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Fund-Management Gender Composition: The Impact on Risk and Performance of Mutual Funds and Hedge Funds

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FUND-MANAGEMENT GENDER COMPOSITION: THE IMPACT ON RISK AND PERFORMANCE OF MUTUAL FUNDS AND HEDGE FUNDS

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Abstract

This paper examines gender differences in fund managers' risk tolerance and performance. We explore these differences in both the universe of U.S. mutual funds and hedge funds using risk and performance metrics that cover one-year, three-year, and five-year horizons. We find that funds managed by women outperform those managed by men with less risky portfolios. The outperformance persists after adjusting for risk. Overall, the results indicate that female fund managers are severely underrepresented despite their quality performance. A workgroup comprised more equally of male and female managers is likely to lead to greater stability in the financial markets due to a better blend of investment approaches and risk tolerances.

Introduction

Women are fading from the U.S. finance industry. In the past 10 years, 141,000 women, or 2.6% of female workers in finance, left the industry. The ranks of men grew by 389,000 in that period, or 9.6%, according to a review of data provided by the federal Bureau of Labor Statistics. Since 2000, the number of women between the ages of 20 and 35 working in finance has dropped by 315,000, or 16.5%, while the number of men in that age range grew by 93,000, or 7.3%.

(Stock 2010)

Given recent volatile markets and much scrutiny over reckless risk-taking, these gender shifts are intriguing. Sizeable psychological research focused on overconfidence and gender biases, which will be reviewed in the subsequent section, documents that men tend to be overly confident and risk-seeking, whereas women tend to be risk-averse, especially in male-dominated areas such as finance. In an environment where individuals are offered excessive incentives for risk-taking, an analysis of over-confidence, gender bias, and risk characteristics in mutual funds and hedge funds warrants further research.

The current study is unique. Using data for one-year, three-year, and five-year horizons, we are able to analyze market participants' reactions to huge market swings, specifically the 2008 financial crisis, and whether males and females react differently. Although sizable literature already documents that differences in risk propensity between men and women exist, we have yet to find research outlining these biases for fund managers during a financial crisis. We question whether stereotypical economic behavior anomalies between men and women, such as overconfidence and gender bias, hold during economic turbulence. Having concluded that males and females do indeed react differently, while simultaneously finding that female fund managers are underrepresented, we argue that a work environment composed more equally of male and female fund managers is likely to promote stability in the financial markets.

I. Literature Review

A. The Efficient Market Hypothesis

The efficient market hypothesis (EMH) has been a central component of modern finance for several decades. Eugene Fama defines an efficient financial market in his classical statement as one in which security prices always fully reflect available information. Therefore, a market is efficient if security prices adjust rapidly to the arrival of new information. Fama states that the EMH "rules out the possibility of trading systems based only on currently available information that have expected profits or returns in excess of equilibrium expected profit or return" (Fama 1970). The aforementioned statement is profound, for it asserts that an average investor will not be able to consistently beat the market; if EMH holds, an investor should passively hold the market portfolio, as opposed to actively managing his or her money.

The theoretical foundation for the EMH has three main arguments to support it. First, investors are rational; hence, they value securities rationally. Second, if some investors are not rational, then their trades are not and therefore, cancel each other without affecting prices. The second argument relies heavily on the assumption that irrational investors have uncorrelated trading strategies. Third, if investors are irrational in similar ways, then they are met in the market by sophisticated investors, who eliminate their influence on prices. Specifically, even if irrational investors have correlated trading strategies, rational arbitragers will reset prices to equilibrium (Fama 1965). Consequently, the two broad predictions of the EMH are the quick and accurate reaction of security prices to information, and that prices should not react to changes in supply or demand of a security that are not accompanied by news about the security's fundamental value.

The empirical foundations of the EMH are stated in three forms: weak form, semi-strong form, and strong form. The three forms of EMH allow Fama to distinguish between three types of "stale" information, which are of no value to those who wish to make money, that is, to make a superior return after an adjustment for risk. The weak form EMH states that current prices reflect all security-market information. Therefore, the relevant stale information is characterized as past prices and returns. The weak-form

EMH implies that past rates of return and other market data should have no relationship with future rates of return. This form of EMH reduces the "random walk hypothesis," which Fama defines as the statement that stock returns are entirely unpredictable based on past returns (Fama 1965). The overall evidence supports the weak form of EMH. Fama has found no systemic evidence of profitability of "technical" trading strategies (Fama 1965).

The semi-strong form EMH states that current security prices reflect all past market information, as well as all public information. As soon as information becomes publicly available, the information is immediately incorporated into prices; hence, the semi-strong form EMH implies that decisions made on new information after it is public should not lead to above-average risk-adjusted profits from those transactions. The overall evidence for the semi-strong form EMH is mostly supportive. An event study conducted by Keown and Pinkerton (1981) analyzed the returns to targets of takeover bids around the announcement of the bid. The researchers show that share prices of targets begin to rise prior to the announcement of the bid as the news of a possible bid is incorporated into prices, and then jump on the date of the public announcement to reflect the takeover premium offered to target firm shareholders. Nonetheless, Keown and Pinkerton's data shows that the jump in share prices on the announcement is not followed by a continued trend upward or downward, indicating that prices of takeover targets adjust to the public news of the bid instantaneously, consistent with the semi-strong form EMH. Additionally, the substitution hypothesis is consistent with the semi-strong form EMH that stock prices do not react to non-information (Scholes 1972). Scholes' work dealt with the central issue to the arbitrage arguments in the efficient markets hypothesis, the availability of close substitutes for individual securities. When arbitrage is needed to make markets efficient, individual stocks must have close substitutes for such arbitrage to work properly. When close substitutes are available, arbitragers can sell overpriced securities and buy cheaper close substitutes, equalizing their relative prices and making markets efficient. If stocks do not have close substitutes, investors become indifferent as to which stock to hold. Consequently, Scholes illustrates the willingness of investors to adjust their portfolios to absorb more shares without a larger influence on the price.

