THE EFFECT OF INVESTOR BIAS AND GENDER ON PORTFOLIO PERFORMANCE AND RISK

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ABSTRACT

We survey 84 finance and accounting majors to determine the behavioral factors that males and females exhibit when making investment decisions. The survey results are linked to student performance in the Stock-Trak Global Portfolio Trading Simulation. We find that males and females exhibit different behavioral biases and these behavioral biases can ultimately affect investment performance. We also find evidence to support previous research showing that males are more risk tolerant than females. However, our findings indicate that this behavior may be due to a difference in the perception of the actual risk being taken rather than an inherent desire to engage in more risky behavior.

JEL: D03, G02; G14

KEYWORDS: Behavioral Bias, Gender, Risk Aversion, Stock-Trak

INTRODUCTION

It has been well established in the academic literature that investment risk differs between genders. However, the current research does not address how this relationship extends to investment performance (i.e. risk and return). Although it is the subject of much interest, there has been relatively little empirical research that has investigated the various behavioral biases as they relate to gender and their effect on both investment risk and return. Wilcox (2011) notes that while the hedge fund industry accounts for nearly $2.5 trillion, only three percent of the assets are managed by women. Wilcox indicates that this discrepancy is cause for concern because many industry professionals believe that an optimal trading team is comprised of a diverse and balanced group of individuals that represent all nationalities, ethnicities and especially gender. We use the Stock-Trak simulation to track the behavior and investment performance of male and female college students to investigate this relationship.

Stock-Trak is a widely used portfolio simulation tool.This paper contributes to the literature in four distinct ways. First, while many studies have demonstrated the impact of cognitive and emotional biases on the general decision-making process, we distinguish the relevant literature that can apply the impact of these biases to investors and investment decisions. For the sake of our study, we classified each behavioral bias into the categories discussed in Pompian (2006). We have provided a comprehensive summary of the academic literature that provides supporting evidence for each of these biases in Appendix A. Second, we tested each bias shown in Appendix A to determine if there are any significant differences in the occurrence of these behavioral biases based on gender.

Third, while this previous research has focused on the impacts of biases on investor decisions, this study also focuses on the impacts of biases on the outcomes of investor decisions (i.e., investment portfolio performance and risk). Finally, by including behavioral biases in our analysis of portfolio performance and risk, we provide academics and practitioners a more comprehensive summary of how behavioral biases and gender interrelate to overall investment performance.

The paper proceeds as follows. The Literature Review and Background section presents a review of the relevant literature, which includes gender differences and behavioral biases on investment performance and risk. We then provide a section that outlines the study's methodology, which is followed by the empirical results and analysis section. The paper concludes with a discussion of our results and implications for industry and research.

LITERATURE REVIEW AND BACKGROUND

Previous research suggests that gender can play a role in investor behavior, and these differences in behavior are likely to have implications for portfolio performance. For example, research by Barber and Odean (2001) provides evidence to suggest that men are likely to be more active portfolio managers, trading 45 percent more than women. Their investigation of the trading records of approximately 35,000 households also found that this excessive market trading could have a potentially negative impact on performance as the net returns for men were significantly lower than women.

In addition, the authors found that this relationship was even more pronounced when comparing single men and single women. A more recent study, however, did not find results consistent with this research. Bliss and Potter (2002) studied 3,200 equity mutual fund returns by gender and found no significant differences in trading frequency or performance Although several studies have addressed the impacts of gender on portfolio performance, much less work has been done relating bias to performance. Barber and Odean (2001) found that the higher frequency of trading in male portfolios could be attributed to overconfidence bias, which is predominant in men. Another notable study examined hindsight bias, which is the failure to remember how little an individual initially knew, or the feeling that he or she "knew it all along." Biais and Weber (2009) examined 85 investment bankers in London and Frankfurt who were tested for hindsight bias. The authors found that traders who exhibited hindsight bias had lower portfolio performance. Many studies have also examined the differences in risk-taking behavior by gender, which is often attributed to behavioral biases. One example again is the overconfidence bias. Several studies have found that gender differences in overconfidence have been found in jobs that are considered to be masculine [See Deaux and Farris (1977); Lenny(1977); and Beyer and Bodwen (1997)]. Bliss & Potter (2002) suggest that the low proportion of women in the financial services industry is sufficient evidence to deem stock trading as a masculine task. Lewellen, Lease and Schlarbaum (1977) also find results that suggest managing investment portfolios is a masculine task. The study found that men not only spent more time and money, but they also traded more frequently than women.

