The Irrational Investor's Risk Profile

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I. INTRODUCTION

Webster defines the term irrational as “(1): not endowed with reason or understanding (2): lacking usual or normal mental clarity or coherence” (Webster, 2010). The average, normal investor is an individual who has chosen to delay current consumption and save money for his future. An individual who saves and invests for the future could hardly be defined as someone who lacks understanding or coherence. To the contrary an investor understands the need to plan for the future, and the desire to have his money work for himself in the interim, whether that is by investing in a savings account, CD, stocks, bonds etc… It is true that many investors, and the average investor, are irrational, but not in the way Webster defines it. Traditional finance defines a rational investor as one who makes choices that attempt to maximize his utility, or return on investment for a given level of risk. The rational investor is not affected by emotions, cognitive biases, or external factors that do not directly affect his stated utility. The irrational investor is subject to cognitive biases, and is influenced by emotions such as fear, greed, and anxiety – which may cause the investor to be influenced by short-term phenomena, even though his goals are long-term in nature. In other words, the irrational investor is a normal human being - his utility contains benefits that cannot be understood or programmed into a computer (Statman, 2011). Traditional finance theory treats investors as if they are not affected by biases or emotions, and has developed models and tools for the rational, emotionless investor. Unfortunately, because the average investor is not rational, the traditional approach and corresponding tools may be a detriment to investors, as evidenced by the poor return on investments average investors have historically achieved (Dalbar, 2010).

Over the past 20 years, the average investor has experienced investment returns significantly lower than those generated by a passive, non-managed portfolio of S&P 500 stocks (Dalbar, 2010). Dalbar, Inc. reports that the annualized return of an average equity (stock) investor for the past 20 years (ending 12/31/2009) was 3.17% compared to an annualized return of 8.20% for the S&P 500 index. An index, such as the S&P 500, is an unmanaged basket of securities that are selected at a point in time that have few, if any, changes over the course of several years. It is not only stock investors that underperform their benchmark. Those who invest in a diversified portfolio of securities (stocks and bonds), as well as those who invest only in bonds, also underperform their respective benchmarks. The average diversified investor had an annualized return of 2.34%, and the average bond investor had a return of 1.02%, which were significantly lower than the respective benchmarks, and did not even keep pace with inflation during that period (Dalbar, 2010). This is surprising, given the great flexibility and many tools investors have compared to a passive index of similar securities. An investor should be able to benefit from the flexibility of excluding poor investments, and actively managing his portfolio based upon the economic environment and future expectations.

Investors have access to many tools to help them decide which securities to invest in and how to create a portfolio that is commensurate with their preference for risk and return. Some of these tools include analysts' research reports as well as access to the opinions and forecasts of financial experts. An investor could take advantage of the various books and articles written on how to be a successful investor and generate superior returns over time, and even utilize diversification instruments available through financial institutions and found on the web. Yet despite all these tools, the average investor's return is significantly lower than that achieved by an index of similar securities. An index is always invested (that is, the entire value of the portfolio is held in non-cash assets), irrespective of an analyst's outlook for a specific stock or general economic outlook, and experiences the severity and duration of all stock market gains and losses. To the contrary, an individual investor can be fully invested, partially invested, or choose to remain un-invested based upon his future expected return and economic forecast. While individual investors have so many tools at their disposal and the flexibility to adjust their portfolio based upon new information, why do they consistently perform so poorly compared to a passive index?

The analysis by Dalbar (2010) is derived from reports regarding investors moving money in and out of many mutual funds, and the timing of such movements. This allows Dalbar to decipher the performance of the average investor across stocks, bonds and a diversified portfolio. Their results are not unique; a report by the investment research company, Morningstar®, on specific mutual funds found that investors also experienced significantly lower returns than were earned by the very mutual funds they were invested in (Haig, 2009). In other words, Morningstar® found that because of the timing of investors' purchases and sales of fund shares, investors performed worse than if they had simply held the fund through good and bad times. Dalbar found that the average hold period for any type of investor is between 3.2 – 4.3 years, meaning investors tend not to "buy and hold." There have been other studies confirming that investors jump in and out of the market, accumulating less money on average than a buy and hold strategy (Statman, 2011). What causes a long term investor to make short term choices that may jeopardize his ability to achieve his long term goals?

The purpose of this thesis is to identify the various factors that affect an individual investor's decisions and cause chronic underperformance. Much of the research to date has been with respect to optimization models, such as the Modern Portfolio Theory, that recommends a portfolio of securities that have the most favorable risk/reward tradeoff (portfolio efficiency). These optimizers are implemented after the investor's utility (risk preference) has been defined and input into the optimization model. The most common manner to define the risk preference of the investor is through a risk profile questionnaire. These questionnaires are promoted by financial institutions, both full-service firms such as Merrill Lynch®, and self-service firms such as Fidelity®, to help the investor define his risk profile. Financial firms will usually recommend an allocation of securities based upon the calculated risk profile that it believes will provide the investor with the optimal allocation of securities given the risk preference.

There have been many articles and books written to teach an individual how to invest and ultimately improve his investment returns for a given level of risk. The majority of the research with respect to constructing portfolios and improving investor performance has been dedicated to portfolio selection and management after the utility function (risk profile) is defined. This thesis takes a step back to examine whether the tools used to find the investor's risk profile are valid and result in accurate profiles. If the current risk profile questionnaire elicits an incorrect risk profile, then any optimization model, no matter how good it is, may not produce a portfolio of securities commensurate with the investor's true risk profile. It is imperative that the risk profile is accurately determined before we can move on to optimization and other investment techniques aimed to enhance investor performance.

I will begin the thesis by reviewing published research and literature on current portfolio tools available to investors (i.e. portfolio optimizers) with their respective strengths and weaknesses. I will also review behavioral finance research with respect to biases that influence investors to make decisions contrary to their expected utility, as well as research that challenges the traditional methods of measuring an investor's risk tolerance. I will then lay out the framework for this study and explain what questions the study will attempt to answer along with the outcomes I anticipate. The study will consist of a survey to gather information, and I will explain how that data was obtained and what methods were used to interpret the data. The results of the data will then be revealed along with their interpretation. Finally I will conclude by summarizing what was learned through this study and recommending ideas for implementation and future research.

II. LITERATURE REVIEW

Various studies have been undertaken in an attempt to explain the reason(s) for investor underperformance and provide suggestions that help investors have a more positive investment experience. The following literature review describes some of the more prominent studies that have influenced the investment community in the past, as well as more modern studies that challenge the assumptions made by traditional finance models and introduce behavioral aspects into the theory.

Modern Portfolio Theory

In 1952, Harry Markowitz introduced a quantitative model to create an efficient portfolio for investors (Markowitz, 1952). Markowitz defines efficiency as a portfolio that maximizes expected return for a given level of risk, or minimizes the level of risk for a given return. The resulting portfolio reduces the unsystematic risk of the portfolio through diversification of various assets. His model is based upon the precepts that investors prefer a portfolio with less volatility, and that they will maximize expected utility, which he defines as the return of the portfolio (for a given level of risk). The model and theory behind it later became known as the Modern Portfolio Theory (MPT). While the framework for the MPT was first published in the 1950's, it was not well recognized by the financial community until Markowitz was awarded the Nobel Prize in Economics in 1990 for his work and findings. This summary will review the basic tenets of the theory along with its strengths and weaknesses; for a more detailed analysis the reader is referred to his article in the *Journal of Finance* (Markowitz, 1952) and his subsequent book, *Portfolio Selection* (Markowitz, 1959).

The MPT was created for the institutional investor – one that is assumed to be rational and not limited by a time horizon, illiquidity or investment restrictions. Markowitz makes this assumption very clear in his papers, but the financial community has mostly ignored his instruction, and heavily promoted the MPT to both institutional and retail investors. It is interesting to note that Wall Street firms did not begin using the

MPT in their marketing and portfolio models until Markowitz won a Nobel Prize for his findings, even though they were published and available to the public since 1959.

The basic premise behind the theory is to define the investor's utility function, and then create a portfolio of securities that will maximize the expected return and minimize the level of risk. Markowitz used a mean variance analyzer to consider not only the expected risk and return of an individual security, but also how that security interacted with others in the portfolio (covariance). Before Markowitz' findings, portfolios were constructed based upon the characteristics of each individual security without respect to diversification. Mean variance analysis found that an asset that was deemed too risky for a portfolio could actually reduce the risk of the portfolio as a whole because of its low correlation to other assets. These findings brought about the idea of diversification, not only among individual securities but also asset classes. A conservative investor who may have had a portfolio of 100% bonds found that by adding a small percentage of stocks to the portfolio, he could actually reduce his total portfolio risk. The result for the conservative investor was a portfolio with greater expected return and less portfolio risk…a more efficient portfolio.

Financial experts and firms preach the gospel of diversification among differing securities and asset classes, especially those with low or no correlation to other securities. While the MPT has brought important discoveries to the investment community, it is by no means a complete, foolproof way to invest. Financial institutions and advisors, who unquestioningly use the MPT, are applying a model created for institutional investors to the mass population of investors without recognizing the pitfalls, or properly educating the retail investor of this misapplication.

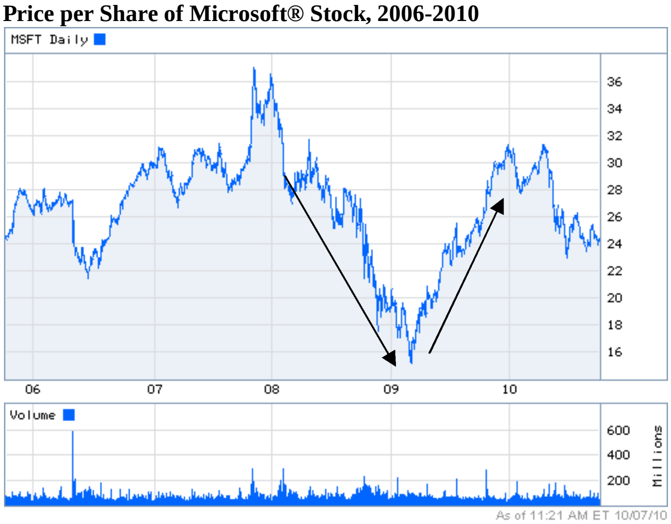
It is quite common that economic and financial studies have both strengths and weaknesses. It is just as important to understand the weaknesses of a study, and its effects, as it is to embrace its strengths. The primary weakness of the MPT, besides its misapplication to the retail investor, is its simplifying assumptions. Assumptions are an important part in economic models so long as they hold true; in the case of the MPT some of the assumptions have been disproved through empirical evidence, and therefore should be scrutinized.

MPT Assumptions

1. *Returns are random and normally distributed*

One assumption Markowitz makes is that security returns are random and normally distributed. Security returns may certainly be random from day to day, but empirical evidence shows that securities tend to trend over time. The prevalence of trends has brought about a type of investing called technical analysis, in which investors invest based upon certain trends and patterns of security prices. It is beyond the scope of this paper to analyze the success or failure of such methodology, but a study published in 1994 reports that investors who take market statistics into account and practice technical analysis do better than those who do not (Blume & O'Hara, 1994). The fact that trends exist among securities should not be surprising since stock prices tend to follow the business cycle. The growth phase of the business cycle typically results in a company experiencing increased revenues, cash flows and earnings. The improved financial condition of the company may result in an increase in dividends and/or an increase in reported net earnings, both of which have been shown to be major factors that determine a security's price (Gordon, 1959). The growth may continue for some time, as that particular phase of the business cycle runs its course. Returns from bonds and other asset classes will trend as well with respect to their correlation to the business cycle. Figure 1 is a chart of Microsoft's stock price for the past five years. As a result of the financial crisis of 2008, the economy entered into a severe contraction and the stock price of Microsoft was in a downward trend for 15 months. As leading indicators turned positive, so did the stock price of Microsoft - it entered an upward trend that lasted for 9 months. Contrary to the assumption that security prices are random, the evidence shows security prices may trend for extended periods of time (Pring, 1991).

Figure 1: **Price per Share of Microsoft® Stock, 2006-2010**



The assumption of a normal distribution has greater consequence for the investor. Markowitz makes this assumption because a normal distribution is required to consider important statistical measures to be valid, such as variance, standard deviation and covariance. The problem is that the normal distribution quantifies the occurrence of an isolated event as being extremely rare, and the probability of an isolated event occurring decreases at an exponential rate. This means that many isolated, outlying events are simply ignored under the normal distribution, because their chance of occurrence is so remote. A study of over 800 years of economic data and 66 countries finds that these outlying events occur more frequently than we think, and more frequently than the normal distribution predicts (Reinhart & Rogoff, 2009). In the decade of 2000, we experienced two significant stock market losses which were not predicted, and were ultimately classified as anomalies, or outlier events. The normal distribution predicts outlying events with much less frequency than we actually experience; therefore any security analysis assuming that returns are normally distributed may understate the actual risk of said security. As stated previously, the MPT was created specifically for institutional investors, those that have access to all investments, a long term time horizon and are "rational." Endowment funds fit this description, and religiously follow the theory. The largest endowment funds, which all follow the precepts of the MPT, are those managed by Harvard, Yale and Stanford. In fiscal year 2009, which included the crash of 2008, they each suffered substantial losses. Harvard and Stanford both lost 27%; Yale lost 25% and the equity market, as measured by the S&P 500, was down 30% during that period (McDonald, 2010). The extent of the loss in 2008, even for a diversified portfolio, may be acceptable for an institution with a perpetual time horizon, but could cause havoc and great concern for an individual investor who plans to retire in the near future. The fact that outlying events occur more often than the theory predicts should be an important factor when determining the composition of the portfolio for the investor.

There have been attempts to improve upon the assumption of the normal distribution in an attempt to find a distribution that more accurately resembles the stock market. Initial analyses attempted to better explain the distribution of returns by adding statistical moments to the data, such as skewness (Kraus & Litzenberger, 1976), and creating a lognormal distribution of returns instead of the normal distribution (Elton & Gruber, 1974). Despite these attempts to find a better distribution for stock prices, they were shown to be more data intensive and did not produce a more desirable portfolio than did the mean variance optimizer (Elton & Gruber, 1997). Studies continue in the present day trying to find the distribution that best fits the distribution of stock returns and the predictability of said distributions (Egan, 2007; Cenesizoglu & Timmermann, 2008).

2. *Security forecasts are accurate*

Markowitz also makes the assumption that a security analyst can effectively forecast the expected return and variance of an individual security as well as its correlation with other securities. The theory recommends that a detailed analysis is done on each individual security in the universe, and then a portfolio is developed based upon the forecasts of the security analyst and the findings of the mean variance optimizer. After the year is over, the portfolio is liquidated and the analysis starts over again to find next year's optimal portfolio. The requirement to have an accurate forecast for each security's expected return, volatility, and correlation is essential for the mean variance optimizer to produce a valid output. The analyst must be able to understand the critical cycles shaping both the current and future economic environment. She needs to understand what decisions a company will make, how her actions will affect earnings and how the investing public will perceive that information. The analyst must then also forecast the company's covariance with that of other securities. The core of any optimizer, including the mean variance optimizer, relies upon accurate forecasts. If forecasts are not accurate, then the mean variance optimizer will provide an incorrect allocation strategy. This is where the problem lies. While the assumption for accurate forecasts is crucial to this theory, it is not realistic, and empirical evidence shows that forecasts are generally not accurate.

There are several examples of experts' inability to accurately forecast the future, especially when it comes to forecasting specific values. Experts are good at forecasting the status quo, but not a change in direction or any significant deviation from the norm. A review of 2,000 past economic predictions found that economists didn't predict anything; their prediction was just an extrapolation of prior data (Bouchaud & Potters, 2003). There are several examples in recent history of significant events that were not predicted or represented by mainstream economists or Wall Street strategists. Who forecast "The Lost Decade" in Japan when they were near invincible during the late 1980's? How many people forecast the "Dot Com Bust" during the technology boom of 1998-1999? When oil was trading at $11/barrel in 1998, how many forecast it would go up to $147 within 10 years? (Dent, 2008). There may have been a few individuals who predicted these events, but their predictions were not accepted or implemented in mainstream economic models. Individuals and experts alike are unable to account for outlier events in their forecasts. A group of researchers (Lichtenstein et. al, 1982) performed an experiment in which they asked subjects to provide estimates for future security returns along with confidence intervals in which they were 90% certain future returns would fall. They found that subjects gave a smaller range of distribution than actually occurred, or in other words they failed to account for outlying events. Behavioral finance professor, Werner De Bondt, studied the accuracy and value of forecasts by security analysts and economists. He found that the average forecast does not accurately predict future occurrences, and therefore is not useful when developing an investment strategy (De Bondt, 1991).