The strong-form EMH states that stock prices reflect all information from past market information and private information. It implies that no group of investors should be able to consistently derive above-average risk-adjusted rates of return, even if they are trading on information that is not yet known to all market participants; insiders' information quickly leaks out and is incorporated into prices. The strong form of EMH assumes perfect markets where information is cost-free and available to everyone at the same time. The overall evidence for strong-form EMH is mixed.

B. Behavioral Finance Casts Doubt on Rational Expectations

The notion that investors are fully rational is difficult to sustain. Therefore, Fischer Black (1986) illustrates that many investors react to irrelevant information in forming their demand for securities; they trade on "noise" rather than information. By reacting to this "noise," investors are not abiding by the passive strategies Fama expected of market participants.

Individuals deviate from rational decision-making in their attitudes toward risk, expectation formation, and framing of problems. First, according to "prospect theory," individuals do not assess risky gambles following the precepts of rationality; that is, people do not look at the levels of final wealth they can attain. Instead, people look at gains and losses relative to some reference point, which may vary from situation to situation, and display loss aversion, meaning individuals are risk-averse over gains, but risk-seeking over losses (Kahneman and Tversky 1979). Second, individuals try to predict future uncertain events by taking a short history of data and asking what broader picture this history represents; therefore, people often do not pay attention to the possibility that the recent history is generated by chance rather than by the implicit model they are constructing (Kahneman and Tversky 1973). Third, in choosing investments, investors allocate more of their wealth to stocks rather than bonds when they see a very impressive history of long-term stock returns relative to those of bonds, even though they only see the volatile short-term stock returns (Benartzi and Thaler 1995).

Individuals are not the only investors whose trading strategies are difficult to reconcile with rationality. Professional managers contribute much of the money in the financial markets for individuals and corporations. Not only are professionals subject to the same biases as individual investors, but as agents managing other people's money, their role introduces further distortions into their decisions relative to what a fully informed sponsor might wish (Lakonishok, Shleifer, and Vishny 1992). For instance, in order to minimize the risk of underperforming their benchmarks, portfolio managers may "herd," that is, select stocks other managers have selected, or choose portfolios that are close to their benchmarks. Moreover, professional portfolio managers may add stocks to their portfolio that have recently done well, and sell stocks that have recently done poorly, in order to impress investors who receive end-of-quarter and end-of-year reports on portfolio holdings (Lakonishok et al. 1991).

The understanding of limited arbitrage, combined with an understanding of investor sentiment, helps individuals generate predictions about the behavior of security prices and returns. This is precisely where behavioral finance comes into play. The theoretical argument for the EMH depends on the effectiveness of arbitrage, taking the other side of an unsophisticated demand for securities in order to return prices to their fundamental values. First, behavioral finance argues that limited substitutes for many securities are not always available, making arbitrage risky and limited. Even when substitutes are available, risk is not always completely eliminated with arbitrage; prices do not converge to fundamental values instantaneously. Therefore, prices do not adjust to information as they should. In fact, prices may react to irrelevant information, causing unnecessary changes in demand. Second, in order to understand the form market inefficiency might take, one must understand investor sentiment, how investors actually form their beliefs and demands for securities. By understanding investor sentiment, one comes to understand the disturbances to efficient prices, the common judgment errors made by a substantial number of investors, rather than the uncorrelated random mistakes.

C. Overconfidence and Activity in the Financial Markets

Overconfidence is a well-established bias characterized by an individual's subjective confidence in the accuracy of his or her own judgments, as compared to objective accuracy. Research of the calibration of these subjective probabilities supports the idea that people tend to overestimate their knowledge and abilities. In a confidence-intervals task, subjects were asked to record their judgmental fractals for several quantities unknown to them at the time of assessment. Prior to their participation in the training exercise, all of the subjects were exposed to basic fundamental biases. Nonetheless, subjects still showed a high degree of overconfidence (Alpert and Raiffa 1982). For instance, Alpert and Raiffa found that the forecasted 99% intervals of individuals included the true quantity only approximately 60% of the time. If individuals were well calibrated, the number of future values that fall outside the estimated 99% confidence interval should be approximately 1 out of 100. The high reported values indicate that individuals perceive that they can estimate future values with much greater accuracy than is actually the case. In fact, subjects tended to be overconfident on the hard profiles and underconfident on the easy profiles. Consequently, overconfidence appears to be greatest for difficult tasks, as well as for tasks with low predictability, and sluggish, unclear feedback (Fischhoff, Slovic, and Lichtenstein 1977; Lichtenstein, Fischhoff, and Phillips 1982; Griffin and Tverksy 1992). Upon selecting a particular security in which to invest, an investor will not receive clear and concise feedback in a quick fashion. Due to low predictability and "noisy" feedback, one may conclude that stock selection is a difficult task, and therefore a task for which people are most overconfident.

In order to calculate the amount by which an overconfident investor overestimates his or her precision of knowledge, Odean has developed a new model of overconfidence (1998). Odean concludes that overconfidence may result from investors overestimating the precision of their private signals, or overestimating their abilities to correctly interpret public signals. Moreover, overconfident investors strongly believe their personal assessments of a security's value are more accurate than the assessments of others; thus, overconfident investors become strongly attached to their own valuations, and are less concerned with the valuations of others.

The aforementioned concept is referred to as "difference in opinion." Varian focuses on differences in prior beliefs as opposed to differences in models. Varian shows "the relationship between the equilibrium price and volume of trade and the equilibrium probability beliefs about those assets" (1989). Harris and Raviv, on the other hand, provide a model of speculative trading volume and price dynamics (1993). They show that trading is generated by differences of opinion among traders regarding the value of the asset being traded. These differences of opinion result from different interpretations of public information. The authors assume that traders are rational in their model, meaning "all the behavior in the model is maximizing," in order to help explain the observed behavior of speculative markets. Harris and Raviv are able to ignore learning from market prices and to dispense with noise traders in their differences-of-opinion model.