In general, it has been well established that women are more risk-averse than men [See Hersch (1996) and Pacula (1997)]. However, more specifically, Jianakoplos and Bernasek (1998) found that women are also more averse to financial risk than men (as measured by portfolio volatility, size, and beta). Female mutual fund managers have been shown to have more stable investment styles that are characterized by lower portfolio allocation to risky assets and lower turnover ratios than men [See Niessen and Ruenzi (2005); Barber and Odean (2001), Bernasek and Shwiff (2001), Riley and Chow (1992), Cohn, Lewellen, Lease and Schlarbaum (1975), Jianakoplos and Bernasek (1998) and Sunden and Surette (1998)].

Interestingly, one study by Bliss and Potter (2002) found the opposite: women tolerated more risk and earned higher raw returns than men.Again, while multiple studies have investigated the impacts of behavioral biases on investor decisions, few studies have tied these biases to portfolio risk. One notable exception is found in an experiment of 67 students conducted by Biais and Weber (2009). They found that hindsight bias reduced portfolio volatility estimates. The feeling that they "knew it all along" misled many investors to form an incorrect viewpoint on market and fund volatility. When reviewing historical trends, the investors did not perceive any surprise at how the market had reacted, leading them to develop lower volatility estimates. In light of these research streams, the goal of our study is to extend the literature by investigating the relationship between gender and behavioral biases on portfolio performance and risk. Most of the previous research has focused only on the hindsight and overconfidence biases as they relate to investment decisions. We extend this previous research by testing the interaction of multiple gender differences across 23 cognitive and emotional biases identified by Pompian (2006).

DATA AND METHODOLOGY

All study participants were finance and accounting majors at a metropolitan U.S. university with an enrollment of approximately 10,000 students. The participants were enrolled in a required upper-level finance course (either "Investments" or "Security Analysis and Portfolio Management"). Each course was co-listed as a graduate finance course. Of the 84 total participants (55 male, 29 female), eight were graduate students (five male, three female) and 76 were undergraduates (50 male, 26 female).

During the semester, the students were required to participate in the Stock-Trak project, a portfolio simulation useful in behavioral investment research (e.g., Felton, Gibson and Sanbonmatsu (2003)). The project required students to manage a $500,000 portfolio using "real time" market prices. The portfolio was originally 100% invested in cash and the goal was to make the highest absolute returns. Students were required to establish a minimum of one option or futures position, one short sale (of a stock), and a minimum of 30 total transactions during the semester-long simulation. Each student was allowed 100 transactions in total, with a commission fee of $7 per trade. The investment choices included stocks, options, futures, bonds, mutual funds, and international stocks. In addition to the simulations, the students were required to turn in a written summarization of transactions and trading strategies, along with quantitative and qualitative assessments.

Portfolio performance was evaluated both in terms of absolute returns and in terms of the Sharpe Ratio, a measure of the risk-adjusted returns for a portfolio. The Sharpe Ratio is calculated by taking the ratio of the portfolio's risk premium over its standard deviation. Other measures, such as the Treynor Measure and Jensen's Alpha were not used because of lack of consistency.

Table 1: Descriptive Statistics of the Sample

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Return minus S&P 500	84	-0.536%	9.02%	-23.22%	53.12%
Beta	84	0.5538	0.5567	-1.04	3.33
Standard Deviation	84	2.40%	2.404%	0.06%	15.83%
Holding Period Return	84	5.46%	8.912%	-16.65%	57.89%
Sharpe Ratio	84	1.775	9.935	-81.01	27.01
GPA	84	3.302	0.4732	2.0	4.0

This table provides descriptive statistics that summarize the sample data that was used in the project. The average holding period return for all students was 5.46% and the average Sharpe Ratio (or risk-adjusted return) was 1.775. The average Beta (or systematic risk) of the portfolios was 0.5538 and the average standard deviation (or unsystematic risk) was 0.024.

The semester-long Stock-Trak simulation project had a significant impact on the student's overall course grade. The performance metrics discussed above were used to evaluate the overall financial performance of the portfolio. Based on this rubric, students were given the incentive to take calculated risks in an attempt to achieve optimal holding period returns. They were encouraged to implement portfolio investment theories discussed in class to achieve this objective.

While this project provides relevant data from a simulated experiment, we also recognize that it does contain limitations. The study covers only the fall semester of 2009, which prevents us from isolating any current business cycle effects. The behavioral biases are determined through a cross-sectional survey. This may be subject to common method bias and does not allow us to capture possible evolution in biases that may occur in response to changes in the market.