The inability to accurately forecast is not unique to security analysts and economists. Philip Tetlock, a professor of Organizational Behavior at the University of California, Berkeley, analyzed over 82,000 forecasts from over 300 experts in the fields of academics, economics and public policy. He compared those forecasts to real-world actual outcomes. In an interview with Money Magazine he said, “My research prepared me for widespread forecasting failures. We found that our experts’ predictions barely beat random guesses – the statistical equivalent of a dart-throwing chimp – and proved no better than predictions of reasonably well-read nonexperts. Ironically, the more famous the expert, the less accurate his or her predictions tended to be” (Schurenberg, 2009, p.2). There is a popular joke among forecasters: “Economists exist to make weather forecasters look good.” There may be some truth to this joke. Tyszka & Zielonka (2002) found that security analysts were worse at predicting, but had greater confidence in their prediction than weather forecasters. The tendency of economists and security analysts to forecast only events within the norm begs us to ask whether expert forecasts provide any value to investors. The MPT makes a crucial assumption of accurate forecasts, but empirical evidence and numerous studies show that forecasts are rarely accurate. This reality significantly weakens the final output of Markowitz' mean variance optimizer. Even if all other assumptions hold, the allocation recommended by the optimizer should have the following disclosure: *If the forecast provided by security analysts are incorrect, then the recommended portfolio will be incorrect. Numerous empirical studies have shown forecasts are seldom accurate*.

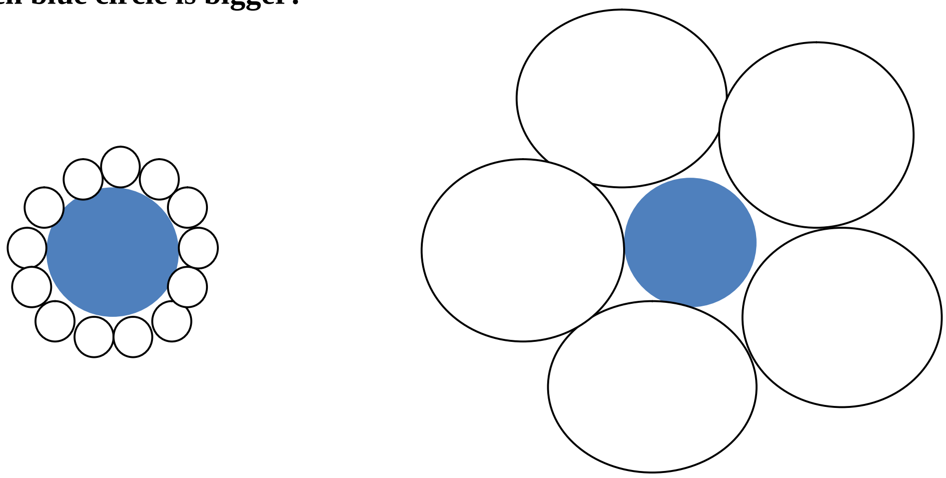
3. *Investors are rational*

A rational individual is one that makes choices based upon sound reason and logic, one whose decisions follow the expected utility maxim. The expected utility maxim is a hypothesis in which an individual's preferences are calculated and compared in the face of uncertainty. A rational investor is expected to maximize his utility given his preferences as defined in the utility function. Markowitz, who assumed investors are rational, acknowledges that the rational person does not exist in reality, but that we can still use the theory of rational behavior as a guide (Markowitz, 1959). An institution may be more rational than an individual investor, but the problem is that the model is being used for the individual, irrational investor. What good is an efficient, optimal portfolio that assumes rationality for an investor who is irrational? Do investment tools that assume investor rationality do more harm to the long term success of the investor, because they do not account for the investor's inherent irrationality?

The expected utility theory has several axioms that must hold true for it to be valid, yet studies show that the axiom of independence is commonly violated. The axiom of independence states that a choice (preference) will hold independent of the possibility of another outcome. Allais (1997) performed tests to see if the axiom of independence was violated in a set of lotteries. In his experiment, participants were asked to choose among two lotteries, each representing different potential payouts and their respective probabilities. Then the participants were asked to choose among another set of lotteries with differing payouts and probabilities. Allais found that the participants were not able to evaluate the lotteries independently from each other – choices were influenced by the outcome of another lottery. The main findings, of what is now known as the "Allais Paradox", were that participants made inconsistent, irrational choices. These irrational decisions could be because the individual simply made an error in judgment, but others believe outside factors not accounted for in the utility function – such as hope, fear and suspense come into play (Markowitz, 1959). Recently there has been much study on the irrationality of the individual and what causes such behavior.

Dan Ariely, a professor of Behavioral Economics at Duke University, has studied whether irrational behavior can be predicted. Many of his findings have been published in a single book, *Predictably Irrational* (Ariely, 2008). Mathematical models and algorithms, such as the MPT, measure and forecast the absolute values of variables. In contrast, Ariely says people forecast the relationship between the value of a variable and a baseline value. This is because a person obtains utility, not from his current position, but from his position relative to something else. An example of this can be illustrated by the following graphic:

Which blue circle is bigger?



At first glance, the blue circle on the left appears bigger, because relative to the circles surrounding it, it is much bigger. However, the actual size of the blue circle is identical in both pictures. This type of relative reasoning could explain why individuals violate the axioms of expected utility - people make different choices based upon how they perceive them, even though the absolute outcome is the same.

Ariely also looked at how well an individual could predict his own behavior at times of great emotion (Ariely, 2008). He held a study at the University of California, Berkeley with a group of male college students. He asked the students to answer a series of questions regarding what sexual behaviors they may undertake on a date and which sexual activities they deem as appropriate. The questions were asked and answers recorded when the students were in a calm, rational state of mind. Days later, Ariely asked the same students if they would be willing to answer the same questions again, but this time they were to answer the questions during a period of great emotion. He exposed the students to pornography, and at the moment of greatest stimulation asked that they answer the same questions again. He found that the students grossly underestimated their behavior in an emotional state. He found they were likely to engage in more risqué sexual activity than they had predicted, and some behaviors that were deemed by the students as inappropriate in the calm state were judged to be appropriate in the state of high emotion. The prediction of future behavior was wrong by a large margin, and therefore Ariely concludes that we are unable to accurately predict how we will act in future situations of intense emotions.

Experiments and empirical evidence have challenged the idea that humans are fundamentally rational. Psychologists and behavioral experts believe irrationality comes from the way our brains are wired and that there is some explanation for irrational behavior. Some, such as Ariely, believe that our irrationality may be predictable. Decisions that are not made in line with the neoclassical utility model may be termed "irrational," but that does not mean they cannot be predicted. Opaluch and Segerson (1989) report that the literature on this topic shows several examples where "irrational" behavior can be explained by alternative models for decision making. The MPT assumes rationality when the evidence is clear that individuals do not follow the expected utility maximization theory, and are therefore defined as irrational.

Improving upon the MPT

There have been several attempts to improve upon some aspects of Markowitz' mean variance algorithm to obtain a better portfolio for the investor. Resampled Efficiency and the Post-Modern Portfolio Theory incorporate different statistical, data and behavioral assumptions into the optimizer, while Prospect Theory incorporates the irrational investor into the utility model.

1. Resampled Efficiency

Resampled Efficiency is an optimization method that attempts to improve upon the weaknesses of both normal distributions and the need for accurate forecasts. Resampled Efficiency was created because its author, Richard Michaud (1998), was bothered by the exactness of inputs required by most optimization algorithms and the fact that forecasts are imperfect. After much analysis Michaud patented an optimization method that uses a Monte Carlo simulation instead of relying on accurate forecasts. Monte Carlo is a sophisticated simulation method that obtains its results from repeated random sampling. It is mostly used when an exact or accurate measurement is not possible through traditional computing methods (Hubbard, 2007). Michaud believes the Monte Carlo method allows for a more correct output from the optimizer in the event stock market returns are different from what was expected (Rockel, 2010).

An article written by the Michauds (Michaud &Michaud, 2008) discusses the results of a simulation test performed by Nilufer Usman (Markowitz & Usman, 2003) comparing the resampled efficiency optimizer to the mean variance optimizer. The simulation test was performed between the two methods using ten years of data, and the results were astounding: the resampled efficiency optimizer achieved a more efficient portfolio than the mean variance optimizer in 30 out of 30 tests. Michaud explained this occurred because the mean variance optimizer requires exact data and assumes perfect information (Michaud & Michaud, 2008). A word of caution on these results - the experiment was done on a very small data set, only 20 stocks representing only very large companies (in terms of market capitalization). Any results from such a limited study should be thoroughly scrutinized, as it was in an empirical analysis written just two years after the findings of the initial experiment were made public. In a report by Kohli (2005), the author compared the results of both the resampled efficiency and the mean variance optimizers for 60 portfolios of 75 stocks each for a total of 4500 stocks between 2001 and 2003. The findings of the analysis were at odds with Usman's test; resampled efficiency offered little advantage when compared to the mean variance optimizer. It should be pointed out that the empirical analysis only covered a period of 1 year and 5 months, while the Usman experiment lasted for 10 years. There is an obvious discrepancy between the findings of the two experiments, and the Usman test lacks a large sample size, while the Kohli analysis is limited in its duration. Given the discrepancy and weaknesses in both analyses, one cannot conclusively state which optimizer is superior to the other.

As in the tests performed above, many optimizers are compared to each other to determine which creates a more efficient portfolio. No matter how many times a portfolio is simulated, the actual results can only be determined in real time market experiences – which entail investor irrationality. In the case of resampled efficiency we can gather information from actual returns versus market returns. The Michauds run an investment company, New Frontier Advisors, which offers the resampled efficiency method through a portfolio that any investor can access, and therefore provides actual performance data. Regardless of whether the resampled efficiency optimizer or mean variance optimizer is better, how has the resampled efficiency portfolio performed in real life over the past few years, which included both good and bad markets? One would expect a good optimizer to produce above average returns in good years, or at the very least not lose as much as passive stock market indices in bad years. Listed below are New Frontier's conservative and aggressive portfolios compared to their respective benchmark indices. All performance numbers are through 6/30/2010:

	1 YR	3YR	5YR	3yr Std. Dev.
New Frontier Conservative	**7.6%**	**1.0%**	**2.0%**	**7.3**
80% Bond - 20% Stock Index	6.3%	5.1%	4.6%	7.3
New Frontier Aggressive	**12.4%**	**-11.3%**	**-0.5%**	**24.1**
S&P 500 Total Return	14.4%	- 9.8%	-0.8%	20.7

Source: New Frontier Advisor Marketing Materials, Genworth Wealth Management

In many cases, the portfolios had lower returns than the benchmark while having the same, or higher risk as measured by standard deviation. While the jury may be out on whether the resampled efficiency optimizer is superior to Markowitz', the portfolios generated by New Frontier's optimizer have not consistently provided superior risk/return results than their respective benchmarks.

2. Post-Modern Portfolio Theory

The Post-Modern Portfolio Theory (PMPT) also attempts to improve upon Markowitz' mean variance optimizer. The primary difference is that Markowitz defines risk in terms of standard deviation, and the PMPT defines risk only as downside risk. Downside risk is defined as the risk of loss, risk of underperformance, or of not meeting one's goals. Frank Sortino, author of PMPT, believes standard deviation is not an accurate measure of risk because it assumes normal distributions and is focused on the mean return (Swisher & Kasten, 2005). Downside risk recognizes that returns are not normally distributed and focuses on a minimum acceptable return to the investor, which more closely captures the investor's risk tolerance than a portfolio's standard deviation. Sortino believes the downside risk optimizer begins to incorporate behavioral finance into the model, which is lacking in the mean variance optimizer and the assumption of rationality. In an extensive analysis that used past data and ran simulations of future market values, the downside risk optimizer resulted in a higher expected portfolio value than did the mean variance optimizer (Swisher & Kasten, 2005). In fact, the two often gave contradictory results, where the least risky portfolio as defined by the mean variance optimizer was actually the most risky portfolio as defined by the downside risk optimizer. As witnessed with resampled efficiency, just because one optimizer provides better returns in a simulated environment does not mean it performs well in real life situations, especially when the market experiences an outlier event. Sortino employs the downside risk optimizer through the asset management firm, Sortino Financial Advisors®. The portfolios Sortino manages were incepted at different times, and lack long term performance, but there exists performance figures for the years 2007 and 2008. 2008 is of special interest because that was the year of the financial crisis "anomaly." The figures for the Sortino portfolio:

Portfolio	2007	2008
Sortino Aggressive	7.6%	-29%
S&P 500 Total Return	5.5%	-37%

Source: Sortino Investment Advisors

While it is clear the downside risk optimizer outperformed the market for those two years, it is also clear that they were not immune from outlier events. In a letter to his investors in 2008, Sortino explained that the financial crisis was different from prior crises, and that a new strategy may be needed going forward (Sortino, 2008).

3. Prospect Theory

Prospect theory, developed by behavioral finance experts, challenges the notion of investor rationality and specifically the expected utility theory. As stated earlier, various studies have shown that investors do not make decisions according to the expected utility maxim, and for that they are labeled "irrational." Kahneman and Tversky (1979) developed a utility theory called prospect theory that recognizes that axioms of expected utility theory are violated, and attempts to account for behavioral biases in the model. Prospect theory incorporates the findings of several studies on human behavior, namely that people do not analyze outcomes correctly, suffer from loss aversion and regret aversion, and engage in mental accounting. People tend to underweight outcomes that have a small probability of occurrence compared to outcomes that have a more certain outcome. An investor exhibits loss aversion when he is risk-averse when facing gains and is risk taking when facing losses. He may, therefore, end up taking more risk than he is comfortable with (Schmidt & Traub, 2002). Regret aversion encourages investors to hold on to assets that have lost value to avoid the pain from having made a poor investment decision, leading to a riskier portfolio and lower returns (Odean, 1998). Mental accounting is the way investors perceive their investment outcomes, how they track their investments and how often they evaluate their portfolios.

There are two phases to prospect theory - the editing phase and the evaluation phase. In the editing phase the brain attempts to simplify new information. The six steps to editing are:

1) Coding – Recognize whether an outcome is a gain or a loss
2) Combination – Combine probabilities with identical outcomes
3) Segregation – Segregate riskless from risky prospects
4) Cancellation – Cancel variables where probabilities and outcomes are same in both prospects
5) Simplify – Round up or down
6) Exclude Dominated Items – Throw out choices strictly dominated by another

Once the brain has simplified the choices as much as it can, it moves on to the evaluation phase. In the evaluation phase, the individual gives a certain weighting to each decision, calculates the problem (decision tree), and chooses the decision with the highest expected outcome. The weight given to each decision is what ultimately determines the utility function and decision made. Prospect theory is not a solution in itself; rather it is a way to more accurately decipher an individual's utility curve by relaxing the tenets that underlie rationality (Barberis & Thaler, 2003).

Behavioral Finance

Behavioral finance is the study of psychological effects on the individual pertaining to choices made with respect to money and investing. It recognizes that the decisions individuals make are influenced by one or more behavioral biases. This is contrary to traditional finance, where the individual is assumed to be rational and follow the expected utility theory as previously described. While the precepts of behavioral finance have been around for several years, there has been very slow progress to adapt its findings in the financial markets.

Behavioral biases are generally classified as being of either a cognitive or emotional type. Some believe that a proper understanding of these biases and knowing the biases a person exhibits can allow these "irrationalities" to be predicted and modeled (Ariely 2008). A summary of some of the most prominent biases are below.

1. *Cognitive Biases*

Availability: An individual makes decisions based upon the information that is available and her awareness of it. An investor who does not dedicate the necessary time to understand all aspects of the information (both good and bad) may make an incorrect decision based upon limited information.

Representativeness: An individual makes decisions based upon history and stereotypes. An investor may try to replicate past performance by investing in stocks that gained value in the recent past and avoiding stocks that recently lost value. Studies have shown the opposite is true. A portfolio containing the best performing 35 stocks in the prior three year period had returns less than the average return for New York Stock Exchange (NYSE) index over the subsequent three year period. A portfolio containing the worst performing 35 stocks in the prior three year period had returns significantly greater than the NYSE return over the subsequent three year period (De Bondt & Thaler, 1985).