Grossman and Stiglitz create a model as an extension of the noisy rational expectations model (1980). Their results indicate that there is “an equilibrium degree of disequilibrium;” rational investors only trade and only purchase information when doing so increases their expected utility. Therefore, prices partially reflect the information of informed individuals, arbitragers, so that those who incur costs to obtain information do receive compensation. However, overconfident, irrational investors lower their expected utility by trading too frequently. According to Odean, overconfident investors are unrealistic; they overestimate the likelihood that they will reap unrealistically high returns and their ability to precisely estimate these high returns. Additionally, Odean concludes that overconfident investors expend too many resources, such as time and money, on investment information. Moreover, overconfident investors hold riskier portfolios than rational investors even when both the overconfident investors and the rational investors have the same degree of risk aversion (1998).

Finally, research concludes that investors decrease their expected utility by trading too much (Odean 1999; Barber and Odean 2000). In his study conducted in 1999, Odean finds that the individual securities investors buy underperform those they sell. When he controls for liquidity demands, tax-loss selling, rebalancing, and changes in risk aversion, the investors underperform even more, which suggests that investors are willing to act on too little information and are willing to act even when they are wrong. With a different data set, Barber and Odean show that after accounting for trading costs, individual investors underperform their benchmarks. The researchers also discover, as the model of overconfidence predicts, that those who trade more frequently realize the worst performance.

D. Gender and Overconfidence

Overconfidence is evinced in both men and women; however, men are generally more overconfident than women (Lundeberg, Fox, and Puncochar 1994). Discussions of gender differences in overconfidence often lead to task analysis, as research concludes these differences are highly task dependent (Lundeberg, Fox, and Puncochar 1994). Lundeberg, Fox, and Puncochar base their research on a study conducted by Kay Deaux and Elizabeth Farris (1977), who confirmed that, in general, men often claim more ability than do women. The differences in overconfidence are greatest for tasks perceived to be “masculine” (Deaux and Farris 1977).

Finance is considered to be a masculine task; thus, men tend to feel as though they are more competent in dealing with financial matters than do women (Prince 1993). As a result, men are heavily represented in the financial services industry. Additionally, Leeney provides all the more reason to expect that men are more overconfident than women in their ability to make decisions regarding stock investment. According to Leeney, gender differences in self-confidence depend on the lack of clear and unambiguous feedback. When feedback is “unequivocal and immediately available, women do not make lower ability estimates than men. However, when such feedback is absent or ambiguous, women seem to have lower opinions of their abilities and often do underestimate relative to men” (Leeney 1977). Feedback in the financial markets is certainly unclear, which leads females to question their abilities.

The source of investor overconfidence is the self-serving attribution bias (Gervais and Odean 1998). In this model, investors infer their own abilities from their successes and failures. Due to their tendency to take too much credit for their successes, they become overconfident. Research illustrates that the self-serving attribution bias is greater for men than for women; therefore, women are likely to become less overconfident than men. Because men are more overconfident than women, men will trade more frequently than women (Barber and Odean 2001). Research conducted by Barber and Odean demonstrates that trading reduced men’s net returns by 2.65% a year as opposed to 1.72% for women (2001).

E. Gender and Risk Tolerances

According to Slovic, a cultural belief exists that men should, and do, take greater risks than women (1966). This assumption is consistent with Grable’s finding that males have higher propensities for risk than females (2000). However, when comparing risk tolerances of males and females toward abstract and contextual situations, the results deviate from previous findings. Male and female subjects do not differ in their risk propensities toward decisions; yet, in abstract situations, differences in risk propensity do arise. Additionally, the comparative risk propensity of male and female subjects in financial choices strongly depends on the decision frame. Gender-specific risk propensities arise in abstract gambles, with men being more risk-prone toward gains and women more risk-prone toward losses. The aforementioned results appear to question the relevance of stereotypical gender-specific risk attitudes (Schubert, Brown, Gyslet, and Brachinger 1999). Those who study the link between gender and investment prowess say risk management is key to the success of female money managers. Therefore, women are not necessarily afraid of risk; they are just better at managing it (Denmark 2009).

F. The Market's Perception of Female Managers

Women are expected to be more conservative investors than men and are consequently offered investments with lower risk and therefore lower expected returns (Wang 1994). Nonetheless, the market favorably greets the news of selecting a female CEO with statistically significant abnormal stock-price reactions. Tests of the difference between valuation effects of female and male CEO appointments show there is no significant difference, indicating that financial market participants are not less confident in female CEOs (Martin, Nishikawa, and Williams 2009). The researcher of the current study questions whether Martin, Nishikawa, and Williams' finding will hold when referring to female investment managers, due to the fact that they are directly managing money matters. Using data from the U.S. mutual fund industry, research illustrates that although female and male managers do not differ in average performance, female managers receive significantly lower inflows, suggesting that female managers may be stereotyped as less competent (Niessen and Ruenzi 2007).

II. Research Questions

The researcher poses the following questions:

1. Has the perception that female portfolio managers are more risk-averse than male managers diminished as cultural advancement has shattered glass ceilings?
2. Can a work environment comprised more equally of males and females create greater stability in the financial markets, due to a better blend of investment approaches and risk tolerances?
3. Could this greater stability in the financial markets prevent future crises?

