Behavioral biases and investor performance*

Todd Feldman

Finance Department, San Francisco State University, San Francisco, CA, 94122, 1600 Holloway Street.
San Francisco, CA 94122, USA Phone: 415-816-6632, Email: tfeldman@sfsu.edu

Abstract. Research indicates that individual investors trade excessively and underperform the market indices, Barber and Odean (2000). The purpose of this paper is to help explain which behavioral biases, if any, can explain this result using a simulation approach. Results indicate that putting too much weight on the current environment, anchoring, is the largest factor in explaining individual investor underperformance. In addition, loss aversion is the largest factor to explain excessive trading. When these two biases are combined trading activity and underperformance are heightened.

Keywords: Behavioral finance, agent-based models, financial markets. JEL codes: C63, G01, G10

1. Introduction

The purpose of this paper is to examine the behavioral biases that may or may not contribute to individual investor excessive trading and underperformance. Barber and Odean (2000) analyze the brokerage accounts of 66,465 households to find that during 1991 to 1996 US investors earned an annual return of 11.4 percent, while the market returned 17.9 percent. They attribute the underperformance and frequent trading to the behavioral bias, overconfidence. However, Odean (1999) finds that trading is so excessive overconfidence alone is unable to account for it based on 10,000 accounts from January 1987 through December 1993.

Excessive trading and underperformance can only be attributed to using inept stock models which lead to poor investment decisions or behavioral biases. The academic research suggests that even professional investors who have access to better data, technology, and information underperform market indices. Based on this information why would individual investors use stock models to invest?

The first objective of this paper is to determine which behavioral biases may explain excessive trading and underperformance. The second objective is to single out the behavioral bias that has the largest negative impact on performance. The motivation behind these questions is to aid individual investors and financial advisors in avoiding specific behavioral biases that hurt performance. The idea being that some biases may have a marginal affect on performance where as other biases may have a large negative effect. I want to narrow in on the most damaging bias which will allow investors to focus on reducing that specific irrational bias.

To answer these questions one can use an empirical or simulation approach. I refrain from using an empirical approach because the ability to test these questions using actual data is limited for two reasons. First, it is difficult to obtain brokerage data due to privacy laws. Second, it can be difficult to build a testable framework to infer whether investors are affected by behavioral biases using household data. For example, assume an investor chooses a stock based on fundamental analysis. The stock price keeps falling and the investor continues to buy as they believe the stock is becoming more undervalued. A researcher would assume from the data that the investor is holding

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1 One can obtain data through other researchers, however, there may still be agreements to prohibit such activity.
onto losses too long and selling winners to early, the disposition effect. However, the investor is not investing based on emotion but based on an inept stock model. The researcher would then infer behavior that does not exist.

I use an agent-based approach because it allows the modeler to provide the rules that will govern the individual’s behavior. Therefore, the modeler knows the exact behavior of each investor and the ramifications of that behavior on performance and asset prices. The modeler can step back to observe the development of the system over time without further intervention. The disadvantage of the agent-based model is that the results are based on computer generated data and not actual data. However, agent-based models can be used to in conjunction with empirical models to confirm results.

The model that I use is adapted from Friedman and Arbabah’s (2009) agent-based model. The simulation model contains a population of investors who decide every month how much to allocate to a S&P 500 portfolio and cash. It is assumed that each investor does not hold the exact same S&P 500 portfolio as the composition of stocks in the portfolio may differ. Therefore, each investor has a different alpha that updates via a stochastic shock. The S&P 500 price is partly determined by fundamental value and by investor demand. The simulated price updates in the following manner. First, at the beginning of each month, each investor receives a stochastic idiosyncratic shock which affects their individual alpha. Second, each investor makes an allocation decision between the S&P 500 portfolio and cash based on the current return, their updated alpha, and perceived risk. Third, the new demand across all investors affects the price, thus changing return. If the average allocation to the S&P 500 portfolio increases (decreases) the S&P 500 portfolio price increases (decreases). Next month each investor makes a new allocation decision. Every new allocation decision is based on a new shock to the investor and new returns driven by the evolving demand of the population of investors. The new decision then feeds back into prices, returns, and risk resulting in a continuous cycle until the simulation ends.

Using this framework I study four groups of investors. In deciding on their allocation between the S&P 500 and cash the four groups differ in their calculation of risk. The first groups of investors are rational investors, investors who do not invest on emotion, and the remaining three groups are irrational investors, investors who invest on emotion. Group one investors use the mean-variance approach where the inputs are based on long-run averages of the S&P 500. Group two investors heavily weight current returns relative to past returns, recency bias. Group three investors are more affected by losses than by gains, loss aversion. Lastly, group four investors hold on to losers for too long and sell winners too fast, the disposition effect.

