Sex Matters: Gender and Mutual Funds*

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Comments Welcome

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Sex Matters: Gender and Mutual Funds

Abstract

To shed some light on the sophisticated relationship between women, men and money, we investigate gender differences among US equity mutual fund managers. Based on findings from the literature, we hypothesize that female fund managers take less risk than male managers. At the same time female managers are expected to follow less extreme investment styles that are more consistent over time. We also expect them to be less overconfident and therefore to trade less. The results from our empirical study support all of these hypotheses. Given our findings of pronounced behavioral differences, we then turn to the consequences that arise for investors and fund companies. We find no evidence that these differences are also reflected in differences in average fund performance. However, we document that male managed funds are more likely to achieve extreme performance ranks than female managed funds and that the performance of the latter is more persistent. The more surprising appears our finding, that female managed funds have significantly lower inflows: a female-managed fund experiences about 18% lower inflows than an otherwise comparable male-managed fund. As fund families earn their fee income on their assets under management, they seem to have little reason to employ many women. Thus, we search for compensating incentives to employ a female fund manager despite a low fund flow. We find that firms with a high probability of being sued for discrimination, i.e. large and well-established firms, are most likely to employ women. These are also the firms that cater to institutional investors who often require their business partners to proof workforce diversity. Furthermore, female fund managers are more likely to be employed in less conservative states of the U.S. We conclude with implications of our findings for investors and fund management companies.

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1 Introduction

It is a popular perceived notion that women and men are different. A recent bestseller even suggests that men are from Mars and women are from Venus.[1] This paper is concerned with gender differences in the mutual fund industry and the resulting consequences for investors and fund families. The mutual fund industry offers an ideal test setting to analyze gender differences, because the observed behavior is not biased by an artificial environment, i.e. an experimental setting. Furthermore, behavioral consequences are directly reflected in quantitative measures that can be easily used for statistical analysis.

In recent years, studies on investment styles and the success of fund managers with certain characteristics have caught a great deal of attention. For example, Chevalier and Ellison (1999b) and Ding and Wermers (2004) provide evidence that fund performance is positively correlated with manager education and experience. However, surprisingly little attention has been devoted to the influence of gender on fund management.[2] This is astonishing, given that a fund manager's gender is easily observable. Lewellen, Lease, and Schlarbaum (1977) report, that gender is one of the most important determinants of investment style. This paper attempts to fill this gap by offering the first comprehensive study on gender influences in the mutual fund industry. Our empirical study covers all single managed US equity mutual funds from $1994 - 2003$. In this period, the share of female fund managers is stable at around 10%.

The rich empirical and experimental literature in psychology and finance allows us to deduct several new hypotheses on the investment behavior and performance of female and male fund managers as well as on fund investors' and fund management companies' behavior. We start our analysis with an examination of behavioral differences between female and male fund managers.

[1]John Gray: *Men are from Mars, Women are from Venus*, HarperCollins, 1998.

[2]The only exceptions we are aware of are Bliss and Potter (2002) and Atkinson, Baird, and Frye (2003) who examine several fund characteristics using limited samples of equity and fixed income funds mostly focusing on univariate examinations.

Firstly, we expect female fund managers to follow less risky investment strategies. A multitude of studies show that women are more risk averse than men. However, we expect differences in risk taking between them to be less pronounced than for retail investors. The reason for this is that female and male fund managers have comparable educational backgrounds and experiences which leads them to behave more similar than a random sample of men and women. Our results indicate indeed only moderately less risky portfolios of female managers as compared to male managers. Mainly, idiosyncratic risk seems to be lower for female managers than for their male counterparts. This hints at trading styles of male managers that entail more active bets. Thus, in the second step we examine differences in investment styles between female- and male-managed funds. We find that women follow less extreme investment styles. Furthermore, their investment styles are more stable over time. Finally, we take a closer look at trading activity, arguing that the higher overconfidence generally documented for men should also be reflected in a higher turnover ratio of male-managed funds. This reasoning is supported by our empirical results.

These findings are relevant for fund investors, as the fund manager's gender is an easily observable information which can be used as an indication for the investment style of the fund. Furthermore, previous studies argue that investment styles and trading activity are correlated with fund performance (see Barber and Odean (2001), Wermers (2002), and Brown and Harlow (2005)). Therefore, we examine whether gender differences concerning investment behavior of fund managers are also reflected in fund performance. However, using various risk-adjusted performance measures we do not find any significant differences in average performance. Nevertheless, the performance distributions of female and male managers differ significantly. The percentage of male managed funds is much higher among the very best and the very worst funds than among the rest of funds. This indicates that the more extreme style bets of male managers lead to a higher probability of populating extreme performance ranks. Turning to performance persistence, we find that the moderate investment style of female managers also leads to more persistent performance of female managed funds as compared to male managed funds.

In the next step we examine fund investors' behavior. As the ultimate goal of fund companies is to maximize inflows and eventually fee income, understanding the behavior of its investors is vital for them. We analyze the influence of a fund manager's gender on net inflows. We find surprisingly strong evidence, that female managed funds have much lower inflows than male managed funds. The growth rate due to inflows of female managed funds is by 18% p.a. (on an absolute basis) less than that of male managed funds. We argue that this is likely to be due to stereotyping of fund investors who for some reason believe male managers do a better job in managing money.

The question that arises from our findings is why a fund management company should employ women, if they have a negative influence on fund flows? We address this question by analyzing what determines the share of female fund managers a fund company employs. We examine the location of a fund family as well as family characteristics as possible determinants. Firstly, regarding the influence of location, we find that fund companies are more likely to employ women if they are located in less conservative states of the U.S. Secondly, according to Bradford (2005), companies that are large and well-established are more likely to be sued for discrimination. Translated to the mutual fund industry, we would expect large and well-established fund management companies to be more likely to employ female fund managers, because these are exactly the kind of fund families most likely to be sued and to suffer great reputational losses. This reasoning is supported by our empirical results. A provocative interpretation of this finding could be that fund companies only employ as many female fund managers as needed to avoid lawsuits due to gender discrimination. Another possible explanation for this finding is that large institutional investors mainly do business with large and well established fund companies. Anecdotal evidence suggests that these large investors often require a certain degree of workforce diversity from the firms they do business with.

The paper proceeds as follows. In Section 2 we give a short review of the related literature and derive our main hypotheses. Section 3 contains a description of our data and our main variables. We then present our empirical results on differences in the investment behavior between female and male managers, i.e. risk-taking, investment styles and trading activity in Section 4. Resulting consequences of behavioral differences between female and male managers for investors and fund companies are then analyzed in Section 5. Section 6 examines the determinants of a fund family employing female managers. Section 7 concludes.

2 Related Literature and Development of Hypotheses

In this section we review the related literature on behavioral differences between men and women. Based on the rich existing evidence from the psychological and finance literature we develop ten hypotheses.

Our first empirical question is, if there are any differences in risk-taking among fund managers that can be clearly related to their gender. Looking at the existing literature we have indeed reasons to assume so. A meta-analysis of 150 studies conducted by Byrnes, Miller, and Schafer (1999) reports very consistent results of a higher risk aversion of women as compared to men in different frameworks. These findings also hold in the area of financial risk. Balkin (2000) shows that women invest more risk averse than men in their 401(k) retirement plans. Similar results are reported by Jianakoplos and Bernasek (1998) who find that household holdings of risky assets are significantly lower for single women than single men. Using account data for over 35,000 households from a discount brokerage, Barber and Odean (2001) document that women tend to hold less risky positions than men within their common stock portfolios.

