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

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Abstract: I document a new stylized fact about how investors trade assets: individuals are more likely to sell the extreme winning and extreme losing positions in their portfolio ("the rank effect"). This effect is not driven by firm-specific information or the level of returns itself, but is associated with the salience of extreme portfolio positions. The rank effect is exhibited by both retail traders and mutual fund managers, and is large enough to induce significant price reversals in stocks of up to 160 basis points per month. The effect indicates that trades in a given stock depend on what else is in an investor's portfolio.

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Portfolio theory has long advocated that investors combine multiple stocks to create optimally diversified portfolios (Markowitz 1952). While such models are good normative descriptions of how investors *ought* to behave, it is not clear that investors actually *do* behave this way. A number of papers in behavioral finance have examined real world investor trading and documented several stark departures from these theoretical predictions. Individuals often hold too few stocks (Barber and Odean 2000), use naïve diversification strategies (Benartzi and Thaler 2001; Goetzmann and Kumar 2008) and engage in behavior like the disposition effect (the tendency to sell gains more than losses as in Odean 1998; Shefrin and Statman 1985) or overconfidence (trading too much as in Barber and Odean 2000). However, these studies have considered investor trading primarily on a stock-by-stock basis. One consequence of this is that the empirical literature largely examines investors as if they are ignoring the portfolio problem in its entirety. Between one extreme (complex optimization) and the other (stock-by-stock trading) there is the large and largely unexplored middle ground of how investors actually deal with the portfolio problem.

In this paper, I explore one aspect of the investor's portfolio choice problem, namely how the relative performance of stocks within the portfolio impacts trading decisions. I document a new stylized fact about trading in a portfolio setting: investors are more likely to sell both their best and their worst positions, based on return from purchase price. I term this the rank effect.

Using data from a large retail brokerage, I show that on a day an investor sells a position in their portfolio, the investor has a 31% chance of selling the stock with the highest return in the portfolio and a 26% chance of selling the stock with the lowest return, after controlling for a number of factors discussed below. In contrast, a position in the middle of the portfolio (not the top two or bottom two returns) has only an 11% probability of being sold. I define the rank effect as the difference in probability of sale compared to the middle. Thus, in this specification the rank effect is 20% for best-ranked stocks and 15% for worst. Mutual funds also exhibit the rank effect: best-ranked stocks are 12% more likely to be sold than the middle, and worst-ranked stocks are 17% more likely to be sold.

An obvious concern is that rank may be proxying for many possible firm-specific factors. For example, stocks with best and worst ranks may differ in their information flows, returns, volatility and any number of other attributes. I control for this possibility in several ways. Perhaps the cleanest is to examine the behavior of two investors who both hold the same stock on the same day, but differ in whether the stock is extreme-ranked in their portfolio. This sample of stocks, which on the same day are extreme-ranked in one investor's portfolio but not in the other's portfolio, shares the same firm-specific information, such as recent returns, earnings announcement, analyst forecasts, etc. Even in this sample, both individual investors and mutual funds are more likely to sell the stock that is at the extreme rank. This suggests that the rank effect is not driven solely by any firm-specific attributes of extreme-ranked stocks, as the same variation exists purely comparing across investors.

In addition to this broad test of firm-specific information, I examine whether rank proxies for stock performance over the period an investor holds a stock. To rule out a simple explanation based on the disposition effect, i.e., the tendency to sell gains rather than losses, I analyze portfolios where all stocks are at a gain or all stocks are at a loss. I find a greater propensity to sell the best and worst-ranked stocks in both subsamples. Stocks with best and worst ranks have generally experienced high or low returns from purchase. Without controlling for rank, investors display a propensity to sell such positions (Ben-David and Hirshleifer 2012). After controlling for the return of the stock, stock volatility and the length of time the stock is held, the rank effect becomes stronger. For investors, the propensity to sell stocks with high or low returns disappears or reverses after accounting for rank. This suggests the propensity to sell stocks with large returns in absolute value may be better understood as a propensity to sell extreme-ranked stocks.

Tax law may also create incentives to realize extreme positions in systematic ways. For example, by realizing losses to offset previously realized gains. To test whether this explains the effect, I examine trading in both tax deferred accounts and taxable accounts separately and find similar results. Further, a significant rank effect is present every calendar month, whereas other tax-based phenomena tend to manifest themselves towards the end of the year. The rank effect is also not explained by a lack of covariate balance as matching utilizing entropy balancing yields a rank effect. A number of further robustness checks are presented in the internet appendix.

Finally, I show that, in addition to being a robust trading pattern, the rank effect has economically important pricing consequences. In particular, the selling of extreme positions by mutual funds is sufficiently widespread that it induces predictable price pressure. When the information from each mutual fund's report is public, I estimate which stocks are likely to be extreme-ranked for the fund and thus susceptible to price pressure from rank induced selling. In contrast to both a short-term reversal and a momentum strategy, the strategy purchases both best and worst-ranked stocks, as both are predicted to have high subsequent returns.

The portfolio comprised of purchasing worst-ranked stocks has a monthly four-factor alpha of 136 basis points, which increases to 161 once a short term reversal factor is included. The portfolio comprised of purchasing best-ranked stocks has a four-factor alpha of 19 basis points, which increases to 36 when a short term reversal factor is added. This is consistent with my finding that funds sell worst-ranked positions much more heavily than best-ranked positions. Therefore, worst-ranked positions experience more price pressure and subsequently larger returns. Weighting the portfolios towards stocks predicted to have higher selling pressure increases the alphas to as high as 65 basis points for best-ranked stocks and 222 basis points for worst-ranked. Using Fama-Macbeth regressions, I also find that best and worst-ranked positions have positive and significant returns after controlling for a number of other return predictors.

Given that the standard finance explanations above do not appear to explain the rank effect, a natural question arises as to what aspect of extreme-ranked positions is causing investors to sell. One broad class of explanations for the individual investors is that extreme positions are more salient in the investor's portfolio. This may occur because relatively larger returns are more attention-grabbing, or because the investor chooses to research certain stocks based in some part on relative performance in the portfolio. In either case, the extreme positions will be a greater focus of investor attention, potentially resulting in trade.

One prediction of a salience explanation is that the effect ought to occur on the purchase side as well - there is no reason to presume that investors paying more attention to an extreme-ranked stock will only choose to sell it rather than buy more. Consistent with this, I show that investors are more likely to re-purchase more of positions with extreme returns. In addition, a salience explanation suggests that investors will react not only to the rank ordering of stocks but also to how much that stock stands out relative to the rest of the portfolio. Empirically, I find that both effects are present: a direct rank order effect (of being the most extreme position) and a relative size effect (the difference in returns between the extreme position and the next position).

Because stock returns are necessarily correlated with many economic factors, it is difficult to show precisely that rank in returns has a psychological effect, rather than an economic one. To establish that rank and salience in general *can* have purely psychological effects (even if the cause of a return-based rank effect itself is difficult to isolate precisely), I consider the effects of an alternative rank order sorting that is likely to be salient to investors, but less likely to have an economic explanation. Specifically, I examine the tendency of investors to trade based on the alphabetical order of company name - an ordering unique to the portfolio and orthogonal to economic variables. Stock performance is often presented in this order, such as online or in a brokerage statement. I show the first and last positions by alphabetical order are more likely to be sold after controlling for stock by day probability of sale. This lends indirect support to the view that part of the effect of extreme-ranked returns is their increased psychological salience to investors.

In the context of models that assume narrow framing, the results suggest that investors use a reference point based on performance relative to other stocks in their portfolio. This view provides an extension to these theories that assume investors trade based on a specific portion of wealth, such as a stock's return, in isolation.[1] For example, realization utility assumes an investor receives a burst of utility when selling a stock based on the size of the gain or loss (Barberis and Xiong 2012). A large and ongoing debate is what reference point investors actually use to define a gain or loss.[2] Theories that rely on narrow framing alone will struggle to explain why investors trade differently according to the relative performance of positions within 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 attempting to explain the level of trading volume in the stock market (Milgrom and Stokey 1982). In particular, investors may be acting differently towards the same

[1] Such as Barberis, Huang and Thaler 2006; Barberis and Huang 2001; Barberis and Xiong 2012; Ingersoll and Jin 2013; Frydman, Barberis, Camerer, Bossaerts and Rangel 2013; Ben-David and Hirshleifer 2012.
[2] A number of reference points have been suggested, such as a zero return (Odean 1998), the risk free rate (Barberis and Huang 2001), or expectations of performance (Kőszegi and Rabin 2006, Meng 2012).

piece of information about the same stock due to effect that *other* stocks in their portfolio have on the way they perceive the given information.