At the beginning of the semester, a diagnostic behavioral bias survey, developed by Pompian (2006), was administered to measure participant responses to the behavioral biases that have been shown to be relevant to making investment decisions. This comprehensive survey captured participants' responses to the 23 biases shown in Appendix A. The complete survey instrument can be seen in Pompian (2006). In addition, students were required to respond to questions about their experience with the simulation project at the end of the semester. These measures captured trading strategies, personal experience with the project, and demographic information.

RESULTS

The holding period for the Stock-Trak project was from August 31, 2009 to November 6, 2009. Throughout this holding period, the portfolio value for the students averaged $527,278, with a standard deviation of $44,563. If the $500,000 had been invested in the S&P 500 over the same time period, the portfolio would have yielded $523,848, with a standard deviation of $12,128 at the end of the holding period. All project participants completed the behavioral bias questionnaire, as well as the post-hoc project survey, which yielded a final sample size of 84 students.

To evaluate behavioral biases by gender, we calculated the degree of each bias described in Appendix A for each subject as outlined in Pompian (2006). We then conducted t-tests to identify biases that were significantly different between males and females. Our results indicate that three biases were significantly different between males and females. The Anchoring and Adjustment Bias ($p < 0.1$) and Ambiguity Effect Bias ($p < 0.05$) were both more evident in female respondents, while the Mental Accounting Bias ($p < 0.05$) was more evident in male respondents. These results reject the null hypothesis (i.e., that there is no difference between males and females) for three of the behavioral biases tested. Interestingly, only these three of the 23 total behavioral biases showed a statistically significant gender difference. Furthermore, Optimism Bias, which has been shown to be a predominantly male bias, was not one of the three biases that were significantly different.

We began our analysis by comparing the portfolio performance of male and female students. To test this, we evaluated the difference in means across males and females for two measures of financial performance: holding period returns and risk adjusted returns. The holding period return (HPR) for the sample was 5.46 percent. Males had a 6.14 percent HPR while females had an HPR of 4.17 percent. Males earned a 1.97 percent higher return, but the difference was not statistically significant (p-value of 0.22). Risk adjusted returns were measured using the Sharpe Ratio.

The Sharpe Ratio of the full sample was 1.775. The male subsample had a ratio of 1.4678 while the Sharpe ratio for females was 2.3577. The risk adjusted return was higher for females than males, but once again the difference was not statistically significant (p-value of 0.61). Based on this analysis, we do not find a significant difference in portfolio performance due to gender. To evaluate the effect of behavioral biases on investment behavior and portfolio performance, we used holding period and risk adjusted returns to proxy for investment performance over the entire sample. We then regressed these proxies on each bias using a stepwise regression. Table 2 shows the coefficients from the stepwise regression with HPR as the dependent variable. For Table 3, we used risk adjusted return (Sharpe Ratio) as the dependent. Overall, we find that three behavioral biases have a significant impact on investment performance for the full sample (column three) for both performance measures. Certainty Overconfidence (COC) has a negative impact on performance, while Optimism Bias (OB) and Competence Effect (CE) show a statistically significant positive impact on investment performance. The regression equation for the results in Table 2 is:

$$HPR_i = \beta_0 + \beta_1(COC_i) + \beta_2(CE_i) + \beta_3(OB_i) \quad (1)$$

Table 2: The Effect of Behavioral Biases on Holding Period Return

	Males	Females	Full Sample
Intercept	-0.0273	0.0715**	0.0116
	(0.66)	(0.02)	(0.76)
Certainty Overconfidence	-0.0181	-0.0231**	-0.0202*
	(0.26)	(0.04)	(0.08)
Competence Effect	0.0467	0.0168	0.041**
	(0.12)	(0.28)	(0.04)
Optimism Bias	0.0356**	0.0079	0.0249**
	(0.05)	(0.34)	(0.02)
Sample Size	55	29	84
R-Square	0.1087	0.1686	0.0988

*This table shows the results of a stepwise regression that regresses holding period return (HPR) on behavioral biases. The regressions are broken down into three samples. The first column contains only males. The second column contains only females. The third column contains the full sample. P-values are in parentheses. ***, ** and ** indicate significance at the 1, 5 and 10 percent levels respectively.*

Table 2 and Table 3 are also broken down by gender in order to test for differences in returns by gender when exhibiting biases. While Certainty Overconfidence is negative and significant in both tables, the negative impact appears to be primarily from the female sample, which is significant at the five percent level in Table 2 and almost significant in Table 3. Optimism Bias shows a statistically significant positive impact on both investment performance measures, which seems to be caused primarily by the male subsample. In both Table 2 and Table 3, Optimism Bias is positive and significant for the male subsample. The third bias, Competence Effect, also shows a positive impact in the regression for the full sample that appears to be driven primarily by the male subgroup. Table 3 shows a coefficient for the male subgroup that is positive and significant at the ten percent level and is much greater than the female subgroup coefficient. In all three biases, the positive impact appears to be more pronounced for the males and the negative impact more pronounced for the females. Therefore, we conclude that certain personality biases do have an impact on return and these impacts are different for males and females. The regression equation for the results in Table 3 is:

$$Sharpe_i = \beta_0 + \beta_1(COC_i) + \beta_2(CE_i) + \beta_3(OB_i) \qquad (2)$$