Confirmation Bias: An individual who decides upon a course of action or makes a decision will look for evidence to support her decision while either discounting or ignoring evidence to the contrary. This bias may influence another type of bias, anchoring.

Anchoring/Conservatism: People who exhibit this bias are slow to adapt new information into future forecasts and expectations. This bias results in individuals weighting prior beliefs and knowledge more heavily than new information. For instance, an investor may choose to not invest in a company which experienced a positive earnings surprise, because she believes the results were a single period anomaly, even though studies show that companies with strong earnings outperform over time (Bernard & Seyhun, 1997). Conservatism also affects economists and analysts, as evidenced by their forecasts being a culmination of past forecasts and market results. In other words, their future predictions are many times anchored to past results (Bouchaud & Potters, 2003). Anchoring and conservatism may be influenced by the Status Quo Bias, which is an individual's preference for the current state rather than change (Kahneman et. al., 1991).

Overconfidence: Overconfidence is a bias that may affect experts and professionals more often than a novice investor. An overconfident investor may invest a greater portion of her portfolio in a single security or sector that she feels strongly about. Overconfidence results in the investor not recognizing the possibility of being in error, and the risk of that error. Overconfidence may therefore result in a riskier portfolio than anticipated.

Illusion of Money: This bias refers to investors making decisions based upon nominal terms and not real terms. This could lead an investor to believe that income securities, such as certificates of deposit and bonds, will allow her to meet her living needs without accounting for inflation. For instance, a bond that is yielding 5% may be quite attractive in nominal terms, but if inflation is also at 5%, the real return would be 0%. This cognitive error could cause the investor to overestimate the future purchasing power of her investments.

House Money Effect: This bias refers to gains realized in an account and treating those gains as free or "house money." The investor would reinvest those gains into an even riskier security/strategy, which would increase the risk of the portfolio, perhaps to a level that is beyond the investor's desired risk tolerance.

Mental Accounting: This bias refers to how an investor classifies gains and losses and treats accounts differently based upon objectives. This may result in the investor creating a sub-optimal total portfolio, if she does not account for the correlations among securities in the various accounts.

Myopia: This bias is commonly combined with that of loss aversion, because they often occur together. The bias of myopia may result in the investor checking her performance often, and could encourage her to make investment decisions based upon short term portfolio performance.

2. *Emotional Biases*

Loss Aversion: This bias recognizes that the pain of loss is greater than the joy from gain (Kahneman & Tversky, 1979) and is at the heart of prospect theory. Loss aversion leads investors to take greater risk when facing losses, while locking in profits quickly when faced with gains to avoid potential future loss from that security. The effects of loss aversion cause investors to experience poor investment returns (Pompian, 2006). Studies confirm that investors regularly experience loss aversion (Kahneman et. al., 1991)

Pride/Fear of Regret: An investor exhibits this bias when her choices are driven by the joy and instant gratification from selling a security that has a gain, and the desire to not experience the pain from selling a security that has a loss. Pride and regret cause similar results as loss aversion, but for different reasons. Like loss aversion, pride and regret cause investors to sell winners quickly to experience the pride of having made a profitable investment and hold onto losers so not to experience the regret of having made a poor investment decision. Studies show that individuals who are quick to sell winners and slow to sell losers tend to have below average portfolio returns (Odean, 1998).

Optimism: An optimistic investor is one who believes that whatever decisions she makes will turn out to be good ones. An optimist may choose to ignore bad news or negative information that she believes is just a pessimistic outlook. The optimist may also be subject to the bias of overconfidence. Optimism may cause an investor to fail to realize the potential downside of her holdings, and therefore underestimate the risk of loss.

Aversion to Ambiguity: This bias is very similar to the Status Quo bias. People who have this bias prefer the familiar to the unfamiliar, even if the familiar is not a favorable outcome. A classic example of this bias occurred recently with the bailout of AIG and other financial institutions as well as with Long Term Capital Management in 1980. In the case of Long Term Capital Management, it was decided that a bailout was necessary because it was believed that not bailing them out would result in a greater economic harm. (Shefrin, 2000).

Endowment Effect: This bias is an emotional attachment to that which is owned. An investor places higher value on what she owns than the market does. This leads to an investor not getting a "fair" price and holding onto an asset that may not be a good fit for her risk profile (Plott & Zeiler, 2005).

Snake Bite Effect: This bias is exhibited by an investor who has a negative experience, and reverts to a strategy that no longer reflects her needs and goals. An investor who makes poor decisions and has a bad investment experience may become more averse to risk or loss - reducing the probability that she reaches her initial goals.

An individual may experience one or more of these behavioral biases. Imagine the following scenario: Stephanie is very confident in her ability to make a good decision, but doesn't have the time to properly research her investments. One afternoon she watches a well respected analyst on TV, who just touted how the last two forecasts were spot on, and predicts that some security is undervalued and a good buy. The analyst rattles off a few pieces of financial and economic data and says he believes the stock can go up 40% from here. Stephanie recognizes the company and routinely buys goods from them; in addition she agrees with the financial talking points the analyst gave. Stephanie decides to invest a large part of her portfolio in this security because the prospects of return are so good. In this scenario, which is not unrealistic, Stephanie commits the following biases: availability (from only listening to one analyst), representativeness (from following the analyst's advice because of prior success), overconfidence, anchoring (to the 40% return), optimism (from believing things will turn out well), and aversion to ambiguity (because the investor knows the company).

A behavioral trait not directly listed as a bias by behavioral finance experts, but equally important in the decision making process, is how individuals act in the face of uncertainty. Investors not only react to the current state of information, but they make decisions based upon what they perceive the future to be. Anticipatory feelings such as hope, fear, anxiety and suspense play a major role in the decisions we make. A study on the impact of anticipatory feelings found that conventional measures of risk underestimate the effect of uncertainty on asset prices (Caplin & Leahy, 1997). This could cause an investor to make a decision contrary to the expected utility theory, not because of the current situation or any predictable bias, but due to the anxiety she feels about what may happen in the future.

One potential solution to overcoming behavioral biases may be to educate individuals about their biases – make them aware of the biases, so they can work on improving their decision making process. That seems like an easy solution, but does educating about behavioral biases translate into individuals making non-biased decisions? A recent study was undertaken to determine whether knowledge about an individual's behavioral biases could allow her to overcome them when in the decision making state (Menkhoff & Nikiforow, 2009). The study focused only on portfolio managers, because they have a very strong financial incentive to overcome their biases and produce superior returns for their investors. The study found that behavioral biases exist in the financial industry, and while the portfolio managers were able to reduce their biases through learning, they were not able to overcome them entirely. The authors further conclude that we may be able recognize biases in others, but we have a difficult time recognizing, and therefore correcting, our own biases.

Behavioral biases are believed to be a contributing factor as to why the average investor underperforms a passive buy and hold strategy. Traditional finance theory and models do not account for behavioral biases, and therefore may provide incorrect guidance, and may result in the investor making poor investment decisions. Studies show that investors regularly jump in and out of stocks and bonds and accumulate less money on average than investors who buy and hold portfolios (Statman, 2011). The average stock only and bond only investors remain invested for 3.2 years at a time; the average diversified investor remains invested for only 4.3 years at a time (Dalbar, 2010). Investor behavior is a contrary indicator to the stock market, as investors tend to act at the wrong time, allowing their emotions and behavioral biases to overrule rational decisions. A study by the Gallup poll in 1999 (after a huge run up in stock prices) found that a clear majority believed it was a good time to invest in stocks. The same poll was replicated in 2002 (after two years of major stock market losses) with 66% of respondents stating it was not a good time to invest (Gallup, 2002). The traditional utility theory and linear optimization models cannot account for this behavior – whether it be rational or irrational, the evidence is clear that the behavior exists. Instead of ignoring the reality of this behavior and suggest that the human is simply in error, behavioral finance attempts to explain the underlying causes of the behavior in an attempt to predict and model the behavior.

Prospect theory replaces the assumption of rationality in utility theory with allowances for irrational behavior. Prospect theory and behavioral finance go hand in hand to develop a more appropriate model for the average individual that exhibits behavioral biases. Of all the theories that challenge the accuracy of expected utility, prospect theory may be the best tool for financial applications (Barberis & Thaler, 2003).

Risk Profile Questionnaires

The purpose of the present research is to take a step back from the portfolio optimizers and understand who the investor is, so that the proper investment model can be applied. The primary tool to get to know the investor and their preferences is the risk profile questionnaire. Self-service firms such as Fidelity®, Vanguard® and Schwab® make these questionnaires available for investors, so they can classify their preference for risk (from conservative to aggressive) and suggest a portfolio of securities commensurate with that risk profile. Full service firms such as Morgan Stanley®, Merrill Lynch® and independent financial advisors often require these questionnaires when the investor engages in a fee-based relationship with an advisor. While traditional risk questionnaires are widely accepted and used by financial firms, there is much debate over their validity.

Several years ago, John Grable and Ruth Lytton (1999) challenged the simplicity and validity of traditional risk profile questionnaires, and created a multidimensional financial risk assessment that included questions with respect to various measures of risk and prospect theory. Their questionnaire was based upon the recommendations from MacCrimmon and Wehrung (1986) - that a risk assessment should include several distinct financial scenarios and situations. Grable and Lytton constructed a multidimensional, 13-item financial risk questionnaire with the intent of eliciting a more accurate and comprehensive risk profile than the one question risk assessment offered by the Survey of Consumer Finance. Their questionnaire was initially tested in a pilot study consisting of university staff to evaluate its validity and effectiveness. Regression and factor analysis confirmed that the risk assessment instrument was both a valid and effective instrument in describing the investor's risk profile. A few years later, a different study by Grable and Lytton (2003), using an online survey with a different sample, again confirmed the validity of the 13-item financial risk tolerance questionnaire. The underlying purpose of their research was to create a more accurate risk tolerance questionnaire, and they offered the 13-item instrument as a starting point. Their recommendation was for researchers and financial practitioners to test the questionnaire in various scenarios and differing samples to improve upon the questionnaire, and ultimately create a valid, reliable, and standardized risk tolerance questionnaire that would be used by the financial community.

In the eleven years since Grable and Lytton (1999) published their 13-item risk assessment instrument, there has been little progress to update the manner in which investors are profiled. Financial firms continue to use the same traditional methods for measuring the risk profile of an individual, despite evidence that more valid ways to profile investors exist. In this thesis, I build upon the research that has been done to date by performing an experiment that analyzes a firm's specific risk profile questionnaire, and incorporates questions to determine whether participants exhibit a particular behavioral bias.[1] While the traditional questionnaires employed by financial firms are a start to identifying and understanding the investor, the assumption of rationality that is built into the traditional risk questionnaires may yield incorrect results.

III. CONCEPTUAL FRAMEWORK

The question posed at the beginning of this thesis was why the securities chosen by the average investor greatly underperform a similar basket of securities over time. Possible explanations could be that the investor paid commissions or advisory fees that bring down his return, but the difference is much more than that – something else is affecting the average investor's ability to perform as well as a passive index of securities. Current investment tools assume the individual is rational while evidence shows individuals act irrationally in certain situations. The risk profile questionnaire, which is the primary tool used to get to know the investor, also assumes the investor is rational and will follow the expected utility theory irrespective of the investment environment. The notion of "this is how an investor should act" permeates the financial industry without regard to how the investor may actually behave. SmartMoney® Magazine recently published the "Perfect Portfolio" for the 25 year old bachelor that recommended putting 94% of the portfolio in stocks and stated, "With decades before you retire, don't sweat the markets' short-term ups and downs" (Prior & Tarquinio, 2011, 43). The industry projects how an investor should act rather than attempts to understand underlying biases the investor has, and how the biases may affect the investor's decisions

[1] Grable & Lytton did not test their questionnaire against a multi-question risk profile of a specific brokerage firm, nor did their questionnaire attempt to uncover specific behavioral biases.

among various situations. What good is a portfolio comprised mainly of stocks, if the investor cannot tolerate the risk and ends up selling when losses begin to accrue in his account, regardless of his age?

For this study, I constructed a survey with three primary goals. The first part of the survey is a traditional risk profile questionnaire that is representative of what investors currently take online or through their brokerage firm. The purpose of the risk profile questionnaire is to calculate an individual's risk profile – specifically whether the participant is classified as "Growth" or "Not Growth." A "Growth" investor is one who desires his portfolio to grow significantly over time and is willing to accept short term losses and volatility in portfolio value to achieve it. A "Not Growth" investor is one who is willing to earn lower portfolio returns over time in order to have less volatility and minimal short term losses. The second section of the survey includes questions commonly used by researchers to assess whether a subject exhibits one or more behavioral biases – specifically myopia, loss aversion, anchoring and overconfidence. The third part of the survey is a simulation. It includes questions that ask what the participant would do in various stock market and economic scenarios. The scenarios are structured so that the subject's choices provide evidence of behavioral biases. The survey also includes a list of questions about demographic characteristics that could influence a subject's risk tolerance, tendency to exhibit behavioral biases, and investment behavior. These characteristics include age, gender, education, investment experience, the use of a financial advisor, income, and net worth. Finally, the survey includes questions about the respondents' perceptions of the survey, such as whether they believed the information would be kept confidential and how well they understood the survey.

The survey results should allow us to answer the following questions:

- Do participants in the survey exhibit one or more behavioral biases?
- Does the calculated risk profile (from the questionnaire) confirm or contradict any behavioral biases considered in this experiment?
- What investment decisions are expected for individuals with a particular behavioral bias?
- Are there any correlations between the behavioral finance questions and how the respondent answered the simulation questions?
- Are there any correlations between behavioral biases and the participant's risk tolerance (as measured by the risk questionnaire) or demographics?

The Model

The data collected from the survey will be analyzed using multiple regression models. In the survey, seven questions are scored and summed collectively (based upon the risk questionnaire scoring key) to characterize the participant as either "Growth" or "Not Growth." In addition, fifteen questions elicit evidence for the presence of behavioral biases. Each of the sixteen responses constitutes a characteristic of the participant and will be a dependent variable. There will be a total of 16 regression equations, one for each dependent variable with demographic information acting as the independent variables and modeled as follows:

$$\mathbf{Y_1} = \beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Experience}) + \beta_3(\text{Advisor}) + \beta_4(\text{Education}) + \beta_5(\text{Age35}) + \beta_6(\text{Age45}) + \beta_7(\text{Age55}) + \beta_8(\text{NetWorth250}) + \beta_9(\text{NetWorth500}) + \beta_{10}(\text{NetWorth1000}) + \beta_{11}(\text{NetWorth1000p}) + \varepsilon$$

$$\vdots$$

$$\mathbf{Y_{16}} = \beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Experience}) + \beta_3(\text{Advisor}) + \beta_4(\text{Education}) + \beta_5(\text{Age35}) + \beta_6(\text{Age45}) + \beta_7(\text{Age55}) + \beta_8(\text{NetWorth250}) + \beta_9(\text{NetWorth500}) + \beta_{10}(\text{NetWorth1000}) + \beta_{11}(\text{NetWorth1000p}) + \varepsilon$$

Table 1 provides a description for each dependent variable along with its respective variable ID.

Table 1. Description of Dependent Variables

	Variable	Description
Y_1	GR	Risk tolerance of investor (Growth/Not)
Y_2	QLA1	Behavior question #1 on Loss Aversion
Y_3	QLA2	Behavior question #2 on Loss Aversion
Y_4	QLA3	Behavior question #3 on Loss Aversion
Y_5	QAN	Behavior question on Anchoring
Y_6	QOC	Behavior question on Overconfidence
Y_7	QMY	Behavior question on Myopia
Y_8	SMY	Simulation question on Myopia
Y_9	SOC1	Simulation question #1 on Overconfidence
Y_{10}	SOC2	Simulation question #2 on Overconfidence
Y_{11}	SOC3	Simulation question #3 on Overconfidence
Y_{12}	SAN1	Simulation question #1 on Anchoring
Y_{13}	SAN2	Simulation question #2 on Anchoring
Y_{14}	SAN3	Simulation question #3 on Anchoring
Y_{15}	SLA1	Simulation question #1 on Loss Aversion
Y_{16}	SLA2	Simulation question #2 on Loss Aversion

Each dependent variable will take on a value of either 0 or 1. The respondent will receive a "1" if his risk profile is classified as "Growth," or if he exhibits a specific behavioral bias, and a "0" otherwise. The independent variables of gender, experience, advisor and education also take on binomial values. The respondent receives a "1" if male, is an experienced investor (more than 5 years investment experience), works with a financial advisor, or has a college degree (or greater). Age and net worth are tiered in order to interpret any marginal effects, or in other words how an increase/decrease in age or net worth affects the dependent variable. Income will also be collected as a demographic variable, but was not included in the model as explained in the results section. A participant will be classified as exhibiting a behavioral bias if, in the survey, he chooses any response that signals a specific behavioral bias. Some participants may exhibit more than one, or perhaps all of the biases considered.

