BEHAVIORAL FINANCE: A SURVEY OF FINANCIAL LITERATURE

by

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ABSTRACT

Using academic studies and financial literature from over 40 researchers, I investigate if behavioral finance causes investors to not always act in a rational manner. In this thesis, I review the literature on investor behavior and outline the situational factors that contribute to investment decisions that are not consistent with the theory of rational expectations. In particular, I synthesize the departure from the theoretical standard due to gender bias, risk-taking, over confidence based on gender as well as institutional compared to individual investors, investor biases, external environmental influences, and lastly, herd behavior.
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Introduction

Numerous fundamental theories of finance and modern economics rely on the assumption that participants have homogenous expectations and are rational. A rational investor is defined as an individual whose decision-making process is based on optimizing his or her level of wealth or benefit. The Capital Asset Pricing Model (CAPM) is an equilibrium model that provides the foundation for many of today’s modern financial theories. CAPM is used to find a theoretically applicable required rate of return of an asset while taking into account the asset’s sensitivity to non-diversifiable risk, the expected return of the market, and the expected return of a hypothetical risk-free asset. The fundamental basis of CAPM relies on several assumptions, one being that investors are rational mean-variance optimizers (Mullins 1982). The area in finance that takes into consideration the fact that market participants may not always behave rationally has been termed behavioral finance.

Countless authors have pointed out various examples of market participants not behaving completely rationally due to various internal and external factors. Several behavioral discrepancies are found between men and women in regards to financial decision making. To name a few, Charness and Gneezy (2011) conduct several studies relating to the level of risk-aversion preferred by males compared to females. In 2001, Barber and Odean explore whether males or females tend to be more overconfident when it comes to making investment decisions. Tekce, Yilmaz, and Bildik (2016) analyze the
consequences of the disposition effect, familiarity bias, and status quo bias and show that these predispositions are rampant among investors.

The remainder of this paper will synthesize the literature and academic studies from several renowned researchers, showing how behavioral finance can effect a ‘rational’ investor’s decision making process. By exploring the following categories of internal investor characteristics, biased tendencies, and environmental factors, this thesis aims to show that market participants do not always behave entirely rationally.
Chapter I: Risk Taking

Most economic and financial transactions involve taking on some form of risk, which explains why there is a substantial amount of research dedicated to trying to understand how risk is incorporated when investors make decisions. There are numerous underlying factors that can potentially cause individuals to take on levels of risk that are not completely rational. For example, several investor characteristics, such as IQ, financial literacy, and stock market participation can cause investors to assume more or less risk.

Similarly, regarding investment decision making, the gender of the investor can also affect the amount of risk he or she is willing to take. This section explores the disparity between risk that men are willing to take with investments compared to women. There are several studies that seek to explain the underlying causes of the difference in assumed risk between genders, such as perceived knowledge sets, general traits, and stock market participation.

a. Investor characteristics

Although individuals have become increasingly more active in financial markets as the result of easier access to new financial products and services, in the United States only about 50% of households invest in stocks (Grinblatt, Keloharju, Linnainmaa, 2011). In Europe, participation in the stock market is even lower. Research performed by Mark Grinblatt, Matti Keloharju, and Juhani Linnainmaa (2011) seeks to explain how participation in the stock market, and perceived risk taken on by individual investors, is
correlated to IQ. By studying participation in the Finnish stock market at the end of 2000 as a function of IQ, the relation between IQ and various other factors contributing to portfolio risk and return are studied. The researchers obtain IQ data for Finnish males in their twenties because scores are gathered upon entering Finland’s mandatory military service at this age. Stock ownership and mutual fund ownership data is also obtained, along with the tax returns from 2000 of all of the inductees. The results of the study imply that lack of cognitive skill is a fundamental driver of nonparticipation, and is potentially what deters large sums of wealth from entering the stock market.

The researchers were able to use the data they gathered to conclude that Higher-IQ participants are more likely to hold mutual funds, hold a larger number of stocks, and maintain lower-beta portfolios than lower-IQ participants. High-IQ subjects participate more often because they face a superior risk return trade off, and low-IQ subjects are less willing to participate because they are more prone to making investment mistakes. In order to determine if low-IQ subjects’ unwillingness to participate derives from a risk-averse standpoint, Sharpe ratios were estimated from participant’s risky portfolios of individual mutual funds, then regressed against IQ and controls.

The results of this study strongly imply that one’s IQ early in adult life is directly correlated to participation in the stock market, as well as portfolio diversification later in life. As Figure 1 shows, there are more market participants in every above-average IQ stanine, and comparatively less participants in every below-average IQ stanine. Since high-IQ investors are more likely to participate in the stock market, their Sharpe ratios tend to be higher. A higher Sharpe ratio indicates that the investor can expect to receive more excess return on their investment, given the extra volatility they are exposed to by
holding a riskier asset. Investors with higher IQ’s are therefore more likely to be willing to take on additional risk by participating in the stock market and diversifying their portfolios through holding mutual funds and larger numbers of stocks.

Figure 1: Distribution of IQ scores conditional on market participation

Source: Grinblatt, Keloharju, Linnainmaa (2011)

Maarten van Rooij, Annamaria Lusardi, and Rob Alessie (2011) conducted a similar study, but instead looked at how an individuals’ financial literacy affects financial decision-making and participation in the stock market. The researchers find that a lack of understanding finance and economics is a significant deterrent to stock ownership. Therefore, they reached the similar conclusion that those with low financial literacy are much less likely to invest in stocks. Considering the relation between IQ and financial literacy, it is likely that the higher an individual’s IQ, the more financially literate, and
the more likely they will participate in the stock market. This evidence is also consistent with the work performed by Vising-Jørgensen (2004), who found that sophisticated investors tend to behave more rationally, compared to unsophisticated investors, who appear less rational.

b. Male vs. Female

Johan Almenberg and Anna Dreber (2015) took a similar approach to the previously mentioned study, but by adding another variable, they not only analyze the correlation between stock market participation and financial literacy, but were also able to study the relation of gender with these factors. Previous findings have concluded that women participate in the stock market less than men (van Rooij et al., 2011), and also tend to be less financially literate than men (Lusardi and Mitchell, 2008; OECD, 2013). Almenberg and Dreber seek to determine if the gender gap in stock market participation is a direct result of disparities in levels of financial literacy by studying a random sample of the Swedish population and measuring their financial literacy, based on a scale from a basic understanding to advanced knowledge.

The results obtained indicate that women are less likely than men to participate in the stock market, while women also score lower on basic and advanced financial literacy and knowledge. Therefore, these results imply that the gender gap in stock market participation can be attributed largely to gender differences in financial literacy- also forecasting the next series of questions, if basic financial literacy for women is raised, would the gender gap in stock market participation be closed?
It is a common principal of economics that to earn a higher return, one must take on more risk. It has already been established that more frequent participation in the stock market results in taking on higher levels of risk, and men are likely to participate more often than women. This gender disparity leads into the next set of questions regarding the relation between gender and risk when it comes to making financial decisions.

Over the years, several scholars have written academic literature eluding to the idea that women are less likely than men to engage in risky investments. As previously discussed, Almenberg and Dreber (2015) provided results that imply that women are less financially literate than men, which potentially causes them to take part in less risky investment decisions. A caveat of this type of analyses is that these large-scale studies do not control for potential gender differences in knowledge sets – they had not evaluated the effect of context-specific knowledge on the investment decisions people made.

In 2001, Dwyer, Gilkeson, and List conducted a study using national survey data from roughly 2000 mutual fund investors. They investigate the relation between the gender of the investor and the level of risk taking, in regards to mutual fund investment decisions, while holding the financial investment knowledge of individual investors constant. Mutual fund data was used because mutual funds are common investment choices for many people and are consistently discussed in the popular press, therefore providing a relatively unambiguous decision context for both men and women.

The survey used for data collection was conducted jointly by the Office of the Comptroller of the Currency and the Securities Exchange Commission in 1995. Dwyer, Gilkeson, and List (2001) randomly selected 2000 mutual fund investors, and asked the participants a series of questions regarding their demographic traits, the types of mutual
funds they owned, where they purchased these mutual funds, as well as questions to
determine their knowledge of basic financial concepts. In regards to the question for type
of fund owned, the study focused on three isolated pieces of information: “the type of
mutual fund that respondents had purchased for their largest single investment, their most
recent (last) investment, and their riskiest investment” (152). In order to measure the
riskiest investment for mutual funds, the researchers coded the fund types on a scale from
0-4, with 0 being the lowest risk level and 4 being the highest. Money market and
municipal money market funds received a 0, municipal bond funds received a 1, bond
funds received a 2, mixed/balanced funds received a 3, and stock funds received a 4. Due
to complications regarding participants’ largest investment category, the researchers
decided to modify their study and shorten the remaining responses, leading to a 0-3 risk
scale for this category (money market:0, municipal bond:1, mixed:2, and stock:3). The
researchers found overwhelming evidence that, across the three investment categories,
women took less risk in their investments than men. The researchers realize that there are
other factors besides gender that influence risk taking, such as education, age, and
income, therefore they collected data on these attributes as well.

