)
Return*Gain		-0.010	-0.012
		(-4.23)	(-5.14)
Return*Loss		-0.047	-0.037
		(-7.30)	(-5.93)
Gain		-0.009	-0.008
		(-9.56)	(-8.74)
Return*Gain		0.000	0.000
*√Holding Days		(3.81)	(4.50)
Return*Loss		0.002	0.002
*√Holding Days		(7.41)	(7.05)
Variance *Gain		0.589	0.563
		(3.43)	(3.52)
Variance *Loss		-0.720	-0.647
		(-2.59)	(-2.67)
√Holding Days		-0.001	-0.001
		(-21.02)	(-20.44)
Observations		1,766,461	1,766,461
Adjusted R^2		0.042	0.048

Column [1] presents the difference in sale probability between the indicated rank stock and a stock not in the top or bottom two returns. Columns [2] and [3] present the marginal effects from logit regressions of a dummy variable equal to 1 if more of a stock that is already held is purchased. Only days where a stock is purchased are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio and 2^{nd} Best (2^{nd} Worst) is a dummy for the second highest (lowest) return. Gain (Loss) is a dummy variable indicating a positive (non-positive) return. Return is the return since purchase price, Data covers January 1991 to November 1996. The top number is the marginal effect, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account.

Table 9 –Alphabetical Ticker Ordering

	Selling			Buying		
	First and Second Ticker Only	Last and Second to Last Ticker Only	All Tickers	First and Second Ticker Only	Last and Second to Last Ticker Only	All Tickers
	[1]	[2]	[3]	[4]	[5]	[6]
First Ticker	0.018		0.057	0.005		0.015
	(5.38)		(16.62)	(3.02)		(10.08)
Last Ticker		0.026	0.062		0.006	0.017
		(7.14)	(17.33)		(3.32)	(10.67)
Ticker by Day FE	X	X	X	X	X	X
Observations	211,303	211,261	1,237,715	258,959	257,334	1,626,607

This table presents regressions of a sell dummy (columns [1]-[3]) equal to 1 if a stock is sold or a buy dummy (columns [4]-[6]) on dummies based on ticker ordering and ticker by day fixed effects. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. First (Last) ticker is a dummy equal to one if the stock ticker is the first (last) ticker by alphabetical order in the portfolio. Data covers January 1991 to November 1996. The top number is the coefficient, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account.

Table 10 – Components of the Rank Effect using Various Measures of Extremeness

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Pos*(Return-Avg Return)/Std. Dev.	0.050			-0.024			-0.022	
	(19.31)			(-12.45)			(-11.82)	
Neg*(Return-Avg Return)/Std. Dev.	-0.035			0.023			0.027	
	(-7.45)			(7.15)			(9.42)	
Pos*(Return-Median Return)		0.139			0.019			-0.010
		(8.19)			(1.77)			(-0.89)
Neg*(Return-Median Return)		-0.080			-0.019			0.004
		(-6.05)			(-1.88)			(0.36)
Best*(Best Return - 2nd Best Return)			0.085			0.058	0.055	0.060
			(13.38)			(11.39)	(10.68)	(9.60)
Worst*(Worst Return - 2nd Worst Return)			-0.292			-0.148	-0.162	-0.150
			(-16.07)			(-11.53)	(-13.07)	(-11.11)
Best				0.243	0.183	0.169	0.221	0.170
				(25.28)	(20.70)	(22.11)	(26.77)	(22.22)
Worst				0.171	0.137	0.111	0.142	0.111
				(18.81)	(15.98)	(18.75)	(18.50)	(17.14)
Additional Controls	X	X	X	X	X	X	X	X
Observations	1,282,114	1,282,114	1,282,114	1,282,114	1,282,114	1,282,114	1,282,114	1,282,114
Adjusted R^2	0.023	0.017	0.021	0.050	0.048	0.050	0.052	0.050

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. Return is the return since purchase price. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio. Average return, median return and Std. Dev. (standard deviation) is the given measure for a investor on a given day. Pos is a dummy variable equal to one if the number in parenthesis is greater than 0, and Neg is a dummy equal to one when the number is less than or equal to zero. Additional controls are *Gain*, *Return* Gain*, *Return* Loss*, *Return*√Holding Days*Gain*, *Return*√Holding Days*Loss*, *Variance *Gain*, *Variance *Loss*, and *√Holding Days*. Columns [4]-[8] also include controls for 2nd best and 2nd worst return. Investor data covers January 1991 to November 1996. The top number is the marginal effect, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account.