III. Hypotheses

The following testable hypotheses are the focus of the present inquiry:

1. Portfolios of female managers of mutual funds and hedge funds have higher annualized returns than those of male managers of mutual funds and hedge funds. Annualized returns are absolute returns over a specified period aggregated to a period of one year. Annualized returns are used for the purpose of comparing returns over different periods.
2. Portfolios of male managers of mutual funds and hedge funds have higher standard deviations (σ) of monthly returns than those of female managers of mutual funds and hedge funds. The standard deviation is a statistical measure applied to the weekly, monthly or annual rate of return of a portfolio to measure its volatility. Standard deviation explicates historical volatility and is used by portfolio managers to estimate the amount of expected volatility. Funds with large standard deviations deviate from the expected returns, and are characterized as riskier portfolios.
3. Portfolios of male managers of mutual funds and hedge funds assume more idiosyncratic risk, demonstrated by the R-squared (R^2) statistic, than those of female managers of mutual funds and hedge funds. R^2 is a percentage of systematic risk to total risk. A large R^2 figure indicates that the portfolio's idiosyncratic risk is small. One may mitigate idiosyncratic risk, also known as nonsystemic risk, through diversification.
4. Portfolios of female managers of mutual funds and hedge funds have greater Sharpe ratios than those of male managers of mutual funds and hedge funds due to smart investment decisions, not as a result of excess risk. The Sharpe ratio measures risk-adjusted performance. The ratio is calculated by subtracting the risk-free rate from the rate of return for a portfolio and dividing the result by the standard deviation of the portfolio returns. The Sharpe ratio demonstrates whether a portfolio's returns are due to smart investment decisions or a result of excess risk. Therefore, the greater a portfolio's Sharpe ratio, the better its risk-adjusted performance.

5. The female presence, that is, the proportion of females to males, in mutual funds is larger than that of hedge funds, due to the basic nature of hedge funds (i.e. high risk profiles).

IV. Data and Methodology

The data used for this research is secondary data, gathered from the Bloomberg terminal database. The universe includes U.S. mutual fund data and U.S. hedge fund data compiled using the Bloomberg fund screening function, "FSRC." For each fund, Bloomberg provides information dealing with the fund's holdings, domicile, country of availability, fund manager, etc. All of the screening criteria used for this study, and descriptions of each, can be found in Appendix A.

Two sample data sets are used. The sample set of data for hedge funds include information for 5,022 funds. The sample set of data for mutual funds include 72,271 funds. Not all 77,293 funds are used in this research. Many funds do not include the manager name. For those that do, we only use the mutual funds and hedge funds for which we are able to identify the gender of the manager. If the gender of a manger cannot be determined for a particular fund, it is eliminated. Therefore, the 4,980 mutual funds and 2,962 hedge funds that remain are the funds used in the research. Using Excel, we sort each data set by gender. For each screening criteria within both data sets, the means are taken for the funds managed by women and men. The two-tailed heteroscedastic t-test is used to assess whether the differences between the means of the two groups are statistically significant. Using SAS, we calculate the percentage of female managers to male managers. Additionally, we use SAS to control for Firm Assets Under Management and Management Style for gender comparisons. When controlling for AUM, the following criteria are analyzed in the mutual fund data set: Total Return, Standard Deviation, and Sharpe Ratio. For hedge funds, the following criteria are analyzed: Total Return, Standard Deviation, Sharpe Ratio, and R-Squared.

V. Data Analysis

A. Mutual Funds

Figure 1 presents the results for testing the hypothesis that funds managed by female managers exhibit lower total risk over one-year, three-year, and five-year periods. For the one- year period, we have 4,214 male managers and 293 female managers; for the three-year period, we have 3,357 male managers and 246 female managers; and for the five-year period, we have 2,585 male managers and 204 female managers, for which we have standard-deviation data for fund returns. The average standard deviation is higher for male managers for all three test periods, and the difference is statistically significant with a 5% significant level. Note that the in-group standard deviation is higher for male managers than for female managers, illustrating that male-managed funds are more heterogeneous in their risk exposure. One possible reason for this is the fact that male-managed funds cover a broader range of investment styles than female-managed funds.

— Figure 1 —

Standard Deviation				
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	4214	293	
One year monthly	Mean	17.41560038	16.50331058	
One year monthly	Standard Deviation	14.06585092	6.16270063	**0.0303634**
Three year monthly	N	3357	246	
Three year monthly	Mean	24.12200775	22.92475610	
Three year monthly	Standard Deviation	15.06324513	8.50944204	**0.04732210**
Five year monthly	N	2585	204	
Five year monthly	Mean	20.11493230	18.77171569	
Five year monthly	Standard Deviation	10.46928956	7.08305551	**0.01294118**

Figure 2 examines differences in systematic risk between male- and female-managed funds. We measure systematic risk by beta. Beta measures the exposure of the fund for market moves. Here, we have fewer funds with reported beta. For the one-year period, we have 2,285 male managers and 197 female managers; for the three-year period, we have 2,016 male managers and 172 female managers; and for the five-year period, we have 1,780 male managers and 151 female managers. Female-managed funds have lower systematic risk, especially over the one-year period. The higher beta for male-managed funds reflects either high market exposure or high leverage. However, none of the differences passes the 5% significance test. It is not clear whether the lack of significance is due to smaller sample sizes.

— Figure 2 —

Beta				
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	2285	197	
One year monthly	Mean	1.06875711	0.90477157	
One year monthly	Standard Deviation	6.36631708	0.16409173	**0.220107596**
Three year monthly	N	2016	172	
Three year monthly	Mean	0.90299603	0.93255814	
Three year monthly	Standard Deviation	2.79881465	0.22883476	**0.647935897**
Five year monthly	N	1780	151	
Five year monthly	Mean	0.94061236	0.91403974	
Five year monthly	Standard Deviation	1.35581728	0.23083957	**0.47543734**

The results in Figure 2 tempt us to conclude differences in total risk are driven by differences in systematic risk. Figure 3 confirms this hypothesis. In Figure 3 we examine differences in R^2. Recall that R^2 measures the ratio of systematic risk to total risk. Thus, $1\text{-}R^2$ measures the ratio of unsystematic risk to total risk. Higher R^2 implies lower systematic risk as a percentage of total risk. We have almost the same funds in the sample as those in Figure 2. The differences in R^2 are significant for one-year and three-year periods and border significance for the five-year period.