The risk profile questionnaire has only one objective, to classify the investor's risk tolerance on a scale from conservative to aggressive, although in this study the participant will be classified either as "Growth" or "Not Growth." The only behavioral bias that is expected to have a strong correlation with the risk profile is that of loss aversion. Among participants classified as "Growth," I would expect to see a small percentage of, if any, respondents exhibiting loss aversion. This is because loss averse investors are more concerned about losing money than they are about making money, while growth investors are more concerned with making money over the long term. On the other hand, among respondents classified as "Not Growth," I would expect to see a significant percentage of respondents exhibiting loss aversion. In addition, I would expect age to have a strong positive correlation to loss aversion because as an investor nears retirement, he tends to be more concerned about preserving capital than growing it aggressively. One purpose of this thesis is to determine the interactions of all the variables, and whether there is any explanatory power from the demographic information.

Expected effects of behavioral biases

The loss averse investor is expected to remain in a rational state and abide by the investment plan (allocation) during periods of low stock market volatility. In a period of stock market gains the loss averse investor will harvest his gains quickly, thus limiting upside potential. In a period of stock market and account losses, the loss averse investor may continue to hold the securities, but at some point will likely shift to a more conservative portfolio (or completely cash out of the stock market) for an extended period of time. The practice of limiting the pain of potential future account losses by selling stocks after the market goes down may bring temporary psychological relief to the investor, but it would be a detriment in the long run if he fails to participate in any stock market recovery. Any period where the stock market recovers from a prior loss will likely leave the loss averse investor worse off.

The myopic investor is not expected to be affected by a stock market period with low volatility and will continue to monitor the performance of his portfolio on an occasional basis. In periods of either strong stock market gains or losses (greater volatility), the myopic investor is likely to increase his frequency of viewing the account and, when coupled with another bias, may be influenced by recent account performance to make short-term decisions to the detriment of his initial long term goals. Empirical evidence shows that investors obtain higher returns over time by staying with a long term allocation compared to those who micromanage their accounts (Dalbar, 2010).

The investor who is overconfident is not expected to be affected by a stock market period of low volatility and would keep his initial portfolio intact. However, if a period of low volatility corresponds with gains in the stock market, it could increase his confidence as he experiences positive returns and attributes such performance to his investment ability. In a period of economic expansion, the overconfident investor will increase his risk by becoming more concentrated in only the stocks or funds that grow the most. During a period of economic expansion and stock market gains, the overconfident investor will shift to a portfolio that entails more risk than he is comfortable with as he looks for greater returns, and the success of selecting "winning" stocks would further fuel the investor's overconfidence. In a period of stock market losses, the overconfident investor will hold losing investments and may even add to the losing positions, because he believes the stock price is lower due to the ignorance of other investors, rather than accept the fact that he made a bad investment decision. The overall result for the overconfident investor is greater exposure to risk than elicited in the investor profile, more volatility and greater swings in account value than originally expected.

The investor who has an anchoring bias is not expected to be affected by a stock market period of low volatility and would remain with his original investment plan. In a period of economic expansion and stock market gains, the anchoring investor will do quite well, but if the expansion lasts long enough, the investor may opt for a riskier portfolio as he anchors his future economic outlook and expected account performance to the recent gains and economic prosperity. In a period of stock market losses, the anchoring investor will hold his portfolio without making changes in the very short term as he anchors to the recent gains and expects stocks to continue increasing in value. However, as was the case with stock market gains, if stock market losses continue long enough the investor may eventually adjust his economic outlook and expected returns to be negative and shift his portfolio accordingly. Investors that have an anchoring bias are likely to chase past performance with a lag - encouraging a buy high and sell low investment strategy.

It is expected that the behavioral finance questions in the survey will have some predictive power to how the respondents answer in the simulation ("what if") portion of the survey. For example, if a participant chooses a response that corresponds with loss aversion in the questionnaire, it is expected he will also show loss aversion behaviors in the simulation portion of the survey.

The biases examined in this survey are just a sampling of the many behavioral biases that humans experience. No matter which bias an investor exhibits, biases may influence the choices the investor makes, especially when confronted with uncertainty or periods of emotion, such as greed and fear. It is expected that during periods of stable economic growth and low stock market volatility that the investor will not be influenced by behavioral biases, but in periods that elicit strong emotion or uncertainty the biases will surface and persuade investors to make decisions contrary to their long term investment plan.

IV. DATA AND METHODS

The data for this experiment was obtained using an online survey via SurveyMonkey™. Participants for the survey were solicited via electronic communication and notified that this research was being done by the Applied Economics Department at the University of Minnesota. There were three primary avenues for finding participants: I sent out emails with the survey link through my own network of contacts, a financial planning group sent out emails to their clients with the survey link attached, and a well-read blog posted the survey link online. Participants did not receive any benefit for completing the survey - most were doing so because they either wanted to support the research, or support the individual asking them to complete the survey. I collected responses from January 3, 2011 through January 27, 2011.

The Sample

The primary purpose of using an online survey and distributing the link through multiple channels was to obtain a sample that was representative of the investor population. A total of 292 individual surveys were completed. Only one survey was accepted from each IP address and since there was not any financial incentive to take the survey, it is believed that 292 surveys were completed from 292 distinct individuals. I compared the characteristics from the sample with the general population of investors, as reported by the data tables furnished in the Federal Reserve Board's Survey of Consumer Finance (SCF), to determine how well the sample represented the investor population (Federal Reserve Board, 2007). The 2007 SCF consisted of 4,422 interviews collected, which the Federal Reserve believes represents 116 million families. The ages of respondents from my study were similar to the ages of those in the general investor population. Both my survey and Table #1 (01-07) of the 2007 SCF reported 59% of respondents over the age of 45, though the SCF reported 38% of the respondents were over the age of 55, while my survey had only 25% of respondents over the age of 55. The same SCF table reported that 35% of the investor population had a four year college degree (or higher), while 71% of survey respondents had at least a four year college degree. I was unable to find a breakdown of gender information by the SCF, but the 2008 Census reports 51% of the general population was female (Census, 2008), compared to 66% of the respondents in the survey. Net worth was not an easy characteristic to compare because the SCF provided an average net worth dollar figure, while the survey reported ranges of net worth. The average net worth as reported in Table #4 of the 2007 SCF was $557,000. The survey reported 67% of respondents with net worth less than $500,000, and 33% greater than $500,000. Income was also difficult to distinguish because of comparing a mean value with a range of values. Table #1 (01-07) in the 2007 SCF reported average income of $84,100, while 52% of survey respondents reported income less than $75,000 and 48% reported income greater than $75,000. Survey respondents were predominately Caucasian (95%), while the SCF reported 71% of their respondents as White/Not Hispanic. As a group, the survey respondents were about the same age, more educated, and more predominantly female and white than the general investor population. A complete summary of the characteristics of the respondents in the sample, along with some basic findings, can be found in table 2 on the following page.

The Survey

All data collected from the survey were from the internet; no one received a paper copy to fill out. One of the challenges with an online survey is that the participant cannot ask for clarification on any question or response choice. In developing the survey questions it was important that they were short enough for people to read, and concise enough for them to understand without needing additional clarification. Some behavioral finance questions considered for inclusion in the survey could not be used because pilot tests of the survey resulted in feedback that some of the questions or

Table 2. **Subject Characteristics with Basic Findings**
(292 total subjects)

Characteristic	N*	Percent of Total	Risk Profile: Growth	*Showed Degree of Bias In Survey* Loss Aversion	Over Confidence	Anchoring	Myopia
Male	97	34%	46%	97%	95%	99%	80%
Female	188	66%	71%	96%	95%	98%	73%
Age: Under 25	7	2%	57%	71%	100%	100%	71%
25 - 35	73	25%	85%	98%	97%	99%	79%
36 - 45	68	23%	90%	95%	93%	99%	70%
46 - 55	70	34%	64%	97%	91%	100%	77%
56 - 65	48	16%	21%	98%	98%	96%	79%
66 - 75	24	8%	0%	100%	100%	96%	71%
Over 75	2	1%	0%	100%	100%	100%	100%
Investment Yrs: None	9	3%	89%	78%	100%	100%	78%
Less than 2 yrs	24	8%	79%	96%	100%	96%	62%
2 - 5 years	22	8%	64%	95%	95%	100%	91%
6 - 10 years	49	17%	78%	98%	92%	100%	73%
More than 10 years	185	64%	55%	98%	95%	98%	76%
Use Advisor	194	68%	52%	98%	94%	98%	75%
Do Not Use Advisor	93	32%	83%	95%	96%	98%	77%
Education: HS/Some College	69	24%	46%	96%	96%	97%	74%
Vocational Degree	15	5%	33%	96%	100%	93%	40%
College Degree	89	31%	66%	100%	94%	100%	74%
Some Graduate School	19	6%	68%	99%	100%	99%	77%
Graduate Degree	98	34%	25%	100%	94%	99%	84%
Net Worth: Less than $100k	70	25%	73%	97%	94%	99%	73%
$100k - $250k	67	24%	78%	94%	94%	100%	76%
$250k - $500k	52	18%	50%	96%	100%	96%	65%
$500k - $1MM	55	19%	49%	100%	95%	100%	87%
Over $ 1 Million	38	13%	50%	97%	95%	95%	82%
Income: Less than $25k	20	8%	50%	100%	100%	100%	70%
$25k - $75k	113	44%	54%	96%	96%	99%	78%
$75k - 150k	75	29%	67%	99%	92%	99%	76%
$150k - $250k	36	14%	72%	97%	92%	100%	75%
Over $250k	12	5%	75%	92%	100%	92%	100%
Race: Caucasian	271	95%					
Not Caucasian	15	5%					

* If N does not total to 292, that is because the subject did not answer that question

response choices were not clear. I was very careful to construct the survey in a way in which anyone could understand the survey and complete it in a reasonable amount of time. 92% of the participants said that they understood the survey completely or understood most of the survey, and the average time to complete the survey was less than ten minutes. The survey consisted of 33 questions and was structured in four main sections:

A) Traditional risk profile questionnaire (questions 2 - 8 of the survey)

B) Questions pertaining to behavioral biases (questions 9 -15 of the survey)

C) Simulation questions (questions 16 – 24 of the survey)

D) Demographic information (questions 27 – 33 of the survey)

The survey questions remained in the same order for each participant, but the response choices for questions in part B and part C were randomized for each participant to minimize any framing bias. A copy of the survey can be found in Appendix 1.

Part A of the survey, the traditional risk profile questionnaire, was obtained from Woodbury Financial Services, and is representative of a questionnaire used today by many financial institutions to derive the investor's risk tolerance. Each response in the risk profile questionnaire is given a score and when summed could range anywhere between 7 and 35 points. The total score is then translated into one of five risk categories ranging from conservative to aggressive. However, for this experiment the risk profile categories were reduced from five categories to two: either the investor was classified as "Growth" or "Non-Growth" with any score equal to or above 22 being classified as "Growth." The classification of the investor risk tolerance was important to allow comparisons between the traditional methods of interpreting risk with modern methods that include behavioral biases.

Part B of the survey consisted of questions that attempt to find out if the participant exhibits the biases of loss aversion, myopia, overconfidence and/or anchoring. Questions were patterned after behavioral finance questions used in prior research to determine whether the participant exhibits a specific behavioral bias, and the questions were adapted for the constraints of the online survey (questions had to be brief and concise). In this section there was one question for myopia, one for overconfidence, one for anchoring and four questions for loss aversion. The several questions for loss aversion were necessary because that bias can show up in various circumstances and were intended to represent all instances in which loss aversion might be present.

Part C of the survey consisted of the simulation section of the survey. The questions were structured to simulate what has occurred or may occur in the economy or stock market. Some of the questions were meant to elicit feelings of greed or fear, just as one may encounter in an actual investment scheme. In this part of the survey, three questions were asked to see if the participant exhibited overconfidence, three for anchoring, two for loss aversion and one that tested for myopia. The multiple questions for each bias (except myopia) were given to see if the participant would show a bias in differing scenarios.

Upon developing the survey, there was some contemplation about the questions in section B and section C, since they are both testing for the same biases and all are hypothetical scenarios. There were two main reasons for choosing to administer the survey in the manner it was. First, part B had to do with basic behavioral finance questions without regard to economic or stock market changes, while part C had to do with simulations. Second, I wanted to test whether the questions in part B had a strong correlation (predictive power) with the responses provided in the simulation (part C).

Part D of the survey asked various demographic questions to determine if there were any interesting findings or correlations within the data. Most of the demographic variables also served as the independent variables for the regression analysis. In addition to the demographic variables, participants were asked how confident they were that the information obtained in the survey would only be used for this experiment and would be kept confidential. It is believed that the more confident the participants were in the purpose and confidentiality of the survey, the more likely they would be to furnish honest answers. 96% of participants said they were somewhat or very confident that their results would be kept confidential.

The questions in the traditional risk profile were used primarily to identify whether the participant was growth (1) or not growth (0); the individual questions in the risk profile questionnaire are not part of the regression analysis, but will be analyzed separately. The dependent variables for the regression analysis were comprised of the respondent's risk profile (Part A) and all the questions from Part B and Part C of the survey. Since all of the dependent variables were binomial, it was determined that the regressions would be run using the probit model.

Regression Methods

The complete results from the probit regressions are found in Appendix 2. Regression estimates, using the individual probit model in SAS, are found in the first three data columns of Appendix 2. Few of the coefficients were statistically significant so I ran the same equations using a multivariate probit analysis (MVprobit) in STATA™ to see if I could obtain more statistically significant results. The results of the MVprobit regression can be found in the last three data columns of Appendix 2. Besides providing coefficient estimates for the variables, the MVprobit also constructed a correlation matrix for further interpretation.

The correlation matrix obtained by the MVprobit attempts to capture unobserved preferences or other distinctions that influence the responses of the participants. Factor analysis is used to interpret the correlation matrix and searches for patterns of relationships among the dependent variables and accounts for independent variables, both those observed in the survey and those that were not measured directly. Factor analysis is more ambiguous than regression equations because it requires subjectivity in interpreting the covariance matrix and the subsequent factor titles. However, given the many insignificant coefficients in the regression results, it was felt that factor analysis would provide additional insight not obtained by the regression itself. Factor analysis has been used in past economic reports where coefficient estimates were not statistically significant and/or a more detailed analysis of the data was desired (Hurley & Mitchell, 2009, Grable & Lytton, 1999).

V. RESULTS

The results obtained by the online survey will be reported in three distinct sections: the first will have to do with an analysis of the responses from the traditional risk profile questionnaire section (questions 2 – 8 of the survey), then I will report and discuss the results from the regression analysis – both individual probit results and those obtained using the MVprobit method, and finally I will compare the results obtained from the standard regressions with that of factor analysis.

Results from Traditional Risk Profile

As stated previously, the traditional risk profile questionnaire used for this survey had a total of seven questions asking about the participants' age and income needs, their overall investment objective, and their expectations of investment results in both good and bad markets. Each response receives a score, and the scores are then summed to classify subjects as either a growth investor or not a growth investor. It is common practice that once the risk profile is generated that a portfolio allocation is recommended for that risk profile. There is little, if any, attention given to the responses of individual questions, rather the risk profile is based upon the cumulative score of all the responses. Profiling based upon a total score rather than individual responses leads me to wonder whether there can be responses selected within the risk profile that are contrary to the classified risk profile of the participant. An analysis of the responses within the risk profile questionnaire confirms that contradictory statements can be made, not only among the stated risk profile and specific questions, but among the questions themselves.