However, Johnson and Powell (1994) argue that findings of gender differences in risk-taking are usually deducted from non-managerial populations in which most individuals have no formal management education. Jianakoplos and Bernasek (1998), Balkin (2000) and Barber and Odean (2001) all examine the behavior of retail investors. Their findings do not necessarily apply to managers. Johnson and Powell (1994) conclude that in a managerial sub-population, women and men display similar risk propensity. Since we investigate the behavior of male and female fund managers we can assume that they have similar professional backgrounds and work in a comparable environment. Therefore, they can be defined as a managerial sub-population. Relating our results to the literature on the risk-taking behavior of female and male retail investors (Barber and Odean (2001)), we expect that differences in financial risk-taking play a more important role in a non-managerial population.

Hypothesis 1: Female fund managers take moderately less risk than male fund managers.

Another important issue that is closely related to risk-taking behavior is the investment style a fund manager pursues. Some investors might favor mutual funds with investment styles clustering around a broad market index, whereas others prefer funds that take large active bets. Thus, from an investor's point of view it is interesting to know if gender differences in investment styles exist among fund managers. As a survey conducted by Lewellen, Lease, and Schlarbaum (1977) reports that gender is the third most important determinant of investment style, overriding even characteristics like occupation and educational background, the manager's gender could indeed provide information about a fund's investment style. Furthermore, Sunden and Surette (1998) and Jianakoplos and Bernasek (1998) confirm that female investors allocate their assets significantly different from male investors. Cadsby and Maynes (2005) conclude from experimental testings that women tend to play more like another than men. We expect that this will also be reflected in the extremity of their investment styles, i.e. that we find less extreme investment styles pursued by female fund managers. Hence, we formulate our second hypothesis:

Hypothesis 2: Female fund managers follow less extreme investment styles than male fund managers.

Another question relevant to investors is whether past investment style is a good predictor of future investment style. Concerning gender differences in style variability, Powell (1988) shows that female managers in other industries follow more consistent management styles over time than male managers. We expect this to be the case in the mutual fund industry, too. Thus, our third hypothesis reads:

Hypothesis 3: Investment styles of female fund managers are more consistent over time than investment styles of male fund managers.

Our next hypothesis is concerned with gender differences in trading activity. Several empirical studies suggest that enhanced trading activity, i.e. a higher turnover ratio, can hurt fund performance (See Carhart (1997), Barber and Odean (2001)). A negative relationship between turnover and fund performance appears, if fund managers are overconfident about their trading abilities. Excessive trading then leads to higher transaction costs that are not rewarded with higher fund returns.

Previous studies provide evidence that the degree of overconfidence is higher for men than for women (see Barber and Odean (2001), Estes and Hosseini (1988) and Gysler, Kruse, and Schubert (2002)). Barber and Odean (2001) find that men trade 45 percent more than women. This reduces their net returns by 2.65 percentage points p.a. They argue that gender differences in confidence are greatest for tasks in a masculine domain where feedback is ambiguous. Financial markets are clearly dominated by men and feedback on investment ability is not received immediately. Thus, we expect male managers to be more overconfident. Consequently, our fourth hypothesis is:

Hypothesis 4: Female fund managers trade less than male fund managers.

We now turn to the consequences that can result for an investor, if the above mentioned gender differences among fund managers exist. Our hypotheses suggest that female fund managers follow more consistent investment styles over time and trade less than male fund managers. From previous studies we know that such behavior is positively related to fund performance (see Brown and Harlow (2005), and Carhart (1997)).[3] Hence, we formulate as our fifth hypothesis:

Hypothesis 5: Female fund managers perform better than male fund managers.

Regarding the dispersion of performance of female and male managed funds we expect the more extreme style bets of male fund managers (see Hypothesis 2) to lead to more extreme performance outcomes of male managers as compared to female managers. If the more extreme style bets of a male manager work out, he should perform very well, while he should perform very badly, if his style bets do not work out. This leads to our sixth hypothesis:

Hypothesis 6: Female fund managers are less likely to achieve extremely (good or bad) performance ranks than male fund managers.

Furthermore, it is very likely that the extreme style bets of male managers work out in some years, but not in others. Thus, we would also expect that performance is less stable over time for male managers than for female managers. This is our seventh hypothesis:

Hypothesis 7: The performance of female fund managers is more persistent than that of male fund managers.

Fund management companies are ultimately interested in maximizing their fee income. Therefore, another important issue to consider are the determinants of net-inflows of new

[3]Contradicting evidence is provided in Wermers (2002) who finds that style drift and performance are positively correlated.

money. It is vital for the management of a fund company to know if there is any influence of a fund manager's gender on net inflows. There is some evidence presented in Heilman, Martell, and Simon (1989), Oakley (2000), and Atkinson, Baird, and Frye (2003) that female managers in upper levels of organizations are often associated with inferior management skills as compared to male managers.[4] Thus, we expect that female fund managers are stereotyped as less skilled than male managers by fund investors. Hence, we formulate our next hypothesis:

Hypothesis 8: Female managed funds experience lower inflows than male managed funds.

The share of female fund managers is low and remains at a 10%-level over our sample period. Our final analysis focuses on the determinants of the share of female fund managers in a fund family. We argue that large and well-established families are generally more likely to employ women because they face a higher risk of being sued for discrimination. This view is supported by Bradford (2005) who shows that large and visible firms are indeed more likely to be sued for discrimination. Furthermore, given their size, the potential reputational loss due to anti-discrimination lawsuits is larger for them (see Bradford (2005) and Holzer (1996)). According to Bradford (2005), such costs are especially high for lawsuits due to gender discrimination. Therefore, a fund family should be well interested in avoiding costs that arise from gender discrimination lawsuits. Furthermore, large institutional investors often demand workforce diversity from the fund companies they do business with. Although we have no formal empirical evidence on this, discussions with industry professionals suggest that workforce diversity is an important issue for institutional investors when choosing business partners. As these investors usually only invest with large fund companies, this

[4] Further evidence for this form of "think manager, think male"-stereotyping in a financial environment can be deducted from a survey of Wang (1994), who reports that sales representatives at brokerages spend more time on advising men than women, offer a wider variety of investments to men and try harder to acquire men as customers.

provides another reason why large firms are more likely to employ women than smaller firms. Our ninth hypothesis reads:

Hypothesis 9: Large and well established fund families are more likely to employ female fund managers than other fund families.

Finally, we argue that sociodemographic characteristics of the population in the state where the fund company is located also influence the decision to employ women. We follow the argumentation of Gornick (1999), who find that women's employment rates are significantly lower than men's in conservative regions. Therefore, we expect that fund companies located in conservative states, where the population is more prejudiced against the employment of women, are less likely to employ female managers:

Hypothesis 10: Fund companies located in states of the US where the population is conservative tend to have a lower share of female fund managers than fund companies located in other states.

We test these hypotheses on the US mutual fund market using the methodology described in the following section.

3 Data

3.1 Variable Construction

Our primary data source is the CRSP Survivorship Bias Free Mutual Fund Database.[5] It covers U.S. open-end mutual funds and provides information on fund returns, fund man-

[5]Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. For a more detailed description of the CRSP database, see Carhart (1997) and Elton, Gruber, and Blake (2001).

agement structures, total net assets, investment objectives, turnover rates, fee structures, fund managers' identity, and other fund characteristics.