Table 3: The Effect of Behavioral Biases on Risk Adjusted Return

	Males	Females	Full Sample
Intercept	-5.919	4.162*	-1.131
	(0.40)	(0.05)	(0.79)
Certainty Overconfidence	-2.545	-1.336	-2.153*
	(0.16)	(0.11)	(0.10)
Competence Effect	6.100*	0.8242	4.085*
	(0.08)	(0.46)	(0.07)
Optimism Bias	3.380*	0.4536	2.118*
	(0.10)	(0.45)	(0.09)
Sample Size	55	29	84
R-Square	0.1056	0.1074	0.0722

*This table shows the results of a stepwise regression that regresses risk adjusted return (Sharpe Ratio) on behavioral biases. The regressions are broken down into three samples. The first column contains only males. The second column contains only females. The third column contains the full sample. P-values are in parentheses. ***, ** and ** indicate significance at the 1, 5 and 10 percent levels respectively.*

Our data suggests that there appears to be a disproportional presence of certain behavioral biases among males and females (specifically, Anchoring Bias, Ambiguity Aversion Bias, Competence Effect Bias and Mental Accounting Bias). Of these biases, however, only the Competence Effect Bias seems to have any impact on stock selection performance. We find that two additional biases (Certainty Overconfidence and Optimism) can also impact stock selection performance. These two biases are not overly represented in either gender, but instead seem to impact the genders differently. For males, Optimism Bias has a positive impact on HPR, while for females the Certainty Overconfidence Bias has a negative impact on HPR. Our final analysis was conducted to determine if there were differences in the risk taking behavior of male and female students in our sample. To investigate this claim, we used the Beta of the portfolio as a proxy for risk taking and used it as the dependent variable in an OLS regression shown in Tables 4 and 5. In Table 4, we include several academic and effort-based independent variables in the regression. The first variable, Strategy, is a binary variable that is coded as 1 if the student reported they were following a trading strategy and 0 if the student did not implement a strategy. The next variable (Minutes Weekly) measures how much time, in minutes, the participants spent on gathering and interpreting data each week to make their stock selections. Finally, we control for the academic ability of the student participants by including dummy variables for Graduate status and GPA. The regression equation for Table 4 is:

$$Beta_i = \beta_0+\beta_1(Strategy_i)+\beta_2(Minutes\ Weekly_i)+\beta_3(Grad_i)+\beta_4(GPA_i)+\beta_5(Gender)$$
$$+\beta_6(Gender)(Strategy)_i+\beta_7(Gender)(Minutes)_i+\beta_8(Gender)(Grad)_i+\beta_9(Gender)(GPA)_i \quad (3)$$

Table 4: Results of Ordinary Least Squares Regression

	Males	**Females**	**Full Sample**
Intercept	-0.4522 (0.49)	-0.7219* (0.05)	-0.7219 (0.36)
Strategy	0.1487 (0.16)	-0.1368*** (0.01)	-0.1368 (0.19)
Minutes Weekly	0.0038*** (0.01)	-0.0004 (0.55)	-0.0004 (0.79)
Grad Student	0.0461 (0.81)	-0.0194 (0.86)	-0.0194 (0.93)
GPA	0.1995 (0.29)	0.3619*** (0.00)	0.3619 (0.11)
Gender			0.2697 (0.78)
Gender*Strategy			0.2855** (0.04)
Gender*Minutes			0.0042** (0.03)
Gender*Grad			0.0655 (0.82)
Gender*GPA			-0.1625 (0.56)
Sample Size	51	28	79
R-Square	0.1958	0.457	0.2457

*This table shows the results of an OLS regression that regresses Beta on academic and effort based variables. The regressions are broken down into three samples. The first column contains only males. The second column contains only females. The third column contains the full sample. P-values are in parentheses. ***, ** and ** indicate significance at the 1, 5 and 10 percent levels respectively.*