Table 11 - Mutual Fund Fraction Sold and Liquidation by Rank

	Fraction Sold		Liquidate	
	All	Sell Only	All	Sell Only
Best	0.078	0.023	0.038	0.001
	(13.55)	(3.76)	(10.39)	(0.23)
Worst	0.175	0.141	0.127	0.237
	(16.00)	(12.33)	(14.91)	(16.30)
Return*Gain	0.028	0.000	0.003	-0.047
	(4.78)	(-0.07)	(1.41)	(-7.46)
Return*Loss	-0.264	-0.299	-0.155	-0.300
	(-11.26)	(-12.34)	(-11.85)	(-9.59)
Gain	-0.007	-0.023	-0.011	-0.027
	(-2.88)	(-4.31)	(-4.95)	(-4.44)
Additional Controls	X	X	X	X
Observations	15,603,394	6,068,983	15,603,394	6,068,983
Adjusted R^2	0.044	0.123	0.063	0.090

This table presents a linear regression in the Fraction Sold column where the dependent variable is the number of shares sold on a report date divided by the number of shares held the previous report date. The Liquidate column presents the marginal effects from logit regressions of a dummy variable equal to 1 if all shares of a stock are sold. The "All" column includes all holdings while the "Sell Only" column includes only positions of which some fraction are sold. Additional controls are *Gain, Return* Gain, Return* Loss, Return*√Holding Days*Gain, Return*√Holding Days*Loss, Variance *Gain, Variance *Loss,* and *√Holding Days*. Mutual funds must hold at least 20 stocks to be included in the sample. Stocks are not included on the day their position is opened. Standard errors are clustered by fund (wficn) and date. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio. Gain (Loss) is a dummy variable indicating a positive (negative) return. Data covers January 1990 to December 2011.

Table 12 – Price Effects Based on Mutual Fund Portfolio Rank

	Worst				Best			
α (%)	0.669	0.407	1.366	1.612	0.355	0.448	0.199	0.357
	(1.65)	(1.10)	(4.96)	(5.11)	(1.90)	(2.69)	(1.26)	(1.98)
MKT	1.741	1.629	1.234	1.252	1.074	0.958	1.061	1.073
	(21.09)	(20.06)	(19.15)	(19.18)	(28.22)	(26.20)	(28.78)	(28.75)
SMB		0.833	0.895	0.900		0.306	0.290	0.293
		(6.66)	(9.89)	(9.97)		(5.43)	(5.59)	(5.67)
HML		0.594	0.108	0.088		-0.234	-0.108	-0.121
		(5.14)	(1.21)	(0.98)		(-4.49)	(-2.10)	(-2.34)
UMD			-0.846	-0.865			0.220	0.208
			(-14.89)	(-14.94)			(6.76)	(6.27)
ST_REV				-0.102				-0.066
				(-1.58)				(-1.77)

This table presents Fama-French regressions on monthly equal weighted portfolios. Portfolios are formed based on the rank from mutual fund holdings rank between a report date to 3 months and 10 trading days later. Portfolios are held from the 11th trading day of a month until the 10th trading day of the next month. A stock is included in the worst (best) portfolio if it is ranked worst (best) in at least one fund. Data covers January 1990 to December 2011.