The following observations obtained from the survey were of special interest:

1) 24% of Growth respondents said they would have a hard time tolerating <u>any</u> losses over next three years. An additional 39% of Growth respondents said they could only tolerate a <u>small</u> loss over the next three years.
2) 29% of Growth respondents said they could at most tolerate a loss of 10% in a three month period
3) 68% of respondents who said they expect to mostly track the stock market in a rising market also said they could only tolerate a small loss over the next three years
4) 55% of respondents who said they expect to mostly track the stock market in a rising market also said they couldn't tolerate losses greater than 10% in a three month period
5) 65% of the respondents less than 45 years old said their goal was to grow the portfolio significantly or aggressively
6) 88% of respondents who stated their ultimate goal for their portfolio was to grow significantly or aggressively were classified as a growth investor

A risk profile of "Growth" will typically result in a recommended portfolio of 70% - 95% in stocks, and the remainder in cash or bonds, depending upon the actual score of the risk profile and the brokerage firm recommending it. Because of the significant allocation to stocks, it is expected that a growth portfolio will be volatile and its performance will, for the most part, track the performance of the stock market.

The first two observations listed above were of respondents who were classified as growth investors, and yet responded in the survey that they would not be able to tolerate the downside risk and volatility that is inherent in a growth oriented portfolio, even over the short term. One only has to do a cursory review of the stock market to see multiple examples of when the stock market has gone down more than 10% in a three month period, or has experienced losses over a three-year period. An investor who is classified as growth, and yet does not have the capability to handle losses, may be surprised when significant losses occur, and may be influenced to sell her stock investments in order to limit future losses and/or sleep well at night.

The third and fourth observation had to do with what the respondent would expect from her investment during normal market conditions (positive market returns) and then what she would expect in a down market. I find it interesting that over half of the respondents expect to experience most of the gains of the stock market in an up market, but only experience a portion of losses when the stock market performs poorly. Barring the ability to accurately predict when a good market or when a bad market will occur, these goals are contrary to each other. An investor should not expect to capture most of the upside of the stock market unless she is also willing to capture most of the downside of the market. Perhaps this is an issue with the overall risk profile questionnaire; the fact that the investor can make both selections in the questionnaire may act as reinforcement that she can expect gains in good times and limited losses in bad times. The contrary responses may tell us something about the investor – she may take too much risk when times are good, and too little risk when times are bad, or in other words she may anchor her future expectations to what has recently happened and adjust her portfolio accordingly.

The fifth observation compares the age of the respondent to her stated investment goal (question #4 in the survey). While 65% of young investors (less than age 45) had a stated goal of growth, this also means that 35% of young investors said they either wanted to grow the portfolio moderately or with caution. This is interesting because the financial community regularly says that young investors should be able to tolerate risk and therefore be more aggressive (Prior & Tarquinio, 2011), but in this survey, approximately one-third of young respondents said they did not want aggressive growth. One of the questions in the traditional risk profile questionnaire uses the investor's age as a score for their risk tolerance, as if age was an accurate predictor of a person's ability to tolerate risk. In this survey, 35% of respondents who should want growth (according to rational expectations) are actually more conservative. In addition, 65% of respondents under the age of 45 said they could only tolerate a small loss over the next three years, which is a response more indicative of a loss averse investor, than one who can tolerate the volatility of a growth portfolio. Among survey respondents, an individual's age has little to do with her ability to tolerate risk and loss.

The last observation listed was one that would be expected. 88% of the respondents who said their ultimate goal was either to grow their investments significantly or aggressively were classified as "Growth." Given the high correlation between this one question and the calculated risk profile, it may be possible to do without the other six questions for scoring purposes, and replace those questions with others that will tell us more about the investor and her likely behavior. None of the questions in the traditional risk profile questionnaire indicate how the investor may act in a real investment scheme - one that contains both significant gains and significant losses. In fact, as shown above, many of the responses within the traditional risk profile are contradictory, and thus create confusion about who the investor really is, and what type of portfolio would actually be best for her.

Results from Regression Analysis

As stated above, regression equations were run individually using the probit model in SAS™, and run jointly using the multivariate probit command in STATA™. Statistically significant variables as well as the sign and magnitude of their coefficients were very similar between the probit and MVprobit analysis. While the results are very similar, the MVprobit method is deemed superior because of its ability to jointly estimate the equations, and account for correlation among the variables – and therefore will be used for interpreting the results. The complete regression results of both the probit and MVprobit are found in Appendix 2, however a summary of the statistically significant variables and the direction of their coefficients are reported in Table 3.

Table 3. Summary of Statistically Significant Variables using MVprobit

Indep.	Dependent Variables													
Variable	GR	QLA2	QAN	QOC	QMY	SMY	SOC1	SOC2	SOC3	SAN1	SAN2	SAN3	SLA1	SLA2
Male				-				+	+	-				
InvExp									+				-	
Advisor		+		-		-								
Col4					+	+	-	+				+	+	
Age35			-			-						-		-
Age45	-					+		-						
Age55	-		+				-	+	+					+
Nw250		-									-			
Nw500								+						
Nw1000		-			+									
Nw1000p								+						

The first and third questions on loss aversion are absent from the table because none of the independent variables were statistically significant for those questions. A total 292 surveys were completed. 15 surveys were excluded because they were incomplete, leaving 277 responses used for the regression analysis. A joint hypothesis test was performed on the independent variables to see if any could be excluded from the analysis, and it was found that all variables were jointly statistically significant at 10%. In the regression analysis, a significance level of 10% was also used to determine whether the individual variable was statistically significant.

Demographic information obtained from the survey that is believed to explain the various dependent variables were gender, age, investor experience, whether the participant uses a financial advisor, level of education, net worth and income. It was anticipated that all of these independent variables would be used in the regression analysis, but income had to be omitted because I was unable to get the MVprobit model in STATA™ to converge when including the income variable. Several attempts were made to work around the issue, but I was unable to get the process to run. I found that income and net worth were highly correlated variables, and given the difficulty of obtaining regression results with the income variable, it was decided to drop the income from the regression analysis.

The independent variables (as well as the dependent variables) are binary; they either take on a value of 0 or 1. The variables for age and net worth are tiered to show the additional effect an increase in age and/or net worth has on the response (dependent variable). The coefficients are to be interpreted in an ordinal fashion, as they cannot be easily translated into probability measures. The MVprobit does not calculate the marginal effects of the variables, and while it would be possible to calculate marginal effects with the individual probit regressions, it would be necessary to define the characteristics of the average investor. Marginal effects measure the instantaneous rate of change between the dependent variable and a change in one of the independent variables, keeping all others fixed. This is a common procedure that is easy to calculate for continuous variables, but not for discrete variables that take on a value of either 0 or 1. In this situation, attempting to define the characteristics of the average investor would be subjective, and if not defined correctly, may lead to erroneous conclusions.

The regression results (coefficient, error and significance) for each dependent variable are reported in Appendix 2. The first column lists the independent variables, the next three columns list the data obtained from the individual probit regression, and the last three columns list the data obtained from the MVprobit regression. Items in bold represent the independent variables that had a significant effect upon the dependent variable in the regression model.

The variable for gender (Male) was given a "1" if the participant was male, and a "0" if the participant was female. The behavioral finance question used to determine whether the participant was overconfident (QOC) found that females tended to show more overconfidence than males, due to the negative coefficient for males. However in two simulation questions for overconfidence (SOC2, SOC3), the coefficient for males was positive – meaning they acted more overconfident, believing that they would generate better returns than both their peers and a random portfolio of securities. There was a difference between the three overconfidence questions; the one in which females were more overconfident, (QOC - negative coefficient) had to do with how they perceived another person (the average investor) would perform, while the questions in which the males were more overconfident (SOC2, SOC3 - positive coefficient) had to do with how the participant himself would perform. The results show that with respect to overconfidence, women in the study were too confident in other people's ability, while males were too confident in their own ability. Gender was also statistically significant with one of the simulation questions on anchoring (SAN1). The negative coefficient signifies that women in the survey tended to anchor future investment performance to the average historical performance of the markets.

For investor experience (Invexp), the participant was recognized as experienced and given a "1" if they had invested for six years or more. If they had invested for less than six years, they were given a "0." Investor experience was statistically significant for one of the simulation questions on overconfidence (SOC3), and one of the simulation questions on loss aversion (SLA1). The positive coefficient investors experience in the SOC3 equation, suggests that experienced investors expect to perform better than a portfolio of randomly selected securities, but when compared to the portfolio of others, the result was not significant. This could mean that a more experienced investor believes she can beat a stock market index, and therefore it would be expected that she would engage in activities that attempt to beat an index, such as selecting individual securities (rather than an index fund), and perhaps trying to invest based upon perceived market tops and bottoms. The coefficient for experience was negative in the equation for a simulation question on loss aversion (SLA1). The question asked participants what they would do if the stock market, and their investment portfolio, had experienced a significant loss. Experienced investors were inclined to either hold the portfolio, or add to their stock positions. This would be expected, since experienced investors have likely seen both good and bad stock markets, and are aware of the volatility they could encounter. Whether these investors were ever loss averse, it appears that time and experience in the market may "toughen the skin," and make them less likely to react to the bias of loss aversion when experiencing short-term losses. It may also be worth noting that investor experience in the probit regression had a positive coefficient for classifying an investor as "growth," but was insignificant for the MVprobit regression.

The variable for advisor (Advisor) asked the participant whether they use a financial advisor for any/all of their investment portfolio. If the participant uses an advisor in any fashion she is given a "1." A participant who invests entirely on her own gets a "0." Whether the participant uses an advisor was significant for a question on loss aversion (QLA2), a question on overconfidence (QOC), and a simulation question on myopia (SMY). A positive coefficient for advisor in the QLA2 equation shows that a participant who employs a financial advisor was more likely to exhibit loss aversion when asked whether she would play a game of chance in which there was a possibility of incurring a loss, even though the expected value of the game was positive. This would be expected because people may use an advisor, and their expertise, to help them manage their risk and avoid significant losses. The variable for advisor had a negative coefficient, and therefore a negative impact, on whether the individual was overconfident

(QOC). Another way to say this would be that investors who do not use an advisor tend to be overconfident. This would be expected because if an individual is very confident in her abilities, then she would not need to pay for professional help. Advisor also had a negative coefficient (effect) on the simulation question for myopia (SMY). When asked whether the participant would look at their account value after reading negative news on the economy and stock market, those individuals who had an advisor were less likely to look at their account statements, while those investors who did not have an advisor were more likely to "check-in" and see how they were doing. This outcome may be the result of trust in the financial advisor and in the investment plan, or the knowledge that a trusted advisor is watching over it and will contact the investor if necessary. It would be expected that an investor who has a professional watch over her portfolio, especially when accompanied with an investment plan tailored to her needs, would be less likely to care about the short-term performance of her account.

The variable for education (Col4) describes whether a participant has a 4 year college degree. If a participant had a 4 year college degree (or more) they were given a "1," if they did not have a college degree (even if they went to vocational school) they were given a "0." Education was a significant variable for a question on myopia (QMY), and simulation questions on myopia (SMY), overconfidence (SOC1, SOC2), anchoring (SAN3) and loss aversion (SLA1). Both in the question for myopia and the simulation for myopia(QMY, SMY), a college degree (or greater) had a positive coefficient (effect) on whether the participant was myopic. It is unclear why a college degree would have a positive effect on myopia; perhaps the many years of tests and grades encountered in college conditions the participant to need regular feedback on how she is performing. A college degree had opposite effects (negative coefficient) on two overconfidence questions (SOC1, SOC2). A degree had a negative effect on whether the participant would increase her exposure to a certain sector of stocks, even if she believed the sector was likely to experience significant gains, yet had a positive effect on the participant believing her portfolio results would be superior to others. The opposite effects on two overconfidence questions may seem contradictory on the surface, but it appears that someone with a college degree may remain more disciplined to a diversified strategy, and therefore is confident that she can perform better than other investors. It is interesting to note that while those with a college degree believe they will perform better than other investors, they do not necessarily believe they could beat a random portfolio of securities. This implies that those with a college education may not perform better than a stock index, but they will not make the same investment mistakes others will make, and therefore expect to perform better than other investors. Those with a college degree also showed that they take more time to change their opinion when faced with new information (SAN3). In the face of an earnings surprise and future expected gains, a college degree had a positive coefficient to anchoring to old information and beliefs. It is quite possible that eventually the new information would be digested and the perceived valuation updated, but it may take longer for this to occur for those with a college degree than those without. A college degree also had a positive effect on one of the loss aversion questions (SLA1), specifically what the participant would do in the face of short-term market losses. This type of behavior, coupled with myopia, has the potential to influence an investor to stray from their long term asset allocation plan and make decisions based upon short term events - decisions which are typically to the detriment of the overall portfolio (Dalbar, 2010).

The variable for age (Age35, Age45, Age55) is tiered to show the additional effect of each age group upon the dependent variable. The base group (those under the age of 35) is not tested directly; it is captured in the intercept. Respondents who were above age 35 were given a “1,” those who were above age 45 received another “1” and those above age 55 received an additional “1.” The coefficient for each age group measures the effect on that age group compared to the one below it. For instance, in the age group of 45-55 (Age45) the coefficient shown is the effect of that age group over ages 35-45 (Age35). To find the total effect of the age group of Age45 on the dependent variable, one would need to add its coefficient to the coefficient of Age35. Age was statistically significant for the dependent variables of growth (GR), anchoring (QAN), myopia (SMY), overconfidence (SOC2, SOC3) and loss aversion (SLA2). As one would expect with growth, the older the participant was, the less likely she was to be classified as a growth investor. Those between the ages of 45-55 had an effect of -0.89 on growth and those over age 55 had an additional effect of -1.42 on growth. Younger participants had a negative coefficient (effect) on anchoring (QAN), while older participants showed a greater likelihood to anchor. This means that older individuals are more likely to anchor future expectations to prior beliefs and perceptions. Perhaps this is evidence that we become more stubborn and averse to change as we grow older. Age also had interesting effects on myopia (SMY). Individuals under the age of 45 were less likely to view their account statement regularly, especially in the face of negative economic news. However those between the ages of 46-55 were much more likely to be myopic while those above age 55 showed no additional effect either way. This may have to do with young people having greater risk tolerance and a longer time horizon, while those near retirement are more concerned about the potential to lose money and delay their retirement. It was surprising to see those above age 55 not showing additional myopia in the face of stock market losses, but that could be due to a more conservative portfolio at that age, and therefore not as affected by stock market movements. Age did not have any effect on overconfidence on young investors, but had a negative effect on those between the ages of 46-55 and a positive effect on those over age 55 (SOC2). The question for overconfidence asked participants how their portfolio would perform compared to other investors. These results suggest that as we age we are uncertain about our investment abilities compared to others, but over the age of 55 we become confident that we are not only better than others, but also better than a stock index (SOC3). While confident in their ability compared to others, those over age 55 had a negative effect on whether they would have a portfolio concentrated in a specific security or sector, even if they believed that security/sector was going to increase in value. This suggests that while those over age 55 may be overconfident, they value risk management more than trying to make quick money. Age also had a significant effect on loss aversion (SLA2), specifically whether the investor was quick to harvest gains and let losses ride. Younger investors, as we would expect, had a negative coefficient with respect to loss aversion while older investors, specifically those over age 55 had a positive coefficient to loss aversion, showing a greater likelihood to choose a winning investment to sell than a losing investment. This type of loss aversion is commonly tied in with the biases of regret and pride. An older individual, who may be more over confident and stubborn than a younger one, may have a hard time admitting she made a bad investment decision, as evidenced by selling a losing investment. Instead such an investor would prefer to sell a security that has gone up in value to confirm that she made a good investment decision.