We focus on actively managed equity funds that invest more than 50% of their assets in stocks, excluding bond, money market and index funds. We use the ICDI objective codes identified by Standard & Poor's Fund Services to define the market segment in which a fund operates. This leaves us with 10 different equity fund segments. The ICDI classification is available from 1994 on. Our data ends in 2003. Therefore, our study covers the time period January 1994 to December 2003.

We aggregate all share classes of the same fund to avoid multiple counting. Although multiple share classes are listed as separate entries in the CRSP database, they are backed by the same portfolio of assets and have the same portfolio manager. Following the approach in Daniel, Grinblatt, Titman, and Wermers (1997), we identify classes of a fund by matching fund names and characteristics such as fund management structure, turnover, and fund holdings in asset classes.

Bär, Kempf, and Ruenzi (2005) show that teams and single managed funds behave differently. Thus, we concentrate our analysis on single-managed funds and exclude all team-managed funds and funds for which CRSP gives multiple manager names from our analysis. This allows us to disentangle differences in fund behavior due to management structure (team- vs. single-managed) from differences that can be attributed to gender (female- vs. male-managed).

In the CRSP database there is no field indicating the gender of the fund's manager. However, the first name of the manager is usually given. Based on this information we identify the gender of the managers in our sample. Overall, we were able to identify the manager's gender for 99.39% of all funds. The Appendix provides further details pertaining to the gender identification process.

The performance of a fund is captured by its risk-adjusted abnormal returns. These are measured in several different ways. Specifically, we calculate Jensen's (1973) Alphas, Fama-French (1993) three-factor Alphas, and Carhart (1997) four-factor Alphas. We estimate the following regression equations using OLS to calculate these measures:

$$
\begin{aligned}
R_{i,m,t} - R_{f,m,t} &= \alpha_{i,t} + \beta_{i,M,t}(R_{M,m,t} - R_{f,m,t}) + \varepsilon_{i,m,t}, && (1)\\
R_{i,m,t} - R_{f,m,t} &= \alpha_{i,t}^{TF} + \beta_{i,M,t}(R_{M,m,t} - R_{f,m,t}) + \beta_{i,S,t} SMB_{m,t} \\
&\quad + \beta_{i,H,t} HML_{m,t} + \varepsilon_{i,m,t}^{TF}, && (2)\\
R_{i,m,t} - R_{f,m,t} &= \alpha_{i,t}^{FF} + \beta_{i,M,t}(R_{M,m,t} - R_{f,m,t}) + \beta_{i,S,t} SMB_{m,t} \\
&\quad + \beta_{i,H,t} HML_{m,t} + \beta_{i,MO,t} MOM_{m,t} + \varepsilon_{i,m,t}^{FF}, && (3)
\end{aligned}
$$

where $R_{i,m,t} - R_{f,m,t}$ denotes fund i's excess return over the risk-free rate in month m of year t and $R_{M,m,t} - R_{f,m,t}$ denotes the excess return of the market segment the fund operates in over the risk-free rate, respectively.[6] $SMB_{m,t}$ is the return difference between small and large capitalization stocks, $HML_{m,t}$ denotes the return difference between high and low book-to-market stocks and $MOM_{m,t}$ is the return difference between stocks with high and low previous year's returns in month m of year t.[7] The estimated alphas, $\hat{\alpha}_{i,t}$, $\hat{\alpha}_{i,t}^{TF}$, and $\hat{\alpha}_{i,t}^{FF}$, from (1)-(3) are our performance measures for fund i in year t. We also compute a modified version of the Treynor/Black (1973) appraisal ratio as additional performance measure. It is calculated by dividing the four-factor abnormal return by the standard deviation of the residuals of the four-factor regression:

[6] Alternatively, we also use the Fama and French (1993) market factor. Results (not reported) are not affected by this. All results not reported in the paper are available from the authors upon request.

[7] The market, the size, and the value portfolio were taken from Kenneth French's Web site: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french`, while the momentum factor was kindly provided by Mark Carhart.

$$AR_{i,t} = \frac{\hat{\alpha}_{i,t}^{FF}}{\sigma(\varepsilon_{i,m,t}^{FF})}. \quad (4)$$

In order to be able to directly compare the performance persistence between female and male managed funds, we construct a measure of performance persistence for each individual fund. In the first step, we calculate the performance rank for each fund i in each year t, $PerfRank_{i,t}$. Ranks are based on one of the abnormal return measures introduced above. They are calculated for each segment separately and are normalized so that they are evenly distributed between 0 and 1. The best fund gets assigned the rank number 1. The less this rank varies over time, the more persistent is the fund's performance. Thus, the performance persistence of a fund i, PP_i, is given by the variation of it's yearly performance ranks over time as measured by the standard deviation of ranks:[8]

$$PP_i = STDev(PerfRank_{i,t}). \quad (5)$$

To capture the risk-taking behavior of funds we construct four measures of fund risk. The first measure, $TotalRisk_{i,t}$, is given by fund i's monthly return standard deviation in year t. Total risk is split up in systematic risk and unsystematic risk. We follow Chevalier and Ellison (1999a) and measure a fund's systematic risk, $SysRisk_{i,t}$, by the factor loading on the market factor in model (1), $\beta_{i,M,t}$. The unsystematic risk component, $UnsysRisk_{i,t}$, is measured by the standard deviation of fund $i's$ residual fund return, $\sigma(\varepsilon_{i,m,t})$, from (1).[9]

Barber and Odean (2001) use the loading on the small-firm factor SMB as additional risk-measure, arguing that small firms tend to be riskier. We follow this approach and compute the beta loading on the Fama and French (1993) SMB factor, $\beta_{i,S,t}$, from the

[8] We only calculate PP_i if at least three years of performance ranks are available for fund i. Results are not qualitatively affected if we require at least four or five years of data instead.

[9] Alternatively, we also use the market factor loading from the three- and four-factor model and the respective standard deviation of the residuals from these models as our measures of the systematic and unsystematic risk, respectively. Results (not reported) are very similar.

three-factor model (2) for each fund in each year as fourth risk measure. We denote this measure as $SMBRisk_{i,t}$.

To capture the style of a fund, we compute the factor-weightings, $FactorWeighting^{f}_{i,t}$, on the other factors, where $f = SMB$, HML, and MOM, i.e. $\hat{\beta}_{i,S,t}$, $\hat{\beta}_{i,H,t}$, and $\hat{\beta}_{i,MO,t}$ from (3). Based on these factor weightings we calculate a style extremity measure, $EM_{i,t}$, for each fund i in each year t. According to Bär, Kempf, and Ruenzi (2005), the style extremity of a fund is reflected in unconventional high or low weightings on the SMB, HML, and MOM factor as compared to the average factor weightings calculated for each market segment and style factor for each year, $StyleBenchmark_f$. We calculate the absolute differences between fund factor weightings and the corresponding style benchmarks for each fund in each year. In order to make these differences homogeneous, we rescale them by the mean difference of the corresponding market segment in the respective year. This leaves us with three extremity values for each fund corresponding to the three style factors $f = SMB$, HML, and MOM:

$$EM^{f}_{i,t} = \frac{|(FactorWeighting_f)_{i,t} - (StyleBenchmark_f)^{k}_{i,t}|}{\frac{1}{N^k_t}\sum_{l=1}^{N^k_t} |(FactorWeighting_f)_{l,t} - (StyleBenchmark_f)^{k}_{l,t}|} \tag{6}$$

where k defines the corresponding market segment, N^k_t is the number of funds in this segment in year t and f represents the f^{th} factor. A higher value of EM^f for a fund corresponds to a more extreme factor weighting on factor f, i.e. to a more extreme style of this fund as compared to a (hypothetical) average fund in the respective segment. A typical fund with average extremity has, by construction, an extremity measure of 1 for each of the factors.