Table 13 – Weighted Price Effects Based on Mutual Fund Portfolio Rank

	Worst				Best			
	Number of Funds where Stock is Ranked Worst		Fraction of Marketcap That is Worst		Number of Funds where Stock is Ranked Best		Fraction of Marketcap That is Best	
α (%)	1.816	1.632	2.110	2.223	0.330	0.646	0.209	0.418
	(4.57)	(3.57)	(4.10)	(3.75)	(1.39)	(2.39)	(1.22)	(2.15)
MKT	1.170	1.156	1.280	1.288	1.182	1.205	1.121	1.136
	(12.58)	(12.22)	(10.63)	(10.51)	(21.29)	(21.57)	(28.06)	(28.21)
SMB	0.877	0.874	1.391	1.393	0.228	0.234	0.174	0.177
	(6.71)	(6.68)	(8.22)	(8.21)	(2.93)	(3.02)	(3.09)	(3.18)
HML	0.097	0.112	0.509	0.500	-0.164	-0.189	-0.204	-0.221
	(0.75)	(0.86)	(3.03)	(2.94)	(-2.11)	(-2.44)	(-3.66)	(-3.96)
UMD	-1.096	-1.082	-1.015	-1.024	0.337	0.313	0.269	0.253
	(-13.37)	(-12.89)	(-9.56)	(-9.41)	(6.89)	(6.31)	(7.65)	(7.09)
ST_REV		0.077		-0.047		-0.131		-0.087
		(0.82)		(-0.39)		(-2.37)		(-2.18)

This table presents Fama-French regressions on monthly portfolios. "Number of funds where Stock is Ranked Worst (Best)" weights by the number of funds where the stock is the indicated rank. "Fraction of marketcap that is Worst (Best)" weights by the fraction of marketcap for each stock that is best (worst). Portfolios are formed based on the rank from mutual fund holdings rank between a report date to 3 months and 10 trading days later. Portfolios are held from the 11th trading day of a month until the 10th trading day of the next month. A stock is included in the worst (best) portfolio if it is ranked worst (best) in at least one fund. Data covers January 1990 to December 2011.

Table 14 – Fama-Macbeth Price Effects

	[1]	[2]	[3]
Best	0.001	0.003	0.003
	(0.30)	(2.04)	(2.28)
Worst	0.008	0.007	0.008
	(2.16)	(2.64)	(2.70)
Momentum		0.003	0.003
		(1.32)	(1.34)
Lag Return		-0.018	-0.018
		(-3.08)	(-3.11)
Log(Market Cap)		-0.001	-0.001
		(-1.79)	(-2.32)
Log(Book/Market)		0.001	0.001
		(1.29)	(1.19)
High Volume (GKM)			0.004
			(5.11)
Low Volume (GKM)			-0.005
			(-6.96)
Earnings			0.006
			(7.66)
Predicted Dividend (HS)			0.003
			(2.97)
Constant	0.011	0.023	0.024
	(2.85)	(2.46)	(2.58)
Observations	722,157	658,662	658,662

This table presents Fama-Macbeth regressions on monthly stock returns. A month considered is from the 11th trading day of a month until the 10th trading day of the next month. Ranks are based on the rank from mutual fund holdings rank between a report date to 3 months and 10 trading days later. Best (Worst) is a dummy variable equal to one if a stock is ranked best (worst) in at least one fund. Momentum is the compounded returns from months t-2 to t-12 and Lag Return is the return from t-1. Log B/M is the log of the book to market ratio. High (Low) GKM Premium is a dummy equal to one if the previous day's volume is in the top (bottom) decile of the past 50 trading days. Earnings is a dummy equal to one if there's an earnings announcement in the month. Predicted dividend (HS) is a dummy equal to one if the company padi a dividend 3, 6, 9 or 12 months ago where month is defined from 11 trading days into a month until 10 trading days into the next month. Only stocks held by mutual funds are included. Data covers January 1990 to December 2011.

Table 15 – The Rank Effect Controlling for Tax based Selling Based on Capital Gain or Loss in Tax Year

	All Year		4th Quarter	
	[1]	[2]	[3]	[4]
Capital Gain*Best	0.195	0.242	0.180	0.226
	(25.79)	(25.71)	(22.02)	(22.89)
Capital Loss*Best	-0.004	0.020	0.008	0.034
	(-0.62)	(2.99)	(1.12)	(4.00)
Capital Gain*Worst	0.030	0.060	0.062	0.102
	(5.39)	(9.39)	(8.36)	(11.57)
Capital Loss*Worst	0.335	0.397	0.322	0.389
	(28.89)	(31.83)	(21.07)	(23.89)
Capital Gain*2nd Best		0.144		0.137
		(20.62)		(18.78)
Capital Loss*2nd Best		0.020		0.034
		(3.20)		(4.32)
Capital Gain*2nd Worst		0.037		0.060
		(7.43)		(9.96)
Capital Loss*2nd Worst		0.233		0.212
		(28.04)		(19.91)
Additional Controls	X	X	X	X
Observations	1,282,114	1,282,114	340,571	340,571
Adjusted R^2	0.049	0.070	0.044	0.063