— Figure 3 —

R-Squared				
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	2289	199	
One year monthly	Mean	0.78499782	0.86929648	
One year monthly	Standard Deviation	0.29439818	0.15042535	**3.41238E-11**
Three year monthly	N	2016	172	
Three year monthly	Mean	0.82410714	0.85953488	
Three year monthly	Standard Deviation	0.24419676	0.14245883	**0.00384321**
Five year monthly	N	1780	151	
Five year monthly	Mean	0.81481461	0.83655629	
Five year monthly	Standard Deviation	0.23322077	0.15736601	**0.12056415**

Figure 4 presents the results for testing the hypothesis that funds managed by female managers outperform their male counterparts, as measured by total returns, over one-year, three-year, and five-year periods. For the one-year period, we have 4,237 male managers and 296 female managers; for the three-year period, we have 3,372 male managers and 248 female managers; and for the five-year period, we have 2,602 male managers and 204 female managers. The average annualized total returns for portfolios managed by female managers are higher than those of portfolios managed by male managers for all three test periods, and the mean differences are statistically significant. Note that the in-group standard deviations are higher for male-managed funds across all three time periods; this indicates that returns across all male-managed funds are more heterogeneous than returns across all female-managed funds. Moreover, the three-year results are influenced by the 2008 financial crisis. Female-managed funds still had higher returns than male-managed funds. The results in Figure 4 suggest that female managers make more consistent investment decisions. This may be a more positive trait, especially during a market collapse, than the more aggressive disposition of male managers, as demonstrated in the figures on risk above.

— Figure 4 —

Total Returns				
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	4237	296	
One year monthly	Mean	14.10622138	16.17520270	
One year monthly	Standard Deviation	17.69804969	9.56409192	**0.00089663**
Three year monthly	N	3372	248	
Three year monthly	Mean	2.67392645	4.60112903	
Three year monthly	Standard Deviation	10.53071566	7.59624142	**0.00021804**
Five year monthly	N	2602	204	
Five year monthly	Mean	2.45733666	3.54210784	
Five year monthly	Standard Deviation	6.98182865	4.09210317	**0.00072065**

Figure 5 presents results that compare the average alpha for male-managed and female-managed funds. Alpha is the fund's return adjusted for beta risk. The mean for female-managed funds over the one-year period, 23.8%, far exceeds its male counterpart of 8.3%. While the mean difference is large, it is statistically not significant. Note the in-group standard deviation of the male-managed funds is far larger than its female counterpart. This indicates that the male-managed funds are very heterogeneous compared to the female-managed funds. Such large standard deviation is the result of failing to reject the null hypothesis at a 5% significance level. We reject the null hypothesis with a 15.6% significance level. For the three-year period, the mean difference tilts toward the female-managed funds; yet, the difference is less striking and statistically insignificant.

— Figure 5 —

Alpha				
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	2285	197	
One year monthly	Mean	0.08303282	0.23786802	
One year monthly	Standard Deviation	4.90471054	0.51358536	**0.155341063**
Three year monthly	N	2016	172	
Three year monthly	Mean	0.06343254	0.07936047	
Three year monthly	Standard Deviation	2.83513500	0.46174617	**0.825652897**

Figure 6 presents the results for testing the hypothesis that funds managed by female managers exhibit higher Sharpe ratios over one-year and three-year periods. For the one-year period, we have 4,213 male managers and 293 female managers; for the three-year period, we have 3,356 male managers and 246 female managers. The higher in-group standard deviation for male managers than for female managers illustrates, as previously stated, that male-managed funds are more heterogeneous in their risk exposure. We conclude that mutual funds managed by women have better risk-adjusted performance; superior returns are due to smart investment decisions, not a result of excess risk.

— Figure 6 —

	Sharpe Ratio			
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	4213	293	
One year monthly	Mean	1.41441253	1.64040956	
One year monthly	Standard Deviation	1.37188904	0.85911461	**0.00004059**
Three year monthly	N	3356	246	
Three year monthly	Mean	0.18484207	0.32963415	
Three year monthly	Standard Deviation	0.54788313	0.43759019	**0.00000145**

B. Hedge Funds

Due to the small pool of female managers within the hedge fund data set, some results are not statistically significant. Additionally, note that beta is not available in the hedge-fund data as most hedge funds target zero beta, that is, zero exposure to obvious risk factors, such as equity indices, for their funds.

Figure 7 presents the results for testing the hypothesis that funds managed by female managers exhibit lower total risk over one-year, three-year, and five-year periods. For the one-year period, we have 3,980 male managers and 137 female managers; for the three-year period, we have 2,592 male managers and 91 female managers; and for the five-year period, we have 1,453 male managers and 46 female managers, for which we have standard-deviation data for fund returns. The average standard deviation is higher for male managers for all three test periods, and the difference is statistically significant with a 5% significant level. Note that the in-group standard deviation for male managers is almost twice as high as that for female managers. This illustrates that male-managed funds are more heterogeneous in their risk exposure. As stated previously, a possible reason for this is the fact that male-managed funds cover a broader range of investment styles than female-managed funds.