2. Literature Review

2.1. Relative Evaluation and Rank

Investors typically hold multiple stocks and see their performance presented together, for example online or in a brokerage statement. Behavioral economics provides evidence that when information is presented together, individuals evaluate the information and make decisions jointly, by comparing all the information, rather than separately, where each piece of information is examined on its own. Further, the choices made are often different when decisions are considered jointly, as these tend to highlight differences between the proposed alternatives (Bazerman, Loewenstein and White 1992; Hsee 1996; Hsee, Loewenstein, Blount and Bazerman 1999; Kahneman 2003; List 2002). Thus, in the context of a portfolio, if investors use joint evaluation when making trading decisions, their choices may be quite different than if they evaluated each stock in isolation.

2.2. Salience

The relative performance of a stock in the portfolio may make investors pay more or less attention to a position. When faced with a large number of possibilities, individuals typically do not pay equal attention to each one, 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." A number of stock-specific events have been shown to be attention-grabbing.[3] This paper complements these studies by considering salience not just as a firm-specific attribute, but rather as an individual-specific measure relative attention.

Jointly evaluating positions in a portfolio allows rank to be a meaningful attribute in decision making. Psychology has a long history examining rank, both describing its influence in a variety of situations and explicitly incorporating it into decision theory.[4] As an example, rank-dependent utility models, such as cumulative prospect theory (Tversky and Kahneman 1992), predict that rank ordering impacts salience and the best and the worst-ranked positions are the most attention grabbing. The intuition of rank-dependent utility is that extreme ranks are salient, attention grabbing positions (Diecidue and Wakker 2001).

Individuals often simplify complex decisions by using a basic rule of thumb to decide 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. Varying attention within the portfolio is consistent with investors forming consideration sets as a part of their trading decision – for instance, deciding which stocks to sell by first narrowing down the full portfolio to a smaller list of potential stocks to focus on more closely.[5] In the current context, my results suggest that extreme-ranked positions are more likely to enter the consideration set when investors are choosing which stocks to trade.

The discussion of the cause of the rank effect focuses on individual investors rather than mutual funds. The behavior of mutual funds contains an additional complication, how managers

[3] Such events include 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).

[4] For an overview of the literature see Diecidue and Wakker (2001) and Wakker (2010).

[5] 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 respond to consumers' use of consideration sets (Ellison and Ellison 2009) and models of how such heuristics impact asset prices (Gabaix 2013).

believe their public disclosure will be viewed. Mutual funds could exhibit the rank effect through the same mechanism as individual investors, or because managers strategically trade based on how they think investors will respond to their report (Musto 1999; Solomon, Soltes and Sosyura 2012). Most likely it is a combination of both. Describing how these two effects interact is beyond the scope of the paper, but there is some evidence that managers engage in rank-based window dressing. Section 5 shows funds liquidate worst-ranked stocks at a much higher rate than other positions. While this could represent fund manager preferences, it is 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.

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 in this paper is based on two main datasets. The first contains data on individual investors trading on their personal accounts. These data have the benefit of a large number of accounts with information on the exact day that trading occurs. The analysis is also conducted on mutual funds. Funds control significantly more money traded by professional investors and the data also offer a longer time series. Unfortunately, holdings are only available infrequently, 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) and Strahilevitz, Odean and Barber (2011). The data describe the date, price and quantity of trades made by retail investors from a large discount brokerage from January 1991 through November 1996. The data is augmented using CRSP data on price as well as adjustments for splits.

The analysis examines the portfolio of stocks that an investor could sell on each day that they do sell at least one position (a sell day). Section 4.4 also examines the decision to buy more of a stock each day an investor purchases a stock (a buy day). I use the term sell to indicate a decrease in the number of shares held while I use the term liquidate to refer to a sale where all shares of a given stock are sold. The time of trade is not observed, so if an investor trades the same stock multiple times within a day, the price and quantity used in the analysis is the value weighted average price across transactions and the net quantity. On days that a position is opened (purchased when previous holdings were 0) it is not included in the portfolio as available to be sold because it is unclear if it is in the portfolio at the time a different position is sold. Short positions are excluded from the analysis (about 0.3% of holdings).[6] Some trades have negative commissions which could indicate canceled trades (about 0.5% of observations). All observations of a stock that ever have a negative commission for a given investor are dropped.[7]

Returns at time of sale are calculated between the purchase price and the closing price on the day prior to the sell day.[8] If a position is already in the portfolio and additional shares are

[6] For accounts not present in the first month of holdings data, a position is considered short when it is sold with prior holdings of the position less than or equal to zero, or when a position is purchased and the resulting holdings are zero or negative.

[7] Results are robust to including these positions, or to using a cleaning algorithm that matches the two sides of a cancelled trade and keeps the remaining observations.

[8] This is chosen to keep consistency between the calculation of returns for actual sales and paper gains and losses. The analysis is not materially different if the actual sale price is used on positions that are sold and the CRSP closing

purchased, the purchase price used to calculate returns after this date is the value weighted average of the multiple purchase prices.

In order to study complete portfolios I drop portfolios containing positions for which the purchase price is unknown. This is accomplished by excluding accounts with holdings in the first month of the position files. These positions were purchased before the start of the dataset, thus the purchase price is not known. This excludes roughly 25% of accounts. As the paper examines portfolio rank, investors must hold at least five stocks to be included in the analysis. This excludes about 19% of observations.

Table 1 Panel A shows summary statistics describing the data on individual investors. After the filters are applied the data includes 10,619 unique accounts, 94,671 sell day by account observations with a sale, and 1,051,160 positions held on those days. The average portfolio is comprised of 11.1 stocks. On a sell day, on average 12% of positions in a portfolio are sold, of which 9.6% are liquidated.

The mutual fund analysis combines holdings data from Thompson-Reuters and fund price and volume information from CRSP, and stock return information from CRSP. The Thompson-Reuters and CRSP files are merged by the Wharton Financial Institution Center number (WFICN). Returns are calculated analogously to the investor data, but using report dates because sell dates are not known. A sale is defined as a decrease in the number of shares from the previous report, while a liquidation is defined as not holding any shares in a position which was held in the previous report. To be included in the analysis a fund must hold at least 20 CRSP merged stocks on a report date. I apply the Frazzini (2006) filters to the Thompson-Reuters data

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price used for those that are not, or if the closing price of the sell day instead of the day before the sell day is used. The analysis ignores trading fees, but is nearly identical if returns net of fees are used instead (see Appendix Table IA.22). A stock is included only if there is CRSP information for every observation.

to exclude observations that appear to be errors.[9] The sample period studied is 1990-2010, though to construct the purchase price history I use data starting from 1980.

Table 1 Panel B shows summary statistics for the mutual fund data. There are 4,730 funds holding 120 stocks on average. There are 129,415 report day by account observations with 15.6 million positions held on these days. 38.9% of positions are at least partially sold between report dates and 15.1% of positions are liquidated.

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 Univariate Results

Table 2 shows the rank effect, the tendency to sell the best and worst-ranked stocks, in the simplest specification, with no controls. Stocks are ranked by return from purchase as best, second best, worst, second worst and middle. Middle includes all stocks not ranked in the top or bottom two positions. A stock is ranked best if it has the highest return from purchase price in the portfolio, and worst if it has the lowest. For investors, only days where at least one stock is sold are examined, thus each observation is a stock (*j*) for an investor (*i*) on a sell day (*t*). For mutual funds report days are examined. Thus each observation is a stock (*j*) for a fund (*i*) on a

[9] 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%.

report day (t). Each row is the proportion of positions of the indicated rank that are sold. The best and worst rows are:

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

 # Best Sold is the number of best positions on a sell day (report day for funds) that had their positions decreased and *# Best Not Sold* is the number of best positions where the number of shares increased or stayed the same. Other ranks are defined similarly. The measure is analogous to the proportion of gains (losses) realized used in Odean (1998).

The rank effect can be seen by examining the bottom portion of the table. *Best – Middle* is the difference between the best and middle rows with the t-statistic for the test that they are equal, clustered by date and account, underneath. For individual investors a best-ranked position is 16.3% more likely to be sold than a middle-ranked position and a worst-ranked position is 8.5% 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 sold than a middle-ranked position, and a worst-ranked position is 19.1% more likely to be sold.