The results did not differ in respect to age, but income and education levels
reported by men tended to be higher than the levels reported by women. The researchers
perceived that knowledge of specific investment practices is correlated to preferences for
the level of risk of investments. Investment knowledge of the respondents was measured
by the responses to 12 questions that had scores from 0 to 12. Six of the twelve questions
required answers that could be associated to a known answer (correct answers=1,
incorrect=1). The remaining six questions used a yes or no format to measure each
individual’s self-reported understanding of financial and investment concepts and terms (yes=1, no=0). The result of these findings conclude that men and women have different knowledge sets in regard to investment decisions (average score for women was 6.20, and 7.67 for men), and therefore the results of differences in risk preferences may be due to men and women’s differences in investment knowledge. These results are consistent with the previous study performed by Almenberg and Dreber (2015).

After calculating empirical results for the regression on each of the three dependent variables (largest, last, and riskiest investment types) and including the variable for investor knowledge, the results imply that “wealthier, more educated investors tend to take on more risk than their less educated, less wealthy counterparts” (156).

The empirical results concerning gender differences, imply that when the measure of investor knowledge was excluded, men take on more risk than women when selecting mutual funds. However, when investor knowledge is included, gender differences are only significant in terms of the riskiest investment. The results for respondent’s largest mutual fund investments show that men are roughly 5% more likely than women to invest in stock funds (deemed the riskiest type of mutual fund for this study), and are 3.4% less likely than women to invest in money market funds (the lowest risk).

Although this study found evidence that suggests women take less risk than men in their mutual fund investments, it has also been observed that the difference in risk taking can also be attributed to level of financial knowledge each investor possesses.

Determining if men are more willing than women to take financial risks demonstrates an immediate relevance for many concerns in the economy today. Gary
Charness and Uri Gneezy (2011) pursue an understanding of important differences in risk taking between groups, primarily the gender of the decision makers. The idea that women are more risk averse than men is a common stereotype that plays a role in important behavioral tendencies throughout the financial industry. Although several empirical investigations regarding risk taking in relation to gender differences point in the direction that women take less risk than men, these results are hard to compare. These incomparable results pose a major problem because the experiments vary in their methods used to study the phenomenon, and they often use different decision problems.

Another issue is that some studies were specifically designed to test for gender differences, while others found differences without trying to look for them. Charness and Gneezy (2011) have found difficulty substantiating other studies’ results regarding gender disparity in risk taking because it is hard to know how many experiments were actively looking for gender differences in risk taking and did not find them. Therefore, they feel as if they are left with a “selection bias with a positive finding” (51) because it is easier for researchers to publish articles that report finding a gender difference in risk taking versus a study that does not report a difference.

Charness and Gneezy (2011) set out to solidify the answers to questions regarding risk taking between men and women. They systematically collect existing empirical results from 15 sets of experiments, containing thousands of different researchers’ observations that were conducted in various environments, but based on one simple investment game. A majority of these experiments were conducted by different researchers, in different countries, with different subject pools, procedures, ages etc. and were not designed to investigate gender differences. Because the data was not collected in
order to study risk taking by gender, the researchers do not have uniform designs to their experiments, and the assortment allows the strength of the hypothesis to be tested.

The data acquired is centered around an investment decision, that was presented by Gneezy and Potters in 1997, where the decision maker receives “$X” amount of dollars, and the only decision the participants make in the experiment is how much they wish to keep and how much they wish to invest in a risky option (“$x”). “The amount invested yields a dividend of $kx (k > 1) with probability $p$ and is lost with probability $1 − p$. The money not invested $(X − x)$ is kept by the investor. The payoffs are then $(X − x + kx)$ with probability $p$, and $(X − x)$ with $1 − p$. In all cases, $p$ and $k$ are chosen so that $p \times k > 1$, making the expected value of investing higher than the expected value of not investing; thus, a risk-neutral (or risk-seeking) person should invest $X$, while a risk-averse person may invest less. The choice of $x$ is the only decision the participants make in the experiment” (51). The researchers reported data from each study they were aware used this method of testing for risk aversion. Despite the differences in demographics and environments among the sets of experiments, Charness and Gneezy found results that men consistently choose a higher “$x” than women do.

Charness and Gneezy (2001) were able to establish a significant and consistent gender difference in investment choices, as can be seen from their results in the six panels on Figure 2. When compared to men, women make smaller investments in risky assets, and therefore appear to be more economically risk averse. While the researchers are not arguing that women are *always* more risk averse than men, they believe that these findings regarding investment decisions will provide an “important step in understanding the important features of gender differences in risk taking” (57).
Figure 2:

Source: Charness, Gneezy (2001)
Due to the increase of women participating in the workforce, more attention is being paid to gender differences in financial decision-making, especially regarding levels of risk. Melanie Powell and David Ansic (1997) explore whether gender differences in risk-taking tendencies and financial decision making strategies are due to general traits, or if these differences arise due to contextual factors. By analyzing the results of two systematic laboratory experiments, the researchers seek to answer questions regarding the role that framing of tasks as well as the level an individuals’ familiarity to the task might play in an investor’s risk preference and decision strategies for men and women. The researchers compare the decision behavior of males and females in financial situations of various familiarity and framing, in order to determine the degree, if any, to which women display more risk averse behavior than men.

Several psychological and demographic studies have found evidence implying the existence of gender differences in business decision-making, as previously discussed. Although psychologists have concluded that their discoveries yield confirmation of these differences, it is still undetermined if the results represent evidence of general traits rather than contextual responses to social and environmental factors. Some studies prior to 1980 suggest that women are “more cautious, less confident, less aggressive, easier to persuade, and have inferior leadership and problem solving abilities when making decisions under risk compared to men, reinforcing stereotypical views that women are less able managers” (607); however, more recent studies have shown that gender differences in business decision-making are more ambiguous compared to prior belief (Johnson and Powell, 1994). Although contemporary research demonstrates less
significant findings of gender differences in financial abilities, there has been consistent evidence that women tend to possess a lower preference of risk (608).

While some of these gender differences are interpreted as resulting from general traits, others could be explained by various methodical approaches to the studies, such as the subject’s familiarity or experience to the situation. Familiarity can be linked to the way individuals identify with their own gender role in regards to decision making, specifically, studies have found that masculine influence and feminine articulateness were significant determinants of decision making skills (Radeckie and Jaccard, 1996).

Another aspect that could affect risk behavior is the framing of questions regarding decisions. Evidence was found implying that when decision based questions are framed in terms of losses instead of gains, behavioral differences are more pronounced (Dickson 1982). Therefore, gender differences may seem to be more evident when framed in terms of losses, and less evident when framed in terms of gains. Due to the methodical issues of familiarity and framing, Powell and Ansic (1997) test their hypothesis that gender differences are associated with a difference in decision strategy because females tend to have lower risk preferences than males when tasks are framed in terms of losses instead of gains, when tasks are familiar, and when costs associated with decisions or levels of ambiguity are high (610). This study is conducted in order to examine the importance of factors that vary between different instances in the general context of financial decision making.

Powell and Ansic (1997) created a decision environment for their study that was computer based because they wanted to be sure that individuals were receiving the same information. A computer screen also realistically represents the environment that several
individuals use to make financial decisions, while also removing the issue of peer pressure. Undergraduate and post-graduate students were selected from the business school to participate in the study, which consisted of two separate experiments. Both experiments involved making financial decisions under uncertainty, but different cases of task frames and levels of familiarity were incorporated. The second represented unfamiliar decision making related to entering or leaving a currency market. Information about re-entering that same currency market and the corresponding exchange rates were given to participants, but was framed in terms of gains. Participants were paid the value of the results from one of their decisions, chosen at random, to be sure subjects had incentives to actively participate.

The first experiment gave participants a choice of insurance coverage, so both males and females would be familiar and have similar amounts of experience, and was framed in terms of losses. Participants made 12 independent insurance decisions, with the goal of maximizing wealth holdings. After subjects were given assets and cash, information regarding the cost of insurance, and the risk of potential loss, they were asked to make a choice about insuring their assets. Prior to making their decisions, they were also informed that the insurance premium, their wealth, or the nature of risk would change for each decision; as well as the fact that the value of their assets would either remain the same, be halved through damage or fall to zero if a disaster occurred after their insurance decisions were made. Before the event, they were given five insurance options to choose from: “to insure against damage to insure against disaster, to insure against both, not to insure at all, or to ‘pass’ and let the computer make a random choice for them” (613), and after each of their decisions their subsequent level of wealth was
documented on the screen to help the participant keep track of their performance. Lastly, subjects were allowed as much time as they wanted to make their decisions, but were not aware that time it took them to decide was being monitored. Once the participants completed the experiment, they were asked to complete a questionnaire.