— Figure 7 —

		Standard Deviation		
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	3980	137	
One year monthly	Mean	11.65337688	10.09051095	
One year monthly	Standard Deviation	13.55980118	7.00551330	**0.01497338**
Three year monthly	N	2592	91	
Three year monthly	Mean	16.79795910	14.82241758	
Three year monthly	Standard Deviation	13.23247658	9.38243292	**0.054877379**
Five year monthly	N	1453	46	
Five year monthly	Mean	15.24774948	12.81021739	
Five year monthly	Standard Deviation	10.71614069	6.84625396	**0.02391956**

The findings support the hypothesis that hedge funds managed by women are less risky than those managed by men. Figure 8 shows that in the short term, female-managed funds exhibit less R^2 than male-managed funds. Note that 1- R^2 measures the percentage of unsystematic risk to total risk. For the one-year period, male-managed funds have less unsystematic risk than female-managed funds. In fact, 69.5% of the risk is unsystematic for male-managed funds, while 94.4% of the risk is unsystematic for female-managed funds. Given that female-managed funds have lower overall total risk, it must be the case that female-managed funds have lower systematic risk than their male counterparts. For three-year and five-year periods, we accept the hypothesis that male- and female-managed funds have similar percentages of unsystematic risk relative to total risk. Given that female-managed funds have lower total risk, funds managed by women are likely to have lower systematic risk.

— Figure 8 —

R-Squared				
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	445	14	
One year monthly	Mean	0.19224719	0.05642857	
One year monthly	Standard Deviation	0.30536182	0.12899655	**0.001909128**
Three year monthly	N	338	11	
Three year monthly	Mean	0.39831361	0.50454545	
Three year monthly	Standard Deviation	0.31239260	0.29837438	**0.271093839**
Five year monthly	N	233	9	
Five year monthly	Mean	0.38356223	0.38777778	
Five year monthly	Standard Deviation	0.29611088	0.28769679	**0.96660951**

Figure 9 presents the results for testing the hypothesis that funds managed by female managers outperform their male counterparts, as measured by total returns, over one-year, three-year, and five-year periods. For the one-year period, we have 4,027 male managers and 138 female managers; for the three-year period, we have 2,611 male managers and 93 female managers; and for the five-year period, we have 1,474 male managers and 47 female managers. We conclude that female managers are severely underrepresented in U.S. industry. As a result, very few data regarding female-managed funds' total returns are available. Although the results support our hypothesis, the mean differences between male- and female-managed funds are not statistically significant.

— Figure 9 —

Total Returns				
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	4027	138	
One year monthly	Mean	7.54148249	9.04224638	
One year monthly	Standard Deviation	17.76002648	16.92985300	**0.30833247**
Three year monthly	N	2611	93	
Three year monthly	Mean	1.15693987	4.37623656	
Three year monthly	Standard Deviation	11.95479112	17.51611853	**0.08198478**
Five year monthly	N	1474	47	
Five year monthly	Mean	4.46278155	7.01404255	
Five year monthly	Standard Deviation	8.37717389	16.83044132	**0.30593023**

Figure 10 presents results that compare the average alpha for male-managed and female-managed funds. Recall that alpha is the fund's return adjusted for beta risk. The mean for female-managed funds over the one-year period, 15.9%, exceeds its male counterpart of 12%. However, the mean difference is statistically not significant. Note that the in-group standard deviation of the male-managed funds is far larger than that for female-managed funds. This indicates that the male-managed funds are very heterogeneous compared to the female-managed funds. For the three-year period, the mean for female-managed funds is 69%. This is more than twice the mean of male-managed funds at 27.7%. Although the difference is striking, it is statistically insignificant. Again, we find that the male-managed funds are very heterogeneous compared to the female-managed funds due to much larger in-group standard deviation. Such large standard deviation is the cause of failing to reject the null hypothesis at a 5% significance level. We reject the null hypothesis with a 12.5% significance level.

— Figure 10 —

		Alpha		
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	445	14	
One year monthly	Mean	0.12033708	0.15857143	
One year monthly	Standard Deviation	1.82339838	0.88235574	**0.880827534**
Three year monthly	N	338	11	
Three year monthly	Mean	0.27730769	0.69000000	
Three year monthly	Standard Deviation	1.52435466	0.78640956	**0.12512061**

Figure 11 presents the results for testing the hypothesis that funds managed by female managers exhibit higher risk-adjusted performance, measured by the Sharpe ratios, over one-year and three-year periods. We find that in the short term, funds managed by women have higher Sharpe ratios than those managed by men. However, for the three-year period, funds managed by women have lower Sharpe ratios than funds managed by men. Nonetheless, the results are not statistically significant for either time period. Note that the Sharpe ratio is accentuated by investments that don't have a normal distribution of returns. Many hedge funds use dynamic trading strategies and options that give way to skewness and kurtosis in their distribution of returns.

— Figure 11 —

	Sharpe Ratio			
	Statistics	**Male**	**Female**	**T-test Prob**
One year monthly	N	3977	136	
One year monthly	Mean	0.96820971	1.26823529	
One year monthly	Standard Deviation	3.15647719	4.54834978	**0.446749638**
Three year monthly	N	2592	91	
Three year monthly	Mean	0.26243827	0.25197802	
Three year monthly	Standard Deviation	1.22958312	1.09317501	**0.929011617**

C. *Female Presence*

As hypothesized, the female presence in mutual funds was larger than that in hedge funds; however, the difference was not as large as anticipated. The female presence in mutual funds was 8.72%; the female presence in Hedge Funds was 4.25%. The small sample size of females strengthens the argument that female fund managers are underrepresented in both mutual funds and hedge funds.

D. *Control for Firm Assets Under Management*

We observe that female fund managers are concentrated in funds with lower levels of Assets Under Management (AUM) (Figure 12), insinuating female managers are more likely to be hired by small firms. Given the concentration of female managers in funds with relatively low AUM, we were concerned that if funds with low AUM outperform those with large AUM, then gender difference would be confounded with AUM differences. Within our small subset of funds, there are no significant differences in return and risk between funds with low levels of AUM and high levels of AUM (Appendix B). Therefore, in our sample, the gender differences are not driven by AUM differences.