I run various simulations where each simulation period lasts one hundred years. I use the simulation data to calculate portfolio turnover for all four groups. In addition, I calculate which group outperforms in the long-run and quantify the magnitude of underperformance for the worst performing group.

The first main result from analysis of the simulation data indicates that loss averse investors trade the most excessively and rational investors trade the least. Loss averse investors react strongly and quickly to losses and less so to gains. This reaction to losses leads to excessive trading. Recency investors, who overweight certain information similar to overconfident investors, also trade excessively relative to the rational investor. This result helps support Barber and Odean’s (2000) claim that overconfidence is to blame for excessive trading. However, I find loss aversion is the bigger culprit to induce excessive trading than overweighing specific information.

The second main result is that the recency bias, putting too much weight on the current environment in predicting the future, is the main bias to avoid. The tendency to believe that the current market environment will continue for the foreseeable future has the most negative consequence on performance relative to the other two biases. I find that the rational investor outperforms all three groups of irrational investors on an absolute and risk-adjusted basis. The magnitude of their outperformance is approximately 2% per year compared to the disposition affected and loss averse group and 7% per year compared to the recency group. Recency investors tend to get trapped into buying at market tops and selling and market bottoms. The loss average and disposition affected investors underperform but the underperformance is insignificant at times depending on the parameter configuration.

The last main result is that irrational investing leads to lower market returns, higher standard deviation, and lower Sharpe ratio. As the number and magnitude of irrational behavior increases the returns of all investors including rational investors decline.
2. Literature Review

Behavioral finance researchers have documented that individual investors tend to trade too much which leads to underperformance. Barber et al. (2007) obtain a complete trading history of all investors in Taiwan. They document that the aggregate portfolio of individuals suffers an annual performance penalty of 3.8 percentage points using this household data. Barber et al. (2009) create a data set that allowed them to identify trades made by individuals and by institutions. Their empirical results indicate that individuals lose and institutions win. The question then becomes why are individual investors trading so much given their underperformance and trading costs associated with trading? Why not leave their money in index funds? Are behavioral biases to blame?

The most well documented behavioral biases in the literature include recency bias, overconfidence, disposition effect, and loss aversion. Nofsinger (2001) describes overconfidence as an overestimation of knowledge and underestimation of risks. Odean (1999) studies ten thousand customer accounts from a brokerage house to identify whether overconfidence exists. He finds that individual investors trade excessively even after eliminating most trades motivated by liquidity demands, tax loss selling, portfolio rebalancing, or a move to lower-risk securities. In fact, the Odean concludes that trading is so excessive that the result cannot be explained by overconfidence alone.

The recency bias is the tendency to overweight the most current information and underweight previous history in the prediction of the future. Pompian (2008) writes that the recency bias ran rampant during the bull market period between 1995 and 1999 when many investors wrongly presumed that the market would continue its enormous gains forever.

The disposition effect was coined in a paper by Shefrin and Statman (1985). Shefrin and Statman predict that because people dislike incurring losses much more than they enjoy making gains. Therefore, investors hold onto stocks that have lost value (relative to the reference point of their purchase) and sell stocks that have risen in value. Odean (1998) analyses the trades of 10,000 accounts at a discount brokerage between the years 1987 and 1993. He documents that winners are sold at roughly twice the rate of losers controlling for other factors such as taxes, rebalancing, and transaction costs. Barber et al. (in press) find that these trading patterns involving previously owned stock are driven by a desire to avoid or at least limit anticipated regret. The decision to repurchase is based on emotion rather than rational decision making.

The principle of loss aversion was first introduced by Kahleneman and Tversky (1979). In their 1979 paper they create a model of decision making under risk, prospect theory, which uses experimental evidence to argue that people get utility from gains and losses in wealth, rather than from absolute levels. In the context of investing, loss averse investors are more impacted psychologically by their losses than they are by their gains. This leads investors to panic during financial crises and buy near the top during stock market booms.

In this paper I study three behavioral biases, loss aversion, recency bias, and the disposition effect. Loss aversion and the disposition effect are different in how investors treat losses. Loss averse investors sell when experiencing losses because of fear where as disposition efected investors buy when experiencing losses to offset regret. Loss averse investors are frightful of losing money. They are also less affected by gains. Therefore, it takes loss averse investors significant time experiencing gains before buying after experiencing large losses. Disposition effected investors want to limit the regret of losing money. Therefore, they buy when losses occur, cost averaging down, and sell too early when gains occur. Lastly, the recency bias describes the common human tendency to rely too heavily on one piece of information when making decisions similar to overconfidence. I exclude overconfidence because recency and overconfidence are both biases that overweight certain factors and therefore the modeling of each bias would be similar.