The post experiment questionnaire revealed no significant gender differences in past experience and knowledge of insurance coverage, as well as no significant gender difference in the participants’ understanding of the process and perception related to the difficulty of the tasks. In order for Ansic and Powell (1997) to test the hypothesis that females tend to have a lower risk preference than males, the frequency of the chosen insurance coverage was analyzed. The study found that men chose damage coverage more frequently, where women chose disaster coverage more frequently; hence, the conclusion that females show a lower risk preference than males regarding their behavior measured by their choice of insurance coverage.

Ansic and Powell (1997) also measured the time it took participants to make decisions in order to identify differences in decision making strategies. They found that males took an overall significantly longer time to make choices, compared to females. The results also show that strategies for both men and women involve analyzing statistical information and patterns of variation, but males tend to consider more sources of information. While testing the impact of ambiguity on gender and risk strategy, it was found that when the degree of ambiguity was higher, and the risk indicator was low, the longest amount of time was taken to make a decision. Therefore, the level of ambiguity is a more essential element of risk strategy than gender, and “there is no evidence to suggest that gender differences in strategy are affected by the ambiguity of the task” (618).
The second study conducted by Ansic and Powell (1997) involved 66 male and 35 female participants, and was similar to the previous insurance experiment. The volunteers were asked to trade currency within a time constraint, under conditions of the four different seasons, represented by different entry costs into the market. Participants were given an initial amount of cash, and level of earnings was dependent on the ECU-dollar exchange rate. If the rate was higher than the entry rate, the participants earned more. The cost of entry increased throughout each of the 4 rounds, and subjects were allowed to leave the market at any time, but once leaving, no additional gains could be made.

The purpose of this study was to place participants in an environment that was not familiar to them, and have them trade without prior experience. The amount of time spent in the market was measured as the time in the market when price is below entry price. Most individuals will need to be sure of making gains on re-entry as the re-entry cost rises, and therefore will spend less time in the market overall. The results of this experiment show that females demonstrate a lower risk preference because they were more likely to withdraw from the market before maximizing their profit, compared to males.

These two experiments revealed evidence on gender differences in risk behavior relevant to financial decision making by examining the impact of framing, cost ambiguity, and familiarity as context factors that determine risk factors. The evidence from these experiments imply that “gender differences in financial risk preference exist in management populations and are not explained by the context instance of familiarity, ambiguity or gains and loss of framing” (623). The results show that females are less risk-seeking than men. Although men and women tend to adopt different strategies in
their financial decision making, their respective strategies do not have a substantial impact on their ability to perform. Lastly, these studies suggest that “because strategies are more easily observed than either risk preference or outcomes in day to day decisions, strategy differences may reinforce stereotypical beliefs that females are less able financial managers” (605) compared to men.
Chapter II: Overconfidence

Overconfidence by investors is another example of a behavioral attribute that can cause individuals to not act purely rationality. Two seminal, but different, studies of the effect overconfidence has on investment decisions deal with gender bias and institutional investors compared to individual investors. Substantial contributors to the gender bias research literature are Brad M. Barber and Terrance Odean, who provide research and insight regarding the differences in overconfident investing between men and women, and the reasons behind the incongruity. Overconfidence in investors is also examined on the basis of whether informed professional investors display more overconfident behavior than uninformed individual investors.

a. Gender Bias

Several theoretical models predict that excessive trading can be due to overconfidence of investors. Meanwhile, psychological research suggests that, in financial areas, men tend to be more overconfident than women. Therefore, combining these two rationales, it is expected that men will tend to trade more excessively than women. In the study “Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment”, Brad M. Barber and Terrance Odean (2001) analyze the common stock investments of men and women from February of 1991 to January of 1997.
Barber and Odean (2001) believe that “human beings are overconfident about their abilities, their knowledge and their future prospects” (261) and this overconfidence explains the high levels of trading that occur on financial markets. Odean [1998] explains that overconfident investors are those who “believe the precision of their knowledge about the value of a security is greater than it actually is” (261). They believe more strongly in the accuracy of their own personal valuations of securities, and less in the assessments of others. This sense of overconfidence leads to more frequent trading, the tendency to exhaust more resources than necessary, and lower expected utilities due to unrealistic beliefs related to high levels of returns. Rational investors “only trade and purchase information when doing so increases their expected utility” (263), therefore, overconfident investors trade more excessively and hold riskier portfolios than rational investors.

The tendency for individuals to overestimate their precision of knowledge has been observed in several professional fields, and “overconfidence is greatest for difficult tasks, for forecasts with low predictability, and for undertakings lacking fast, clear feedback” (263). Barber and Odean (2001) analyze common stock investments of men and women because stock selection is a task where people tend to express high levels of overconfidence. Choosing common stocks that will outperform is a difficult task, with low predictability, and feedback is unclear.

Men and women can both exhibit overconfidence, however several studies have shown evidence that men tend to exhibit more overconfident behavioral tendencies. As previously discussed, women are more inclined to express financially risk-averse behavior compared to men, which causes females to display more caution while making
financial-decisions, and therefore trade less frequently than males. Since overconfidence and excessive trading go hand in hand, it can be assumed that men to be more confident than women in regards to their ability of making common stock investment decisions.

Barber and Odean (2001) expand on the findings of psychologists who have found that in financial areas, men express more overconfidence than women; leading to the hypothesis that “men will trade more often than women, and the performance of men will be hurt more by excessive trading than the performance of women” (262). By analyzing account data obtained from a large discount brokerage firm, the researchers focused on the common stock investments for over 35,000 households that the gender of the person who opened the household’s account can be identified. By testing this prediction on the basis of gender as a variable, a natural proxy for overconfidence is provided.

The primary data set is information on the investments of 78,000 households, obtained from the same large brokerage firm for six years beginning December, 1996. Information regarding the end of month positions and trade history allow Barber and Odean (2001) to estimate monthly returns beginning February 1991 through January 1997. The secondary data set is demographic information, also provided by the brokerage firm, that identifies the gender of the person who opened the household’s first account at the firm. Information on roughly 35,000 households was provided, of which 79% of accounts were opened by males and 21% were opened by females.

In order to calculate the investment performance of men and women, the gross and net return performance for each household is computed. After reasonably accounting for an impact in the market, commissions, and bid ask spread of each individual trade, the
net return performance is calculated. In order to estimate the gross monthly return on each common stock investment, two simplifying assumptions were made that yield slight differences in return calculations. The first assumes that all securities are bought or sold on the last day of the month. Therefore, the returns earned on stocks purchased from the purchase date to the end of the month are ignored, and the returns earned on the stocks sold from the sale date to the end of the month are included. The second assumption, is that intermonth trading is ignored, but short term trades that yield a position at the end of the month are included in the analysis. Monthly portfolio turnover was calculated as one-half the monthly sales turnover plus one-half the monthly purchase turnover for each household.

Barber and Odean (2001) also calculated an ‘own-benchmark’ abnormal return for individual investors that represents the potential return that the household would have earned had they held their beginning-of-year portfolio for the entire year. For example, if the household did not trade throughout the year, their abnormal return relative to the benchmark would be zero for each of the 12 months throughout the year. Since there is no universally accepted model of risk, using the own-benchmark abnormal return measure is advantageous because it does not adjust returns according a specific risk model. The own-benchmark model allows each household to individually select the risk profile and investment style they prefer, which emphasizes the effect trading has on performance (274). Because inferior security selection could also be a cause of underperformance, it was measured by comparing the returns of stocks bought with the returns of stocks sold.
The results from this study conclude that women tend to hold slightly smaller common stock portfolios, and women turn over their portfolios less than men (53% annually for women compared to 77% annually for men). Comparing returns to those earned by the portfolios held at the beginning of the year, women earned gross monthly returns that were 0.041% lower, while men earned gross monthly returns that were 0.069% lower, which yields a 0.34% difference annually. Regarding net-own benchmark returns, it was found that net monthly returns compared to the portfolio held at the beginning of the year were 0.143% lower for women and 0.0221% lower for men, which is a 0.94% difference annually. Both of these shortcomings are significant, and show that men and women both reduce their returns by trading, but men tend to do so more frequently.

In conclusion, Barber and Odean’s (2001) empirical results are consistent with their predictions that men trade more frequently because they are more overconfident. Compared to women, men lower their returns due to excessive trading, not because their security selections are worse. These findings also support the behavioral finance model. Individuals turn over their common stock investments about 70% annually and mutual funds have similar turnover rates, but the individuals and funds that trade the most tend to earn the lowest rates. Barber and Odean believe that overconfidence explains the high levels of counterproductive trading in financial markets (289). These results are consistent with results obtained by Tekce and Yilmaz (2015), who also found strong evidence that implies that males tend to exhibit more overconfident behavior, and overconfidence has a negative effect on portfolio wealth.
Mark Grinblatt and Matti Keloharju (2009) conduct a similar study to Barber and Odean’s (2001), but by controlling gender (focusing only on males), they attempt to determine if a portion of trading is driven by behavioral attributes. In particular, they focus on the extent that the role of sensation seeking and overconfidence play on the tendency for investors to trade stocks.