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio and 2nd Best (2nd Worst) is a dummy for the second highest (lowest) return. Capital Gain (Loss) is equal to the realized gain (loss) from purchase price of all securities in the portfolio from the beginning of the tax year up to that date of the tax year. Additional controls are *Gain, Return* Gain, Return* Loss, Return*√Holding Days*Gain, Return*√Holding Days*Loss, Variance *Gain, Variance *Loss,* and *√Holding Days*. Data covers January 1991 to November 1996. The top number is the marginal effect, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account.

Table 16 – Rank Effect after Entropy Balancing

	Investor		Mutual Fund	
	Unweighted	Entropy Balanced	Unweighted	Entropy Balanced
Best - Not Best	0.117	0.122	0.115	0.107
	(23.43)	(48.77)	(15.08)	(19.14)
Worst - Not Worst	0.047	0.081	0.188	0.158
	(8.98)	(36.91)	(20.92)	(21.23)

This table presents the proportion of best (worst) positions sold minus the proportion of not best (worst) positions sold. The "Unweighted" column is the simple difference. "Entropy Balanced" is the weighted average difference based on entropy balancing of the sample each day. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. A stock is considered best (worst) if the stock has the highest (lowest) return in the portfolio. Investor data covers January 1991 to November 1996. Mutual fund data are from January 1990 to June 2010. Dates examined are report dates. A fund must hold at least 20 CRSP merged securities to be included in the analysis. The top number is the difference, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by account.

Appendix A - Rank Effect with Controls for Mean, Variance and Past Performance

	[1]	[2]	[3]	[4]
Best	0.143	0.142	0.142	0.143
	(22.03)	(21.06)	(20.92)	(21.87)
Worst	0.105	0.104	0.104	0.105
	(15.75)	(16.17)	(15.80)	(15.50)
High CAR	0.009			0.009
	(4.85)			(4.44)
Low CAR	0.006			0.005
	(3.64)			(3.21)
Short Term: High ΔVar		0.014		0.013
		(12.09)		(11.20)
Short Term: Low ΔVar		-0.004		-0.005
		(-4.15)		(-4.99)
Long Term: High ΔVar			0.008	0.008
			(6.84)	(6.55)
Long Term: Low ΔVar			-0.001	0.000
			(-1.04)	(0.21)
Other Controls	X	X	X	X
Observations	1,165,807	1,262,185	1,242,127	1,153,367
Adjusted R^2	0.035	0.034	0.034	0.035

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day their position is opened. Standard errors are clustered by account. Best (Worst) is a dummy variable equal to 1 if the stock has the best (worst) return in the portfolio. Best (Worst) Ret is the highest (lowest) return in a portfolio and 2nd Best (Worst) Ret is the second highest (lowest). For CAR and the variance (Var) variables, high refers to the highest quintile and low refers to the lowest. CAR is from the most recent earnings announcement and is calculated from two days before the announcement to one day after. Short term Var is the Var calculated over the previous month divided by the variance from two months prior. Long term is the previous 6 months divided by the 6 months prior. Pos (Neg) is a dummy variable indicating a positive (negative) return. Other Controls include *Gain, Return* Gain, Return* Loss, Return*√Holding Days*Gain, Return*√Holding Days*Loss, Variance *Gain, Variance *Loss,* and *√Holding Days*. Percentiles are calculated for each investor day combination. Data covers January 1991 to November 1996.