Researchers have also developed quantitative models of behavioral biases to study the affect on asset prices by running agent-based model computer simulations in addition to documenting and testing for behavioral biases. The agent-based framework includes the modeling of individual agent behavior and running computer simulations to understand how the individual agent’s behavior and interaction lead to seemingly random macro phenomena. Friedman and Arbaham (2009) create an agent-based model where they formalize the idea of loss aversion in order to study bubbles and crashes. They model portfolio managers who make decisions based on the trade-off between return and risk where risk is defined by the aggregate losses in the market, not volatility as in traditional models. They find that loss aversion is a key ingredient in understanding how bubbles and crashes form. Maymin (2009) also finds that loss aversion can
result in fat tails, excess kurtosis, and skewness even when the underlying business risk has no extremes.

I use the Friedman and Abraham agent-based framework to study two classes of investors, rational and irrational investors. Rational investors are defined as investors that are not influenced by emotion where as irrational investors are impacted by the behavioral biases described above. I specifically model individual investors as opposed to portfolio managers as in Friedman and Abraham. In Friedman and Abraham the agents are portfolio managers who price risk based on aggregate losses. Here individual investors price risk differently. In addition, in Friedman and Abraham portfolio managers invest based on a payoff gradient instead of portfolio optimization.

3. Model Framework

Investors in the model are individual investors or retail investors. The rational investors can be considered institutional investors who are assumed from the research to exhibit less behavioral biases in their investment decision making. Each investor buys and sells a single safe asset with constant return and a single risky asset with variable return. Their investment decision making. Each investor buys from the research to exhibit less behavioral biases in considered institutional investors who are assumed or retail investors. The rational investors can be instead of portfolio optimization.

\[ R = \bar{V} \delta. \]

Asset supply comes from fundamental-oriented market participants such as issuers of stocks and bonds, and perhaps other individual investors. It is assumed that the net asset supply function has constant elasticity \( a > 0 \) so, after suitable normalization, it is \( S = (P/V)^a \). Normalized asset demand by investors is \( D = \bar{u} \). Solving \( S = D \), one can write the price of the risky asset as in equation 1, where \( \delta = 1/\alpha > 0 \).

\[ \text{Price of the risky asset is equal, less than or greater than fundamental value whenever normalized demand } \bar{u} \text{ for the risky asset is equal, less than or greater than 1.0.} \]

An interpretation is that the investors exert buying pressure whose intensity is parameterized by \( \delta \). Even though supply does not change, one can simulate different environments where a low \( \delta \) is consistent with small supply.

The return on the risky asset, \( R_1 \), is determined from breaking down the price function into the dividend yield and the capital gains rate. The dividend yield is simply earnings per dollar invested, \( e^{yt}/P(t) = (R_s - g)\bar{u}^{-\delta} \). Use the notation \( \dot{y} = dy/dt \) and take the log-derivative of (1) to obtain the capital gains rate \( \dot{P}/P = \dot{V}/V + \dot{\alpha} / \bar{u} = g + \alpha \bar{u} / \bar{u} \). Hence the realized yield on the S&P 500 is

\[ R_1 = (R_s - g)\bar{u}^{-\alpha} + g + \alpha \bar{u} / \bar{u}. \]

The first term is the dividend yield, the second term captures capital gains due to economic growth, and the third term reflects capital gains due to financial market activity. Note that \( R_1 \) is equal to the discount rate \( R_s \) as in the CAPM when \( \bar{u} = 1 \) and \( \bar{u} = 0 \).

What is the discount rate \( R_s \)? The discount rate is \( R_s = R_o + d_R \) where the term \( d_R \geq 0 \) represents all other factors. These factors include \( g \), since economic growth is known and economy-wide.

\[ \text{The theoretical model is continuous. However, I create a discrete model when programming as investors rebalance every month. Therefore, I omit the subscript } t \text{ throughout the model, except when describing the idiosyncratic stochastic shock.} \]