Grinblatt and Keloharju (2009) recognize that gender can be linked to several other attributes that can potentially affect trading, and therefore also focus on analyzing sensation seeking as a motivation for trading. Sensation seeking is defined as a measurable psychological trait that crosses many domains and is linked to risky behavior, such as gambling, risky driving, drug abuse, and frequent career changes. Sensation seekers tend to search for a variety of intense experiences, “generally associated with real or imagined physical, social, and financial risks” (550). Trading fits this definition of sensation seeking, and is therefore explored as a cause for participation in the stock market. In this study, sensation seeking is measured using number of speeding tickets an investor in the Finnish Stock Market was given over the course of a multiyear period. Zuckerman (1994), an initial pioneer of the concept of sensation seeking, suggests that one of the best observed behaviors for assessing sensation seeking is driving, hence the use of speeding tickets as a measure.

Grinblatt and Keloharju (2009) define overconfidence similar to Barber and Odean (2001), as the tendency to irrationally place an excessive degree of confidence in one’s own abilities and beliefs. In this study, overconfidence is measured by obtaining data from a standard psychological assessment that is given to all Finnish males prior to serving mandatory military service.
The results of this study indicate that men who are sensation seekers and exhibit more overconfidence trade more frequently, therefore, some portion of trading is driven by behavioral attributes. As can be seen in the results in Figure 3, men trade more than women within all age groups tested. These findings coincide with the empirical results of Barber and Odean’s (2001) study, where they also find that overconfident investors, generally men, trade more excessively.

Figure 3: Average Number of Trades as a Function of Gender and Birth Year

![Graph showing average number of trades compared by gender and birth year.](image)

Source: Grinblatt Keloharju (2009)

b. Institutional vs. Individual Investors

Gender differences are not the only distinguishing factors that can be analyzed for discrepancies pertaining to overconfidence, as several researchers have analyzed the level of overconfidence of professional investors versus individual investors. As previously stated, Barber and Odean (2001) show that the higher the degree of overconfidence of an
investor, the more excessively he/she tends to trade. Excessive trading, in turn, causes the investor to choose higher-risk investments. It is very common for financial professionals such as investment advisors, analysts, and fund managers to display overconfident behavior (Moore and Healy, 2008; Menkhoff et al., 2006; Törngren and Montgomery, 2004).

M.H. Broihanne, M. Merli, and P. Roger (2014) conducted research that demonstrates the role that overconfidence and risk perception plays in financial professionals’ risk-taking behavior. The researchers state that “overconfidence manifests itself through miscalibration of probabilities, better than average effect, illusions of control and unrealistic optimism” (65). By using two different measures of miscalibration, they focus on the effects of overconfidence.

Sixty-four high level professionals were interviewed and asked a series of 10 questions that related to risk attitude, risk perception, overconfidence, risk taking, and expectations. The results showed that financial professionals are overconfident in not only financial domains, but also general domains. This conclusion is reinforced by the professionals’ amplitude of their confidence, which leads to overconfident forecasting of future stock prices. Broihanne, Merli, and Roger (2014) also found that the risk that financial professionals were willing to assume was positively influenced by overconfidence and optimism, however was negatively influenced by risk perception.

In the preceding study, it was determined that financial professionals tend to exhibit overconfidence in multiple domains, but the study failed to compare the overconfident tendency of professional investors to individual investors. Numerous researchers explore the degree of overconfidence for making investment decisions
between these two categories. Guided by Barber and Odean’s (2001) previously discussed hypothesis that states, overconfidence leads to excessive trading, Wen-I Chuang and Rauli Susmel (2011) seek to determine who is more overconfident with their trading, individual or institutional investors.

Chuang and Susmel (2011) chose to analyze Asian markets, specifically the Tawainese market, due to psychologists’ findings that Asian cultures exhibit more overconfidence in general knowledge. Therefore, Asian markets provide a worthy environment to test overconfidence hypotheses.

The Tawainese Stock Exchange (TSE) is characterized by several characteristics that differentiate it greatly from the US stock markets. Because the TSE is an order-driven call market, only limit orders are accepted. Every security listed on the TSE is traded through their Fully Automated Securities Trading (FAST) System, where there is a priority structure that is based on a strict price and time procedure dictating when orders are executed. Therefore, orders that are entered into the FAST system are fully executed before an order entered later is executed. Institutions in the TSE are classified into five categories: corporate institutions, financial institutions, mutual funds, securities dealers, and foreign investors (1627).

In order to examine the trading behavior of investors in Taiwan, size and volume-institutional portfolios were formed that were different in terms of institutional categories but similar in terms of trading volume and size. These low and high institutional ownership portfolios allow the researchers to effectively contrast the trading behaviors of individual investors compared to professional institutional investors.
The Bivariate Granger casualty test, which is helpful in determining whether a particular time series is useful in forecasting another, was used on each portfolio constructed. The results of these tests show that there is a significant and positive correlation between portfolio volume and lagged market returns in all portfolios (1643). This positive causal relationship is stronger for portfolios with low institutional ownership, compared to portfolios with high institutional ownership. In other words, the researchers found evidence that implies that market gains cause individual investors to trade more actively and frequently in successive periods compared to institutional investors.

This study also found evidence that when the market is up, more liquid across market return regimes, and less volatile, both individual and institutional investors tend to trade more aggressively, which is consistent with the behavioral finance theory. It also shows that after market gains, only individual investors are more likely to underestimate risk and participate in riskier securities. Evidence also indicates that after market gains in low-volatile market environments, both individual and institutional investors trade more aggressively, when compared to highly-volatile market environments. Lastly, when the researchers compared the trading degrees between individual and institutional investors, they found that market gains not only made individual investors trade more during bull markets and up-momentum markets, but they also are more likely to actively trade in high-volatility market states compared to institutional environments. This research provides extensive evidence that individual investors demonstrate more overconfident trading behavior, and therefore are more overconfident than institutional investors (1643).
These conclusions from Chuang and Susmel (2011) are consistent with the findings of Gervais and Odean (2001), who determine that less-experienced individual investors tend to have more overconfident trading tendencies compared to more experienced institutional investors; as well as discoveries from Tekce and Yilmaz (2015), who found that overconfident behavior is common among individual stock investors, and that sophisticated investors are less prone to overconfidence.

The results of Tekce and Yilmaz (2015) can be seen in Figure 4, providing evidence that individual investors exhibit high levels of overconfidence. By comparing the frequency of annual turnover, overconfidence is measured. Figure 4 shows that a substantial amount of individual investors have high turnover levels, which implies that these investors demonstrate a high degree of overconfidence.

Figure 4: Frequency of annual turnover

Source: Tekce, Yilmaz (2015)
Hsiang-His Liu, Wen-I Chuang, Jih-Jen Huang, and Yu-Hao Chen (2016) conducted a similar study, by exploring the relation between overconfident trading and stock return volatility. By using a double-threshold GARCH model, the researchers analyzed the Taiwanese stock market and examined the overconfident trading behavior of institutional investors compared to individual investors. They analyze the impact that an investors’ over confident trading behavior has on stock return volatility. By using the DT-GARCH model, the researchers are able to estimate the threshold value of market gains, as well as the relation between stock return volatility and overconfident trading. As a result, the researchers determine if there is a variance in the degree of an investors’ overconfident trading outside of the threshold.

The results of this study reveal that investors trade more overconfidently in high market return regimes, causing return volatility to be higher in this type of environment. The results suggest that higher overconfident trading leads to higher return volatilities (538). Consistent with Chuang and Susmel (2011) and Barber and Gervais (2001), Liu, Chuang, Huang, and Chen (2016) also came to the conclusion that individual investors trade more overconfidently compared to institutional investors.
Chapter III: Investor Biases

When further analyzing the effects that behavioral biases have on investors and their financial decision-making, most studies analyze individual investors in developed markets and data that is limited to the subsamples of overall investor groups or a specific individual bias (516). However, Bulent Tekce, Neslihan Yilmaz, and Recep Bildik (2016) conducted the first study that focuses on nationwide data, while also accounting for each transaction on every stock to analyze multiple biases in one experiment. The researchers examined Turkey, an emerging market, and the Istanbul Stock Exchange (ISE) in order to analyze demographic factors. By using a unique database, the researchers determine how these influences affect the behavioral biases of individual investors. Tekce, Yilmaz, and Bildik focus on the behavioral biases of every Turkish individual stock investor that could possibly have an effect on the portfolio selection process of the investors, to understand how prevalent these biases are, how the biases relate to each other, and what factors affect them.

a. Disposition Effect

The first bias analyzed by Tekce, Yilmaz, and Bildik (2016) was the disposition effect. The disposition effect can be easily observed in equity trading, and is defined as the tendency to sell winners early and hold on to losers for too long (516). The researchers hypothesize that individual Turkish equity investors exhibit the disposition
effect, and that more sophisticated investors are less prone to being driven by the
disposition effect. This hypothesis is in line with Odean (1998), who found that investors
demonstrate stronger tendencies to realize winners, rather than losers (516), as well as
Shapira and Venezia (200), Brown et al. (2006), and Dhar and Zhue (2006), who all
provide evidence that sophisticated investors exhibit less disposition effect. The
researchers match every sell transaction with a buy transaction, and analyze each gain or
loss. By calculating the realized gains and losses for each day a sell transaction takes
place, the disposition effect is calculated. The results concur that not only is the
disposition effect common among individual stock investors, but it tends to increase with
age. There is also evidence that female investors exhibit the disposition effect more than
male investors, and wealth tends to increase the disposition effect.