The variable for net worth (Nw250, Nw500, Nw1000, Nw1000p) is tiered similarly to age. Participants who had a net worth of less than $100,000 were in the base group, which was captured by the intercept. Participants were given a "1" for Nw250 if they had a net worth over $100,000. Participants were also given a "1" for Nw500 if their net worth exceeded $250,000, a "1" for Nw1000 if their net worth exceeded $500,000 and a "1" for Nw1000p if their net worth exceeded $1 million. As with the variables for age, each net worth category represented the additional effect from each net worth group, and a summation of coefficients was necessary to find the total effect of a specific net worth. The coefficient on net worth was statistically significant with myopia (QMY), loss aversion (QLA2), overconfidence (SOC2) and anchoring (SAN2). Those Having a net worth between $500,000 - $1,000,000 had a positive effect on viewing the portfolio balance often (QMY). The effect at this one net worth level may be because it is a significant level of wealth, but not enough to ensure complete financial freedom. Having a net worth between $100,000 - $250,000 had a negative effect on loss aversion with respect to playing a game of chance where the expected payoff was a positive value (QLA2), suggesting a tendency to play the game and potentially lose money. Having a net worth between \$250,000 - \$500,000 was not significant, but the value of the coefficient was positive – indicating that having a net worth in that range correlates with a preference to not play the game and avoid the possibility of loss. Having a net worth between \$500,000 - \$1 million also had a positive effect on willingness to play the game. The coefficient on net worth its positive value may indicate a preference to not play the game. It is interesting to notice the effects of net worth among the game of chance, but it is uncertain what may explain the differences in the willingness to play the game (loss aversion) among the various levels of net worth. When participants were asked how the performance of their portfolio would compare to other investors (SOC2), both Nw500 and Nw1000p had very significant and positive coefficients, suggesting they were quite confident in their ability to perform better than others. Nw250 and Nw1000 were insignificant with small coefficients. Overall the results suggest that the wealthier an individual is, as measured by net worth, the more likely she will believe that she is a better investor than others(SOC2). It was also found that net worth had an effect on anchoring (SAN2). Nw250 had a negative coefficient in the regression for anchoring, when subjects were asked about the perceived value of a stock given past prices and current information. The other levels of net worth did not have significant effects and were generally flat or negative. This suggests that individuals with a net worth of \$100,000 or more were more likely to consider new information in determining the fair value of a security, and any increases in wealth did not have much of an effect using new information to value securities.

The regression analysis provides interesting information about what type of participants were likely to exhibit a certain behavior or bias. There are many variables that are not significant that lead me to wonder what type of unexplained characteristics are in the error term and not reported in the results. In order to dig a little deeper to see if there are any unobserved factors systematically influencing participant choices, I analyzed the covariance matrix using factor analysis.

Factor Analysis

The primary purpose of factor analysis is to identify factors that measure and explain similar data. It is used to study relationships among dependent variables with the goal of finding out which independent variables may explain the dependent variable, whether directly measured or not. There are two types of factor analysis, exploratory and confirmatory. An exploratory factor analysis is used when the outcome or variables are unknown beforehand, while a confirmatory factor analysis is used to test specific hypotheses about the structure or variables in the data. Since the survey attempts to understand certain behavioral biases (myopia, loss aversion, overconfidence and anchoring), this will be a confirmatory factor analysis as I am trying to confirm what variables influence investor behavior. The number of factors to analyze is subjective, however there are a few criteria commonly used to determine the correct number of factors for a given set of data. One common method is to select only the factors where the eigenvalue is greater than 1.0 (Kaiser Criterion). Another method which also uses the eigenvalue is the screeplot. The screeplot sketches each factor's eigenvalue in a line plot, and it is recommended to select the factors where line segments have slopes materially different from zero, before the line flattens out (Cattell, 1966). Since this is a confirmatory factor analysis considering four behavioral biases, it was determined that a selection of four factors would be more accurate than relying upon the Kaiser or screeplot method.

Before interpreting the results of the factor analysis, a varimax rotation was used to maximize the variance among the factor weights making the interpretation of the data more clear. The rotated factor analysis from data obtained in the survey is in Table 4 on the following page. The factor analysis has the names of each factor at the top, along with a column for uniqueness. Uniqueness is the variance that is unique to the variable and not shared with the other variables. A high uniqueness number translates into that variable having a small relevance in the factor analysis.

Table 4: Rotated factor loadings and unique variances

Variable	Loss Aversion	Myopic Loss Aversion	Overconfidence	Optimism	Uniqueness
GR	**-0.3787****	**- 0.3729****	**-0.3388****	**0.4033****	0.4401
QLA1	**0.2787***	0.2373	-0.0398	0.0816	0.8578
QLA2	**0.3978****	**0.4718****	-0.1123	0.0047	0.6065
QLA3	**0.6364****	0.0381	0.1813	-0.1056	0.5495
QMY	-0.1366	**0.6656****	-0.0124	-0.1077	0.5265
QAN	-0.0088	**0.2790***	0.1569	0.1295	0.8807
QOC	0.2446	**- 0.2504***	**0.3174****	0.0787	0.7705
SMY	0.0107	**0.4091****	0.0714	0.2405	0.7696
SOC1	0.1298	- 0.0514	**0.3098****	**0.5168****	0.6175
SOC2	**-0.6993****	0.1076	**0.3634****	-0.0655	0.3630
SOC3	-0.1096	- 0.0110	**0.8089****	0.0832	0.3266
SAN1	0.0784	-0.1288	0.0984	**0.4785****	0.7386
SAN2	-0.0913	-0.1697	0.1988	-0.0112	0.9232
SAN3	0.1571	-0.0437	-0.0637	**-0.5365****	0.6815
SLA1	0.2261	0.2034	-0.0503	0.2157	0.8584
SLA2	0.0075	**0.2606***	0.0006	-0.0605	0.9284

* Factor loading greater than 0.25 **Factor loading greater than 0.30

The key to the factor analysis is the factor loadings - the weights and correlations between each variable and factor. Similar to the coefficient in regression analysis, a greater factor load indicates a stronger correlation between the factor and the dependent variable.

The factor analysis reveals the presence of three behavioral biases considered in this thesis (loss aversion, overconfidence, myopia), along with another behavioral bias not directly tested, but quite influential to the participant's responses (optimism). The first factor, loss aversion, explains what kind of choices a loss averse investor is likely to make in an investment environment. My results suggests that loss averse investors are likely to be non-growth investors (negative factor loading for GR), and do not believe that their investments will perform better than the average investor's portfolio (SOC2). It is uncertain whether expectation of subpar performance is due to the past investment performance of the investor, or because she recognizes that her portfolio is less risky than the average investor's portfolio – and therefore expects a lower return than the average. A loss averse investor also prefers situations in which she has little chance of loss, even if she also has little chance of gain (QLA2, QLA3). The prospect of realizing losses is so painful for a loss averse investor that she would prefer to sell a security with a gain quickly (in fear it could go down), and hold onto a losing security in hopes that it goes up so she does not have to realize the loss (QLA1). I find it interesting that the traits for loss aversion were evident in the behavioral finance questions (QLA1, QLA2, QLA3), but not in the simulation questions (SLA1, SLA2). I had expected the behavioral finance questions to be able to predict the behavior in the simulation (i.e. correlation between the two), but that is not the case for loss aversion. In retrospect this should not be too surprising. In the simulation, participants are asked what they would do if there was a lot of bad economic news and the stock market dropped significantly. The responses were given when the participant was in a calm, rational state. Unless the participant is aware of how she has historically reacted in times of financial fear, she may not be able to accurately predict what she would do in an actual situation of fear and uncertainty. A study performed by Ariely (2008) found that individuals in a rational state significantly underestimate how they will react in a future emotional situation. In that case, the simulation questions may not be useful for a behavioral bias such as loss aversion, which may be dormant during times of low volatility, but manifest itself in the circumstances of uncertainty and fear.

The second factor is myopic loss aversion. This is similar to the first factor with the bias of loss aversion, but is coupled with the bias of myopia. Many articles in behavioral finance combine these two biases because they often present themselves together (Thaler, et. al, 1997). In addition to the loss aversion traits above, these individuals require constant feedback with respect to the performance of their accounts, and are likely to view their account balances and security holdings often (QMY). Myopic loss averse investors are also inclined to not be overconfident (negative factor loading for QOC). This type of investor has a very short time frame and is likely to make investment decisions based upon short term market movements in order to appease her emotions, even if the ultimate goal is years away (SMY). Individuals who have myopic loss aversion tend to take less risk, and therefore earn a lower return over time than those who do not have this bias.

The third factor is that of overconfidence. Overconfident investors had an inclination to have a calculated risk profile of "Non-Growth," (negative factor loading for GR) which is surprising. I would expect overconfidence to explain an investor who has a more aggressive risk profile. Investors who are overconfident will likely make decisions that have more risk than they may be comfortable with (SOC1). In the survey, overconfident investors were willing to overweight a single sector of securities if they expected a positive outcome – an activity that seems more reasonable for aggressive growth investors, but not for non-growth investors. Overconfident investors also believe that they are better investors than both their peers and a stock market index (SOC2, SOC3). An arrogant attitude could also cause the investor to take more risk than she is comfortable with as stock price movements contrary to her positions may be viewed as other investors making a mistake, while the overconfident investor is correct in her view. The inclination for an overconfident investor to be classified as "non-growth", yet make decisions commensurate with an aggressive risk profile may cause the portfolio to be riskier than originally intended. An additional finding by factor analysis is that the behavioral finance question on overconfidence (QOC) had a great deal of predictability how the participant behaved in the simulation (SOC1, SOC2, SOC3).

The final factor is that of optimism, perhaps over-optimism. Optimism is a behavioral bias, yet was not tested in this study. This is an example of how factor analysis can be a useful complement to regression analysis. The survey did not directly test how optimistic a participant was, but an analysis of the covariance matrix shows how influential optimism was in explaining decisions a participant made. An optimistic investor believes that the market will increase in value (SAN1), and will tend to have a growth risk tolerance (GR). Optimism also leads to an investor's willingness to have a concentrated portfolio, believing that things will turn out in her favor (SOC1). An optimistic investor also believes good earnings and strong revenue for a company will translate into higher stock prices (negative factor load for SAN3). While it helps to be optimistic in the future, it is more important to be realistic when investing. An optimist may find herself taking on greater risk in good times (concentrated portfolio), and may underestimate the true risks of individual securities and/or the market as a whole.

The factor analysis was a useful tool to determine what variables and factors influence investor decisions. The analysis showed that there were strong predictive powers between behavioral finance questions with respect to myopia and overconfidence, but did not provide feedback with respect to anchoring. The analysis also illustrated the difficulty of creating a realistic simulation where feelings of fear and uncertainty are triggered, and not just assumed. Had real emotions of fear and uncertainty been triggered, there would have likely been a strong correlation between the responses given pertaining to loss aversion in the behavioral finance questions, and choices made during the simulation (Kahneman et. al., 1991).

The overall results of the study using both regression models and factor analysis confirm that participants in this study exhibited behavioral biases in both the behavioral finance questions and the simulation questions. It also found that the risk profile, calculated by the traditional method, sometimes contradicts the actual risk tolerance of the individual, and therefore is not a good predictor of what decisions the investor may make in the future, especially during uncertain times. It was shown that behavioral finance questions can be good predictors of choices individuals will make in future investment scenarios, especially with overconfidence and myopia. The analysis also showed very interesting interactions between an individual's investment experience, level of education, age and net worth and various behavioral biases. The inclusion of behavioral finance questions can help an advisor or brokerage firm learn more about the investor and their true risk preferences than the traditional risk profile questionnaire, which assumes the investor is rational and follows the expected utility maxim.

VI. CONCLUSION

The experiment conducted for this thesis provides evidence that investors have certain behavioral biases, and these biases may influence decisions they make with respect to their investments. As illustrated in the literature review, there are several studies and evidence that behavioral biases are found among the general population, and influence decisions that are deemed irrational by traditional finance theory. Despite the evidence of behavioral biases, the financial community continues to rely upon the traditional risk profile questionnaire, which was designed for rational individuals (such as institutional investors). The disconnect between behavior that is assumed and behavior that is observed poses a problem for investors and advisors who rely upon investment tools to construct a portfolio of securities. As demonstrated in the experiment, the traditional risk profile questionnaire not only fails to describe any biases present in the investor, in many cases it profiles an investor as "growth" when the investor is influenced by loss aversion. The inability of the current risk profile questionnaire to properly profile an investor's true risk tolerance is a contributing factor to why the average investor significantly underperforms their respective benchmark (Dalbar, 2010).

Implementing Results

Behavioral biases have been studied for some time, and there have been several attempts to incorporate behavioral biases into the portfolio optimization problem as was described in the literature review. To my knowledge, this has been the first attempt to study the effects of behavioral biases on the calculated risk profile of the investor. This is an important first step because even if the optimization program were perfected, it would still yield erroneous results if the stated risk profile was incorrect. It is recommended that the financial community acknowledge the extent that behavioral biases influence investors, and update their risk profile questionnaires to recognize the reality of this irrational behavior. There are several ways the risk profile questionnaire could be updated: i) keep the risk profile questionnaire as it is and compliment it with a short questionnaire reflecting the most common biases among investors ii) shorten the risk profile questionnaire (in my experiment one question had a 88% correlation to the ultimate risk profile) and include a few questions on behavioral biases iii) keep the risk profile questionnaires the same but furnish educational materials about behavioral biases, and their influence on future decisions. It is unlikely the financial community will make any drastic changes in the short term. It is more likely firms would complement the current risk profile questionnaire with an optional investor profile that includes behavioral bias questions, and educates investors about their effects. There would be a cost to updating the risk profile questionnaire with behavioral questions, but it would result in a competitive advantage. Brokerage firms, especially self-service firms, are a commodity business. Self-service firms often promote free trades for new customers and inexpensive/free trades for clients with certain account values. Differentiation in a commodity business is a competitive advantage, but the question is who will be the first to make the move. As with any change, there is risk; but as with investments there is little reward without taking some risk.

Incorporating behavioral biases into the investor profile may be easier through a full service firm with a financial advisor because of the human element. A financial advisor could choose to educate herself with respect to behavioral biases, and offer an expanded profile in addition to the firm-required traditional risk profile questionnaire. Investors who are willing to pay a fee to an advisor would likely prefer their advisor to provide advice based upon their actual risk preference rather than the profile dictated by a standard questionnaire that assumes the investor is an emotionless being who will always follow the expected utility maxim. It would be in the advisors best interest to spend extra time with each client to ensure the recommendations properly match the clients' true risk profile to promote a positive and lasting relationship. This would also be a competitive advantage for financial advisors. If a client is paying 1.00% advisory fees each year, would they not prefer to pay that money to an advisor who brings more to the table rather than less? There could be many advisors within the industry that would like to account for behavioral biases, but are unsure how to do it properly, or may be restricted from using any methods/forms not approved by the advisor's compliance department. It is important that full service financial firms, and their compliance departments, implement methods of risk assessments that include the ability for the advisor to accurately profile the complete risk tolerance of the client (including behavioral biases). At the time of this thesis, despite the plentiful research and evidence of behavioral biases, the majority of financial firms continue to rely upon risk questionnaires that have proven to elicit invalid, inaccurate profiles of their clients.

Improving the Experiment

While the experiment resulted in valuable information for the purpose of this research, it was far from perfect. There were two primary shortfalls of the experiment that, if improved upon, could lead to more robust results: conduct the survey with a proctor, and successfully instill emotions of fear and greed during the survey. Conducting the survey online without any interaction between the participants and a proctor resulted in having to omit preferred behavioral bias questions because they were not clear to participants in pilot tests. It may be feasible in the future to improve upon this by creating an online survey that is more interactive so clarifications may be sought by participants, and therefore a larger variety of behavioral finance questions could be asked. It was apparent in the survey how hard it is for individuals (being in a rational state) to predict how they will act in a future situation of heightened emotion. The intent of the simulation was to draw out emotions of both fear and greed so people would answer questions as they really would when faced with that scenario, but the results demonstrate this was not successful. An improvement in the future would be to create an environment in which these emotions are felt by the participants in the survey - perhaps a stock market game with an initial endowment and the ability to either win more or lose the endowment depending upon how well they play the game. There may be other areas of improvement that I am not privy to at this time, and I welcome attempts to create better techniques to study behavioral biases with respect to the investor.