See Appendix for more details.
The base payoff function developed in Friedman and Abraham is the following,

$$ R(u) = u(R_1 - R_0 + \alpha_i) - \frac{1}{2}c_2u^2. \quad (3) $$

This payoff function includes two new characteristics. First, each investor receives an idiosyncratic shock $\alpha_i$ which follows a mean reverting Ornstein-Uhlenbeck process. If the most recent known value is $\alpha_i(t-h)$, then the current value is the variable

$$ \alpha_i(t) = e^{-\tau h} \alpha_i(t-h) + \sqrt{\frac{1-e^{-2\tau h}}{2\tau}} \sigma \nu, \quad (4) $$

for some given volatility parameter $\sigma > 0$ and decay parameter $\tau > 0$, and an independent realization $\nu$ from the unit normal distribution. If $\alpha_i$ is positive (negative) for investor $i$, she outperforms (underperforms) the market, $R_1$. The intuition is that every investor holds a diversified portfolio that mimics the S&P 500 but may differ in the collection of stocks one investor holds. At any point in time one investor may hold a stock that returns a high positive (negative) return that creates a positive (negative) alpha compared to the benchmark S&P 500. This under and outperformance is quantified by their $\alpha$ which nets out to zero in the long-run. Therefore, the investor is not thought to hold exactly the same portfolio, S&P 500, because this is not realistic. However, they hold a portfolio that mimics the S&P 500 which may differ in the composition of stock holdings. The mean reversion of the shock represents a stylistic fact that investors rarely continuously outperform. For example, the top five investment managers year after year in the Wall Street Journal are never the same. Lastly, the idiosyncratic stochastic shock makes the model agent-based by differentiating the investor’s payoff function each time period.

Second, returns are endogenous where the current distribution of investor choices affects investors’ payoff via $R$. The feedback process between choices and prices is as follows. First, each investor chooses an allocation to the S&P 500 portfolio, $u$. Second, the computer program determines the average value of every investor’s $u$, $\bar{u}$. Third, the new $\bar{u}$ impacts the price function in equation 1. Fourth, as the price changes the market return changes in 2. Lastly, investors re-optimize their payoff function, 3, based on the updated $\bar{R}_1$, $\alpha_i$, and risk. This process continues until the simulation ends.

The last element of 3, $c_2$, represents perception of risk. This is where the paper mainly departs from Friedman and Abraham. In Friedman and Abraham $c_2$ represents the aggregate losses of all market participants. The difference lies in the calculation of risk. My contribution is in the modeling of how loss averse, recency biased, and disposition effected investors calculate risk. I then explore how their returns as separate groups differs based on their different ways of pricing risk.

3.1. Groups

I now turn to the objective function for the four groups of investors: rational, recency, loss averse, and disposition effected. All payoff functions below are based on the payoff function, 3. However, the payoff function for each investor differs by how they price risk. The logic is that the behavioral biases may come out through the formation of expected future returns or through their pricing of risk or both. To simplify the model I choose only one way, via the pricing of risk.

3.1.1. Rational

The rational investor uses the mean-variance framework where variance is a static number based on the S&P 500’s long-run average standard deviation of 20%. They re-balance every month as prices change to maintain their optimal exposure given the long-run variance. Their objective function is

$$ \phi(u) = u(R_1 - R_0 + \alpha_i) - \frac{1}{2} \sigma^2 u^2, \quad (5) $$

where $\alpha_i$ is the individual alpha that distinguishes each investor and $\sigma^2$ is volatility. The rational investors optimize their objective function to obtain the optimal amount of risky asset allocation,

$$ u = \frac{(R_1 - R_0 + \alpha_i)}{\sigma^2}. \quad (6) $$

3.1.2. Recency Investors

Recency investors heavily weight current returns relative to past returns. This is formalized by using an exponential average. Recency investors use the exponential average to calculate the mean return in their variance calculation,

$$ \bar{\sigma}^2 = (\bar{R}_1 - \hat{R}_1)^2, \quad (7) $$
where
\[ \hat{R}_1 = e^{-\eta n} \hat{R}_1(t - n) + (1 - e^{-\eta n}) R_1(t). \] (8)

The exponential average is updated from the previous exponential average. In calculating \( \hat{R} \) each data point is weighted differently. The most current return is weighted more than the returns in the past. Therefore, recency investors predict high volatility when markets are volatile and predict low volatility when markets are not volatile. Their pricing of risk is based on the current environment. Plugging in the new variance calculation, recency investors use the following objective function,
\[ \phi(u) = u(R_1 - R_0 + \alpha_i) - \frac{1}{2} (\tilde{\sigma}^2) u^2. \] (9)

The recency investors optimize their objective function to obtain the optimal amount of risky asset allocation,
\[ u = \frac{(R_1 - R_0 + \alpha_i)}{\tilde{\sigma}^2}. \] (10)

### 3.1.3. Loss Averse Investors

Loss averse investors perceive risk based on losses as opposed to volatility. High volatility when prices are rising is not considered risk to a loss averse investor. High volatility when prices are falling is considered high risk. This is what differentiates the loss averse investor from the rational and recency investor.