The results of our regressions are broken down by gender. In the male sample, Minutes Weekly shows a strong positively significant relationship with Beta, meaning that male students who spent more time planning their investment decisions also took greater risks in those decisions. In the female subsample, Strategy shows a strong negatively significant relationship with Beta, meaning that female students who reported following an investment strategy took less risk in their investment decisions. In the full sample, we include interaction terms between the independent variables and gender. In this analysis, we find that males who use a trading strategy and/or spend more time gathering and analyzing stock information will take more risk. In fact, it appears that females who follow a trading strategy or spend more time analyzing stock information will have higher risk avoidance than those who implement no strategy and do not spend as much time on the project. In Table 5, we rerun our analysis, but this time we control for the three biases that were shown to have an impact on stock selection performance. Even with these added controls, our results are stable and remain statistically significant. The regression equation for Table 5 is:

$$Beta_i = \beta_0 + \beta_1(Strategy_i) + \beta_2(Minutes\ Weekly_i) + \beta_3(Grad_i) + \beta_4(GPA_i) + \beta_5(CE) + \beta_6(COC) + \beta_7(OB) + \beta_8(Gender) + \beta_9(Gender)(Strategy)_i + \beta_{10}(Gender)(Minutes)_i + \beta_{11}(Gender)(Grad)_i + \beta_{12}(Gender)(GPA)_i + \beta_{13}(Gender)(CE)_i + \beta_{14}(Gender)(COC)_i + \beta_{15}(Gender)(OB)_i \quad (3)$$

Table 5: Results of Ordinary Least Squares Regression

	Males	Females	Full Sample
Intercept	-0.2670	-1.342***	-1.342
	(0.71)	(0.01)	(0.19)
Strategy	0.1523	-0.1112**	-0.1112
	(0.15)	(0.04)	(0.32)
Minutes Weekly	0.0033**	-0.0009	-0.0009
	(0.01)	(0.25)	(0.60)
Grad Student	-0.0048	-0.1205	-0.1205
	(0.98)	(0.32)	(0.65)
GPA	0.0723	0.4416***	0.4416*
	(0.70)	(0.00)	(0.06)
Competence Effect	-0.2508	0.0423	0.0423
	(0.17)	(0.68)	(0.85)
Certainty Overconfidence	-0.0849	0.0744	0.0744
	(0.37)	(0.30)	(0.63)
Optimism Bias	0.2239**	0.0808	0.0808
	(0.05)	(0.23)	(0.57)
Gender			1.075
			(0.37)
Gender*Strategy			0.2635*
			(0.07)
Gender*Minutes			0.0042**
			(0.04)
Gender*Grad			0.1157
			(0.70)
Gender*GPA			-0.3693
			(0.20)
Gender*Competence			-0.2930
			(0.29)
Gender*Certainty Overconfidence			-0.1593
			(0.37)
Gender*Optimism Bias			0.1430
			(0.41)
Sample Size	51	28	79
R-Square	0.3189	0.4002	0.3626

*This table shows the results of an OLS regression that regresses Beta on the same variables as Table 4, but includes behavioral biases. The regressions are broken down into three samples. The first column contains only males. The second column contains only females. The third column contains the full sample. P-values are in parentheses. ***, ** and ** indicate significance at the 1, 5 and 10 percent levels respectively.*

For robustness purposes, we implement the methodology of Felton, Gibson and Sanbonmatsu (2003) and confirm their results. Table 6 shows the top ten and the bottom ten portfolios based on the final portfolio value for students in our sample. Males account for approximately 65% of the total sample (55/84) and females account for the remaining 35% (29/84). However, Table 6 shows that males account for 90% of the top ten performers and 70% of the bottom ten performers. This provides additional evidence to support Felton, Gibson and Sanbonmatsu's (2003) findings that males may be more likely to implement an "all or nothing" investment strategy.

Table 6: Top and Bottom Ten Performers in the Stock-Trak Simulation

Rank	Final Portfolio Balance	Gender	Beta (Risk)
1	789,464	Male	0.71
2	682,982	Male	0.99
3	622,145	Male	-0.19
4	591,096	Male	0.60
5	570,472	Male	0.65
6	565,829	Male	2.27
7	562,448	Male	0.06
8	560,653	Female	1.17
9	557,095	Male	-0.08
10	556,384	Male	0.90
75	498,746	Female	0.16
76	495,447	Female	0.51
77	493,201	Male	0.17
78	487,097	Male	0.96
79	479,939	Male	1.20
80	473,835	Male	1.02
81	469,394	Female	-0.03
82	467,987	Male	0.50
83	446,797	Male	0.99
84	416,737	Male	0.01
Mean	527,278	n/a	0.55
Std Dev	44,563	n/a	0.56

This table shows the top ten and bottom ten portfolios based on the final portfolio balance. The gender and beta values of each portfolio are also reported alongside the actual portfolio values.