— Figure 12 —

	AUM (millions)			
	Statistics	**Male**	**Female**	**T-test Prob**
	N	24	2	
Mutual Funds	Mean	518.70	101.55	
	Standard Deviation	1335.87	143.05	**0.1664**
	N	352	12	
Hedge Funds	Mean	46824.75	528.79	
	Standard Deviation	235866.38	902.59	**0.0003**

While this suggests the results of the current study are likely to be robust, there is a limitation in the data. Controlling for AUM with more data may change this study's conclusion.

E. Control for Management Style

Concerned that different styles may exhibit different risk-return profiles, we control for management style as defined by Bloomberg (Figures 13, 14, and 15). We find that female portfolio managers are concentrated in only three strategies: Sector Funds (Equity funds), Total Returns (Debt funds), and Value. Therefore, it is difficult to control for fund management strategy. Fuller data sets for future research may change this study's conclusion.

— Figure 13 —

Gender	Management Style	N	Std Dev 1Y M Mean	Std Dev 1Y M Std Dev
Female	Sector Funds (Equity funds)	42	19.3214286	4.25943691
Female	Total Return (Debt funds)	24	8.2066667	1.17741673
Female	Value	36	19.3794444	3.25015511
Male	Sector Funds (Equity funds)	364	20.4550275	4.88703415
Male	Total Return (Debt funds)	209	9.5789952	9.20900722
Male	Value	560	20.1839464	6.44725091

— Figure 14 —

Least Squares Means

Gender	Management Style	Std Dev 1Y M LSMEAN	LSMEAN Number
Female	Sector Funds (Equity funds)	19.3214286	1
Female	Total Return (Debt funds)	8.2066667	2
Female	Value	19.3794444	3
Male	Sector Funds (Equity funds)	20.4550275	4
Male	Total Return (Debt funds)	9.5789952	5
Male	Value	20.1839464	6

— Figure 15 —

Least Squares Means for effect Manager Gender * Management Style

Pr > |t| for H0: LSMean(i)=LSMean(j)

Dependent Variable: Std Dev 1Y M

i/j	1	2	3	4	5	6
1		<.0001	0.9683	0.2790	<.0001	0.4014
2	<.0001		<.0001	<.0001	0.3217	<.0001
3	0.9683	<.0001		0.3380	<.0001	0.4664
4	0.2790	<.0001	0.3380		<.0001	0.5308
5	<.0001	0.3217	<.0001	<.0001		<.0001
6	0.4014	<.0001	0.4664	0.5308	<.0001	

VI. Conclusion

This paper contributes to the existing literature discussing economic behavior anomalies; the current study examines the relationship between risk and performance of U.S. mutual funds and hedge funds and the portfolio manager's gender. Although sizable literature already documents that men tend to be overly confident and risk-seeking, whereas women tend to be risk-averse, we have yet to find research outlining these biases during a financial crisis. Having gathered data for one-year, three-year, and five-year horizons, we are able to analyze whether males and females react differently to huge market swings; three-year results are influenced by the 2008 financial crisis. We find that female managers are, in fact, more risk-averse than male managers. The results indicate that a work environment comprised more equally of male and female portfolio managers is likely to create more stability in the financial markets, due to a better blend of investment approaches and risk tolerances.

Additionally, we observe that female fund managers are concentrated in funds with lower levels of Assets Under Management (AUM). This is due to the fact that female managers are more likely to be hired by small firms. Given the concentration of female managers in funds with relatively low AUM, we were concerned that if funds with low AUM outperform those with large AUM, then gender difference would be confounded with AUM differences. Within our small subset of funds, we find no significant differences in return and risk between funds with low levels of AUM and high levels of AUM. Therefore, in our sample, the gender differences are not driven by AUM differences. We conclude that if female managers outperform male managers, they should attract more funds because people seek better returns.

Despite so-called “shattering the glass ceiling,” female managers are drastically underrepresented, which begs the question: must female managers be “exceptional” to land positions in the first place? And, are they held to a higher standard once they do secure these positions? Given that women who manage to break through harder barriers to become portfolio managers are more exceptional than their male counterparts, it is possible that when women get to have equal opportunity to be hired like men, they may lose part or perhaps all their advantage. However, this question cannot be answered until we have a far more balanced workforce of fund managers. The study should be examined with fuller data sets and more females in the industry to examine the robustness of these results.

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Appendix A. Descriptions of Screening Criteria[1]

A. Management

Fund Manager: Person or persons that make daily investment decisions for the fund.
Fund Manager Start Date—The date that the manager begins managing the fund.

B. Classifications (Prospective Based)

Management Style: The investment strategy the manager implements for investment decisions, as stated in the prospectus.
Strategy: The investment strategy the manager concentrates on for investment opportunities, as stated in the prospectus or offering memorandum.

C. Assets

Firm Assets Under Management: The total assets under management by the investment manager/investment advisor. This includes assets within funds and separately managed accounts. This field displays U.S. dollars (millions).

D. Quantitatives

Total Return 1Y (Performance Metric): One-year total return of a security as of the date of the last close price. Start date is the first business day on or before 12 months (to the date) prior to the ending date (as of date). The return combines price appreciation (or depreciation) and dividend distributions. The dividends are reinvested back into the security. If the ending date is the last day of the month, the start date is derived using end-of-month conventions.
Total Return 3Y/5Y Ann (Performance Metric): The three-year, five-year annualized return on the security including appreciation and dividends, assuming the dividends are reinvested back into the security. If no price is available on the start or end date of the current period, the calculation will look to the fund-pricing frequency for a valid price. If the fund prices daily, the calculation will look back three

[1] Descriptions provided by Bloomberg

business days for a price. If the fund prices weekly, the calculation will look back seven business days for a price. If the fund prices infrequently, the calculation will look back a maximum of 30 business days for a price. If no valid price is found, then N.A. will be returned.
Standard Deviation (Risk Metric): Volatility from the average of returns of defined granularity over time frame specified. It measures how widely spread the values in a period are. The bigger it is, the most risky is the security.