Future Research

Future research could attempt to improve upon any perceived shortcomings of my survey, or build upon these findings by comparing it to future studies. The survey I conducted was during the month of January 2011. The world had recently experienced a financial crisis (2007-2009) in which stock markets dropped by 50%, and subsequent rally in the stock market, in which almost all losses had been reversed. The current environment is one in which investors witnessed a year of one of the most powerful gains in the history of the stock market. It would be of great interest to see how investors would have responded to these same questions in January 2009, after a year of significant stock market losses. Future research could administer this same survey in a like fashion during a period of stock market losses, and compare the results to that of this survey to illustrate how risk tolerance and biases change as the economic environment changes. Another potential research could examine additional behavioral biases. As noted in the literature review, there are several behavioral biases that are common among the investment population. The focused nature of a thesis made it impossible to test for every behavioral bias. Another research topic would be to compare a behavioral finance questionnaire to past investment decisions made by a pool of investors. It would be interesting to team up with a brokerage firm (if privacy rules allow) to conduct a study on trading behavior during periods of positive stock market gains, and periods of stock market losses. To some extent this has already been done (Dalbar, 2010), but a more focused study on how biases influenced past investor decisions would be of great value.

I am hopeful that this research will be accepted by the financial community and, despite its weaknesses, be improved upon and ultimately applied to the individual investor. As a financial advisor for over a decade and Certified Financial Planner™ Practitioner, I have seen first-hand how behavioral biases can influence investors to abandon their long term plans to appease their short-term desires (whether the influence be greed or fear). This research adds to the scientific evidence that behavioral biases exist and may influence investor decisions. It is time for the financial community to accept the scientific evidence, and update the tools used to help investors determine their true risk profile, accounting for any biases they may have.

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Purpose of Study - Consent **Appendix 1**

1. This survey is part of a research project for the Applied Economics Department at the University of Minnesota.

The purpose of this research is to find out the influence that psychology and behavior have on an individual's investment decisions and whether certain behavioral traits can predict future investment decisions.

The information obtained in this survey will be kept confidential and will be used for the sole purpose of this research. No identifiable information will be requested; all answers are anonymous.

If you are 18+ years old and consent to participating in this research, please click "I Consent" to begin the survey. While we encourage you to answer each question completely, you are free to skip any questions or exit this survey at any time by closing the browser window. It is expected that the survey will take 5-10 minutes to complete.

The important aspect is to answer truthfully so we can better understand how emotion and cognitive make up affect investment decisions.

THERE ARE NO RIGHT OR WRONG ANSWERS.

- I Consent
- I Do Not Consent

The first group of questions contains questions from a traditional risk profile questionnaire as well as a few behavioral finance questions to better understand how your mind makes decisions.

THERE ARE NO RIGHT OR WRONG ANSWERS

2. What is your current age?

- Less than 25 years old
- 25 to 35 years old
- 36 to 45 years old
- 46 to 55 years old
- 56 to 65 years old
- 66 to 75 years old
- Older than 75 years

3. When do you expect to start drawing income from your current investment portfolio?

- Not for at least 20 years
- In 11 to 20 years
- In 5 to 10 years
- Not now but within 5 years
- Immediately

4. What is your ultimate goal for your investments?

- To grow aggressively
- To grow significantly
- To grow moderately
- To grow with caution
- To avoid losing money

5. Assuming normal market conditions, what would you expect from your investments over time?

- ○ Generally keep pace with stock market
- ○ Slightly trail stock market, but make a good profit
- ○ Trail the stock market, but make a moderate profit
- ○ Have some stability, but make modest profits
- ○ Have a high degree of stability, but make small profits

6. Suppose the stock market performs unusually poorly over the next decade; what would you expect from your investments?

- To lose money
- To make very little or nothing
- To eke out a little gain
- To make a modest gain
- To be little affected by what happens in the stock market

7. Which of these statements would best describe your attitude about the next three years' performance of your investments?

- I don't mind if I lose money
- I can tolerate a loss
- I can tolerate a small loss
- I'd have a hard time tolerating any losses
- I need to see at least a small return

8. Which of these statements would best describe your attitude about the next three months' performance of your investments?

- Who cares? One calendar quarter means nothing
- I wouldn't worry about losses in that time frame
- If I suffered a loss of greater than 10%, I'd get concerned
- I can only tolerate small short-term losses
- I'd have a hard time stomaching any losses

9. If you were faced with the following choice, which alternative would you choose?

- A sure gain of $240
- A 25% chance to gain $1,000 and a 75% chance to gain nothing

ANSWER KEY:
Must answer "A sure gain" on this question and "75% chance..." on Question 10 -> Loss Averse

10. If you were faced with the following choice, which alternative would you choose?

- ○ A sure loss of $750
- ○ A 75% chance to lose $1,000 and a 25% chance to lose nothing

ANSWER KEY:
Must answer "75% Chance..." on this question and "Sure Gain" on Question 9 -> Loss Averse

11. How often do you plan to monitor the performance of your investments?

- More than monthly
- Every 1 - 3 months
- Semi-annually
- Annually
- Every 2 - 3 years

ANSWER KEY:
Any answer less than semi-annually indicates myopia

12. Fund ABC invests in stocks and has an annualized (yearly) return of 18% per year over the past 10 years. The fund remained invested in stocks during good and bad times.

Investors in the fund can choose to invest or not invest in the fund at various times based upon the economic conditions and expected return.

Given the flexibility investors have, how do you think the average investor in Fund ABC performed?

- Between 15% and 30%
- Between 0% and 15%
- Better than 30%
- Worse than -1%

ANSWER KEY:
Expected returns of 15%+ indicates overconfidence

13. You have been considering making an investment in a health care company that has applied for approval for a drug with the FDA. Upon researching the company, you conclude that there is a 75% chance the drug gets approved and a 25% chance it is denied.

If the drug is approved, the stock will increase 20%, but if it is not approved the stock will lose 50%. Do you make the investment?

75% chance you GAIN 20%
25% chance you LOSE 50%

- No. I do not make the investment.
- Yes. I make the investment.

ANSWER KEY:
Not making the investment -> Loss Averse

14. The earth is 93 million miles from the sun. *Without looking it up,* what do you believe the population of Australia was in 2009?

- Less than 30 million people
- 31 - 60 million people
- 61 - 90 million people
- Over 90 million people

ANSWER KEY:
Answering 31+ million people is anchoring

15. You are going to add an investment to your current portfolio. *__Both investment A and B have the same expected return.__*

If you could only choose one of the investments, which one would it be?

Investment A: 70% probability it GAINS 18%; 30% probability it LOSES 17%.

Investment B: 30% probability it GAINS 25%; 70% probability it LOSES 0%.

- Investment B
- Investment A

ANSWER KEY:
Investment B -> Loss Averse

This final section contains 9 scenarios of various economic and stock market situations.

Please answer questions based upon what you ***would actually do***, not what you think is the right thing to do.

THERE ARE NO RIGHT OR WRONG ANSWERS.

16. You reviewed your investment account and its performance *two weeks ago*. You were pleased with the performance and liked the diversified nature of the portfolio.

Since that time, the stock market has lost 15% in value; two major corporations have announced major layoffs and the Federal Reserve held an emergency meeting to discuss the financial state of the economy. You turn on the TV and find that the stock market is down another 4% today alone.

Do you look at how your account has performed over the past two weeks?

- Yes. And if my account has performed equally poorly I would be aggressive and buy more stocks.
- Yes. And if my account has performed equally poorly I would be conservative and sell some stocks.
- Yes. I don't know if I would make any changes, but I would need to know how I am doing.
- Yes. Regardless of how my portfolio has performed, I would become more conservative.
- No. I just reviewed my portfolio and am not influenced by short-term market movements.

ANSWER KEY:
Yes. Myopic
No. Not myopic

17. The stock market continues to lose money and many analysts are predicting an upcoming recession. You do some research and realize there is not much optimism for the state of the economy in the near future.

The stock market is now down 23% from recent highs. Upon reviewing your diversified portfolio, you notice that it is down 14% year to date.

What would you do at this point?

- I would not do anything.
- I would probably sell all my investments to ensure no more future loss.
- I would probably become more conservative and sell some stocks.
- I would probably become more aggressive and buy more stocks.

ANSWER KEY:
Becoming more conservative -> Loss Averse
Buying stocks or not doing anything -> Not Loss Averse

18. Over the past five years stocks have gained an average of 8% per year. What do you believe the return for stocks will be next year?

- Between -20% and -10%.
- Between +11% and +20%
- Between 0% and +10%
- Between -10% and 0%.

ANSWER KEY:
Between 0% - 10% is anchoring

19. A recent publication touted the great advancements of drugs to treat cancer and are almost certain to receive FDA approval this year. Biotechnology companies that make these drugs would benefit substantially from FDA approval.

After much research, you believe biotech stocks could double in value over the next year.

You currently have a 5% exposure to biotech stocks in your account. But you realize that if you put half of your investments in biotech and it doubles (as you believe) that you will reach your retirement goal 5 years ahead of schedule.

What would you do?

- Increase biotech to 50% of portfolio. Chance to retire 5 years early!
- Increase biotech to 25% of portfolio. Chance to retire 2.5 years early!
- Keep allocation the same. Not going to retire earlier than planned.

ANSWER KEY:
Increasing allocation to either 25% or 50% demonstrates overconfidence

20. You have been very interested in the company ACME Supplies. You do some research on ACME and find they have had financial problems in the past two years, but sell a product that is widely used by major corporations, so there is demand for the products they supply.

There are not any analysts covering ACME at this time, but prior analyst coverage had ACME at a "Strong Buy". You notice that the stock price of ACME has come down a lot in the past two years. It is currently trading at $15 per share and it traded as high as $125 per share two years ago.

Based upon this information what do you think about the potential for the stock?

- Poor potential. Stock is at $15 for a reason.
- Good potential. It may not get back to $125, but will most likely move toward it.
- Excellent potential. This stock has a long way to go to get back to even.

ANSWER KEY:
Excellent or Good potential -> Anchoring

21. Your current investment portfolio has 10 securities in it. Five of the securities have gained an average of 20% from when you bought them and the other five have lost an average of 7% since you purchased them.

You need to sell an investment in order to pay some bills. Which investment would you sell?

- No preference
- I would sell a security that has gone up in value
- I would sell a security that has gone down in value

ANSWER KEY:
Selling a security that has gone up in value -> Loss Averse

22. You have been researching a company that makes applications for cell phones. After reading various analyst reports, you believe the company has great growth potential.

The stock ended trading at $25 yesterday and you were going to buy it later today. But before the market opened, the company announced a record quarter with blowout earnings. The company said they expect revenues and profits to increase substantially into the foreseeable future.

Before the stock market opens, the stock price goes up 30% and is now at $32.50 per share. Do you still buy the stock?

- Yes. It still can go up a lot.
- Not unless the stock came back down to $25

ANSWER KEY:
Waiting for stock to come back down -> Anchoring

23. You enter an Investment Simulation Game sponsored by XYZ News. The investment simulation will compare the performance of your portfolio to that of 99 others over a 3 month period.

All 100 participants will have the same tools, time and resources to make their investment decisions. The participants are quite diverse and vary in educational and professional backgrounds - just like the actual investment population.

Upon completion of the game, how do you believe your portfolio performance will rank relative to others?

- My portfolio performance will rank in the top half of all portfolios
- My portfolio performance will rank in the bottom half of all portfolios

ANSWER KEY:
Answer in top half -> Overconfidence

24. *Continuing with the Investment Simulation Game...*

How would your portfolio performance compare to a portfolio of randomly selected securities obtained by throwing darts?

- My portfolio will perform somewhat better.
- My portfolio will perform significantly better.
- Portfolios will have similar performance.
- The random portfolio will perform better.

ANSWER KEY:
My portfolio performing somewhat or significantly better -> Overconfident

Please answer the following demographic questions. This information is important to see if there are any trends or outcomes unique to a specific investor subset.

25. This survey is being performed by the Applied Economics Department at the University of Minnesota in conjunction with their privacy rules. How confident are you that the answers you provide will remain confidential and only be used for the specific purpose of this study?

- Very Confident
- Somewhat Confident
- Not Confident

26. Overall, how well did you understand the questions and the response choices in the survey?

- I understood the survey completely
- I understood most of the survey
- I understood little of the survey
- I did not understand the survey

27. What is your gender?

- Male
- Female

28. What is your ethnic background?

- African American
- Asian
- Caucasian/White
- Hispanic
- Pacific Islander
- Other

29. For how many years have you had investments other than bank accounts/CD?

- None
- Less than two years
- Between 2 - 5 years
- Between 6 - 10 years
- More than 10 years

30. Do you currently use a financial advisor/planner for any part of your investment portfolio?

- Yes, I use an advisor/planner
- No, I do not use an advisor/planner
- N/A, I have never invested before.

31. What is the highest level of education you have attained?

- High School/Some College
- 4 Year College Degree
- Some Graduate School
- Graduate or Professional Degree
- Vocational School other than College

32. What is your current net worth? (Total Assets less Total Debt)

- Less than $100,000
- $100,000 - $250,000
- $250,000 - $500,000
- $500,000 - $1 Million
- Over $1 Million

33. What is your current income? (household income if married)

- Less than $25,000
- $25,000 - $75,000
- $75,000 - $150,000
- $150,000 - $250,000
- More than $250,000
- Decline to state

In order to take this survey, you must consent to the terms. If you clicked the "I do not consent" button in error, please click on the "Prev" button to return to the start of the survey.

Thank you.

Note: This page was only shown if the participant did not agree to the terms on the first page of the survey, otherwise this page was skipped over to the next page

Thank you for taking the survey. If you have any questions or feedback, please email them to:

moor0762@umn.edu

Appendix 2

Dependent Variable: GROWTH (Risk Profile Results) - Questions #2 - #8 from survey						
GR	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	0.6561	0.2774	0.018	0.6131	0.2828	0.03
Male	-0.2325	0.2178	0.2858	-0.2458	0.2187	0.261
Invexp	0.5032	0.2958	0.0889	0.4397	0.2907	0.13
Advisor	-0.4183	0.2289	0.0676	-0.3712	0.2308	0.108
Col4	0.2445	0.2041	0.231	0.2704	0.2061	0.189
Age35	0.158	0.309	0.6091	0.2379	0.3098	0.443
Age45	**-0.8647**	**0.2972**	**0.0036**	**-0.8897**	**0.3045**	**0.003**
Age55	**-1.399**	**0.2507**	**<.0001**	**-1.419**	**0.2502**	**0.000**
Nw250	0.2282	0.2722	0.4017	0.2757	0.2696	0.307
Nw500	-0.0882	0.3046	0.7721	-0.1259	0.3044	0.679
Nw1000	0.2497	0.3076	0.4169	0.2219	0.3048	0.466
Nw1000p	-0.0771	0.3284	0.8144	-0.084	0.3195	0.793

Dependent Variable: QUESTION LOSS AVERSION (1) - Questions #9 & #10 from survey						
QLA1	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	-0.0306	0.2417	0.8993	-0.0467	0.2426	0.847
Male	-0.0581	0.1845	0.753	-0.0763	0.1854	0.681
Invexp	0.1401	0.2411	0.5612	0.1495	0.2401	0.533
Advisor	0.0403	0.1842	0.8267	0.048	0.1828	0.793
Col4	0.0876	0.1769	0.6203	0.0924	0.1764	0.601
Age35	-0.206	0.2351	0.3808	-0.2129	0.2337	0.362
Age45	0.2787	0.2393	0.2442	0.2819	0.2411	0.242
Age55	0.1591	0.2212	0.4722	0.1498	0.2217	0.499
Nw250	-0.1157	0.2214	0.6012	-0.11753	0.2218	0.596
Nw500	-0.0953	0.2492	0.7021	-0.0827	0.2478	0.738
Nw1000	0.0433	0.2566	0.8659	0.0401	0.2561	0.876
Nw1000p	0.0395	0.2813	0.8882	0.0531	0.2838	0.852

Dependent Variable: QUESTION LOSS AVERSION (2) - Question #13 from survey						
QLA2	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	0.4427	0.2541	0.0815	0.3886	0.2542	0.126
Male	-0.0684	0.1945	0.7252	-0.0246	0.1974	0.901
Invexp	-0.1206	0.253	0.6336	-0.1037	0.2524	0.681
Advisor	0.3144	0.1918	0.1011	**0.3136**	**0.1899**	**0.099**
Col4	0.0592	0.1875	0.7523	0.0914	0.1871	0.625
Age35	0.0696	0.2431	0.7746	0.1072	0.2421	0.658
Age45	0.2147	0.2509	0.3921	0.1926	0.2507	0.442
Age55	0.0906	0.2371	0.7024	0.1	0.2397	0.676
Nw250	**-0.418**	**0.2318**	**0.0713**	**-0.4306**	**0.2307**	**0.062**
Nw500	0.3728	0.2664	0.1618	0.3992	0.2662	0.134
Nw1000	**-0.5666**	**0.2753**	**0.0396**	**-0.6206**	**0.2762**	**0.025**
Nw1000p	0.2924	0.2922	0.317	0.3615	0.3011	0.23