This analysis aggregates across investors, thus it may mask heterogeneity in their tendency to sell extreme positions. For example, the same averages would be observed if two traders are more likely to sell both best and worst-ranked positions, or if one trader sells only best positions, with the other sells only worst. This could occur if certain investors over-extrapolated past performance and always sold their worst performing stocks, while other traders believed in mean reversion and always sold their best.

Figure 1 graphs a heat map of the joint density of the probability of selling best and worst positions for each investor and fund with at least five sell days or report 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 lighter the cell, the more density it has. If half of the investors sold only best-ranked positions, and half sold only worst, the bottom right and top left corners would be white. For both types of traders these are the areas with the lowest density and are black. The correlation between the proportion best sold and proportion worst sold is positive, 0.37 for individual investors and 0.41 for mutual funds. Thus traders tend to sell both best and worst-ranked stocks.

Many theories posit that investors trade to rebalance their portfolio, or after they update their beliefs changing the composition of the optimal portfolio. 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 should be sold and the worst-ranked stock should be purchased. The selling of worst-ranked stocks rules out simple rebalancing with fixed weights and constant beliefs as the cause of the rank effect.

4.2 Controlling For Firm-Specific Factors

One possibility is that rank is simply proxying for firm-specific information. For example, extreme-ranked stocks may be more likely to have had high or low recent returns, increases in volatility, or mentions in the news. Rather than attempting to control for all possible stock-specific characteristics, 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. This group of extreme-ranked stocks and non-extreme-ranked stocks have the identical stock-specific information set and differs only in rank across investors. If investors respond to firm-specific factors the same way regardless of rank, this sample will not exhibit the rank effect.

Table 3 Panel A examines whether there is a rank effect for this subsample. Taking the best row as an example, the sample is limited to stocks that on the same sell day are best-ranked in one investor's portfolio, and not best-ranked in another investor's portfolio. Each observation has a *Sell* variable equal to one if the position is sold and zero if it is not. The difference between this variable for stock ranked best and stocks not ranked best for the same stock on the same day is taken, and the average is reported:[10]

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

Where t indexes each day and $j(t)$ indexes each stock that on day t is best-ranked in one portfolio and not best-ranked in another. *# Pairs* is the number of unique day by stock observations. The worst row contains the same measure for worst-ranked positions.

Extreme-ranked stocks are more likely to be sold than the same stocks in portfolios where they are not extreme-ranked. Individual investors are 10.2% more likely to sell a best-ranked stock than the same stock that is not best-ranked, and are 6.3% more likely to sell a worst-ranked stock than the same stock that is not worst-ranked. Mutual funds are 7.4% more likely to sell a best-ranked stock and 12.6% more likely to sell a worst-ranked stock.

Panel B conducts a similar analysis, utilizing a linear probability model and stock by day fixed effects. A sell dummy variable is regressed on a best dummy variable, a worst dummy variable and interaction fixed effects for each stock and date pair. With this interaction fixed effect, the regression is identified based on variation from stocks that have different ranks on the same day across investors' portfolios. Thus the results are quite similar to Panel A as both individual investors and mutual funds are more likely to sell extreme-ranked stocks.

[10] If the same stock on the same day is best-ranked (or not best-ranked) in multiple portfolios, the average of sell is taken over these investors with the same stock on the same day with the same rank.

I also consider the question of whether the rank effect can be driven by changes in investor expectations of means, variance, or covariances. Table 3 casts doubt on this explanation, nonetheless, I directly test the effect in Appendix Table IA.16 and Appendix Table IA.17 explicitly controlling for changes to expectations of 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 Performance Since Purchase

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.[11] The disposition effect is based on a stock's performance from the time it was purchased, so without further controls rank could be proxying for such performance and driving the rank effect.

The sharpest distinction between the rank effect and simple descriptions of the disposition effect is the tendency for investors to sell their most extreme-ranked *losing* positions, which the disposition effect suggests 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 the simple disposition effect can account for the rank effect.

While the disposition effect is often described purely in terms of gains and losses, the magnitude of the gain and loss can impact trade as well (Ben-David and Hirshleifer 2012). Empirically, investors are more likely to sell a position as it becomes a larger gain, or a larger

[11] 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.

loss. Investors trading on the magnitude of past returns could drive the rank effect as portfolio rank is best with the largest gain and worst with the largest loss.

Return levels and other factors are controlled for to show that relative performance, not return levels, is responsible for the rank effect. Using logit regressions, a dummy variable *Sell*, equal to one if a stock is sold and zero otherwise, is regressed on variables for rank and a number of controls taken from Ben-David and Hirshleifer (2012) and listed in Equation 1: [12]

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

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 with returns (in absolute value) and to have a different slope in the positive and negative domain.[13]

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 an extreme 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**$\sqrt{Holding\ Days}$)

[12] This paper's focus is slightly different than Ben-David and Hirshleifer (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 (see Appendix Table IA.25).

[13] The Internet Appendix contains robustness checks of these specifications and shows that the results are robust to examining subsets of portfolio size (Appendix Table IA.3), days between trade (Appendix Table IA.5) and allowing for non-linear patterns in the level of returns (Appendix Table IA.1).

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 variance over the previous year, is interacted with the gain dummy (*Gain*Variance*) and loss dummy (*Loss*Variance*).[14] All results are presented as marginal effects.

Table 4 column [1] presents the regression for individual investors, with no rank variables. 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, consistent with Ben-David and Hirshleifer (2012), 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 variables to examine the rank effect for individual investors. Column [2] adds dummy variables for the highest return in the portfolio (*Best*) and the lowest (*Worst*). The best-ranked stock is 15.7% more likely to be sold and the worst-ranked stock (*Worst*) is 10.7% more likely to be sold, both with large t-statistics. After including the two dummy variables for rank, the *Loss*Return* and *Gain*Return* coefficients are insignificant and the *Gain* dummy coefficient decreases.

Column [3] includes dummies for the *Best* and *Worst*-ranked stocks as well as *2nd Best* and *2nd Worst*-ranked stocks. The coefficient on *Best* increases from 16.3% in Table 2 without controls to 20.5% with controls. The coefficient on *Worst* increases from 8.5% without controls to 14.7% with controls. Rather than explaining the rank effect, the inclusion of disposition effect controls makes the rank effect larger. After including rank controls, the coefficients on

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

*Loss*Return* and *Gain*Return* switch signs. Together, this suggests that the propensity to sell positions at a larger gain and larger loss observed in Ben-David and Hirshleifer (2012) is better understood as a propensity to realize extreme-ranked positions.

Further, adding rank variables to the basic specification increases the explanatory power of the regressions. Examining the R^2 presented below columns [1] and [3] there is an increase from 0.010 to 0.047. While this R^2 indicates much more is needed to fully explain trading behavior, including controls for rank 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 11.9% and the coefficient on *Worst* is 16.9%, both are highly significant. The coefficients on *Loss*Return* and *Gain*Return* decrease in size after the rank variables are added, but, unlike the individual investor specification, retain their sign and significance. 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 2nd 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 with the addition of the controls the importance of being the highest, or lowest return becomes clear.

To provide a more precise control for the disposition effect, Table 5 repeats the analysis, restricting the sample to individual investor portfolios where all positions are at a gain and all positions are at a loss (omitting the gain and loss dummies).[15] This restricted sample still exhibits

[15] The test is limited to individual investors as there are very few mutual fund reports where all positions are at a gain or a loss. Funds have 129,415 report days of which 301 are all at a gain and 159 are all at a loss.

the rank effect. Traders with all positions at a gain are 6.2% more likely to sell their worst stock and 11.7% more likely to sell their best compared to a middle stock. Traders with all positions at a loss are 5.8% more likely to sell their worst and 4.5% more likely to sell their best stock compared to a middle-ranked position.

In the context of models of trade based on narrow framing, these results suggest that the reference point needs to incorporate performance relative to the portfolio. The Ingersoll and Jin (2013) realization utility model with a reference point of the purchase price offers an illustrative example. In this model investors narrowly frame on each stock and sell a stock when its price is above an upper cutoff or below a lower cutoff. If such an investor holds a portfolio with all positions at a gain, each position is above the lower cutoff and so the worst-ranked position will never be sold. Similarly, when all positions are at a loss the best-ranked position is not sold. Table 4 and Table 5 shows this is not the case.[16]

Alternatively, a standard Ingersoll and Jin investor can use a reference point based on relative evaluation within the portfolio and display the rank effect in such situations. When all positions are at a loss, such a reference point would allow the investor to sell a best-ranked position, and similarly sell a worst-ranked position when all positions are at a gain. Thus the empirical results suggest that the reference point cannot be based solely upon those mooted in the literature and must vary with relative performance in the portfolio.