To get an aggregate measure of the extremity of each fund, we average the three individual factor extremity measures as defined in (6) on the fund level:

$$EM_{i,t} = \frac{1}{3} \sum_f EM_{i,t}^f. \quad (7)$$

Similarly as EM^f, the aggregate extremity measure, EM, of a fund with average overall style extremity is by definition 1. A higher value of EM indicates a more extreme style.

To analyze the style consistency of a fund, we employ the style variability measures developed in Bär, Kempf, and Ruenzi (2005). These measures capture a fund's style variability through time, based on its weightings on the SMB, HML, and MOM portfolios.[10] We use an absolute and a relative version of the style variability measures indicated by *abs* and *rel*. For the absolute style variability measures, we first calculate a style variability measure for each individual factor f based on the following equation:

$$SVM_i^f(abs) \quad = \quad \frac{STDev(FactorWeighting_f)_i}{\frac{1}{N_t^k} \sum_{l=1}^{N_t^k} STDev(FactorWeighting_f)_l}. \quad (8)$$

$SVM_i^f(abs)$ represents the absolute style variability of fund i with respect to a specific factor f. It is calculated as the rescaled standard deviation $STDev$ of its factor loading f over time. Standard deviations are rescaled as to make them homogeneous across factors and market segments.[11]

[10]Commonly used measures for style consistency are a fund's tracking error or the R^2 (e.g. Brown and Harlow (2005)). The former can be estimated as the volatility of the difference between fund returns and those of a corresponding benchmark. The latter, R^2, captures the portion of a fund's variability that is explained by the variance of benchmark portfolios. These variables can indicate a fund's active risk. However, they do not necessarily capture a fund's style variability through time. A low R^2 as well as a high tracking error can result either from a constant investment strategy with a high level of unsystematic risk or from changing style bets.

[11]To calculate this measure, we proceed in two steps, similar to the computation of our extremity measure in the previous section. For each fund, we first compute the standard deviations of a fund's yearly factor weightings over time. We exclude funds that have less than 3 years of data and funds with a manager change

In a last step, the individual factor style variability measures, SVM^f, are aggregated on the fund level to get a measure for the overall consistency of a fund's style over time:

$$SVM_i(abs) \quad = \quad \frac{1}{3}\sum_f SVM_i^f(abs). \tag{9}$$

Alternatively, we also measure a fund's style variation SVM_i^{rel} relative to the movements of a fund with average style characteristics in the respective market segment k. This allows us to control for shifting style-characteristics of the market segment a fund belongs to. For each fund, $SVM(rel)$ is calculated as the rescaled standard deviation, $STDev$, of the difference between each factor weighting f and the respective style benchmark:[12]

$$SVM_i^f(rel) \quad = \quad \frac{STDev\Big((FactorWeighting_f)_i - (StyleBenchmark_f)^k\Big)}{\frac{1}{N_t^k}\sum_{l=1}^{N_t^k} STDev\Big((FactorWeighting_f)_l - (StyleBenchmark_f)^k\Big)}. \tag{10}$$

The overall relative style variability measure of a fund, $SVM_i(rel)$, is defined as the average style variability with respect to the three factors:

$$SVM_i(rel) \quad = \quad \frac{1}{3}\sum_f SVM_i^f(rel). \tag{11}$$

during the observation period of at least 3 years. In the second step, we rescale the results by the average standard deviation of the respective factor loading of all funds in the same market segment.

[12]As $SVM^f(abs)$, this measure is also calculated in two steps. However, in this case we first compute the standard deviations of the difference between the individual fund factor weightings and the corresponding style benchmarks (as defined above). Accordingly, we rescale the results by the average standard deviation of this difference in the second step.

A higher value of the factor-individual as well as aggregate absolute (relative) style variability measures indicate a less consistent fund style over time (as compared to the style movements of a hypothetical fund with an average style variability in the same segment). A typical fund with average style variability has, by construction, a relative and absolute variability measure of 1. This holds for the factor-individual style-variability measures as well as for the aggregate style variability measures.

There are no data on real inflows of new money into individual funds contained in our database. Thus, we rely on the methodology suggested in Sirri and Tufano (1998) and calculate relative fund inflows by subtracting the internal growth of a fund due to the returns earned on assets under management, $r_{i,t}$, from the total growth rate of the fund's total net assets, TNA, under management:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}, \tag{12}$$

where $TNA_{i,t}$ is the size of fund i in year t measured in million USD.[13] $Flow_{i,t}$ implicitly assumes that all new money flows into the fund at the end of the period.[14]

Finally, we calculate two proxies for the political attitude of the population in the state a fund family is located. These proxies are calculated based on survey answers from the American National Election Studies Survey.[15] As a first proxy, we use the median degree of conservatism of all respondents in the state firm j is located in, $MDCons_j$, arguing that a more conservative population is generally less favorable of the employment of women. As an alternative proxy we calculate the median attitude towards women liberation from that survey, $MDWomLib_j$. Details on the construction of these proxies can be found in the Appendix.

[13] Ber and Ruenzi (2006) compare synthetic measures of funds inflows and actual fund inflows and show that (12) is a good proxy for actual inflows.

[14] Our results are very similar if we assume that all flows occur at the beginning or in the middle of the year.

[15] The National Election Studies, Center for Political Studies, University of Michigan. The ANES Guide to Public Opinion and Electoral Behavior (http://www.electionstudies.org/nesguide/nesguide.htm).

3.2 Summary Statistics

Our final database contains 13,547 fund year observations, out of which 12,075 have a male manager and 1,472 have a female manager. These observations are from a total of 3,333 distinct funds. Figure 1 graphs the total number of male and female managed funds as well as the percentage share of female managed funds over our sample period.

— Please insert FIGURE 1 approximately here —

While the total number of female managers increases slightly over time, the percentage of female managed mutual funds is low and constant at around 10% in each year.

Table 1 reports summary statistics for various characteristics of male and female managed funds from our sample.

— Please insert TABLE 1 approximately here —

It gives some interesting indications for our further analysis. Firstly, female managers are responsible for smaller funds. The average size of a female-managed fund is 676.53 million USD, while the average size of a male-managed fund is 806.08 million USD. The mean age of the funds managed by male and female managers is similar (10.12 vs. 10.07 years). Regarding manager tenure, findings indicate that female managers have an average tenure of four years, while male manager's tenure is about five years. With respect to fees, we find no clear pattern. Funds with a female manager have on average slightly lower expense ratios.[16] In contrast, average load fees are nearly 0.5% higher for female managed funds than for male managed funds. All differences are significant at the 1%-level. These figures have to be interpreted cautiously, as they are univariate in nature. However, they show that funds managed by male and female managers differ with respect to various characteristics. Thus, these fund-individual characteristics have to be controlled for in the following analysis.