This study suggests that men and women significantly differ in only three of the 23 behavioral biases examined. The Mental Accounting Bias was significantly higher for male respondents, which suggests men have a greater tendency to separate their portfolio into various categories and track them separately. The Anchoring and Adjustment Bias and the Ambiguity Effect Bias were both significantly higher for female respondents. This result is particularly intriguing because it suggests that female investors have the tendency to avoid circumstances that have the illusion of being more risky than others. When presented with the same information, men and women can perceive riskiness of that information differently and therefore reach different conclusions. The perception of risk appears to have a larger impact than the risk itself.

Our study found no significant difference in portfolio performance and gender. This result is interesting considering that we do find a significant difference between risk and gender. The risk and return relationship is well established for risk-averse investors. However, the particular sample group used in our study (college-aged student investors) could exhibit different characteristics than more experienced and mature investors. It is certainly plausible that there would be a much more pronounced difference in the financial risk tolerance of males and females in their early twenties compared to those in their thirties or forties. This could be due to asset allocation or even simply the lack of investment experience.

We expanded our analysis to include the impact of behavioral biases on portfolio performance, and found that three biases were significant: Certainty Overconfidence bias, Optimism bias, and Competence Effect. Glaser, Langer and Weber (2007) has also shown that overconfidence has an impact in investment decisions and performance. Our study found Certainty Overconfidence bias to impact portfolio performance, but found no effect for Prediction Overconfidence. This may be for two reasons. First, previous studies have considered overconfidence as a single construct; in these cases, "certainty" may be the driving subcomponent. Second, overconfidence may be a bias that develops over time and with experience. Indeed, Glaser et al (2007) found that professionals are generally more overconfident than students in investment trading decisions.

Finally, we examine portfolio risk among male and female students and examine the role that effort plays in investment risk. In line with many other studies, our results suggest that males generally take more risk than females [See Barber and Odean (2001), Bernasek and Shwiff (2001), Riley and Chow (1992) and Felton et. al (2003)]. Our study also indicates that this result is independent of other personality biases that may be present or are generally gender specific.

Our expanded analysis examines the relationship between effort (measured by Minutes Weekly) and risk (Beta), and the implications of these results are intriguing. We provide evidence of a cause for this observed behavioral difference in regards to gender. The results suggest that males and females interpret information differently and this difference may be the cause of how they respond to the information. We argue that when men and women are presented with the same information and do not spend time analyzing that information, they will act upon it in a similar manner from a risk taking perspective. However, if males and females do take the time to examine and interpret the information, it will lead to a difference in how they behave. This is shown by the positive and significant coefficient on the interaction of the Gender variable with both Minutes Weekly and Strategy in Table 4 and Table 5. As effort increases, in light of the optimism bias seen in the male investors, we argue that males tend to focus on the possibility of a positive return contained within the information set while the females tend to overemphasize the possibility of the potential loss contained within the same information set. In other words, when presented with the same information, males tend to focus on the potential return while females tend to focus primarily on the risks that are involved. This suggests that a combination of male and female portfolio managers would result in a healthy balance of risk taking.

If we consider the investment decisions simply as an individual's effort spent in the evaluation of available information rather than as a response to objective reality, we can argue that individuals respond based on their own distinct perceptions. We argue that it is then the perceived difference in risk and reward that causes males and females to act differently. Both males and females can act rationally to the information at hand and yet respond differently because they are acting in accordance to their perception of risk and reward. However, this perception can be distorted by behavioral biases, which may cause what appear to be irrational actions.

CONCLUDING COMMENTS

The main objective of this research is to better understand the behavioral differences between males and females and if those differences relate to investment performance. This goal is important for two reasons. First, our results may lead to improved predictability of portfolio performance. Second, these results have broader implications for balancing males and females in top decision making roles for corporations.

We implement several methods to achieve the objective of this paper. First, we provide a comprehensive summary of the current academic literature as it pertains to behavioral biases, gender and investment performance in Appendix A. Second, we run t-tests to determine if the 23 behavioral biases are significantly different between genders. We find that only three of the 23 behavioral biases have a statistically significant difference; the anchoring and adjustment bias is more prevalent in females at the 10% level of significance, the ambiguity effect bias is more common in females at the 5% level of significance and the mental accounting bias is more common in males at the 5% level of significance. Next, we test whether there is a statistically significant difference in the performance of males and females. We find that males have a higher holding period return, while females have a higher risk-adjusted return. However, the differences of these values are not statistically significant.