Appendix B - Rank Effect with Controls for Covariance and Past Performance

	Level		Short Term		Long Term	
	[1]		[3]		[5]	
Best	0.140		0.142		0.140	
	(20.85)		(21.17)		(21.00)	
Worst	0.105		0.106		0.104	
	(16.09)		(16.13)		(15.41)	
	High	**Low**	**High**	**Low**	**High**	**Low**
Mkt	0.010	0.001	0.004	0.005	0.003	0.002
	(7.46)	(1.05)	(3.55)	(3.52)	(2.95)	(1.74)
Div	0.001	0.004	0.002	0.003	0.000	0.001
	(0.89)	(2.39)	(1.99)	(2.31)	(-0.06)	(1.12)
Term	0.005	0.003	0.004	0.004	0.001	0.002
	(3.60)	(2.41)	(3.78)	(3.44)	(1.12)	(1.71)
Default	0.005	0.004	0.002	0.002	0.004	0.005
	(4.25)	(2.65)	(2.00)	(1.76)	(3.19)	(3.94)
Rf	0.003	0.008	0.002	0.003	0.004	0.002
	(2.50)	(5.40)	(1.99)	(2.68)	(3.59)	(2.04)
High hml	0.006	0.008	0.003	0.004	0.006	0.005
	(4.81)	(5.68)	(3.07)	(3.85)	(3.35)	(3.80)
High smb	0.008	0.001	0.002	0.004	0.003	0.002
	(4.42)	(0.98)	(1.60)	(2.76)	(1.97)	(2.15)
Other Controls	X		X		X	
Observations	1,262,182		1,221,683		1,181,479	
Adjusted R^2	0.036		0.035		0.034	

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included. Stocks are not included on the day their position is opened. Standard errors are clustered by account. High (Low) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio. High (Low) Ret is the highest (lowest) return in a portfolio and 2nd High (Low) Ret is the second highest (lowest). The covariances are calculated similar to Petkova (2006), but utilizing daily data to avoid staleness. Petkova uses monthly data, so this study makes a different measure each day utilizing 20 trading day increments to mimic a month. The measure from the day before a sell day is used in th eregression. Other Controls include *Gain, Return* Gain, Return* Loss, Return*√Holding Days*Gain*, *Return*√Holding Days*Loss, Variance *Gain, Variance *Loss,* and *√Holding Days*. Data covers January 1991 to November 1996.

Appendix C – Robustness Checks For Rank Effect with Controls for Past Performance

	Panel A: Number of Holdings					
	5-8 Stocks		8-13 Stocks		13+ Stocks	
	[1]	[2]	[3]	[4]	[5]	[6]
Best	0.105	0.101	0.068	0.065	0.062	0.060
	(29.20)	(28.38)	(14.71)	(13.83)	(9.54)	(9.56)
Worst	0.050	0.032	0.069	0.058	0.077	0.067
	(15.18)	(9.28)	(14.98)	(12.10)	(8.44)	(10.81)
Best*(Best Ret - 2nd Best Ret)		0.024		0.016		0.005
		(3.53)		(2.49)		(0.97)
Worst*(Worst Ret- 2nd Worst Ret)		-0.143		-0.085		-0.050
		(-9.57)		(-4.52)		(-2.21)
Observations	352,439	352,439	282,459	282,459	627,399	627,399
Adjusted R^2	0.023	0.023	0.018	0.018	0.020	0.020

	Panel B: Days Since Last Trade					
	1-20 Days		21-250 Days		250+ Days	
	[1]	[2]	[3]	[4]	[3]	[4]
Best	0.238	0.261	0.184	0.164	0.092	0.079
	(18.58)	(19.43)	(21.87)	(22.72)	(14.64)	(13.62)
Worst	0.095	0.083	0.116	0.086	0.093	0.067
	(9.93)	(7.72)	(18.34)	(15.69)	(10.48)	(10.73)
Best*(Best Ret - 2nd Best Ret)		-0.204		0.082		0.033
		(-3.93)		(7.99)		(7.07)
Worst*(Worst Ret- 2nd Worst Ret)		-0.139		-0.189		-0.107
		(-2.03)		(-10.71)		(-8.44)
Observations	110,532	110,532	582,573	582,573	569,192	569,192
Adjusted R^2	0.049	0.049	0.033	0.034	0.024	0.026