Section 4.2 examines whether rank proxies for common information, while this section examines whether trading based on past returns can explain the rank effect. By utilizing both controls for past performance and also including fixed effects for the interaction of stock and

[16] Table 5 shows this is true for a zero return reference point. As an alternative example, an Ingersoll and Jin investor could use the market return as the benchmark to measure gains and losses. Appendix Table IA.2 presents a similar analysis based on when all holdings beat the market, or do not beat the market and finds a rank effect.

day, the results in Table 6 rule out both simultaneously. Further it controls for investor specific effects by adding fixed effects for the interaction of investor and day.

Even with these fixed effects and controls, the rank effect remains a major determinant of trading behavior. Column [2] and [5] include stock by day fixed effects so the regression is identified based on variation of rank across stocks on the same day. Individual investors are 14.1% more likely to sell best-ranked positions and 10.4% more likely to sell worst-ranked. Mutual funds' best-ranked positions are 9.4% more likely to be sold, and worst-ranked positions are 12.3% more likely to be sold.

Columns [3] and [6] add dummy variables for investor by day fixed effects. This controls for investor-specific characteristics on a given day. These two sets of dummy variables remove a significant amount of the variation in the data, but the rank effect remains. Investors are 7.9% more likely to realize a best-ranked position and 5.1% more likely to realize the worst-ranked. Funds are 3.7% more likely to realize their best-ranked position and 7.7% more likely to realize their worst. The results indicate that neither stock specific effects nor investor specific effects, allowing for separate effects on each day, are responsible for the rank effect.[17]

4.4 Rank Effect Mechanism

The salience of extreme outcomes offers one possible explanation for the rank effect for individual investors. If an investor holds multiple stocks they can pay more or less attention to certain stocks in their portfolio. If investors pay more attention to extreme-ranked stocks they will be more likely to trade these stocks which could account for the rank effect.

If extreme positions are salient, investors will not only be more likely to sell, but also more likely to buy additional shares of a stock with the best or worst return. Investors decide to

[17] Appendix Table IA.12 and Appendix Table IA.13 present analysis using fixed effects without using the date interaction. These specifications yield a similar magnitude, and if anything are slightly stronger.

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 7 column [1] presents summary statistic results similar to the difference rows in Table 2. A best-ranked position is 0.6% more likely to be realized than a middle position and a worst-ranked is 3.8% more likely to be. Table 7 columns [2] and [3] present the same specification as Equation 1 controlling for returns since purchase, but uses a dummy *Buy*, equal to one if additional shares 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 1.7% 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 purchased than the baseline middle probability of 2.6%.

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 the extremes of ordering are attention grabbing, ideally investors would see stocks presented in an order uncorrelated with economic outcomes. While investors do not see stocks presented in a random order, they often see their holdings presented alphabetically by company name in a brokerage statement or online.[18] Alphabetical order is unlikely to exhibit significant correlation with economic variables of interest, after controlling for stock-specific information.

Table 8 shows that the stocks with the names that come first or last in the portfolio by alphabetical order are more likely to be both purchased and sold. The table presents regressions of *Sell* or *Buy* on a dummy variable for the first and last name in the portfolio, along with stock by day fixed effects. The fixed effect limits identification to variation from stocks that are alphabetically first or last in one portfolio and not first or last in another portfolio on the same

[18] Unfortunately I do not have brokerage statements associated with this dataset. Alphabetical by name is consistent with the internal stock identifier used by the brokerage. Similar results are obtained using ticker instead of company name (see Appendix Table IA.19).

day, thereby controlling for stock specific information on a given day. Columns [1] and [4] limit the data to the first and second name by alphabetical order. The first name is 2.6% more likely to be sold than the second name and 0.8% more likely to be purchased. Columns [2] and [5] limit the sample to the last and second to last name. The last name is 2.9% more likely to be sold than the second to last name and 0.8% more likely to be purchased. When the entire sample is considered in columns [3] and [6] both the first and last name are 6.1% more likely to be sold than a middle name and both are 1.7% more likely to be purchased. The unconditional probability of sale is 11.3% and 3.3%, respectively for sales and purchases. In these regressions, company names contain no economically meaningful information, but still have a meaningful impact on the probability a position is sold because of the salience induced by being at the extreme of an ordering.

To empirically understand what aspect of rank is important for the rank effect, I examine three potential mechanisms suggested by various theories of salience:

1) *Rank Extremeness:* As discussed in Section 2, rank-dependent utility models (such as Tversky and Kahneman 1992) predict that extreme returns receive the most attention.
2) *Average Extremeness:* Models such as Bordalo, Gennaioli, and Shleifer (2012) predict a position becomes more salient as it becomes more extreme relative to a portfolio benchmark, such as the average holding return in the portfolio.
3) *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 (Hauser 2013).

Empirically, both rank extremeness and outlier extremeness are significant aspects of the rank effect. This is consistent with the theory of consideration sets suggesting that the choice of what to pay attention to is an important aspect of the trading decision.

Average extremeness is suggested by the model of Bordalo, Gennaioli, and Shleifer (2013) where certain stocks are salient because they are most different from a benchmark. Salient assets, such as those considered safe or with positive skewness, receive attention because they are “most different or salient relative to the average” in the market. A stock-specific benchmark is ruled out in section 4.2, but if this model is extended to include a portfolio specific benchmark, such as the average return in the portfolio, it predicts the salience of extreme positions because they are the most different from this average.

Two possible benchmarks for average extremeness are utilized, the difference from the average and the difference from the median. The average variable is scaled by the standard deviation of portfolio returns ((*Return-Avg Return)/SD Portfolio*) while the difference from the median return (*Return-Med Return*) is included as a level variable without scaling.[19] Scaling by standard deviation normalizes the measure across portfolios to examine extremeness in the distribution of portfolio returns. The unscaled measure controls for a level effect.

The third measure captures outlier extremeness, how much of an outlier a position is compared to the next closest return, motivated by models of consideration sets. An individual utilizes a consideration set if they simplify a complex problem by first using a rule of thumb, a heuristic, to consider only a subset of the initial options. A common heuristic is to consider any option that has at least one attribute that an investor cares about, and ignore options that lack all of these attributes (Hauser 2013). This is known as a disjunctive decision rule which in a portfolio setting can lead to outlier extremeness.

For example, assume an investor utilizes such a rule and that one attribute that warrants consideration is the investor viewing a stock as having performed well or poorly.[20] When deciding which stocks have done well or poorly the investor is deciding what stocks are in the

[19] 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*. See Appendix Table IA.20 for these specifications.

[20] In addition they can also use other “excitement” criteria such as stocks that were in the news, had high recent returns or stocks that caught their eye at the top of the brokerage statement. This paper focuses on rank, but that does not preclude other avenues that may induce salience.

middle so they can be ignored. If the performance of the 2nd ranked stock appears different relative to the extreme stock it, along with other stocks in the middle, is excluded from the consideration set. Thus, outlier extremeness between the extreme-ranked stock and the 2nd most extreme stock can impact the attention an extreme-ranked position receives. Outlier extremeness is measured as the difference between the best and second best return *Best*(Best Return - 2nd Best Return*) and the worst and second worst return *Worst*(Worst Return - 2nd Worst Return*).

Table 9 presents the results for different specifications to determine which measures of extremeness best capture the rank effect.[21] Examining columns [1], [2] and [3], each of the variables on its own is associated with more selling. However, after adding dummy variables for the top two and bottom two positions in columns [4] and [5] the average return variables switch signs while the median return variables become smaller and insignificant for the negative coefficient. The variables for outlier extremeness decrease with the addition of rank dummies, but remain economically meaningful and significant. Columns [7] and [8] include both measures of extremeness and the variables proxying for average extremeness are unable to account for the rank effect. Thus both rank and outlier extremeness are significant aspects of the rank effect. This is consistent with investors utilizing consideration sets as a part of their trading decision.

5. Price Effects

The rank effect has a large impact on trading behavior, but is there enough rank based selling to induce predictable returns? Given heavy selling and downward sloping demand, selling pressure from rank-based trade will impact the returns of extreme-ranked stocks leading to a decrease and subsequent reversal. Using the mutual fund data, a trading strategy is constructed to exploit this predictable impact on prices.