The loss averse investors price risk using a moving average of past losses called loss aversion risk. Loss aversion risk, \( \hat{L}_i \) is determined in two steps. First, it is determined by picking up losses, \( L_i = \max \{0, -R_{Gi}\} \), where \( R_{Gi} \) is the gross return. Next, the losses over time are averaged using a moving average. This step is distinct from an exponential averaging in that current and past losses are weighted equally. I assume loss averse investors remember losses for two years based on empirical evidence from Feldman (2010). When calculating successive values, a new value comes into the sum and an old value drops out,
\[ \hat{L}_i = L_{i-t} + \frac{L_{i,t-n}}{n} + \frac{L_{i,t}}{n}. \] (11)

The payoff function for the loss averse investor becomes
\[ \phi(u) = u(R_1 - R_0 + \alpha_i) - \frac{1}{2} \hat{L}_i u^2. \] (12)

Maximizing the payoff function the optimal allocation is,
\[ u = \frac{(R_1 - R_0 + \alpha_i)}{\hat{L}_1}. \] (13)

### 3.1.4. Disposition effected investors

The disposition effected investors tend to buy or hold when incurring losses and sell when the market increases. To formalize this process I calculate disposition risk, \( D_i = \max \{0, R_{Gi}\} \). When disposition effected experience gains disposition risk is high and therefore they tend to sell. If they experience losses, disposition risk is low and they tend to hold or buy more shares. The formalization of this process means these investors cost average down. For example, as the price of the risky asset falls, investors buy more of the risky asset reducing their cost basis. Similar to the loss averse investors, disposition effected investors average their \( D_i \) for several years weighting observation equally,
\[ \hat{D}_i = \hat{D}_{i,t-h} + \frac{D_{i,t-n}}{n} + \frac{D_{i,t}}{n}. \] (14)

The objective function for the disposition effected investor becomes
\[ \phi(u) = u(R_1 - R_0 + \alpha_i) - \frac{1}{2} \hat{D}_i u^2. \] (15)

Maximizing the payoff function the optimal allocation is,
\[ u = \frac{(R_1 - R_0 + \alpha_i)}{\hat{D}_1}. \] (16)

### 4. Simulations

I run simulation using an agent-based program called NetLogo. Figure 1 displays a static NetLogo interface. In brief, the simulation consists of investors i=1,Ε,M whose leverage \( x_i \) (horizontal coordinate) and portfolio size \( z_i \) (vertical coordinate) are floating point numbers that adjust in discrete time. The figure shows sliders that control all the parameters including population size for the four groups. The simulation is at monthly frequency (Freq = 12). The “altitude” sets the middle of the initial \( z \) distribution, and “width” and “height” control the bounds on the rectangle. At the start of the simulation each investor randomly
starts off with a different initial leverage and portfolio values. The initial conditions change at the beginning of every new simulation run. Each simulation lasts one hundred and twenty years or 1,440 months. I delete the first twenty monthly because of initial conditions. Therefore, there exist 1,200 observations per simulation run. I run ten simulation periods for each regime to ensure stochastic do not play a role in the results. Therefore, there exist 1,200 * 10 = 12,000 data points per regime. The portfolio value of any investor is capped at four. Therefore, no one investor can dominate the market.

I run various regimes where the population of the four different groups differ in each regime. The reason being is that the interaction of the individual agents is an important aspect of agent-based models. The resulting price dynamics are therefore affected by how the modeler configures the population size for each group. The first or base regime contains an equal population of all investor groups. The following regimes are a variation of the base regime,

1. Regime 1, Equal: An equal population of ten investors per group for a total population of forty investors.
2. Regime 2, Rational: Thirty seven rational investors and one investor from each of the irrational groups.
3. Regime 3, Irrational: One rational investor and thirteen irrational investors from group 2, thirteen from group 3, and thirteen from group 4.
4. Regime 4, Recency: Thirty seven recency investors and one investor from each of the remaining groups.
5. Regime 5, Loss Averse: Thirty seven loss averse investors and one investor from each of the remaining groups.
6. Regime 6, Disposition: Thirty seven disposition effect investors and one investor from each of the remaining groups.

In addition to setting population parameters it is necessary to set other parameters as well. The parameters are configured based on long-run averages of the S&P 500. For example, the long-run standard deviation of the S&P is approximately 20% and the long-term real GDP growth rate is approximately 3%. I also define a financial crisis as a 30% fall from the peak in the last six months.