	Panel C: Non-Linear V-Shape			
	[1]	[2]	[3]	[4]
Best	0.147	0.137	0.150	0.140
	(21.69)	(21.33)	(21.33)	(20.20)
Worst	0.104	0.074	0.103	0.074
	(15.95)	(15.53)	(16.08)	(15.63)
Best*(Best Ret - 2nd Best Ret)		0.030		0.025
		(5.32)		(4.22)
Worst*(Worst Ret- 2nd Worst Ret)		-0.163		-0.164
		(-11.72)		(-11.67)
Pos*Return	-0.008	-0.016	-0.019	-0.020
	(-1.25)	(-2.38)	(-2.50)	(-2.75)
Pos*Return^2	0.002	0.002	0.008	0.004
	(8.01)	(5.36)	(5.55)	(2.97)
Pos*Return^3			0.000	0.000
			(-3.00)	(-1.45)
Pos*Return^4			0.000	0.000
			(2.06)	(0.93)
Neg*Return	-0.065	-0.082	-0.188	-0.217
	(-2.74)	(-3.44)	(-4.21)	(-4.84)
Neg*Return^2	-0.143	-0.216	-0.634	-0.786
	(-7.16)	(-10.58)	(-3.12)	(-3.75)
Neg*Return^3			-0.566	-0.716
			(-1.50)	(-1.85)
Neg*Return^4			-0.133	-0.224
			(-0.58)	(-0.96)
Observations	1,262,297	1,262,297	1,262,297	1,262,297
Adjusted R^2	0.034	0.035	0.035	0.036

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if a stock is sold on characteristics of the stock being held. Panel A splits the sample by number of holdings as indicated in the top row and Panel B splits the sample based on number of days since the previous trade. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day their position is opened. Standard errors are clustered by date and account. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio. Best (Worst) Ret is the highest (lowest) return in a portfolio and 2nd Best (Worst) Ret is the second highest (lowest). Median Ret is the median return in the portfolio. Pos (Neg) is a dummy variable indicating a positive (negative) return. Regressions include all controls specified by equation 1. Data covers January 1991 to November 1996.

Appendix D – Buying Extremeness

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Pos*(Return-Avg Return)/SD Portfolio	0.004			-0.009			-0.009	
	(3.55)			(-7.21)			(-6.63)	
Neg*(Return-Avg Return)/SD Portfolio	-0.007			0.006			0.007	
	(-6.02)			(4.48)			(4.96)	
Pos*(Return-Med Return)		-0.014			-0.029			-0.036
		(-3.49)			(-9.96)			(-11.77)
Neg*(Return-Med Return)		-0.005			0.012			0.016
		(-0.70)			(2.12)			(2.74)
Best*(Best Return - 2nd Best Return)			0.011			0.009	0.006	0.016
			(5.46)			(4.69)	(3.23)	(8.03)
Worst*(Worst Return - 2nd Worst Return)			-0.057			-0.023	-0.027	-0.030
			(-12.16)			(-6.26)	(-7.66)	(-6.82)
Best				0.040	0.025	0.018	0.037	0.021
				(12.84)	(8.37)	(6.93)	(12.03)	(8.44)
Worst				0.038	0.031	0.025	0.033	0.026
				(8.08)	(8.96)	(10.71)	(7.98)	(9.68)
Additional Controls	X	X	X	X	X	X	X	X
Observations	1,766,461	1,766,461	1,766,461	1,766,461	1,766,461	1,766,461	1,766,461	1,766,461
Adjusted R^2	0.039	0.038	0.040	0.049	0.049	0.049	0.050	0.050

This table presents the marginal effects from logit regressions of a dummy variable equal to 1 if more of a stock is purchased on characteristics of the stock being held. Only days where a stock is sold are included and an investor must hold at least 5 stocks to be included in the sample. Stocks are not included on the day that position is opened or on days when all stocks are liquidated. Return is the return since purchase price. Best (Worst) is a dummy variable equal to 1 if the stock has the highest (lowest) return in the portfolio. Average return, median return and Std. Dev. (standard deviation) is the given measure for a investor on a given day. Pos is a dummy variable equal to one if the number in parenthesis is greater than 0, and Neg is a dummy equal to one when the number is less than or equal to zero. Additional controls are *Gain*, *Return* Gain*, *Return* Loss*, *Return*√Holding Days*Gain*, *Return*√Holding Days*Loss*, *Variance *Gain*, *Variance *Loss*, and *√Holding Days*. Columns [4]-[8] also include controls for 2nd best and 2nd worst return. Investor data covers January 1991 to November 1996. The top number is the marginal effect, and the lower number in parenthesis is the t-statistic. Standard errors are clustered by date and account.