[16] This might be due to lower management fees or lower trading costs. The data we have available does not allow us to disentangle these two effects.

4 Management Behavior of Female and Male Fund Managers

We start our empirical investigation by examining whether male and female managers manage their funds differently. Specifically we analyze differences in fund managers' behavior with respect to their risk-taking, their investment-style, and their trading activity.

4.1 Risk-Taking

Our Hypothesis 1 states that female fund managers take moderately less risk than male managers. We start by comparing the average risk taking of female and male fund managers in a univariate setting. We analyse total fund risk, $TotalRisk_{i,t}$, systematic risk, $SysRisk_{i,t}$, unsystematic risk, $UnsysRisk_{i,t}$, and small-firm risk, $SMBRisk_{i,t}$, as defined in Section 3. Results are presented in Panel A of Table 2.

— Please insert TABLE 2 approximately here —

Looking at total and systematic risk, we find that women take on average slightly less risk. However, the difference is not significant at conventional levels. When analyzing small-firm risk and unsystematic risk, we find that women take significantly less risk.[17] Thus, our findings of moderate differences in risk taking provide support for our Hypotheses 1. In a similar setting, Atkinson, Baird, and Frye (2003) also find significant influence of gender on the risk taking of fixed-income fund managers.[18] However, their and our hitherto presented findings are univariate. As we have shown earlier that fund characteristics between female and male managed funds differ (see Table 1), we have to control for these fund individual characteristics. Thus, we extend our examination and relate different measures of a fund's

[17] The difference in small-firm risk is only significant if we use the SMB-loading from the three factor model. It looses it's significance if we use the respective loading from a four-factor model instead (see Column 2 in Panel A of Table 3).

[18] Employing a limited sample, Bliss and Potter (2002) report higher average risk of female managed funds. Unfortunately, they do not provide information on the statistical significance of their univariate result.

risk to its manager's gender and other potentially relevant fund characteristics by estimating the following multivariate regression:

$$\begin{aligned} FundRisk_{i,t} &= \beta_1(FemDummy)_{i,t} + \beta_2(Age)_{i,t-1} + \beta_3(Size)_{i,t-1} \\ &\quad + \beta_4(Turnover)_{i,t-1} + \sum_k \beta_k(Segment)_{i,t} \\ &\quad + \sum_{y=1994}^{2003} \alpha_y \cdot D_y + \varepsilon_{i,t} \end{aligned} \tag{13}$$

In this equation, $FundRisk_{i,t}$ reflects one of our four risk measures for fund i in year t. $FemDummy_{i,t}$ is an indicator variable that equals one if the manager of the respective fund is female, and zero otherwise. $Age_{i,t-1}$ and $Size_{i,t-1}$ denote the logarithm of fund i's age in years and the logarithm of its total net assets in million USD (TNA), respectively. $Turnover_{i,t-1}$ is fund i's yearly turnover rate.[19] We include a set of segment and yearly dummy variables, $Segment_{i,t}$ and D_y, to capture segment- and year-specific effects. They take on the value one, if a fund belongs to segment k in year t and if the observation is from year t, respectively, and zero otherwise.[20] Panel B of Table 2 summarizes the findings.

We still find only weak evidence that female fund managers take less risk than their male counterparts. The coefficient of the female dummy is negative for all four risk measures analyzed, but its influence is only significant for small-firm risk and unsystematic risk. This confirms our univariate findings and again provides support for our first hypothesis. There are differences in risk-taking. However, they are less pronounced than the differences documented e.g. in Barber and Odean (2001) analyzing retail investor, who find highly significant differences irrespective of the specific risk-measure analyzed.

[19] We lag these explanatory variables by one year to mitigate potential endogeneity problems.

[20] We chose the 'Growth- and Income' segment as base segment and the year 1994 as base year and therefore leave out the respective dummy variables. Our results do not hinge on this specific choice of the base segment and year.

With respect to our control variables, findings correspond to Chevalier and Ellison (1997), who report a negative relationship between fund age and risk. The influence of fund size is nonuniform and differs depending on the specific risk measure analyzed. Similar as Golec (1996) we also find that a fund's turnover ratio is positively correlated with risk.

Although we could only document weak evidence for differences with respect to various risk measures, the significant difference in unsystematic risk documented above is a hint that male managers pursue more active investment styles and that they take more active bets. We examine differences in investment styles in the following section.

4.2 Average Investment Style

We start our inquiry of differences in investment styles by comparing the average styles followed by female and male fund managers. We calculate yearly factor weightings, $FactorWeighting^{f}_{i,t}$, on the SMB, HML, and MOM portfolios and compare the average factor weightings between female and male fund managers. Results are presented in Panel A of Table 3.

— Please insert TABLE 3 approximately here —

We find no pronounced differences in average investment styles with respect to the three factors. While the loading on the SMB factor seems to be lower for female managers and the loadings on the HML and MOM factor are a little bit higher for female managers. Only the difference with respect to the momentum factor is marginally significant.

To explore the robustness of this result, we now examine the style characteristics of a difference portfolio: We compute the return difference between an equally weighted portfolio consisting of all female-managed funds (F) and one consisting of all male-managed funds (M). This difference (F–M) is then regressed on the four Carhart (1997) factor portfolio returns. The respective factor loadings of the female-managed, the male-managed, and the difference portfolio are presented in Panel B of Table 3. Our findings confirm the results from above. We find no significant factor loadings of the difference portfolio with the exception of the loading on the momentum-factor. However, this methodology still does not take into account fund-individual characteristics.

Thus, as a third approach, we directly regress a fund's factor weightings, $FactorWeighting^f_{i,t}$, on a female dummy, $FemDummy$, and other potentially relevant fund characteristics:

$$
\begin{aligned}
FactorWeighting^f_{i,t} \quad = \quad & \beta_1(FemDummy)_{i,t} + \beta_2(Age)_{i,t-1} \\
& + \beta_3(Size)_{i,t-1} + \beta_4(Turnover)_{i,t-1} \\
& + \sum_k \beta_k(Segment) + \sum_{y=1994}^{2003} \alpha_y \cdot D_y + \varepsilon_{i,t},
\end{aligned} \tag{14}
$$

where f denotes the index for the f^{th} factor portfolio, i.e. $f = SMB, HML$ and MOM, respectively. Age, $Size$, and $Turnover$ are defined as in (13). To capture segment- and year-specific effects we include a set of segment and yearly dummy variables, $Segment_{i,t}$, and $D(y)_{i,t}$. Results are presented in Panel C of Table 3.

Findings generally confirm our results from above. The loading on the SMB factor is marginally lower for female managed funds. The loading on the momentum factor is significantly higher for female managers. This effect is significant at the 5%-level. A possible explanation for this result is given by the following reasoning: A momentum strategy requires to buy past winners and to sell past losers. We argue that it might be easier for women than for men to not hold on to their losers too long. The tendency to hold on to losers too long is called disposition effect (Shefrin and Statman (1985)). A strong disposition effect can be driven by cognitive dissonance. Cognitive dissonance leads investors to overestimate the past performance of their stocks and thus prevents them from selling their losers. Blanton, Pelham, DeHart, and Carvallo (2001) show that overconfidence and cognitive dissonance are positively related. Taken together with the findings of Barber and Odean (2001) that men are more overconfident than women, this might explain why women are less prone to the disposition effect and eventually are more likely to follow momentum strategies.