[21] Appendix Table IA.15 presents the analogous results for buying, finding a similar pattern.

First, I examine the selling intensity of mutual funds and show that mutual funds sell a larger proportion of their best and worst-ranked positions, and are more likely to liquidate entire positions for both best and worst-ranked positions. Further, the selling is more intense for worst-ranked stocks compared to best-ranked stocks.

Table 10 shows the results. The *Fraction Sold* columns present linear regressions, with the number of shares sold divided by the number of shares held on the left hand side. The *All Holdings* 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 and 2.3% of the best-ranked are sold compared to all stocks that are sold. Worst-ranked stocks have a significantly larger fraction sold of 17.5% more compared to all other stocks (14.1% compared to 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 the sell dummy is replaced with a dummy equal to one if a position is liquidated. 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. Worst-ranked stocks are sold the heaviest, so they should receive more price pressure and exhibit larger price effects.

The analysis shows that mutual funds sell extreme-ranked positions before the next report date and they sell these positions heavily, especially for worst-ranked positions. 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. In the simplest specification, 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. The same is done with worst-ranked stocks. I subsequently examine portfolios weighted more heavily towards stocks predicted to have received more price pressure. 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 portfolio held from June to July is based on funds reporting 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.[22] 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, the best-

[22] See Appendix Table IA.14 for summary statistics of the stocks that comprise these portfolios.

ranked stocks will have positive returns while the worst will 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 11 presents CAPM, Fama-French three factor, four-factor and five-factor regressions (including a one month reversal factor) for the equal-weighted 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 to 20 basis points 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 10 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 12 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 strategy 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 13 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) with return the month after ranking (multiplied by 100) as the dependent variable. Column [1] presents the results from the regression including only dummy variables for being the best or worst-ranked position on the right hand side. 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 0.253 and a t-statistic of 2.04 and *Worst* having a coefficient of 0.743 and a t-statistic of 2.64.

Next controls are included for five anomalies for which rank may proxy - the earnings announcement premium (Beaver 1968; Frazzini and Lamont 2007), the Gervais, Kaniel and Mingelgrin (2001) high-volume return premium, the dividend month premium (Hartzmark and Solomn 2013), idiosyncratic volatility (Ang, Hodrick, Xing and Zhang 2006) and share issuance (Pontiff and Woodgate 2008).[23] 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-based incentives may induce the trade of extreme-ranked positions. U.S. tax law creates time varying incentives to sell positions throughout the year, especially for losses (Constantinides 1984). Figure 2 repeats the specification from Table 4 column [3] separately for each calendar month. It graphs the coefficients on *Best* and *Worst* along with their 95% confidence intervals as dotted lines. As expected, there is a seasonal pattern where losses are more likely to be realized in November and December due to tax considerations. The reverse pattern is apparent for the best positions which are most likely to be sold in January. Even so, the 95% confidence intervals are always far above zero. Thus even though the coefficients exhibit seasonality, the effect in each month for both *Best* and *Worst* is large and significant.

Roughly 20% of the observations in the data come from deferred tax accounts. Such tax deferred accounts lack many of the tax induced incentives that might account for the rank effect.

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[23] 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 or in the bottom five by volume. 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. Idiosyncratic volatility for stock j on day t is calculated as the standard deviation of the residuals from a regression of excess return on *MKT*, *SMB* and *HML* from t-1 to t-21. Share Issuance for stock j with holding period ending in month M is the log of shares outstanding at M-6 minus the log of shares outstanding at M-17 using the same month definition as the predicted dividend variable.

Thus finding the rank effect in these accounts suggests trading based on short term tax incentives does not account for the effect. Table 14 separates the analysis by the tax status of the accounts. Tax deferred accounts exhibit a rank effect of a similar magnitude to the standard taxable accounts. Thus tax incentives do not appear to be responsible for the rank effect.

6.2 Covariate Balance

If the data lacks the requisite covariate balance, logit regression may not identify the effect of becoming extreme-ranked. Covariate balance refers to the similarity of the empirical distributions of the covariates for extreme rank and middle rank. A lack of balance can increase model dependence and bias the estimation of the effect of being extreme-ranked (for example Abadie and Imbens 2007; Ho, Imai, King and Stuart 2007). There is a mass of high return values that are ranked best with 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.[24] 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

[24] Similar results are obtained using these more traditional methods. Appendix Table IA.24 presents a similar analysis using a nearest neighbor propensity score match.

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 15 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 Table 2.[25]

The second column contains these values utilizing 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 (626 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 2nd column labeled Entropy shows that after entropy balancing, the rank effect increases and remains significant for both individual investors and mutual funds. For individual investors, the values of 12.8% for best and 8.4% for worst are both slightly smaller than the coefficients with simple controls in the logit. For funds, the values of 11.6% for best and 16.5% for worst are of a similar magnitude to the previous coefficients. These tests measure the same difference as the logit regressions of Table 4 columns [2] and [5] yield similar results. Thus the

[25] The magnitude is smaller as the comparison groups now contains extreme-ranked positions (i.e. *Not Best* contains worst-ranked stocks) and the 2nd best and 2nd worst positions making the comparison group mean slightly higher.

entropy balancing results underscore the significance of the effect and suggest the logit results are not driven by a lack of covariate bias.

As a final example of the robustness of the rank effect I show that it is large and robust when the entropy balanced sample is examined separately day by day. Figure 3 graphs the mean difference of the entropy balanced sample for each day. The x-axis indicates the daily entropy balanced mean for Best-Not Best or Worst-Not Worst, with the dotted red line indicating a 0 difference. The y-axis graphs the number of days with that difference. Thus mass to the right of the red line represents days with a positive rank effect, and mass to the left indicates days without a rank effect. 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 days (719 of 756 for Best and 693 of 756 for Worst) extreme-ranked stocks were more likely to be sold, indicated by a positive value on the x-axis. For best-ranked stocks, 524 days have a positive and significant difference (the red bars), while no day has a negative and significant difference. For worst-ranked positions, 327 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 (the purple bars). The results suggest that a lack of covariate balance is not a significant factor in the initial analysis.

7. Conclusion

This paper documents a new stylized fact which I term the rank effect. The effect refers to the finding that best and worst-ranked positions are more likely to be sold compared to positions in the middle of the portfolio. This effect is present for 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 returns of 40 basis points per month for best-ranked stocks and 160 basis points per month for worst.

The paper shows that portfolio specific salience is an important component to the trading decisions of individual investors. The alphabetical order in the portfolio by company name is not related to a stock's fundamentals, and thus offers a clean test of the salience induced by ordering. Demonstrating the importance of portfolio specific salience shows that an integral portion of the trading process that has hithertofore not been emphasized, is deciding what stocks to pay attention to through the formation of consideration sets.

The rank effect illustrates a fundamental component of investor behavior, namely that how a stock is viewed is based in part on how it compares to other holdings in a portfolio. This is in stark contrast to the commonly used assumption of narrow framing, where each stock is assumed to be evaluated in isolation without regard to the other holdings in a portfolio. While investors are not forming optimal portfolios, the portfolio is a relevant and important component to trading behavior.