Similarly, Alex Frino, Grace Lepone, and Danika Wright (2014) concluded that
the disposition effect is more prevalent in women and older investors. They found
corresponding evidence by using a large sample of individual investor accounts at a
leading local retail brokerage. The results also imply that several behavioral biases tend
to act as predictors of the disposition effect. Some of these include frequent trading, the
investor’s level of diversification in their portfolio, and round size trading heuristics.

Another seminal experiment conducted by Newton Da Costa Jr., Marco Goulart,
Cesar Cupertino, Jurandir Macedo Jr., and Sergio Da Silva (2013) analyzed whether the
disposition effect was more significant on experienced or unexperienced investors. In
using experienced investors and undergraduate students (as the inexperienced investors),
they were able to determine that both human subjects show the disposition effect.
However, the more experienced investors were less affected by it; these results are consistent with the numerous studies mentioned previously.

Yan Li and Liyan Yang (2012) analyze the disposition effect by using it as a channel to also study the asset pricing and volume implications of prospect theory. The disposition effect is a highly studied trading behavior and was first defined by Shefrin and Statman (1985). The disposition effect is defined as the tendency of investors to be more likely to sell their assets with higher values since they were purchased, rather than sell their assets with lower values since purchase. As a potential explanation of the disposition effect, Li and Yang seek answers from the prospect theory.

Prospect theory is a prominent theory of decision-making, first proposed in 1979. Prospect theory assumes three things: first, under this theory, investors evaluate outcomes based on their perception of gains and losses compared to a reference point (usually the purchase price), instead of evaluation of outcomes based on wealth. Investors tend to be loss averse, meaning they are more sensitive to losses, relative to gains of the same size. Lastly, investors have diminishing sensitivity tendencies, for gains they are risk-averse, and risk-seeking for losses.

The third assumption (diminishing sensitivity) is often viewed as the underlying instrument of the disposition effect. An investor would be likely to sell a stock if it is being traded at a gain, because the investor is highly risk averse. And vice versa, if a stock is currently being traded at a loss, the investor would be highly risk-seeking, and therefore would tend to hold on to the stock. Li and Yang (2012) build a general equilibrium model for the purpose of examining the repercussions of prospect theory for the disposition effect, trading, pricing, and volume.
The results concluded by Li and Yang (2012) imply that a time-varying risk attitude story links the prospect theory to disposition effect, prices, and volume. Because of diminishing sensitivity, a prospect theory investor’s risk aversion is positively correlated to stock returns, which causes a disposition effect. The positive relation between risk aversion and stock returns also results in price momentum, a positive correlation between return and volume, and reduced volatility of returns. Although the disposition effect can result in a positive correlation between return and volume, when the disposition effect is weaker, the correlation tends to be stronger. The general equilibrium model shows that a reversed disposition effect and price reversal for stocks with normal dividends tends to be predicted by a general equilibrium model.

Figure 5: A hypothetical value function:

Source: Kahneman and Tversky (1979)
b. **Familiarity Bias**

A defining property of familiarity bias is when people are offered two different alternatives, individuals tend to favor the one with which they are familiar. This defining property carries over to investment decisions, Merton (1987) developed the capital equilibrium model, which implies that investors make their investment decisions based on the stocks with which they are familiar (517). In regard to the familiarity bias, the researchers predict that a significant portion of individual investors invest in stocks they are familiar with, and that sophisticated investors exhibit a lower degree of familiarity bias. Familiarity bias is measured based on previous ownership under the assumption that after an investor buys a stock, the stock in turn becomes more familiar. Therefore, higher previous ownership indicates a higher tendency for familiarity bias. The results from this data imply that familiarity bias is prevalent in individual Turkish investors, and is higher among males and younger investors. It was also found that investors hailing from more developed regions are less likely to exhibit familiarity bias when compared to those from less developed regions. It also should be noted that the researchers found supporting evidence that Turkish individual stock investors do not chase stocks with positive past returns.

Similarly, Bulipopova, Zhdanov, and Simonov (2014) investigate the impact of the familiarity bias on the individual investor’s reluctance towards realizing losses. The researchers conducted a total of 714 different tests, in which different participants could sell two different stocks (winners and losers). One group of participants had owned familiar assets and the other group of participants worked with completely new portfolios. This experiment yields results that show an individual investor’s tendency to
hold onto losers too long is almost twice as high for unfamiliar stocks (as can be seen in Figure 6), compared to when the assets are familiar to the stock holder. Because the level of familiarity increases an investor’s reluctance to sell off their losing stocks, this could protect the issuer’s market capitalization. Holders of familiar stocks are better able to support the stock’s price, and most likely prevent it from plummeting.

Figure 6: Brief Experimental Results:

<table>
<thead>
<tr>
<th>First portfolio type</th>
<th>Number of respondents</th>
<th>$\Sigma$RG</th>
<th>$\Sigma$RL</th>
<th>$(\Sigma$RG + $\Sigma$RL)/N</th>
<th>$\Sigma$(PRG–PRL)*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anonymous</td>
<td>353</td>
<td>1151</td>
<td>960</td>
<td>5.98</td>
<td>2.29%</td>
</tr>
<tr>
<td>Familiar</td>
<td>361</td>
<td>1273</td>
<td>906</td>
<td>6.04</td>
<td>5.01%</td>
</tr>
</tbody>
</table>

*RG=realized gains; RL= realized losses; PRG= proportion of realized gains; PRL=proportion of realized losses

Source: Bulipopova, Zhdanov, Simonov (2014)

Huberman (2001) found that familiarity bias leads to the home country bias, where investors simply prefer to invest in familiar stocks and ignore the principle of portfolio theory’s advice to diversify. When an investor is selecting his/her portfolio, he/she are trying to maximize their wealth, and in order to avoid assuming too much risk, investors typically diversify their portfolios. Kang and Stulz (1997) observe that normally, investors will benefit greatly from international diversification, yet most individuals tend to ignore this and only invest in their home countries.

The results of this study imply that investors do not optimize along objective risk-return trade-offs. Instead, by exhibiting familiarity bias, investors tend to shy away from...
foreign stocks and concentrate their portfolios on stocks they are familiar with – whether that is within their home country, their own company’s stock, or stocks that are discussed favorably in the media.

c. Status Quo Bias

Status quo bias tends to be evident when individuals prefer things to stay in their current state by not changing anything, or by using a previously made decision as a baseline, or status quo, to maintain one’s current decision (Samuelson and Zeckhauser 1988). For example, since there are several alternatives in terms of equity investments, in order to prevent facing the difficulties of making decisions, individuals could exhibit status quo bias and maintain their current standings. Overconfidence and status quo bias have inverse relationships with investor trading. While men tend to be more overconfident than women (Barber and Odean 2001), women exhibit a higher degree of status quo bias than men. Tekce, Yilmaz, and Bildik (2016) hypothesize that a portion of stock investors exhibit status quo bias and keep their portfolio positions unchanged, women display a higher degree of status quo bias than men, and sophisticated investors demonstrate less status quo bias compared to less sophisticated individuals.

To measure status quo bias, end of day portfolios were constructed for each investor using all buy and sell transactions. The more an investors’ portfolio changes, the more decisions the individual makes, and less status quo bias is demonstrated. Portfolio percentage change was measured every day, therefore, higher portfolio percentage changes indicate lower status quo bias. The results show that demographic characteristics affect status quo bias in the opposite direction than does overconfidence (524), which is
consistent with the findings from Tekce and Yilmaz (2015). It was also found that status quo bias is more evident in female investors, increases with age, and investors that exhibit status quo bias have higher trade performance.

Samuelson and Zeckhauser (1998) experimentally determine the presence of the status quo bias in financial decision making. The researchers examined individuals by forming a questionnaire that consists of a series of decision problems requiring a choice to be made from a fixed number of alternatives. Preferences were controlled, and the set of choice alternatives were held constant. Choices were either neutrally framed or framed under the status quo. For neutral framing, a list of potential alternatives was presented, with no labels attached. Every option was equal to each other. For status quo framing, one specific choice alternative was placed in a “status quo position”, therefore making the others alternatives to the status quo. For some experiments, the researchers manipulated the status quo condition. For the remaining, the status quo option was selected subsequently by the participant’s initial choice.