- 1Y Monthly Annually (Std Dev 1Y-M)
- 3Y Monthly Annually (Std Dev 3Y)
- 5Y Monthly Annually (Std Dev 5Y)

Sharpe Ratio (Risk/Return Metric): A risk-adjusted measure developed by William F. Sharpe that calculates the excess performance with respect to the Risk Free Rate (in our case the yield three months linked to the currency), per unit of volatility over the time frame specified. Performance is measured as mean return. Components are annualized. The higher the Sharpe ratio, the better the fund's historical risk-adjusted performance.

- Sharpe 1Y Monthly
- Sharpe 3Y Monthly
- Sharpe 5Y Montly

R-squared (Tracking and Correlation Metric): A measurement of how well a security's performance correlated with the performance of a benchmark index, such as the S&P 500, and thus a measurement of what portion of its performance can be explained by the performance of the overall market or index. Values for r-squared range from 0 to 1, where 0 indicated no correlation and 1 indicates perfect correlation.

- 1Y Weekly
- 3Y Monthly
- 5Y Monthly

Alpha (Tracking Metric): Intercept of the regression line of the security and benchmark returns of defined granularity over time frame specified. A coefficient which measures risk-adjusted performance, factoring in the unsystemic risk, rather than market risk (systemic risk). An indication of whether a security is undervalued or overvalued in relation to other securities with similar systemic risk.

- 1Y Monthly
- 3Y Monthly
- 5Y Monthly

Beta (Tracking Metric): Slope of the regression line of the security and benchmark returns of defined granularity over time frame specified. A coefficient which measures systemic risk. A beta over 1 is more volatile than the overall market, while a beta below 1 is less volatile.

- 1Y Monthly
- 3Y Monthly
- 5Y Monthly

Appendix B. Control for Firm Assets Under Management

A. Mutual Funds

Total Return 1Y

GLM Procedure ─ Total Return 1Y					
Parameter		Estimate	Standard Error	t Value	Pr > |t|
AUM	---	15.663	0.25327954	61.84	<.0001
AUM	High	31.465	7.11327811	4.42	<.0001
AUM	Low	15.1573	3.03311198	5.00	<.0001

		-----Total Return 1Y-----	
Level of AUM	N	Mean	Std Dev
---	3155	15.6629857	14.2514006
High	4	31.4650000	13.9608464
Low	22	15.1572727	9.859138

Standard Deviation 1Y

GLM Procedure ─ Standard Deviation 1Y					
Parameter		Estimate	Standard Error	t Value	Pr > |t|
AUM	---	18.1628	0.20646135	87.97	<.0001
AUM	High	18.785	5.78091774	3.25	<.0012
AUM	Low	19.4273	2.46499161	7.88	<.0001

		-----Standard Deviation 1Y-----	
Level of AUM	N	Mean	Std Dev
---	3136	18.1628061	11.6001163
High	4	18.7850000	8.8285087
Low	22	19.4272727	3.0450806

Sharpe Ratio 1Y

GLM Procedure ─ Sharpe Ratio 1Y					
Parameter		Estimate	Standard Error	t Value	Pr > |t|
AUM	---	1.67441	0.15657484	10.69	<.0001
AUM	High	2.205	4.38339655	0.50	0.615
AUM	Low	1.31455	1.86908657	0.70	0.4819

		-----Sharpe Ratio 1Y-----	
Level of AUM	N	Mean	Std Dev
---	3135	1.67440510	8.80016906
High	4	2.20500000	0.34539832
Low	22	1.31454545	0.56457086

B. Hedge Funds

Total Return 1Y

GLM Procedure ─ Total Return 1Y					
Parameter		Estimate	Standard Error	t Value	Pr > |t|
AUM	---	8.71107	0.50167926	17.36	<.0001
AUM	High	10.4121	2.90658796	3.58	0.0003
AUM	Low	6.84392	1.51997984	4.5	<.0001

		-----Total Return 1Y-----	
Level of AUM	N	Mean	Std Dev
---	2249	8.7110716	24.6950263
High	67	10.4120896	13.5079275
Low	245	6.8439184	16.3139922

Standard Deviation 1Y

GLM Procedure ─ Standard Deviation 1Y					
Parameter		Estimate	Standard Error	t Value	Pr > |t|
AUM	---	11.6036	0.40930427	28.35	<.0001
AUM	High	12.4338	2.37543985	5.23	<.0001
AUM	Low	11.3833	1.23797784	9.20	<.0001

		-----Standard Deviation 1Y-----	
Level of AUM	N	Mean	Std Dev
---	2223	11.6036122	20.1721864
High	66	12.4337879	11.7933406
Low	243	11.3832922	10.8783374

Sharpe Ratio 1Y

GLM Procedure ─ Sharpe Ratio 1Y					
Parameter		Estimate	Standard Error	t Value	Pr > |t|
AUM	---	1.36064	0.36928070	3.68	0.0002
AUM	High	1.13742	2.14171231	0.53	0.5954
AUM	Low	1.18786	1.11616902	1.06	0.2827

		-----Sharpe Ratio 1Y-----	
Level of AUM	N	Mean	Std Dev
---	2220	1.36063514	18.5231124
High	66	1.13742424	1.9167170
Low	243	1.18786008	3.5932446

R-Squared 1Y

GLM Procedure ─ R-Squared 1Y					
Parameter		Estimate	Standard Error	t Value	Pr > |t|
AUM	---	18.4516	17.4461356	1.06	0.2912
AUM	High	0.25250	137.0937718	0.00	0.9985
AUM	Low	0.12261	57.1720550	0.00	0.9983

		-----R-Squared 1Y-----	
Level of AUM	N	Mean	Std Dev
---	247	18.45161940	287.782773
High	4	0.25250000	0.28194300
Low	23	0.1226087	0.2748750