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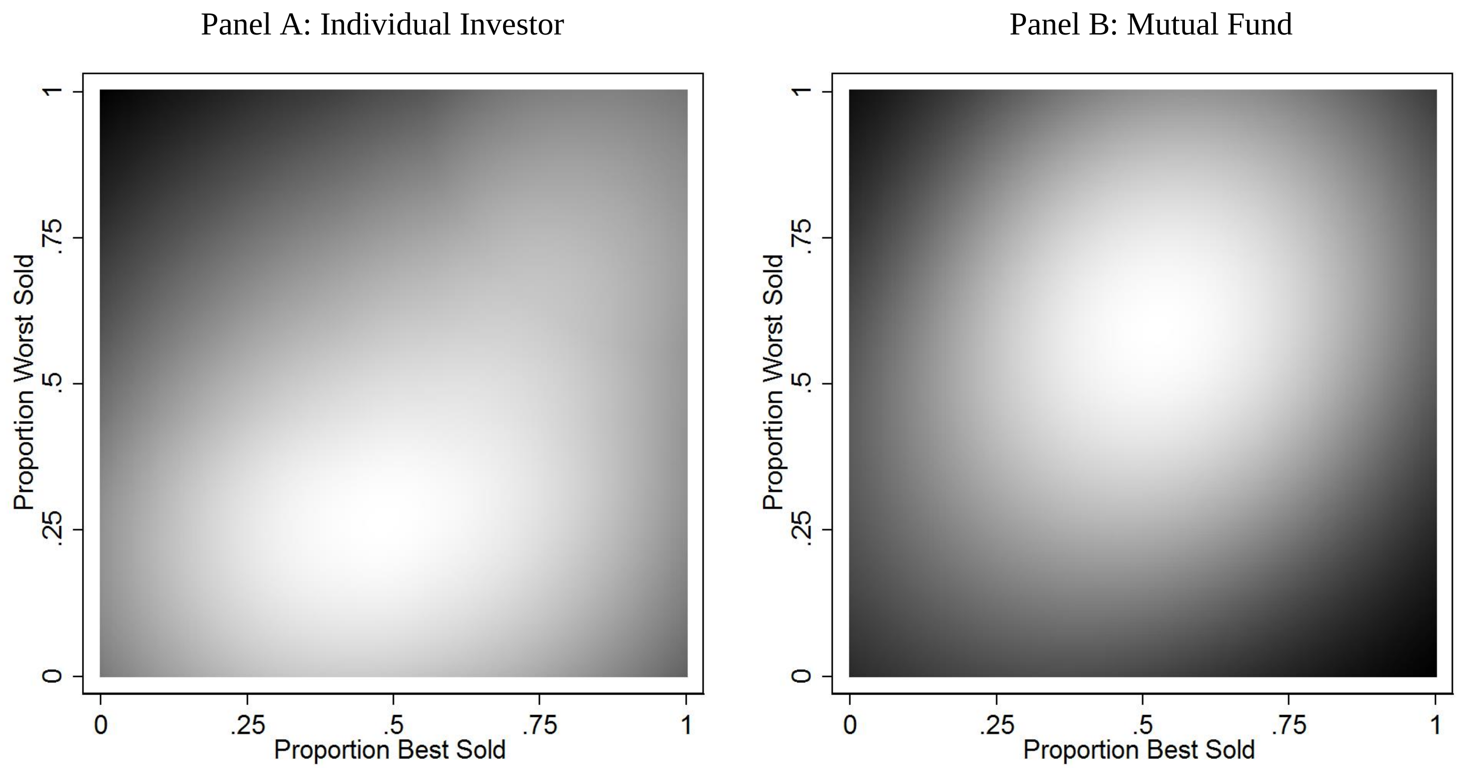
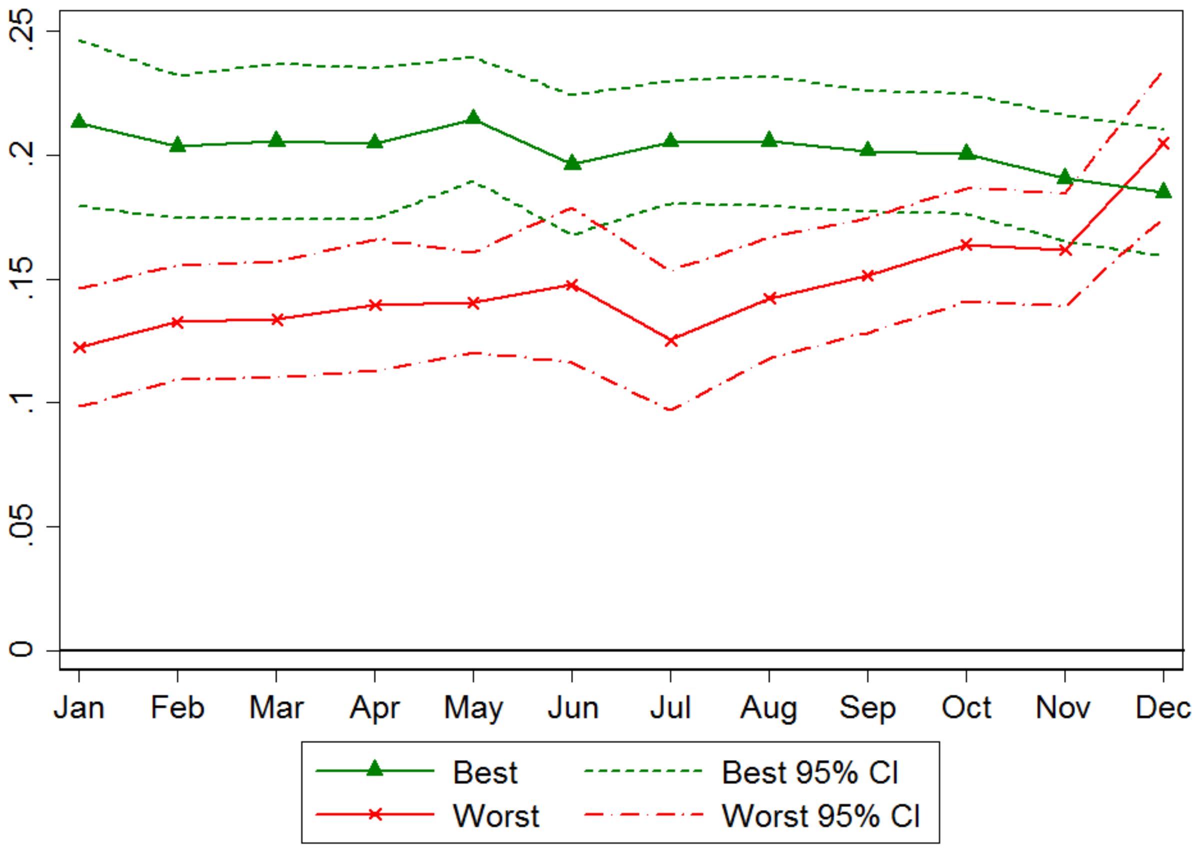
Figure 1 - Heterogeneity of Rank Based Selling



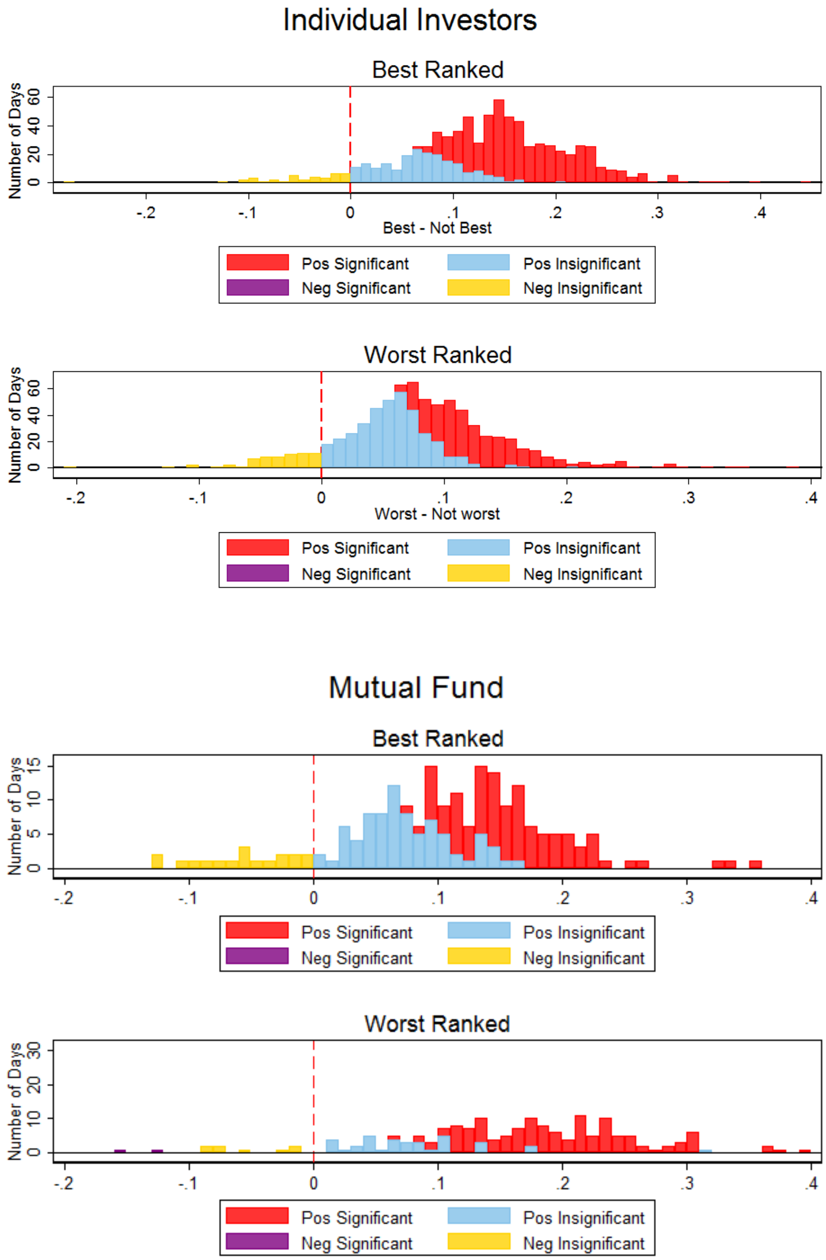
These figures present the joint density between the investor specific proportion worst realized (#Worst Sold/(#Worst Sold+#Worst Not Sold)) and the investor specific proportion best realized (#Best Sold/(#Best Sold+#Best Not Sold)) for individual investors and fund managers that have at least five sell days, or report days in the data. Lighter shading corresponds to a higher the density with white indicating the densest portion. Darker shading corresponds to less density with black indicating the lowest density. Investor data covers January 1991 to November 1996 and mutual fund data covers January 1990 to June 2010.