We then perform a stepwise regression using the same measures of performance as our dependent variable. We again find that only three of the 23 behavioral biases are significant (certainty overconfidence, competence effect and optimism bias). The same three biases are significant for both samples (holding period return and risk adjusted return). Finally, we run another stepwise regression using a measure of risk (beta) as our dependent variable. When controlling for these behavioral biases, we find that females with a higher GPA took more risk and females that implemented a strategy took less risk. We find that males that spent more time on their portfolio took more risk.

While this project provides relevant data from a simulated experiment, we also recognize that it does contain limitations. The study covers only one semester, which prevents us from isolating any business cycle effects. The behavioral biases are determined through a cross-sectional survey, which does not allow us to capture possible evolution in biases that may occur in response to changes in the market. However, these limitations are difficult to overcome due to the nature of the data. We believe that this project has established a base from which future research can be conducted. The analysis can easily be expanded by using a different cross-section of investors and different time period.

Our study is unique in that we examine biases in terms of gender and we relate the survey results to stock performance in the Stock-Trak project. We find that males and females do in fact exhibit different behavioral biases and that these behavioral biases can ultimately affect investment performance. We are able to confirm prior studies that show males are more risk tolerant than females. However, our findings suggest that this behavior could be due to a difference in the perception of risk and return by males and females rather than the actual level of risk and return. These results have important practical implications as they indicate that it may be optimal to have a more gender balanced approach to trading teams since females tend to focus more on risk and males focus more on returns.

APPENDICES

Appendix A: Biases Included in This Study

Bias	Definition	Prior Research
Ambiguity Aversion	Likelihood of investors to avoid circumstances that have the illusion of being more risky than others.	Caskey (2009) found that ambiguity-averse investors prefer to make investment decisions based on aggregate data
		Graham, Harvey and Huang (2009) found that investors who perceived themselves as more confident were more likely to be ambiguity averse and more likely to trade excessively
		Bhandari, Hassanein and Deaves (2008) found that decision support systems can help investors avoid biases, including ambituity bias
Anchoring and Adjustment	Tendency to make decisions based on irrelevant information, such as the price at which a stock was purchased.	George and Hwang (2004) suggest that traders may use a stock's 52-week high as an anchor
		Bromiley (1987) found that some organizations exhibit anchoring and adjustment bias when forecasting

Bias	Definition	Prior Research
Availability	Inclination of investors to be persuaded to make false assumptions based on what they encounter in their own lives. For example, an investor may be more likely to purchase a particular security if he or she hears recurring information about the firm.	Barber and Odean (2008) found that both individual and institutional investors are more likely to purchase stocks of companies that have recently caught their attention
Base Range Neglect Representativeness	Investors tend to analyze new investment opportunities in familiar terms, thus potentially ignoring important variables that could substantially impact their investment	Bhandari et al. (2008) found that decision support systems can help investors avoid biases, including representative bias
Certainty Overconfidence	Belief that the investor has abnormally exceptional judgment and decision making skills when compared to other investors	Barber and Odean (2001) combined COC and POC and found that overconfident investors traded too much and experienced decreased returns; males were more likely to be overconfident than females.
		Odean (1999) found that overconfidence (COC and POC) was tied to excessive trading.
Cognitive Dissonance	Investors ignore information that conflicts with their original assessment due to the discomfort they feel from being incorrect.	Goetzmann and Peles (1997) found that mutual fund investors are more likely to remember positive past performance
Competence Effect	Suggests that investors who view themselves more financially savvy are more likely to trade more actively.	Graham, Harvey and Huang (2009) find that when individuals feel competent in their own judgments, they are willing to take more risks.
Confirmation	Susceptibility of investors to place more emphasis on investments that confirm their viewpoints and devalue investments that contradict them.	Fisher and Statman (2000) provide a discussion of confirmation bias in investor decisions and market forecasting
		Hirshleifer (2001) suggests that investors ascribe more weight to information that confirms earlier decisions and interpret ambiguous information consistent with existing beliefs
Conservatism	Occurs when investors are too slow to update their beliefs and do not properly consider new information.	Barberis et al. (1998) find that investors often over-weight prior beliefs, making them slow to react to new information
		Hirshleifer (2001) suggests that investors are slow to update their beliefs because processing new information is difficult
Endowment	Investors deem an asset more valuable if they own it.	Samuelson and Zeckhauser (1988) found the minimum selling price of a good in the individual's possession tends to exceed maximum purchase price of the same good that he or she does not already own.
Framing	Occurs when investors respond to information according to the manner in which it is presented.	Shinong and Chaopeng (2005) suggest that Chinese investor reactions vary with the earnings information they are given
		Kumar (2009) suggests that investors are more likely to be affected by framing in more uncertain conditions
		Bhandari et al. (2008) found that decision support systems can help investors avoid biases, including framing bias
Hindsight	Inability to correctly remember one's prior expectations after observing new information.	Biais and Weber (2009) found that hindsight bias reduces portfolio volatility estimates among students and that investment bankers with greater hindsight bias realize lower portfolio gains.
		Cooper et al. (2005) suggest that money managers are unfairly criticized due to hindsight bias
		El-Sehity et al. (2002) did not find evidence that hindsight bias was a general phenomenon among traders.
Illusion of Control	Misperception that investors can control, or at least influence, the outcome of their investment.	Moore et al. (1999) show that investors consistently predict that their portfolios will outperform the market
		Fellner (2004) conducted an experiment which showed that investors preferred to make investments over which they believed to have control