5. Results

Table 1 contains summary statistics for each regime. These statistics are calculated by averaging over the ten simulation runs per regime. One finding is that fewer financial crises occur in the regimes where one group dominates and more in the regimes where
Table 1

<table>
<thead>
<tr>
<th>Regime</th>
<th>Mean Price</th>
<th>Min</th>
<th>Max</th>
<th>St.Dev</th>
<th># of Crises</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Equal</td>
<td>30.17</td>
<td>1.17</td>
<td>60.39</td>
<td>18.13%</td>
<td>6.2</td>
</tr>
<tr>
<td>2. Rational</td>
<td>11.40</td>
<td>8.30</td>
<td>17.07</td>
<td>12.60%</td>
<td>0.00</td>
</tr>
<tr>
<td>3. Irrational</td>
<td>38.62</td>
<td>0.59</td>
<td>70.33</td>
<td>35.38%</td>
<td>9.39</td>
</tr>
<tr>
<td>4. Recency</td>
<td>91.45</td>
<td>44.12</td>
<td>193.56</td>
<td>12.75%</td>
<td>1.80</td>
</tr>
<tr>
<td>5. Loss Averse</td>
<td>34.93</td>
<td>18.29</td>
<td>62.20</td>
<td>13.43%</td>
<td>1.40</td>
</tr>
<tr>
<td>6. Disposition</td>
<td>15.11</td>
<td>11.21</td>
<td>21.96</td>
<td>12.89%</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Note: Table 1 displays summary stats for six regimes. Each regime had ten simulation runs. # of crises is the number of crises per century. Statistics are averages across those ten runs per regime.

there is greater heterogeneity. Even irrational behavior cannot induce many financial crises if only one irrational type dominates. It takes the interaction of different investor types whether rational or irrational to induce financial crises.

Table 2 displays the return statistics per group over all six regimes. The first result is that the loss averse investors trade the most excessively relative to all other investor groups. This result can be found by examining the variable called Sum. Sum is the total amount of shares traded for an average simulation period. Results indicate that the loss averse investors trade the most excessively and rational investors trade the least. The loss averse investor become scared easily when they experience losses and that can lead to emotional investing during financial crises.

The second main result is that the recency group underperforms all other groups. The recency group returns an average of $-2.3\%$ which is statistically significantly different than the rational group return of $5.69\%$. Therefore, the hypothesis that the disposition effected investors would underperform is incorrect. Investors that put too much weight on the current environment are the underperformers, underperforming the rational group by seven percentage points on an annual basis. In addition, the rational investor group outperforms all the irrational groups on an absolute and risk-adjusted basis but only on a statistically significant basis for the loss averse and recency investor groups.

In Table 3, I break down the returns for each group by regime. In the equally distributed regime,

Table 2

<table>
<thead>
<tr>
<th>Group</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>St.dev</th>
<th>Sharpe</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Rational</td>
<td>5.69%</td>
<td>2.36%</td>
<td>8.39%</td>
<td>5.27%</td>
<td>0.68</td>
<td>18.15</td>
</tr>
<tr>
<td>2. Recency</td>
<td>$-2.30%$</td>
<td>$-23.81%$</td>
<td>12.04%</td>
<td>33.02%</td>
<td>$-0.31$</td>
<td>26.07</td>
</tr>
<tr>
<td>3. Loss Averse</td>
<td>4.60%*</td>
<td>$-4.23%$</td>
<td>16.65%</td>
<td>11.54%</td>
<td>0.17</td>
<td>34.64</td>
</tr>
<tr>
<td>4. Disposition</td>
<td>4.96%</td>
<td>0.11%</td>
<td>7.28%</td>
<td>5.88%</td>
<td>0.36</td>
<td>20.16</td>
</tr>
</tbody>
</table>

Note: Summary return statistics per group. All statistics are annualized over a one hundred year simulation period. The mean, min, max, standard deviation, Sharpe, and sum are computed by averaging over then simulation runs per regime and then across the six regimes. Sum is the total of shares trades and signifies turnover. F tests were run to detect whether the recency, loss averse, and disposition group returns were statistically different than the rational group returns.

*significant at 5%; **significant at 1%.

Table 3

<table>
<thead>
<tr>
<th>Regime</th>
<th>Rational (Grp 1)</th>
<th>Recency (Grp 2)</th>
<th>Loss Averse (Grp 3)</th>
<th>Disposition (Grp 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Equal</td>
<td>7.16%</td>
<td>0.54%**</td>
<td>4.83%**</td>
<td>4.97%**</td>
</tr>
<tr>
<td>2. Rational</td>
<td>6.22%</td>
<td>$-16.36%$**</td>
<td>2.30%**</td>
<td>3.01%**</td>
</tr>
<tr>
<td>3. Irrational</td>
<td>6.77%</td>
<td>9.56%**</td>
<td>5.74%</td>
<td>6.98%</td>
</tr>
<tr>
<td>4. Recency</td>
<td>6.22%</td>
<td>3.44%**</td>
<td>7.85%*</td>
<td>5.88%</td>
</tr>
<tr>
<td>5. Loss Averse</td>
<td>4.08%</td>
<td>$-5.53%$**</td>
<td>4.41%</td>
<td>4.90%</td>
</tr>
<tr>
<td>6. Disposition</td>
<td>4.70%</td>
<td>$-5.42%$**</td>
<td>2.47%*</td>
<td>3.99%</td>
</tr>
</tbody>
</table>

Note: Returns by group across all six regimes. F tests were run to detect whether the recency, loss averse, and disposition group returns were statistically different than the rational returns.