Dependent Variable: QUESTION LOSS AVERSION (3) - Question #15 from survey						
QLA3	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	1.0726	0.2814	0.0001	1.0175	0.2677	0
Male	0.345	0.21	0.1004	0.3292	0.2084	0.114
Invexp	0.1887	0.2705	0.4855	0.1387	0.2694	0.607
Advisor	-0.2386	2074	0.2499	-0.2576	0.209	0.218
Col4	-0.1866	0.2028	0.3577	-0.1585	0.2026	0.434
Age35	-0.1227	0.2626	0.6402	-0.0948	0.2569	0.712
Age45	0.1747	0.2675	0.5137	0.2112	0.262	0.429
Age55	-0.0681	2508	0.7859	-0.1131	0.2512	0.653
Nw250	-0.3032	0.2507	0.2267	-0.2337	0.291	0.348
Nw500	0.0432	0.2739	0.8749	0.0585	0.2786	0.833
Nw1000	-0.3891	0.278	0.1616	-0.3969	0.2804	0.157
Nw1000p	0.519	0.3239	0.1091	0.5075	0.324	0.118

Dependent Variable: QUESTION ANCHORING - Question #14 from survey						
QAN	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	0.3848	0.2454	0.1169	0.3802	0.2434	0.118
Male	0.0106	186	0.9544	0.0085	0.1861	0.964
Invexp	0.0717	0.2448	0.7698	0.0788	0.2469	0.75
Advisor	-0.0564	0.1862	0.7618	-0.0623	0.1862	0.738
Col4	-0.0405	0.1783	0.8203	-0.0383	0.1792	0.83
Age35	**-0.4741**	**0.2384**	**0.0467**	**-0.4748**	**0.2408**	**0.049**
Age45	-0.0861	0.2396	0.7192	-0.0738	0.241	0.759
Age55	**0.4847**	**0.2223**	**0.0292**	**0.4804**	**0.2222**	**0.031**
Nw250	0.1393	0.2244	0.5349	0.1369	0.225	0.543
Nw500	-0.2528	0.2517	0.3152	-0.2625	0.2522	0.298
Nw1000	0.0859	0.258	0.7392	0.0872	0.2587	0.736
Nw1000p	-0.1728	0.2828	0.5411	-0.1685	0.2828	0.551

Dependent Variable: QUESTION OVERCONFIDENCE - Question #12 from survey						
QOC	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	0.0333	0.2448	0.8919	0.03	0.244	0.902
Male	**-0.3393**	**0.1894**	**0.0732**	**-0.3443**	**0.1891**	**0.069**
Invexp	0.0982	0.2453	0.689	0.1182	0.2453	0.63
Advisor	**-0.376**	**0.1883**	**0.0459**	**-0.3746**	**0.1888**	**0.047**
Col4	-0.2144	0.1785	0.2297	-0.2162	0.1773	0.223
Age35	0.0457	0.2398	0.849	0.0124	0.2412	0.959
Age45	0.345	0.2439	0.1571	0.3567	0.2468	0.148
Age55	0.035	0.2246	0.8762	0.0111	0.2231	0.96
Nw250	-0.0698	0.2255	0.7568	-0.0574	0.2261	0.799
Nw500	0.1717	0.2538	0.4989	0.1518	0.2527	0.548
Nw1000	0.0244	0.2588	0.9248	0.0531	0.2592	0.838
Nw1000p	-0.4531	0.2909	0.1193	-0.4497	0.2908	0.122

Dependent Variable: QUESTION MYOPIA - Question #11 from survey						
QMY	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	-0.413	0.2478	0.0956	-0.4319	0.2485	0.082
Male	0.2278	0.1976	0.2488	0.2429	0.1978	0.219
Invexp	0.0771	0.2439	0.752	0.6034	0.2425	0.794
Advisor	0.1368	0.1906	0.4729	0.1247	0.1925	0.517
Col4	**0.3345**	**0.1847**	**0.0701**	**0.3318**	**0.1846**	**0.072**
Age35	-0.1236	0.2406	0.6076	-0.1015	0.2387	0.671
Age45	-0.0043	0.2505	0.9864	-0.2605	0.2541	0.918
Age55	0.1498	0.2402	0.5349	0.1602	0.2371	0.499
Nw250	0.3102	0.2234	0.165	0.3119	0.2239	0.164
Nw500	-0.2403	0.2531	0.3423	-0.2172	0.2538	0.392
Nw1000	**0.953**	**0.2876**	**0.0009**	**0.9445**	**0.2865**	**0.001**
Nw1000p	-0.52	0.3233	0.1078	-0.5218	0.3186	0.102

Dependent Variable: SIMULATED MYOPIA - Question #16 from survey						
SMY	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	0.2085	0.2476	0.3996	0.2231	0.2485	0.369
Male	0.131	0.1873	0.4843	0.1527	0.1884	0.417
Invexp	-0.1483	0.2451	0.454	-0.1398	0.2453	0.569
Advisor	**-0.3304**	**0.1887**	**0.08**	**-0.3524**	**0.899**	**0.064**
Col4	**0.3325**	**0.1807**	**0.0658**	**0.2992**	**0.1804**	**0.097**
Age35	**-0.6371**	**0.2422**	**0.0058**	**-0.6607**	**0.246**	**0.007**
Age45	**0.6367**	**0.2472**	**0.01**	**0.6598**	**0.249**	**0.008**
Age55	-0.0782	0.2227	0.7255	-0.0973	0.2217	0.672
Nw250	-0.1542	0.2264	0.4958	-0.1453	0.2262	0.521
Nw500	-0.0848	0.2557	0.7401	-0.07726	0.2566	0.763
Nw1000	0.3852	0.2609	0.1399	0.3773	0.2594	0.146
Nw1000p	-0.2524	0.2827	0.372	-0.2294	0.2851	0.421

Dependent Variable: SIMULATED OVERCONFIDENCE (1) - Question #19 from survey						
SOC1	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	1.0407	0.2697	0.0001	1.031	0.7869	0
Male	-0.0924	0.1891	0.6251	-0.0872	0.19	0.646
Invexp	-0.1852	0.2595	0.4753	-0.1842	0.257	0.474
Advisor	0.173	0.1943	0.3733	0.1847	0.1963	0.347
Col4	**-0.4284**	**0.1904**	**0.0244**	**-0.41**	**0.1915**	**0.032**
Age35	0.1711	0.2511	0.4956	0.1532	0.2496	0.539
Age45	-0.2247	0.2507	0.3701	-0.2271	0.2541	0.371
Age55	**-0.5663**	**0.2267**	**0.0125**	**-0.5746**	**0.2272**	**0.011**
Nw250	-0.1842	0.2364	0.4355	-0.1773	0.2339	0.448
Nw500	-0.1945	0.256	0.4475	-0.1811	0.256	0.479
Nw1000	-0.0002	0.2605	0.9993	-0.00124	0.2622	0.996
Nw1000p	-0.0289	0.2854	0.9194	-0.0405	0.2854	0.887

Dependent Variable: SIMULATED OVERCONFIDENCE (2) - Question #23 from survey						
SOC2	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	-0.3143	0.2481	0.2052	-0.3048	0.2455	0.214
Male	0.3212	0.1974	0.1038	**0.3653**	**0.2026**	**0.071**
Invexp	0.2809	0.247	0.2554	0.2644	0.2436	0.278
Advisor	-0.1477	0.1936	0.4455	-0.1421	0.1948	0.466
Col4	**0.3954**	**0.1852**	**0.0327**	**0.4297**	**0.1828**	**0.019**
Age35	-0.0487	0.2431	0.8411	-0.0531	0.2425	0.827
Age45	**-0.4407**	**0.2524**	**0.0808**	**-0.4503**	**0.2522**	**0.074**
Age55	**0.5473**	**0.2433**	**0.0245**	**0.5803**	**0.2445**	**0.018**
Nw250	-0.0359	0.2238	0.8725	-0.0531	0.2251	0.811
Nw500	**0.5745**	**0.2624**	**0.0285**	**0.5661**	**0.2622**	**0.031**
Nw1000	-0.1657	0.2735	0.5448	-0.1855	0.2776	0.504
Nw1000p	**0.6953**	**0.347**	**0.0451**	**0.8346**	**0.3612**	**0.021**

Dependent Variable: SIMULATED OVERCONFIDENCE (3) - Question #24 from survey						
SOC3	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	-0.6404	0.2543	0.0118	-0.6261	0.2535	0.014
Male	**0.5891**	**0.1951**	**0.0025**	**0.5901**	**0.1947**	**0.002**
Invexp	**0.6656**	**0.2515**	**0.0081**	**0.6902**	**0.2508**	**0.006**
Advisor	-0.0543	0.1903	0.7754	-0.0255	0.1884	0.892
Col4	0.2219	0.1863	0.234	0.1659	0.1876	0.377
Age35	-0.198	0.2423	0.4137	-0.2729	0.2437	0.263
Age45	0.0205	0.2452	0.9334	0.0189	0.2461	0.939
Age55	**0.5327**	**0.2401**	**0.0265**	**0.4987**	**0.2378**	**0.036**
Nw250	-0.0639	0.2274	0.7788	0.0027	0.2263	0.99
Nw500	0.0183	0.2587	0.9426	-0.0273	0.2598	0.916
Nw1000	0.00684	0.2694	0.9797	0.0628	0.2687	0.815
Nw1000p	0.2563	0.315	0.4159	0.2343	0.3093	0.449

Dependent Variable: SIMULATED ANCHORING (1) - Question #18 from survey						
SAN1	Individual Probit Equations			Multivariate Probit Equations		
Parameter	Estimate	Error	P>ChiSq	Estimate	Error	P>z
Intercept	0.825	0.2821	0.0034	0.7902	0.2938	0.007
Male	**-0.3573**	**0.2161**	**0.0983**	**-0.3599**	**0.2168**	**0.097**
Invexp	-0.0443	0.2847	0.8763	-0.0521	0.2769	0.851
Advisor	-0.0718	0.2224	0.7469	-0.0982	0.2224	0.659
Col4	0.1735	0.2066	0.401	0.2192	0.2105	0.298
Age35	0.1043	0.2779	0.7073	0.1569	0.2761	0.57
Age45	0.1286	0.29	0.6573	0.1071	0.2915	0.713
Age55	0.0128	0.2628	0.9612	0.0758	0.2643	0.774
Nw250	0.1289	0.2644	0.6259	0.169	0.2701	0.531
Nw500	-0.0832	0.2976	0.7799	-0.1795	0.3037	0.554
Nw1000	0.1252	0.3076	0.6839	0.1989	0.3077	0.518
Nw1000p	-0.0458	0.3339	0.8908	-0.1258	0.3335	0.449

Dependent Variable: SIMULATED ANCHORING (2) - Question #20 from survey						
SAN2	**Individual Probit Equations**			**Multivariate Probit Equations**		
Parameter	**Estimate**	**Error**	**P>ChiSq**	**Estimate**	**Error**	**P>z**
Intercept	0.6045	0.2549	0.0177	0.5843	0.2549	0.022
Male	-0.1338	0.1869	0.4741	-0.1314	0.1878	0.484
Invexp	0.2538	0.2524	0.3147	0.2587	0.2532	0.307
Advisor	-0.0867	0.1913	0.6503	-0.0789	0.1891	0.676
Col4	0.1186	0.1821	0.515	0.1176	0.1828	0.52
Age35	-0.0446	0.2453	0.8558	-0.0592	0.2441	0.808
Age45	0.0868	0.2464	0.7248	0.1251	0.2482	0.614
Age55	-0.0926	0.2235	0.6788	-0.1164	0.224	0.604
Nw250	**-0.5668**	**0.2347**	**0.0158**	**-0.5375**	**0.234**	**0.022**
Nw500	-0.2726	0.2503	0.2761	-0.3095	0.2513	0.218
Nw1000	0.0539	0.2565	0.8335	0.0693	0.2572	0.788
Nw1000p	-0.059	0.2802	0.8332	-0.0708	0.2818	0.802

Dependent Variable: SIMULATED ANCHORING (3) - Question #22 from survey						
SAN3	**Individual Probit Equations**			**Multivariate Probit Equations**		
Parameter	**Estimate**	**Error**	**P>ChiSq**	**Estimate**	**Error**	**P>z**
Intercept	-0.8316	0.2618	0.0015	-0.8744	0.2701	0.001
Male	0.1761	0.1903	0.3546	0.1515	0.1881	0.42
Invexp	0.0946	0.2543	0.7098	0.1361	0.2557	0.594
Advisor	0.1861	..1927	0.3341	0.2163	0.1931	0.262
Col4	**0.3466**	**0.1883**	**0.0657**	**0.3597**	**0.1877**	**0.055**
Age35	**-0.4968**	**0.2493**	**0.0462**	**-0.5442**	**0.2498**	**0.029**
Age45	0.0649	0.252	0.7967	0.1161	0.255	0.649
Age55	-0.079	0.228	0.7289	-0.0848	0.2243	0.705
Nw250	0.2717	0.2356	0.2489	0.2621	0.2379	0.271
Nw500	0.3954	0.256	0.1224	0.4134	0.2574	0.108
Nw1000	-0.3657	0.2629	0.1642	-0.3979	0.2615	0.128
Nw1000p	0.2855	0.2844	0.3153	0.3267	0.2847	0.251

Dependent Variable: SIMULATED LOSS AVERSION (1) - Question #17 from survey						
SLA1	**Individual Probit Equations**			**Multivariate Probit Equations**		
Parameter	**Estimate**	**Error**	**P>ChiSq**	**Estimate**	**Error**	**P>z**
Intercept	-0.6969	0.2636	0.0082	-0.6331	0.2572	0.014
Male	-0.1624	0.2009	0.4188	-0.1688	0.2015	0.402
Invexp	**-0.7657**	**0.2624**	**0.0035**	**-0.7584**	**0.2594**	**0.003**
Advisor	0.1478	0.2026	0.4658	0.1342	0.2042	0.511
Col4	**0.3794**	**0.1982**	**0.0556**	**0.3404**	**0.1965**	**0.083**
Age35	0.0789	0.2626	0.7637	0.119	0.2613	0.649
Age45	0.0973	0.2642	0.7128	0.0292	0.2701	0.914
Age55	0.2486	0.2378	0.2957	0.2286	0.2383	0.337
Nw250	0.224	0.2469	0.3643	0.1528	0.2496	0.54
Nw500	0.1198	0.2667	0.6533	0.1709	0.2675	0.523
Nw1000	0.0958	0.269	0.7217	0.097	0.2656	0.715
Nw1000p	-0.2759	0.3034	0.3632	-0.2692	0.3044	0.413

Dependent Variable: SIMULATED LOSS AVERSION (2) - Question #21 from survey						
SLA2	**Individual Probit Equations**			**Multivariate Probit Equations**		
Parameter	**Estimate**	**Error**	**P>ChiSq**	**Estimate**	**Error**	**P>z**
Intercept	-0.7035	0.2613	0.0071	-0.6771	0.2538	0.008
Male	0.2821	0.1903	0.1383	0.2711	0.1903	0.154
Invexp	0.4096	0.2602	0.1154	0.3969	0.2651	0.134
Advisor	-0.1566	0.1944	0.4204	-0.1848	0.1955	0.345
Col4	0.1889	0.187	0.3126	0.1764	0.1847	0.34
Age35	**-0.5465**	**0.2543**	**0.0317**	**-0.569**	**0.2606**	**0.029**
Age45	0.2976	0.2571	0.247	0.3459	0.2621	0.187
Age55	**0.4225**	**0.2261**	**0.0616**	**0.4192**	**0.2268**	**0.065**
Nw250	-0.0396	0.2352	0.8664	-0.0326	0.2369	0.89
Nw500	0.1117	0.2604	0.6678	0.0927	0.2626	0.724
Nw1000	-0.0333	0.2623	0.8989	-0.0074	0.2609	0.977
Nw1000p	-0.3478	0.2921	0.2338	-0.3541	0.2921	0.225