Both parts of the experiment show that status quo framing has significant and predictable effects on an individuals’ decision making. Samuelson and Zeckhauser (1998) found that across a diverse range of decisions, participants exhibit substantial status quo bias. The degree of the bias was correlated with the strength of the participant’s partiality, as well as with the number of alternatives given in the set of choices. If an individual’s preference for a select alternative was strong, the bias was weaker; and the greater the number of options presented in the set of choices, the more apparent was the relative bias for the status quo.
Alexander Kempf and Stefan Ruenzi (2006) examine the status quo bias and its effects in the mutual fund market, specifically focusing on whether or not the status quo bias is dependent on the number of alternatives offered, by analyzing how cash inflows into a specific mutual fund depend on prior influxes into the same fund. Mutual fund data was gathered for all United States equity mutual funds from 1993 to 2001. The number of alternatives for mutual fund investors in each segment is measured by the number of funds in that particular segment, and because this number varies among the different segments, the researchers can analyze the relation between number of alternatives and the status quo bias in a real-world situation.

Kemkpf and Ruenzi (2006) not only found a positive correlation between previous growth and current growth in mutual fund segments with a large number of funds, but also in segments of the industry that are smaller. The researchers noted that this influence is extremely stable, and is not affected by the specific model chosen. These results imply that the status quo bias in repeated decisions strongly depends on the number of relevant alternatives. Therefore, the status quo bias is more significant in segments where there are more mutual funds to choose from, which is consistent with the findings of Samuelson and Zeckhauser (1998) previously discussed.

d. Confirmation Bias

Stock message boards have become increasingly prevalent when trying to determine investor behavior tendencies because they are becoming a popular platform for investors to clarify, pursue, and exchange information. The increasing popularity and use of message boards has caused questions regarding how investors use the information they
gather from these message boards to, in turn, make financial decisions. The study conducted by JaeHong Park, Prabhudev Konana, Bin Gu, Alok Kumar, and Rajagopol Raghunathan (2010) investigates “how investors process message board information and analyzes the impact of their information gathering activities on their return expectations and investment performance”. By analyzing how investors process information, the researchers are better able to understand if these message boards are detrimental or beneficial to investors and their investment decision making abilities.

This study is beneficial to understanding behavioral finance and investors irrational tendencies because the researchers develop several hypotheses motivated by the confirmation bias. Confirmation bias is defined as the tendency to process certain information by interpreting the information in a way that is consistent with one’s existing beliefs.

By analyzing if psychological factors influence how individuals process information from virtual communities, it can be determined if this behavior influences investment expectations and even actual performance. In order to answer these questions, the researchers hypothesize that investment-related virtual communities (i.e. stock message boards) will not benefit investors because it is likely they are exhibiting confirmation bias and seeking information that aligns with their prior beliefs. Since the information posted on virtual communities are likely to reinforce prior beliefs, investors will feel a sense of overconfidence thus be more prone to excessive trading, as previously detailed. This behavior would lead to less informative investment decisions, and cause lower returns.
A field experiment on investors that use Naver.com, the largest online portal website in South Korea and also popular virtual message board community, was used to test these hypotheses. 502 participants were examined first by completing an online questionnaire, including questions on specific stocks related to the stock message board such as their opinion of the stock, current investment amount, and expected return. To measure the degree of the investors’ confirmation bias, specific messages were posted on the message boards, and participants were asked a series of questions relating to which message appeared to have the most convincing argument, most support, and which is most strongly backed by information from the stock. Investors that possessed a sense of confirmation bias, were more likely to be drawn to the messages consistent with their beliefs.

The results of this experiment show strong evidence that investors inefficiently process information from stock message boards and heavily exhibit confirmation bias. It was found that investors containing strong prior beliefs are far more likely to accept opinions that coincide with their own from virtual communities. This study also indicates that investors who are driven by stronger confirmation bias tend to exhibit more overconfidence and perceived competence, which in turn adversely affects their investment performance because the investors trade more often, have higher expectations about their performance, and have lower realized returns, as seen in Figure 7 and Figure 8.
When individuals seek new information, the search procedures are usually biased in favor of their preexisting expectations, beliefs, or desired conclusion. Abundant research has shown that after people make a decision, they typically prefer supporting information over conflicting information. Eva Jonas, Stefan Schulz-Hardt, Dieter Frey,
and Norman Thelen (2001) conduct a total of four experiments, that were designed to investigate if confirmation bias in the evaluation of information occurs when information is presented and analyzed sequentially.

The first experiment involved comparing sequential information seeking with simultaneous information seeking, in order to evaluate if a confirmation bias can be observed for both procedures. A group of thirty-six students volunteered to participate and were tested through a questionnaire that was created by the researchers. The results of this first experiment show that biased information extends to situations where information is processed sequentially. The researchers also found that the confirmation bias was significantly stronger for sequential information seeking condition than the bias in the simultaneous condition.

The second experiment analyzes two questions. The first questions if the stronger confirmation bias in sequential information search can be replicated, compared to simultaneous information search. If the answer to the first question is yes, the researchers wonder if the effect is due to different information presentation, or if it is the result of different information processing in sequential search versus simultaneous search. The results from the second experiment replicated the results of the first, that the confirmation bias is stronger when the information search is performed sequentially, versus simultaneously. The researchers also prove that the strength of the confirmation bias is independent of the processing mode. If the information was presented sequentially, rather than simultaneously, the confirmation bias was stronger.

The third experiment was created to directly test the biasedness restriction hypothesis. The researchers tested the biasedness restriction hypothesis by assuming that
if people are trying to not be too biased, they first seek their information in the sequential presentation mode, then if the articles are subsequently presented simultaneously, they will use this second phase to counteract their bias exhibited in the first phase. The results of the third experiment strongly contradict the biasedness restriction hypothesis. Even after the individuals were given the chance to realize their bias and counteract it in the next simultaneous phase, they did not.

Lastly, the fourth experiment tested the focus hypothesis in two different ways. First off, a participant could try to induce a decision focus in the simultaneous condition, in order to see if the subsequent confirmation bias becomes as strong as it does in the sequential condition. The researchers chose the second way to test the focus hypothesis, where instead of provoking a decision focus in simultaneous information search, one could also try to remove the decision focus in the sequential condition in order to evaluate whether the confirmation bias in sequential information search decreases relative to the level of the simultaneous search condition. The results of this experiment strongly support the decision focus hypothesis. It was found that if an information focus hypothesis was induced in the sequential condition, the effect of presentation mode disappears. In other words, the researchers provide strong evidence that implies the increase in strength of the confirmation bias under sequential presentation, is the result of an increased commitment due to the participant’s heightened focus on their decision.

Brad M. Barber and Terrance Odean (2001) explore how the internet is changing the way information is delivered to investors, and the ways in which investors can base their decisions off of this information. Regarding confirmation bias, the focus of their study is arguing against the proposition that more information leads to better decision
making, because it relies on the applicability of the information to the investment decision and how well-equipped the decision maker is to use the information.

Barber and Odean (2001) suggest that because of the Internet, there have been transformations in investing that increases the overconfidence of on-line investors by providing an illusion of knowledge and control, also changing the decision criteria for investors. The researchers argue that a greater increase in volume and variety of information will more likely increase the illusion of knowledge. Investors are more probable to be impressed by the arguments that they already agree with, meanwhile discounting any opposing views. Barber and Odean also argue that due to the Internet, people will actively seek out confirming evidence by visiting chat rooms of similar-minded investors, and are likely to be convinced by those with whom they already have corresponding beliefs. The researchers also find that investors who believe acquiring more information makes them superior investors are not likely to seek out or acknowledge evidence that indicates against their beliefs. Therefore, on-line investors exhibit greater confirmation bias, in turn, making them more overconfident investors.
Chapter IV: Environmental Influences

It has been argued through several clinical psychological studies that weather has significant impact on human behavior, explaining the changes in mood that occur on cloudy or rainy days versus sunny days. There is no doubt that the presence of sunshine impacts one’s mood, which has led researchers to question whether the weather affects the stock market. The traditional efficient market view would assume that it is unlikely that the occurring weather outside of the stock exchange should affect the rational price of the nation’s stock market index.

A contrasting view incorporates the idea that since sunlight positively affects one’s mood, individuals most likely tend to evaluate future prospects more optimistically when they are in better moods compared to when they are in bad moods. If an investor’s good mood extends to investments, they could subconsciously relate this feeling to favorable life prospects. Therefore, misattribution of investors could potentially affect the stock market and cause stock prices to fluctuate in response to the mood of investors. Investors in better moods see positive material as more noticeable and available than negative material, which is not exactly rational and contrasts greatly with traditional efficient market views.

The idea that external influences, such as weather, can affect the stock market differs with many accepted patterns of stock return. Therefore, causing an inconsistency between psychological and rational explanations, which is why examining the effects of
weather on the stock market is an effective way to test if psychological biases can affect stock returns.

a. Seasonal Affective Disorder

Several external influences, such as environmental factors, have also been studied due to their effects on financial decision making. For example, seasonal affective disorder (SAD) has been linked with depression and is a condition that has been known to affect several people during the seasons in which there are fewer hours of daylight. Several psychological experiments have shown a clear correspondence between lowered risk-taking behaviors and depression in several settings, including financial.