Figure 2 - Seasonality of the Rank Effect for Individual Investors



Marginal effect from logit regression as specified in Table 4 column [3]. 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 3 – 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. 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 June 2010. Standard errors are clustered by account or fund and indicated significance is at the 5% level.

Table 1 – Summary Statistics

Panel A: Individual Investor

	Observations	Mean	Std. Dev.	Minimum	25th Pctile	Median	75th Pctile	Maximum
#Accounts	10,619							
#Sell Days	94,671							
Proportion Sold	1,051,160	0.120						
Proportion Liquidated	1,051,160	0.096						
Portfolio Size	94,671	11.103	13.887	5	6	8	12	429
Holding Days	1,051,160	340.299	381.702	1	66	194	477	2,148

Panel B: Mutual Fund

	Observations	Mean	Std. Dev.	Minimum	25th Pctile	Median	75th Pctile	Maximum
#Funds	4,730							
#Report Days	129,415							
Proportion Sold	15,604,501	0.389						
Proportion Liquidated	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. 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	0.121	0.389
Worst	0.169	0.576
2nd Worst	0.137	0.529
Middle	0.084	0.384
2nd Best	0.195	0.487
Best	0.247	0.503
Worst-Middle	0.085	0.191
	(15.20)	(20.97)
Best-Middle	0.163	0.119
	(28.36)	(15.36)
Observations	1,053,065	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. For example, the Best row reports #Best Sold/(#Best Sold+#Best Not 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. 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 one Portfolio and Not Extreme-Ranked in Another Portfolio

Panel A: Same Stock Match		
	Individual Investor	Mutual Fund
Best - Not Best	0.102	0.074
	(20.77)	(25.45)
	37,374	48,079
Worst - Not Worst	0.063	0.126
	(16.94)	(30.64)
	30,219	46,260

Panel B: Stock by Day Fixed Effects		
	Individual Investor	Mutual Fund
Best	0.094	0.075
	(15.81)	(15.09)
Worst	0.064	0.125
	(11.36)	(12.69)
Stock by Date FE	X	X
Observations	1,048,549	15,603,394
R^2	0.111	0.053

Panel A presents the difference in probability between a best (worst) ranked stock and a not best (worst) ranked. The sample includes only stocks on the same day are extreme-ranked for at least one investor and not extreme-ranked for at least one other investor. First the average sale probability is taken for each stock date by extreme rank observation. Next the difference between this value for extreme rank and not extreme rank is taken. The Best – Not Best row reports this difference in probability for best-ranked, and the Worst – Not Worst row reports this difference for worst. The number in parenthesis is the t-statistic clustered by date and cusip and the number below that is the number of cusip by day observations. Panel B presents a linear regression of sell on a best and worst dummy with a fixed effect for each stock by day pair. The top number is the coefficient, 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. 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. 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 June 2010.

Table 4 –Rank Effect with Controls for Past Performance

	Individual Investor			Mutual Fund		
	[1]	[2]	[3]	[4]	[5]	[6]
Best		0.157	0.205		0.109	0.119
		(20.15)	(21.10)		(11.61)	(12.01)
Worst		0.107	0.147		0.163	0.169
		(19.93)	(20.06)		(12.17)	(12.25)
2nd Best			0.125			0.105
			(16.51)			(12.61)
2nd Worst			0.085			0.122
			(14.37)			(10.40)
Return*Gain	0.045	-0.002	-0.019	0.034	0.024	0.017
	(4.55)	(-0.28)	(-2.58)	(6.93)	(4.57)	(3.15)
Return*Loss	-0.155	-0.036	0.004	-0.272	-0.242	-0.222
	(-7.47)	(-1.84)	(0.19)	(-12.39)	(-11.21)	(-10.27)
Gain	0.037	0.029	0.026	-0.013	-0.014	-0.014
	(9.60)	(8.31)	(8.00)	(-3.92)	(-4.24)	(-4.29)
Return*Gain	-0.002	-0.001	-0.001	0.000	0.000	0.000
*√Holding Days	(-5.00)	(-3.36)	(-2.41)	(-4.59)	(-3.57)	(-2.87)
Return*Loss	0.004	0.002	0.002	0.008	0.007	0.007
*√Holding Days	(3.83)	(2.82)	(2.03)	(11.09)	(11.08)	(11.05)
Variance *Gain	5.914	4.475	3.790	4.971	5.088	5.111
	(2.94)	(2.90)	(2.81)	(1.85)	(1.90)	(1.92)
Variance *Loss	-3.644	-3.306	-3.047	-2.557	-2.329	-2.039
	(-3.45)	(-3.70)	(-3.87)	(-1.97)	(-1.94)	(-1.83)
√Holding Days	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-8.90)	(-9.64)	(-10.37)	(-5.29)	(-5.27)	(-5.28)
Observations	1,048,549	1,048,549	1,048,549	15,603,394	15,603,394	15,603,394
R^2	0.010	0.032	0.047	0.005	0.006	0.007

This table presents marginal effects from logit regressions. The dependent variable is a dummy variable equal to 1 if a stock is sold. 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. Investor data covers 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. Mutual fund data are from report dates from January 1990 to June 2010. 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 5 – Rank Effect for Individual Investors with Controls for Past Performance When All Positions in a Portfolio are at a Gain or Loss

	All Gain	All Loss
Best	0.117	0.045
	(8.31)	(2.09)
Worst	0.062	0.058
	(5.29)	(3.10)
2nd Best	0.073	0.007
	(7.19)	(0.41)
2nd Worst	0.040	0.025
	(3.88)	(1.64)
Return	0.001	0.119
	(0.04)	(1.35)
Return*√Holding Days	-0.001	0.003
	(-0.81)	(0.74)
Variance	18.006	-2.502
	(5.16)	(-1.49)
√Holding Days	-0.001	-0.003
	(-1.66)	(-1.60)
Observations	23,679	8,898
R^2	0.013	0.012

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. 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.

Table 6 - Rank Effect with Fixed Effects for Stock by Day and Account by Day

	Individual Investor			Mutual Fund		
	[1]	[2]	[3]	[4]	[5]	[6]
Best	0.118	0.141	0.079	0.041	0.094	0.037
	(27.52)	(23.24)	(10.74)	(10.46)	(11.69)	(10.97)
Worst	0.060	0.104	0.051	0.110	0.123	0.077
	(14.45)	(17.83)	(6.80)	(21.45)	(12.25)	(17.22)
2nd Best	0.057	0.092	0.044	0.039	0.080	0.034
	(21.63)	(19.16)	(7.82)	(14.26)	(12.51)	(13.38)
2nd Worst	0.019	0.058	0.014	0.073	0.088	0.051
	(7.45)	(12.70)	(2.59)	(18.86)	(10.78)	(15.20)
Return*Gain	0.013	-0.050	-0.017	0.034	0.005	0.029
	(1.78)	(-4.58)	(-1.26)	(10.34)	(1.05)	(9.51)
Return*Loss	-0.032	0.183	0.089	-0.226	-0.160	-0.143
	(-1.40)	(5.30)	(1.94)	(-12.72)	(-5.11)	(-11.56)
Gain	0.031	0.037	0.045	-0.007	-0.016	-0.009
	(7.99)	(8.20)	(7.58)	(-3.78)	(-6.15)	(-6.29)
Additional Controls	X	X	X	X	X	X
Account x Date FE	X		X	X		X
Stock x Date FE		X	X		X	X
Observations	1,048,549	1,048,549	1,048,549	15,603,394	15,603,394	15,603,394
R^2	0.128	0.677	0.769	0.326	0.108	0.389