There is no significant difference with respect to the HML factor. Overall, differences in average investment style are - with the notable exception of loadings on the momentum factor - very small. However, note that these findings are with respect to *average* fund styles only. It is still possible, that the individual managers in one of the groups (male and female) take much more active style bets in opposite directions, an effect that might be canceled out when looking at average styles. To address this issue, we specifically examine the extremity of the styles of individual funds in the next section.

4.3 Style Extremity

In the following analysis we test our Hypothesis 2 and examine whether female fund managers pursue less extreme investment styles than male managers. We start by comparing the average extremity of female and male managed funds. We analyze the individual factor extremity measures, EM^f, with $f = SMB$, HML and MOM as defined in (6) and the aggregate extremity measure, EM, as defined in (7). Results are presented in Panel A of Table 4.

— Please insert TABLE 4 approximately here —

The higher average EM for male-managed funds than for female managed funds in Column 2 suggests that men indeed follow more extreme investment styles. The difference is highly statistical significant. This finding confirms our expectation that female fund managers deviate less from their specific market benchmark than their male counterparts.

Columns 3 to 5 show the average deviation of female and male fund managers from the corresponding style benchmarks for each of the three factors separately. Our results not only hold for the aggregate level of factor deviations, but also for all of the three factors individually.

We now turn to a multivariate examination of style extremity. We relate a fund's style extremity to a female-dummy and the same independent variables as in model (14). Results are presented in Panel B of Table 4. We find a highly significant negative influence of the female dummy on our extremity measures, confirming our univariate finding that women follow less extreme investment styles. Again, this finding holds for the aggregate style extremity measure, EM, (Column 2) as well as for the three individual style extremity measures, EM^f, (Columns 3-5). Overall, these results lend very strong and robust support in favor of our Hypothesis 2 that women follow less extreme investment styles.

4.4 Style Consistency Over Time

In the next step we examine how stable investment styles of male and female managed funds are over time. This allows us to test our Hypothesis 3, according to which we expect the investment styles of women to be more consistent over time than those of men.

To compare the style consistency of funds with female or male fund managers, we employ our style variability measures, $SVM(abs)$ and $SVM(rel)$, as defined in (9) and (11), respectively. They capture a fund's style variability through time, based on its weightings on the SMB, HML, and MOM portfolios. Results are presented in Table 5.

— Please insert TABLE 5 approximately here —

Column 2 of Table 5 shows the (absolute and relative) average style variability measures for female- and male-managed funds. $SVM(abs)$ and $SVM(rel)$ are significantly lower for funds with a female manager than for those with a male manager (0.79 versus 1.01 and 0.85

versus 1.01). We find that female fund managers, more than their male counterparts, hold on to their style decisions in absolute terms as well as in relation to the style movements of a typical fund with average style characteristics in the respective segment. This finding also holds for each of the three factors separately (Columns 3–5). We observe that female fund managers follow a significantly more consistent investment style in all of the three style dimensions, both in absolute terms as well as relative to a corresponding style benchmark. These results provide clear evidence in support of our Hypothesis 3.

4.5 Trading Activity

We now turn to the examination of our last behavioral hypotheses. According to Hypotheses 4 we expect female fund managers to be less overconfident and thus to trade less than male fund managers.

We use a fund's turnover ratio to measure the fund manager's trading activity. Univariate results of a comparison of the turnover ratios of male and female fund managers do indeed indicate that the average turnover ratio of the latter is significantly higher than that of the first (see Panel A of Table 6).

— Please insert TABLE 6 approximately here —

To examine this difference in some more detail, we turn to a multivariate model. Nicolosi, Peng, and Zhu (2004) argue that previous performance might reinforce a manager's overconfidence and eventually trading activity. Therefore, we have to control for the influence of lagged performance. Furthermore, Fortin, Michelson, and Jordan-Wagner (1999) find that manager tenure is negatively related to a fund's turnover ratio. Therefore, it is also included as explanatory variable. We relate a fund's annual turnover ratio to a female dummy and further potentially relevant fund characteristics using the following multivariate model:

$$
\begin{aligned}
Turnover_{i,t} &= \beta_1 FemDummy_{i,t} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} \\
&\quad + \beta_4 Perf_{i,t-1} + \beta_5 MgerTenure_{i,t} + \\
&\quad + \sum_k \beta_k (Segment) + \sum_{y=1994}^{2003} \alpha_y \cdot D_y + \varepsilon_{i,t}. \qquad (15)
\end{aligned}
$$

In this equation, $Turnover_{i,t}$ is a fund's annual turnover ratio. $Perf_{i,t-1}$ and $MgerTenure_{i,t}$ denote lagged performance measured by the Carhart (1997) four-factor alpha and the tenure of fund i's manager in years, respectively.[21] The other independent variables are defined as above. Panel B of Table 6 summarizes the findings.

Our results confirm the univariate findings and show that female fund managers trade less than male fund managers. Although the coefficient is only significant at the 10%-level, the estimate for the influence of the female dummy is -0.09, indicating that female fund managers, ceteris paribus, decrease the turnover ratio by an economically meaningful 9% p.a. This confirms our Hypothesis 4.

We also confirm findings of Nicolosi, Peng, and Zhu (2004) and Fortin, Michelson, and Jordan-Wagner (1999) on the positive relationship between turnover ratio and lagged performance and on the negative relationship between turnover ratio and manager tenure, respectively.

To sum up, we find convincing evidence of strong behavioral differences between male and female managers. Although differences in risk taking seem to be moderate, there are pronounced differences between the investment styles of women and men. Male managers tend to be more aggressive, which is reflected in more extreme investment styles that change more rapidly over time than those of female managers. Furthermore, their trading activity is significantly higher than that of female fund managers. Taken together, our findings show

[21] Using one-factor alphas, three-factor alphas or the modified Appraisal Ratio as defined in Section 3 instead of the four-factor alphas as performance measure does not influence the results.

that fund investors can generally use the manager's gender as a clear and easily observable indication for a fund's style characteristics. Potential consequences of the behavioral differences documented on performance and fund flows are analyzed in the following section.

5 Consequences of Managers' Gender on Performance and Fund Inflows

5.1 Performance

Based on our findings on behavioral differences between female and male fund managers from the previous section and according to Hypothesis 5 we expect male managers to underperform female managers. We start our examination with a portfolio approach, comparing the performance of a portfolio consisting of female- and male-managed funds. Then, we examine performance in a multivariate setting, relating fund performance to the manager's gender as well as other fund characteristics.

5.1.1 Portfolio Evidence

Our first approach is to examine gender differences in the performance of fund portfolios with solely female and male managers, respectively. We measure fund performance by abnormal returns. We employ a one-factor market model, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model as described in Section 3. At the end of each year, we assign all funds according to their manager's gender to a female-managed fund portfolio (F) or a male-managed fund portfolio (M). For each portfolio we compute a return time series by equally weighting the funds' returns in each group. To examine potential gender specific performance differences, we analyze a portfolio that is constructed by subtracting male-managed fund portfolio returns from female-managed fund portfolio returns (F-M). We examine abnormal returns before as well as after subtracting expenses. Returns before expenses better assess the actual investment ability of a fund manager, whereas mutual fund investors are ultimately interested in returns after expenses. Table 7 summarizes our results.