In research performed by Norman E. Rosenthal, he found that approximately 10 million Americans were suffering from SAD, and 15 million more endure a milder form of SAD known as “winter blues”. In a clinical sense, SAD is defined as a form of major depressive disorder (2). In the National Institute of Mental Health study by Robert M. Cohen et. al. (1992), positron emission tomography (PET) scans revealed that abnormalities in the prefrontal and parietal cortex areas were caused as the result of diminished daylight. In other words, it has been scientifically and biologically proven that shorter days can lead to depression in certain individuals. SAD symptoms, such as social withdrawal, lethargy, loss of energy, sleep disturbance, and several others, usually begin to appear around the time of the autumn equinox in September (Steven C. Dilsaver, 1990).

Research has also been performed that has correlated a direct link between depression and increased risk aversion tendencies. Risk taking tendencies are measured
by using a scale of “sensation seeking” propensity, developed by Marvin Zuckerman (1994). Studies have shown that levels of depression and anxiety are related to one’s willingness to take a risk. An individual with greater anxiety or depression is less willing to take risk, and has reduced sensation seeking behavioral tendencies.

In “Winter Blues: A SAD Stock Market Cycle” Mark Kamstra, Lisa Kramer, and Maurice Levi (2002) investigate the role SAD plays on stock market returns. The researchers gather information on daily stock index return data obtained through four indicators in the United States and eight from other countries, chosen explicitly to represent large economies at different latitudes in both hemispheres. Indicators in Australia, Britain, Canada, Germany, Japan, New Zealand, South Africa, and Sweden were chosen specifically to control for market seasons and other environmental factors, and daily percentage returns and indexes were analyzed for each country over a period of time.

The results of this experiment found overwhelming evidence the proves the existence of SAD on stock market returns around the world. The results conclude that stock returns are significantly related to the amount of daylight throughout fall and winter. The returns for the United States indices are significantly lower in the September-November months compared to the rest of the months, as seen in figure 9. The link between seasonal depression and seasonal variation can also be seen in different patterns regarding the different latitudes. Markets residing in a higher latitude show more defined SAD effects, while the results obtained from the Southern Hemisphere (lower latitude) are six months out of phase when compared to the Northern, in line with the seasons.
Figure 9: Individual plots of data for each of the United States Indices:

The effects of SAD have also been observed in terms of if this condition affects investors’ immediate reactions to earnings announcements and post earnings announcement drift (PEAD). In the study by Mei-Chen Lin (2013), it was found that investors tend to respond significantly more negatively when earnings are announced in the fall, the most prominent season of SAD, compared to the others. This is due to the fact that when individuals are suffering from SAD, their general level of pessimism tends to increase. In turn, an investors’ willingness to take risk may decrease, causing them to trade less and with more caution – even when hearing good earnings surprises. Mei-Chen Lin found that the effects of SAD cause trading volume to be lower in the fall, and investors are more willing to hold risky investments in the following seasons where there is an increase of hours of daylight in the winter.

Results from Mei-Chen Lin (2013) resonate with results obtained by Symeonidis, Daskalakis, and Markellos (2010) who similarly found that good mood is associated with increased trading and volatility.

Dolvin, Pyles, and Wu (2009) extend research on SAD by examining the potential effect of the disorder on stock analysts’ earnings estimates. By analyzing the error in stock analyst’s annual earnings estimates compared to actual earnings from 1998-2004 and concentrating specifically on pessimistic bias associated with SAD, the researchers hypothesize that earnings estimates made during SAD periods (fall and winter months) will be associated with a pessimistic bias when compared to estimates made during other times of the year (spring and summer months).

The researchers found strong evidence of increased pessimism in analysts’ estimates during fall and winter and more significant pessimism for analysts located in
Northern states, which are most likely to be influenced by a reduction in daylight and the
depression that it causes. However, since analysts’ estimates typically show an optimistic
bias, SAD and its associated pessimism actually has the potential to offset the existing
positive bias, and cause analyst estimates to be more accurate.

Although initial public offerings (IPOs) are intentionally underpriced, Keef, Keefe, and Khaled (2015) found that seasonal influences (SAD) cause IPOs to be even more underpriced. The reason for this is, as previously explained, changes in length of daylight lead to changes in moods of the investor or issuer, causing changes in asset prices. In this case, SAD leads to IPO underpricing to be more pronounced.

b. Hours of Sunshine

Another obscure environmental factor that can affect an investors’ decision
making abilities is the number of hours of sunshine per day, not dependent on season or
time of year. It has been proven that sunshine has the ability to affect mood and shape
behavior, leading Mitra Akhtari (2011) tested if weather is related to economic outcome
and market returns. In order to study the relationship between the weather and equity
prices over time, various measures of the change in weather and market return were
taken. By using regressions from 1948 to 2010, the return on the Dow Jones Industrial
Average (DJA) index was compared to the daily cloudiness and lack of sunshine in New
York City.

Weather data was obtained through the National Climatic Data Center fo the
National Oceanic and Atmospheric Administration (www.ncdc.noaa.gov) for LaGuardia,
New York City, due to its close physical proximity to Wall Street. Akhtari (2011)
measured the daily cloud cover, since hours of sunshine are inversely related to cloud presence, and constructed a variable that approximates daily levels of sunshine. Daily index returns were collected from the Dow Jones Industrial Average to measure market performance.

Results from the data indicate that the return on the DJI is not predicted by New York City weather. However, local cloud cover was found to be significantly correlated with the returns. Therefore, “the correlation between local weather and the close-to-close overnight return of the DJI can be attributed to how weather is related to within day return, as opposed to overnight return” (18). Hirshleifer and Shumway (2003) yielded similar results, concluding that the weather forecasts for a particular day that predict sunshine, do not cause an immediate positive stock price reaction. Instead, prices move due to the physical occurrence of sunshine.

Akhtari’s (2011) results can further prove that since the effects of weather seem to be driven completely by the within day return, rather than overnight return, individuals’ psychological state is affected by the current weather. Because overnight return and weather are unrelated, it can be concluded that it is the present day’s existence of sunshine that drives the weather effect – not people’s forecasts regarding possible sunshine that day. The conclusions from this study support several previous findings, and not only support the fact that stock prices are significantly correlated with the hours of sunshine on Wall Street, but also the viewpoint that stock prices are influenced by investor psychology. These conclusions are similar to those found by Frühwirth and Sögner (2015), whose study also discovered that cloud cover influences the returns on the stock market.
The conclusions from this study correlate with the findings from Saunders (1993), who also showed that the returns on the New York Stock Exchange are negatively related to cloud cover in New York City. Saunders’ results imply that the weather in New York City has a long history of correlations that has a significant impact on major stock indexes. Thus, supporting the view that investor psychology influences asset prices. This experiment demonstrates important information regarding how weather influences mood, and therefore the mood changes most people experience on sunny days versus gloomy days.

Hirshleifer and Shumway (2003) evaluate the relationship, across 26 different countries from 1982 to 1997, between sunshine in the city of the country’s leading stock exchange and daily market index returns. Similar to previously mentioned studies, Hirshleifer and Shumway tested the hypothesis that sunshine affects returns by examining the relationship between daily cloudiness and daily nominal return on the nation’s stock index, for each city. Weather data was obtained from the International Surface Weather Observations (ISWO), and specifically examined for the measure of total sky cover (SKC). In order to rule out that the results were derived from well-known seasonal stock return effects, the researchers analyzed the deviation between the ordinary expected degree of cloudiness for that day of the year and the day’s actual cloudiness. Daily index returns were collected from Datastresam, and all cities that have data from 1988 to 1997 are included in the study.

The researchers find that daily stock returns are highly significantly correlated with sunshine, and after controlling for sunshine, it is determined that returns are unrelated to other weather conditions such as rain and snow. Hirshleifer and Shumway (2003)
struggle with finding a rational explanation for why sunshine would predict later returns or why a sunny day near a country’s stock exchange is associated with high returns on a national market index. However, these results are consistent with the indication that sunlight affects mood, and mood affects prices.

The researchers conclude that by becoming aware of their moods, investors can benefit by avoiding mood-based errors in judgment and trade decisions. Hirshleifer and Shumway (2003) also suggest broader implications regarding these results and asset pricing. In confirming the effect of mood on asset prices and noting that sunshine is just one of several influences on mood, this study implies that other mood effects may be important for understanding how people interpret markets in a broader sense.
Chapter V: Herd Behavior

A fundamental principle of the classical economic theory is that individuals rationally form expectations to make investment decisions, and that these decisions are made by efficiently using all available information. Since humans, by nature, are influenced by others in almost every activity, it is possible this influence can affect financial and investment decisions. This view contrasts the classical economic theory, assuming that investments can be driven by group psychology where the influence of others may not be entirely rational, which in turn, weakens the correlation between market outcomes and available information.