This table presents coefficients from linear 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. Account x Date FE indicates a fixed effect for each interaction of account and date. Stock x Date FE indicates a fixed effect for each interaction of cusip and date. 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. 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 where 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 coefficient, 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 7 – Rank Effect for Buying

	Summary Statistics	Regression	
	[1]	[2]	[3]
Best	0.006	0.017	0.022
	(2.20)	(6.24)	(6.51)
Worst	0.038	0.021	0.030
	(13.91)	(9.80)	(9.57)
2nd Best	0.009		0.017
	(3.37)		(6.27)
2nd Worst	0.032		0.022
	(12.22)		(8.42)
Return*Gain		-0.015	-0.017
		(-5.61)	(-6.46)
Return*Loss		-0.062	-0.051
		(-7.35)	(-6.20)
Gain		-0.010	-0.009
		(-8.87)	(-7.98)
Return*Gain		0.000	0.000
*√Holding Days		(5.91)	(6.64)
Return*Loss		0.003	0.002
*√Holding Days		(7.00)	(6.77)
Variance *Gain		1.068	1.036
		(2.86)	(2.86)
Variance *Loss		-1.704	-1.533
		(-3.21)	(-3.29)
√Holding Days		-0.001	-0.001
		(-20.02)	(-19.33)
Observations		1,440,981	1,440,981
R^2		0.041	0.046

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 and an investor holds at least 5 stocks are included in the sample. Stocks are not included on the day that position is opened. 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 8 –Alphabetical Ordering by Company Name

	Selling			Buying		
	First and Second Name Only	Last and Second to Last NameOnly	All Names	First and Second Name Only	Last and Second to Last Name Only	All Names
	[1]	[2]	[3]	[4]	[5]	[6]
First Name	0.026		0.061	0.008		0.017
	(3.80)		(10.69)	(2.31)		(6.43)
Last Name		0.029	0.061		0.008	0.017
		(3.52)	(11.02)		(2.22)	(6.53)
Stock x Date FE	X	X	X	X	X	X
Observations	185,253	185,145	1,016,954	237,293	237,200	1,396,848

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 dummy variables based on the alphabetical ordering by company name ordering and stock by day fixed effects. Only days where a stock is sold are included in columns [1]-[3] and only days a stock is purchased are in cluded in columns [4]-[6]. 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. First (Last) name is a dummy equal to one if the stock name is the first (last) name 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 9 – Components of the Rank Effect using Various Measures of Extremeness

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Pos*(Return-Avg Return)/Std. Dev.	0.056			-0.022			-0.022	
	(19.75)			(-11.17)			(-11.28)	
Neg*(Return-Avg Return)/Std. Dev.	-0.032			0.027			0.032	
	(-8.34)			(8.47)			(10.47)	
Pos*(Return-Median Return)		0.174			0.034			0.004
		(14.94)			(4.02)			(0.44)
Neg*(Return-Median Return)		-0.074			-0.016			0.009
		(-4.80)			(-1.33)			(0.77)
Best*(Best Return - 2nd Best Return)			0.091			0.057	0.057	0.057
			(14.63)			(10.64)	(10.49)	(9.35)
Worst*(Worst Return - 2nd Worst Return)			-0.308			-0.151	-0.167	-0.155
			(-24.53)			(-14.32)	(-16.39)	(-15.04)
Best				0.253	0.197	0.186	0.234	0.185
				(23.74)	(20.39)	(20.94)	(25.52)	(21.09)
Worst				0.180	0.142	0.116	0.153	0.118
				(17.78)	(16.78)	(18.00)	(16.93)	(16.43)
Additional Controls	X	X	X	X	X	X	X	X
Observations	1,047,057	1,047,057	1,047,057	1,047,057	1,047,057	1,047,057	1,047,057	1,047,057
R^2	0.020	0.014	0.017	0.048	0.047	0.048	0.050	0.048

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. 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 portfolio 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 2^{nd} best and 2^{nd} 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 10 - Mutual Fund Fraction Sold and Liquidation by Rank

	Fraction Sold		Liquidate	
	All Holdings	Sell Only	All Holdings	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
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 Holdings* column includes all holdings while the *Sell Only* column includes only accounts on days where some positions 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 (non-positive) return. Data covers January 1990 to June 2010.

Table 11 – 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 mutual fund holdings rank. Rank is based on the return from purchase price to 3 months and 10 trading days after the report month. Portfolios are held from the 11^{th} trading day of a month until the 10^{th} 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 June 2010.

Table 12 – 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 portfolios by the number of funds where the stock is best (worst) rank. "Fraction of marketcap that is Worst (Best)" weights by the fraction of marketcap for each stock that is ranked best (worst). Portfolios are formed based on mutual fund holdings rank. Rank is based on the return from purchase price to 3 months and 10 trading days after the report month. 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 June 2010.

Table 13 – Fama-Macbeth Price Effects Based on Mutual Fund Portfolio Rank

	[1]	[2]	[3]
Best	0.065	0.253	0.257
	(0.30)	(2.04)	(2.22)
Worst	0.843	0.743	0.941
	(2.16)	(2.64)	(3.82)
Momentum		0.290	0.270
		(1.32)	(1.28)
Lag Return		-1.846	-2.063
		(-3.08)	(-3.53)
Log(Market Cap)		-0.107	-0.162
		(-1.79)	(-3.59)
Log(Book/Market)		0.141	0.067
		(1.29)	(0.74)
High Volume			0.353
			(4.57)
Low Volume			-0.503
			(-6.72)
Earnings			0.574
			(7.45)
Predicted Dividend			0.217
			(2.44)
Idiosyncratic Volatility			-4.740
			(-0.89)
Share Issuance			-1.267
			(-5.65)
Constant	1.106	2.328	3.032
	(2.85)	(2.46)	(4.46)
Observations	722,157	658,662	631,518

This table presents Fama-Macbeth regressions with monthly stock returns multiplied by 100 as the dependent variable. A month runs from the 11th trading day of a month until the 10th trading day of the next month. Rank is based on the return from purchase price to 3 months and 10 trading days after the report month. 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 *M*-2 to *M*-12 and Lag Return is the return from *M*-1. Log(Book/Market) is the log of the book to market ratio. High (Low) Volume measures the Gervais, Kaniel and Mingelgrin Premium using 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 measures the dividend month premium from Hartzmark and Solomon using 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 a month until 10 trading days into the next month. Idiosyncratic volatility (Ang, Hodrick, Xing and Zhang 2006) for stock *j* on day *t* is calculated as the standard deviation of the residuals of a regression of the excess return on *MKT*, *SMB* and *HML* from *t*-1 to *t*-21. Share Issuance (Pontiff and Woodgate 2008) for stock *j* with holding period ending in month *M* is [Log(Shares outstanding, *M*-6)- Log(Shares outstanding, *M*-17)]. Only stocks held by mutual funds are included. Data covers January 1990 to June 2010.

Table 14 – The Rank Effect by Taxable Status of Account

	Deferred Tax Account	Taxable Account
	[1]	[2]
Best	0.194	0.205
	(17.16)	(17.90)
Worst	0.141	0.147
	(12.90)	(17.42)
2nd Best	0.124	0.125
	(20.29)	(13.72)
2nd Worst	0.084	0.083
	(13.03)	(12.04)
Return*Gain	-0.001	-0.027
	(-0.04)	(-3.43)
Return*Loss	-0.038	0.015
	(-0.65)	(0.84)
Gain	0.026	0.025
	(4.63)	(6.66)
Additional Controls	X	X
Observations	225,770	808,442
R^2	0.039	0.049

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 and an investor holds at least 5 stocks are included in the sample. Deferred tax accounts are those categorized as IRA or Keogh in the data. Stocks are not included on the day that position is opened. 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. 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 15 – Rank Effect after Entropy Balancing

	Individual Investor		Mutual Fund	
	Unweighted	Entropy Balanced	Unweighted	Entropy Balanced
Best - Not Best	0.120	0.128	0.116	0.116
	(19.74)	(21.36)	(15.12)	(12.40)
Worst - Not Worst	0.059	0.084	0.188	0.165
	(9.15)	(18.85)	(20.74)	(10.03)

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. 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 and date.