*significant at 5%; **significant at 1%.
Regime 1, rational investors outperform groups 3 and 4 by approximately 2-3% and group 2 by 7%. The returns for the irrational investors are significantly different from the rational investor group’s returns. In the rational regime, Regime 2, rational investors outperform group 3 and 4 by approximately 2-3% and group 2 by almost 20%. In addition, it can be seen that as the environment becomes irrational returns across the board for all investors falls. Irrational investors drive down the returns of the market.

In Table 4, I break down the Sharpe ratios for each group by regime. Results from Table 4 confirm results found in Table 3. However, the rational investor outperformance is magnified when comparing on a risk-adjusted basis. The rational investor earns higher returns with less risk compared to the other three groups. In addition, the recency investor Sharpe ratio is negative in five out of the six regimes and is significantly different than the rational group Sharpe ratio. The bias of putting too much weight on the current environment when pricing risk has the greatest negative effect on performance. Investors typically forecast the market based on current market conditions. I find this behavior is the most devastating to performance.

Lastly, results from Table 5 displays the number of shares traded over an average simulation period. The loss averse investors trade the most excessively in all regimes expect for Regime 5. The bias of being fearful of losing money leads the individual investors to trade more than the other investor types. Recency also leads to greater trading activity relative to the rational investor and the disposition effected investor trades more than the rational investor but that much more.

Since I find that loss aversion has the largest impact on excessive trading and recency has the greatest impact on underperformance, I combine the two to study how the combination affects trading and

Note: Sharpe ratio for all groups across all six regimes. Sharpe is calculated by subtracting the mean return above from the static risk free rate of 3% and dividing by the average standard deviation. F tests were run to detect whether the recency, loss averse, and disposition group returns were statistically different than the rational group Sharpe ratios.

* significant at 5%; ** significant at 1%.
underperformance. In this case only the loss averse and disposition effected investors objective function is changed. Instead of using a moving average to average across time I use an exponential average similar to the recency investors. Therefore, the loss averse investors pricing of risk is updated as,

$$\hat{L}_1 = e^{-\eta n} \hat{L}_1(t - n) + (1 - e^{-\eta n})L_1(t)$$  \hspace{1cm} (17)

and the disposition effected investors pricing of risk is updated as,

$$\hat{D}_1 = e^{-\eta n} \hat{D}_1(t - n) + (1 - e^{-\eta n})D_1(t).$$  \hspace{1cm} (18)

The only difference in this change is that current losses or gains are now weighted more heavily than past losses or gains instead of being weighted equally.

In Table 6, I compare the returns from the first phase to the second phase where recency is combined with loss aversion and the disposition effect. I distinguish the two phases by putting an asterisk on the phase two returns.

Results from Table 6 reveal that not only do the loss averse and disposition effected investors perform worse than originally, all investor groups perform worse. This result confirms again that putting too much weight on past returns can hurt one’s portfolio in a significant way. It also confirms that the more irrational behavior there exists in the market the more returns for all investors including rational investors fall.

6. Conclusion

I use an agent-based approach to understand why individual investors trade too much and underperform market indices. I use an agent-based framework which allows the modeler to completely understand the behavior of all the agents. The agent-based model consists of four investor groups where one group is rational and the other three groups are irrational, invest based on emotion.

Results indicate that the most damaging behavioral bias that an individual investor uses to make investment decisions is putting too much weight on the current environment. When investors make predictions about the future based on what is happening at the current time they underperform the rational group by 7% per year over the long-run. In addition, I find that excessive trading is due to a separate bias, loss aversion. Loss averse investors become fearful easily and when downturns occur they tend to trade more than is optimally called for. Lastly, the combination of loss aversion and recency has the affect of hurting performance even more.

The results of this study help confirm Barber and Odean’s assumption that behavioral biases were the underlying cause for the excessive trading and underperformance. Odean also cited in his 1999 paper that the bias he assumed to explain excessive trading could not explain all of it. I find that not only does overconfidence or putting more weight on certain info explain excessive trading but loss aversion has a more significant affect.