Bias	Definition	Prior Research
Loss Aversion	Specifies that investors feel a stronger need to avoid losses than to acquire gains.	Thaler et al. (1997) found that myopic loss aversion leads investors to accept more risks if they receive investment information less often
		Barberis and Huang (2001) suggest that an investor's degree of loss aversion depends on prior gains and losses
		Berkelaar et al. (2004) suggest optimal portfolios for loss averse investors and estimates the level of loss aversion in historical stock market data
		Haigh and List (2005) argue that both students and professional investors make investment decisions consistent with myopic loss aversion, a theory that combines loss aversion and mental accounting
Mental Accounting	Tendency to place investments into "boxes" and track each of them separately.	Grinblatt and Han (2005) show that some investors hold on to losing stocks because of prospect theory and mental accounting
		Shefrin and Statman (1985) found that many biases - including mental accounting - cause investors to sell strong stocks too soon and keep losing stocks too long
		Barberis and Huang (2001) argue that mental accounting significantly affects asset prices
		Haigh and List (2005) argue that both students and professional investors make investment decisions consistent with myopic loss aversion, a theory that combines loss aversion and mental accounting
Optimism	Belief by investors that bad investments will not happen to them, only to others.	Lutje and Menkhoff (2007) suggest that fund managers have a preference for home country assets, which is attributed to their relative optimism toward domestic investments
		Lovallo and Kahneman (2003) cite optimism bias as a major factor in poor investment decisions
		Shiller et al (1996) suggest that investors view prospects in their home country more optimistically than foreign prospects
Prediction Overconfidence	Unjustifiable belief that the investor has superior reasoning, judgment and wisdom in predicting future events when compared to other investors	Clarke and Statman (2000) found that most subjects were overconfident (POC) and incorrect in their DJIA predictions
Recency	Investors place too much emphasis on recent events, while ignoring the long term performance of the investment.	Lovallo and Kahneman (2003) cite recency bias as an important factor in investor decisions
		Offerman and Sonnemans (2004) suggest that recency bias is less a factor in overreaction in investment decisions than other theories (e.g., hot hand)
Regret Aversion	Leads investors to avoid making decisions to prevent remorse in the future.	Odean (1999) found support for regret aversion among traders by analyzing 10,000 accounts at large brokerage houses
		Muermann et al. (2006) found that regret-averse investors will influence investments in defined contribution plans
		Shefrin and Statman (1985) argue that regret aversion prompts investors to prefer stocks that pay dividends
Sample-Size Neglect Representativeness	Misperception that a small sample represents the entire population and therefore can lead investors to infer patterns too quickly.	Chen et al. (2007) found that Chinese investors appear to believe that past returns are indicative of future returns
Self-Attribution	Suggests that the investor believes good decisions were the result of his or her talent whereas bad decisions were the product of bad luck.	Doukas and Petmezas (2007) found that managers who make merger decisions often credit themselves with initial success, which in turn, leads to overconfidence.

Bias	Definition	Prior Research
Self-Control	Tendency of investors to prefer consumption today at the expense of saving for the future.	Lusardi and Mitchell (2007) found that future retirement planning had a significant impact on portfolio choice, with less self control associated with a greater likelihood of investing in stocks
		Laibson et al. (1998) found that investors are less likely to plan for retirement, and therefore, less likely to have adequate investments
		Shefrin and Statman (1985) found that many biases - including self control - cause investors to sell strong stocks too soon and keep losing stocks too long
Status Quo	Likelihood of investors to find comfort in numbers and strictly follow the actions of other investors and analysts.	Kempf and Ruenzi (2006) found evidence for the status quo bias among investors in the US equity mutual fund market; they find this to be more pronounced in cases with multiple options
		Rubaltelli et al. (2005) found that when stock returns are described as ratios, investors were more likely to exhibit the status quo bias
		Shapira and Venezia (2001) suggest that the status quo bias may explain why individual accounts are less diversified than professionally managed accounts

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