John Maynard Keynes (1936), in The General Theory, expresses views that investors may be hesitant to act according to their own beliefs, values and information, in fear that their contrasting behavior will harm their reputations as practical decision makers. Keynes suggests that professional executives will tend to “follow the herd” if there is apprehension about how others will evaluate their ability to make rational judgements. Herd behavior can have a significant impact on various settings, including the stock market and corporate investments.

David S. Scharfstein and Jeremy C. Stein (1990) examine some of the forces that potentially result in herd behavior in investment decisions. By using a “learning” model, the researchers evaluate situations in which managers use their investment decisions to influence the labor market’s assessments regarding their ability. In this case, ability
represents the manager’s aptitude for making decisions. Scharfstein and Stein assume that there are different types of managers. The first group is “smart managers”, who receive informative signals about the value of a specific investment. The second group is “dumb managers” who only receive noisy signals about the value of an investment. At first, the managers nor the labor market know if they are in the smart or dumb category. After the managers have made an investment decision, the labor market has the ability to update its beliefs based on whether the manager’s behavior was different or similar to the behavior of the other managers, and whether or not the manager made a profitable investment.

If managers follow the decisions of others, they will be more positively assessed, than if their behavior contrasts with the other managers. Therefore, if a manager makes an unprofitable decision, it is not as bad for his or her reputation when others make the same mistakes, because they can share the blame if there are unpredictable fluxes in the market. The “sharing the blame” effect arises due to the act that since smart managers are all observing truthful information, they tend to receive correlated signals. Meanwhile, the dumb managers are only observing unrelated noise, so the dumb ones do not receive correlated signals.

If a manager decides to mimic the behavior of others, it is suggested to the labor market that they have received a signal that is related to the others, and therefore is more likely to be a smart manager. On the other hand, if a manager takes a contradictory position compared to others, the market perceives them to more likely be a dumb manager. Herd behavior is analyzed in this study because even if a manager’s private information regarding an investment has a negative expected value, the investor may still pursue it if others before them have. And conversely, the investor could potentially reject
the investments that they identify as having positive expected value, if others before him have also refused them.

Scharfstein and Stein (1990) found that managers possess herd behavior tendencies, by simply mimicking the investment decisions of other managers, and ignoring applicable private information under certain circumstances. The effects of herd behavior can occur in several settings, as a result of rational attempts by managers to improve their perceived reputations as decision makers. Apprehension concerning reputation is just one of the factors that influence herding. The “sharing the blame” effect is also a common component that causes managers to herd. Scharfstein and Stein’s results also imply that herding is more likely to occur when opportunities for managers are relatively unattractive, and when their compensation depends on absolute ability evaluations, rather than relative ability evaluations.

Abhijit V. Banerjee (1992) conducts a similar study to Scharfstein and Stein (1990), but incorporates a different model to study herd behavior. By developing a simple model, Banerjee studies the rationale behind herd behavior decision making, and the further implications of it. The basic model is set up by using a population of agents, who each try to maximize asset returns, while remaining risk-neutral. The set of assets are indexed by numbers, and it is assumed that the excess return on one specific asset (i*) is greater than the return on all other assets. Therefore, all investors would want to invest on the higher-return asset, but none of the participants know which one it is. If i* is selected by a decision maker, he/she will receive a signal. Banerjee assumes that some participants may have some prior investment knowledge, so they could potentially have an idea of which asset i* is.
The decision making procedure in this model is sequential, where one participant, chosen at random, makes their decision first. Next, the following participant, chosen at random, is allowed to watch the choice made by the previous person, and he/she makes their investment decision. Therefore, the participants that follow can benefit by observing the information obtained from the previous participants’ investment decisions. However, whether or not the participant before was given the signal that they selected \( i^* \) is not allowed to be known. The game continues, with each new participant making their decision based on the history of the past decision makers, and their own signal if they are given one.

The results of this study show that the decisions made are characterized by extensive herding. Banerjee (1992) found that agents abandon their own signals and shadow others, even when they are not sure if the other person is correct. The consequence of this herd behavior is that investors base their decisions on previous incorrect investment choices. The implications of these results show that investment decisions are chosen by optimizing individuals, and are characterized by herd behavior. Therefore, investors are more likely to do what other investors are doing, instead of using their own private information, thus the resulting equilibrium of this behavior is inefficient.

Omar Camara (2017) extends the study of herd behavior by examining the relation of herd behavior to the capital structure of firms for four major United States industries (manufacturing, construction, wholesale, and services). Specifically, by analyzing the likelihood firms exhibit herd behavior tendencies in the corporate finance decision making environment.
All firms in the Annual Compustat database from 1996 to 2015, with ten years of continuous data, were analyzed and their annual gross domestic product (GDP) was also examined from the World Bank database. The cross-sectional absolute dispersion (CSAD) approach was used in order to identify capital structure herding behavior within and across industries. The industry means capital structure for each year and the mean capital structure of the industry leader for each year were used to compute CSAD.

Camara (2017) found that when analyzing industry median, during bear markets, there is significant evidence of herding in the Services industry. During bull markets, there is significant evidence of herding in the Manufacturing industry when leader criteria is incorporated. In terms of herding across industries, it was found that Manufacturing, Construction, and Services industries all herd around the Wholesale industry. The Manufacturing industry exhibited the most significant within industry herd behavior, compared to the other industries. The high level of herd behavior within the Manufacturing industry could be the fact that manufacturing firms’ long term capital structure strategy is to maintain an industry average capital structure, which would cause the participants in the Manufacturing industry to follow what the others are doing.

Jayendu Patel, Richard Zeckhauser, and Darryll Hendricks (1991) analyze the annual debt-to-equity ratios for over 180 firms, from 1971-1989, to examine factors that may lead to herd behavior. “Free riding” in regards to obtaining information is the first reason they described. As the result of asymmetric information, investors with less or lower quality information and resources to acquire relevant information tend to imitate the decision choices of investors who are perceived to have higher quality and more relevant information. Proximity to the group may also be a reason that leads to herd behavior. A
closer proximity to the group may potentially offer protection against the costs associated with deviation from the herd, which is similar to the “sharing the blame” effect described by Scharfstein and Stein (1990). Lastly, investors tend to have a greater level of regret when their decision to diverge from the herd turns out to have a negative outcome. For example, if the deviating firm experienced financial ratios that fell below the industry average, they may be more likely to follow the group norm for subsequent circumstances.

Rama Cont and Jean-Philippe Bouchaud (1998) use a basic model to examine the effects of imitation and herding for the statistical properties of price fluctuations and market demand. The goal of Cont and Bouchaud’s study is to analyze how the presence of herd behavior among market participants may potentially lead to large fluxes in the aggregate excess demand, which is portrayed by a heavy-tailed non-Gaussian distribution. Heavy-tailed distributions are described as probability distributions with non-exponentially bound tails. Therefore, the tails are “heavier” than a normal exponential distribution.

The simple model used by Cont and Bouchaud (1998) provides a relation between the heavy tails observed in the distribution of herding behavior in financial markets and stock market returns, two well-known market phenomena. The results also specifically provide evidence of a link between the excess kurtosis, meaning excess sharpness of the peak of the frequency-distribution curve seen in asset yields, the inclination of market contributors to imitate each other, and the market order flow.

As a result of the 1990s financial crises, several researchers have performed studies suggesting that herd behavior may be a cause for the fragility of financial systems and excess price volatility. Marco Cipriani and Antonio Guarino (2005) study herd behavior
in a laboratory market setting, where subjects receive private information regarding the value of a specific security, and are allowed to observe the history of past trades. After participants receive private information on the securities and their trading history, they are given the opportunity to sequentially choose if they want to buy, sell, or not trade the asset.

Cipriani and Guarino (2005) detect the presence of herding by examining the way participants use their private information and respond to the decisions of the previous traders. The results show that in some circumstances, participants decide not to use their private information and choose not to trade. Where in other circumstances, participants ignore their private information to engage in contrarian behavior and trade against the market. The researchers believe that their results imply that in order to understand herd behavior in actual financial markets, reputational concerns or non-informational motives could be potential explanations, which is consistent with the study by Scharfstein and Stein (1990) previously discussed.
Conclusion

After reviewing, researching, and synthesizing over 40 articles and academic studies on behavioral finance, I have concluded that investors do not always behave rationally. The gender of the investor is an important factor that seems to cause investors to not act completely rationally. As detailed in chapters I and II, several studies have shown that men, compared to women, tend to be willing to assume more risk in their investments, and display a higher degree of overconfidence, thus leading to excessive trading.

The disposition effect, familiarity bias, status quo bias, and confirmation bias are also all investor biases that cause individuals to make illogical investment decisions, and are not consistent with modern financial theories that assume investors act rationally. External environmental influences also have drastic effects on investors, including Seasonal Affective Disorder (SAD), which is a possible explanation for why trading volumes tend to be lower in the fall months, when there is less sunshine. Lastly, several investors tend to possess herd behavior, by acting against their own beliefs or individual information, and “follow the herd” for fear that acting on their own intuition will harm their reputations as rational decision makers.
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