Since the study is conducting using simulation data, results cannot replicate the analysis of real data. However, simulation results do open avenues of empirical research that perhaps would have never been identified before. The results of this paper could lead to several different empirical papers. For example, I find that putting too much weight on current information has serious negative consequences for one’s portfolio. This can be tested using actual data to try to confirm the result.

Table 6

<table>
<thead>
<tr>
<th>Regime</th>
<th>Rational</th>
<th>Rational*</th>
<th>Recency</th>
<th>Recency*</th>
<th>Loss Averse</th>
<th>Loss Averse*</th>
<th>Disposition</th>
<th>Disposition*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Equal</td>
<td>7.16%</td>
<td>5.17%</td>
<td>0.54%</td>
<td>−2.01%</td>
<td>4.83%</td>
<td>4.07%</td>
<td>4.97%</td>
<td>4.29%</td>
</tr>
<tr>
<td>2. Rational</td>
<td>5.22%</td>
<td>4.95%</td>
<td>−16.36%</td>
<td>−8.48%</td>
<td>2.30%</td>
<td>2.06%</td>
<td>3.01%</td>
<td>2.12%</td>
</tr>
<tr>
<td>3. Irrational</td>
<td>6.77%</td>
<td>5.57%</td>
<td>9.56%</td>
<td>−0.30%</td>
<td>5.74%</td>
<td>4.38%</td>
<td>6.98%</td>
<td>4.72%</td>
</tr>
<tr>
<td>4. Recency</td>
<td>6.22%</td>
<td>5.41%</td>
<td>3.44%</td>
<td>2.89%</td>
<td>7.85%</td>
<td>5.16%</td>
<td>5.88%</td>
<td>4.14%</td>
</tr>
<tr>
<td>5. Loss Averse</td>
<td>4.08%</td>
<td>3.89%</td>
<td>−5.53%</td>
<td>−6.01%</td>
<td>4.41%</td>
<td>2.89%</td>
<td>4.90%</td>
<td>3.22%</td>
</tr>
<tr>
<td>6. Disposition</td>
<td>4.70%</td>
<td>4.19%</td>
<td>−5.42%</td>
<td>−5.98%</td>
<td>2.47%</td>
<td>0.98%</td>
<td>3.99%</td>
<td>1.56%</td>
</tr>
</tbody>
</table>

Note: Groups without an asterix are the only original regimes. Regimes with an asterix are simulations where loss averse and disposition effected investors calculated risk using an exponential average as opposed to a moving average.
References

Barber, B., Odean, T., Strahilevitz, M., in press. Once burned, twice shy: how naïve learning, counterfactuals, and regret affect the repurchase of stocks previously sold. Journal of Marketing Research.

7. Appendix

7.1. Portfolio Value, $z_i$

Investors routinely reinvest positive returns and do not cover negative returns. Hence, other things equal, the fund grows at the fund’s gross rate of return, $\hat{z}_i/z_i = R_{Gi} = (R_1 - R_0 + \alpha_i)u_i + R_0$.

7.2. Simulation Details

The simulation model contains seven parameters to configure. The growth rate, standard deviation, risk-free rate, and discount rate were calibrated based on long-term averages of the US economy and US stock market. The real growth of the US economy over the past century was 3%. The risk-free rate over the past century was 3%. The discount rate used was 6%. The other parameters were calibrated based on simulations run by Friedman and Abraham. They ran thousands of simulations to find the range of parameters where price dynamics were similar to actual dynamics. I used their baseline case. Table 7 shows a description of the parameters, meaning, and base numbers.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Base #</th>
<th>Definition</th>
<th>Meaning</th>
<th>Theory</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_o$</td>
<td>3%</td>
<td>risk-free rate</td>
<td>↑⇒ allocate more to risk-free asset</td>
<td></td>
</tr>
<tr>
<td>$dR$</td>
<td>6%</td>
<td>discount-rate</td>
<td>↑⇒ allocate more to risk-free asset</td>
<td></td>
</tr>
<tr>
<td>$g$</td>
<td>3%</td>
<td>growth-rate</td>
<td>↑⇒ allocate more to risky asset asset</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>20%</td>
<td>standard deviation</td>
<td>variability of a manager’s idiosyncratic shock</td>
<td></td>
</tr>
<tr>
<td>$\tau$</td>
<td>0.70</td>
<td>persistence of idiosyncratic shock</td>
<td>how long a shock persists through time</td>
<td></td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.70</td>
<td>memory rate</td>
<td>how much is put on current versus past losses</td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>2</td>
<td>elasticity</td>
<td>how much changes in demand change price</td>
<td></td>
</tr>
</tbody>
</table>

↑⇒ more crises