— Please insert TABLE 7 approximately here —

We find that the female as well as the male managed fund portfolio generally generates negative abnormal returns even before expenses (Panel A). The only exception is the abnormal return from a one-factor market model for the portfolio of female fund managers, where the abnormal return is slightly positive. However, none of the abnormal returns is significantly different from zero on a before expenses basis. When comparing the portfolio of female-managed funds to the one with male managers, we find no statistically significant difference. This runs counter to our hypothesis that female fund managers outperform male managers.[22]

Looking at abnormal returns after expenses (Panel B) we find negative alphas for the female and the male manager portfolio, irrespective of which model we use. Applying the three- and four-factor model, the abnormal returns for both groups are significant at the 5% and 10% level, respectively. Again, the abnormal return of the difference portfolio F–M is not statistically significant. To confirm this finding, we extend our analysis to a multivariate regression framework.

5.1.2 Multivariate Regression Evidence

The following approach examines the management-performance relation at the individual fund level rather than at the fund portfolio level. It enables us to control for fund characteristics according to which female- and male-managed funds differ and that are possibly

[22]Instead of testing equally weighted portfolios, we also analyze value-weighted fund portfolios. Results on performance differences are very similar. We still find no significant difference between the performance of the female- and the male-managed fund portfolio.

related to fund performance. To analyze the influence of the manager's gender on fund performance, we estimate the following regression:

$$
\begin{aligned}
Perf_{i,t} \quad = \quad & \beta_1(FemDummy)_{i,t} + \beta_2(Perf)_{i,t-1} + \beta_3(Age)_{i,t-1} + \beta_4(Size)_{i,t-1} \\
& + \beta_5(Expenses)_{i,t-1} + \sum_k \beta_k(Segment) + \sum_{t=1994}^{2003} \alpha_t \cdot D_t + \varepsilon_{i,t}. \qquad (16)
\end{aligned}
$$

In this equation, $Perf_{i,t}$, is the performance of fund i in year t. It is measured by abnormal returns from the one-, three- and four-factor model. Additionally, we also analyze an extended version of the Appraisal Ratio of Treynor and Black (1973), $AR_{i,t}$, as defined in (4). Performance is related to a female dummy, $FemDummy_{i,t}$, and other potentially relevant characteristics like age, size, and turnover (as defined in the previous sections). $Expenses_{i,t-1}$ denotes the fund's yearly total expense ratio. To control for segment- and year-specific effects, (16) also includes segment- and time dummies. Results are presented in Table 8.

— Please insert TABLE 8 approximately here —

Like in our portfolio analysis, there is no significant difference due to the manager's gender for the alpha measures (Column 2–4). The influence of the female dummy is never significant at conventional levels.

Findings from Section 4.1 suggest that female fund managers take significantly lower levels of unsystematic risk. To take into account the effect of unsystematic risk, we use the Appraisal Ratio as defined above as alternative performance measures. Results are presented in Column 5. Consistent with our earlier findings, we do not find any significant influence of a fund manager's gender on fund performance.[23] Although female and male fund managers differ in terms of investment behavior, these differences are not reflected in differences in

[23] Atkinson, Baird, and Frye (2003) report a similar finding for their sample of fixed income funds.

performance. These results suggest that the market for mutual fund managers is efficient. It is not possible to generate abnormal returns by following an investment strategy in mutual funds based on a manager characteristic as easily observable as the manager's gender.

5.2 Dispersion of Performance Ranks

Although average performance is similar, it is still likely that the dispersion of performance ranks differs between female and male managed funds. According to Hypothesis 6 we expect the more extreme style bets documented in Section 4.3 to be reflected in more extreme performance ranks. To get a first idea about the dispersion of performance ranks, we compute the share of male managers in different percentiles of the performance distribution. Results are summarized in Figure 2.

— Please insert FIGURE 2 approximately here —

We observe a clear U-shaped relationship between the share of male managers and performance percentiles, where performance is calculated as Jensen's alpha. This indicates that female managers are more likely to achieve moderate performance ranks, while male managers are more likely to achieve extreme (good or bad) ranks. This is also confirmed by the numbers underlying Figure 2, which are summarized in Table 9.

— Please insert TABLE 9 approximately here —

The share of male managed funds is 94.1% (96.0%) among the best (worst) 1% of all funds in a year. This is clearly more than the unconditional share of male managed funds in our sample of 89.14 %. Looking at the top- and bottom 5% of all funds it is still above 90%. In contrast, the share of male managers drops to below 90% for the middle 80% of the performance distribution.

We now extend our analysis to a multivariate framework. This allows us to take into account fund individual characteristics that might influence the extremity of performance outcomes. We relate the probability of a fund achieving specific performance percentiles to a female dummy and various fund characteristics in the following logit model:

$$\begin{aligned} Prob(Percentile)_{i,t} &= \beta_1(FemDummy)_{i,t} + \beta_2(Age)_{i,t-1} \\ &+\beta_3(Size)_{i,t-1} + \beta_4(Turnover)_{i,t-1} \\ &+\sum_k \beta_k(Segment) + \sum_{y=1994}^{2003} \alpha_y \cdot D_y + \varepsilon_{i,t}, \end{aligned} \tag{17}$$

where $Prob(Percentile)_{i,t}$ is the probability that fund i is in the indicated percentile, *Percentile*, in year t. We test the probability of a fund being among the top or bottom 1% and 5%, respectively, of all funds in a given year t. Results are presented in Table 10.[24]

— Please insert TABLE 10 approximately here —

Panel A, Column 2, presents results for the probability of achieving a performance among the best or worst 1% of all funds, while Column 3 (4) contains the results for the probability of achieving a performance among the best (worst) 1% of all funds. Results indicate that women are significantly less likely to achieve a performance among the best or worst 1% of all funds. This result is driven by a lower probability of achieving a very good as well as a very bad performance. If we control for the styles followed by the fund manager and analyze 3- and 4-factor alphas, we find no significant differences between female and male managers anymore. This confirms our reasoning that more extreme performance outcomes of male managers are driven by the more extreme style bets they take.

[24] For the sake of clarity we only report estimated coefficients for the influence of the female dummy.

Results are similar if we look at the probability of a fund achieving a performance among the 10% most extreme outcomes (top 5% and bottom 5%). We still find a significantly lower probability of a female manager ending up among the best or worst 5% of all funds. However, in this case only the probability of being among the very worst funds is lower for female managers. They are not significantly less likely to achieve a rank among the top 5% of funds. Again, this finding only holds if we analyze Jensen's alphas and vanishes if we control for the styles followed by the fund.

5.3 Performance Persistence

We now turn to the examination of the question whether the higher probability of male managers achieving extreme performance ranks leads to less persistent performance, as argued in Hypothesis 7.

In order to directly examine differences in performance persistence we analyze our fund individual performance persistence measures, PP_i, defined in (5) as the standard deviation of return ranks over time. We expect female fund managers to exhibit lower levels of PP_i than male managers, which corresponds to lower persistence in performance of the latter. Results on the average levels of PP_i for different performance measures are presented in Table 11.

— Please insert TABLE 11 approximately here —

If we base return ranks on Jensen's Alphas, PP_i is 23.40% for female managers and 25.12% for male managers. The difference is significant at the 1%-level. This suggests that performance ranks of male managers are more variable over time and lends strong support to our Hypothesis 7 that female managed funds are more persistent in their performance. This result holds irrespective of the specific performance measure chosen to calculate ranks. Using 3- and 4-factor Alphas, the difference is even more pronounced.

5.4 Fund Inflows

In order to examine the influence of a manager's gender on the investment decisions of mutual fund investors, we analyze inflows of new money. According to Hypothesis 8 we expect stereotyping of fund investors to cause female managed funds to have lower inflows, because many investors may think women are worse than men when it comes to managing money (see Section 2).

To get a first idea about differences in fund flows we examine univariate differences in a fund's relative net inflows between female and male managed funds. Results are presented in Panel A of Table 12.

— Please insert TABLE 12 approximately here —

Findings indicate, that female-managed funds have lower net-inflows than male-managed funds. While the first have annual inflows of 15%, the latter have nearly double the inflows (29% p.a.). The difference is statistically significant at the 1%-level. This lends first supportive evidence in favor of our Hypothesis 8.

As fund flows are related to many other charcteristics besides gender, we now turn to the examination of fund inflows in a multivariate setting. We relate inflows of new money into the fund to a female dummy and several characterstics that have proven to influence fund inflows. Specifically, we have to control for the influence of past performance on fund inflows. Ippolito (1992) has shown, that past performance has a nonlinear impact on fund inflows. Thus, we use two alternative models suggested in the literature to capture this non-linearity. Firstly, we follow Barber, Odean, and Zheng (2004) and Ruenzi (2005) and estimate a quadratic performance flow relationship:

$$Flow_{i,t} = \beta_1(FemDummy)_{i,t} + \beta_2(Flow)_{i,t-1} + \beta_3(PerfRank)_{i,t-1} + \beta_4(PerfRank)^2_{i,t-1}$$

$$+\beta_5(Risk)_{i,t-1} + \beta_6(Age)_{i,t-1} + \beta_7(Size)_{i,t-1} + \beta_8(Turnover)_{i,t-1}$$
$$+\beta_9(Fees)_{i,t-1} + \beta_{10}(SegmentFlow)_{i,t} + \beta_{11}(FamilySize)_{i,t-1}$$
$$+\beta_{12}(FamilyAge)_{i,t-1} + \beta_{13}(FamilyFlow)_{i,t} + \sum_{y=1994}^{2003} \alpha_y \cdot D_y + \varepsilon_{i,t} \tag{18}$$

To capture the influence of the manager's gender on a fund's relativ net inflows, $Flow_{i,t}$, we use a female dummy, $FemDummy$, as explanatory variable. Besides, we control for the influence of several other variables that are used in the literature: $Flow_{i,t-1}$ are the lagged inflows of fund i.[25] We use the lagged return-rank of a fund in its segment, $PerfRank_{i,t-1}$, and the square of the past performance rank to capture the nonlinear performance-flow relationship.[26] We also control for the influence of fund risk, $Risk_{i,t-1}$, measured by the return standard deviation. We include fund age, size, and turnover. They are defined in the same way as in the previous regressions. $Fees_{i,t-1}$ is defined as the sum of the yearly total expense ratio and $\frac{1}{7}$ of the total load fees.[27] To capture family-specific effects, we include family size, $FamilySize_{i,t-1}$, the age of the fund's family, $FamilyAge_{i,t-1}$, and the relative inflows into the fund's family (net of the funds own inflows), $FamilyFlow_{i,t}$, in our regressions. To control for factors affecting inflows of new money into the whole segment the fund belongs to, we add the growth rate due to inflows of the respective market segment, $SegmentFlow_{i,t}$. We also add a set of yearly dummies as defined in previous regressions.

[25] Patel, Zeckhauser, and Hendricks (1991) find a positive influence of lagged inflows on actual inflows and argue that this might be due to fund investors being subject to a status-quo bias. This bias leads them to repeatedly buy the same fund which eventually leads to positive autocorrelation of fund flows (see Kempf and Ruenzi (2006)).

[26] We use ranks based on returns as Patel, Zeckhauser, and Hendricks (1991) have shown, that ordinal performance measures can explain fund inflows much better than cardinal measures. Ranks are calculated based on raw returns for each year and segment separately and are distributed between 0 and 1. Instead of using ranks based on raw returns, we also use ranks based on other performance measures like the three- or four-factor alpha. Results (not reported) are very similar.

[27] This measure for the total fee burden is suggested in Sirri and Tufano (1998). They assume an average holding period of fund investors of 7 years.

We estimate (18) using a pooled regression approach as well as Fama and MacBeth (1973) regressions.[28] Estimation results are presented in Columns 2 and 4 of Panel B in Table 12.

Our findings confirm our univariate results and suggest, that net inflows of a female managed fund are significantly lower than those of a male managed fund. The estimate for the influence of the female dummy is highly economically significant: a female managed fund grows by 17% p.a. less than a comparable fund that is managed by a male fund manager. This result remains very stable, irrespective of whether we use Fama and MacBeth (1973) regressions (Column 2) or pooled regressions (Column 4). This lends surprisingly strong support for Hypothesis 8.

Regarding our results on the influence of the control variables, we find evidence for a convex performance-flow relationship as indicated by the significantly positive influence of the squared performance rank. This result and the influence of the other control variables are generally in line with results reported in the literature (see, e.g., Sirri and Tufano (1998) and Ruenzi (2005)).

As an alternative approach we use the piecewise-linear regression approach suggested in Sirri and Tufano (1998) to capture the convexity of the performance-flow relationship in order to assess the robustness of our surprisingly strong finding. Therefore, we replace $PerfRank_{i,t-1}$ and $PerfRank^2_{i,t-1}$ by the piecewise linear regression coefficients $Quintile1_{i,t-1}$ for the lowest performance quintile, $Quintile2-4_{i,t-1}$ for the three middle quintiles grouped together and $Quintile5_{i,t-1}$ for the top quintile.[29] This methodology allows us to estimate distinct slope coefficients for different performance quintiles. Results are

[28] While estimating the annual Fama McBeth regressions, the yearly dummies are replaced by a constant.

[29] The piecewise linear regression coefficients are calculated according to the following definitions: $Quintile1_{i,t-1} = \min(PerfRank_{i,t-1}, 0.2)$, $Quintile2-4_{i,t-1} = \min(PerfRank_{i,t-1} - Quintile1_{i,t-1}, 0.6)$ and $Quintile5_{i,t-1} = PerfRank_{i,t-1} - (Quintile1_{i,t-1} + Quintile2-4_{i,t-1})$. Results (not reported) are very similar if we model a distinct slope coefficient for each of the five performance quintiles instead of grouping the three middle quintiles together.

presented in Columns 3 and 5 of Panel B of Table 12 and confirm our earlier findings of a convex performance-flow relationship.

The estimates for the influence of the female dummy are not substantially affected by the modelling technique. Depending on how we model the convexity of the performance flow relationship, results still indicate that female-managed funds have relative inflows that are by 17-18% p.a. lower than those of male-managed funds. This confirms our earlier findings and lends further support in favor of Hypothesis 8.

The most pronounced difference between female- and male managed funds in Table 1 is with respect to assets under management that are much smaller in female managed funds. At the same time, the influence of fund size on fund inflows is very strong. To further analyze the stability of our result, we want to make sure that we also capture possible non-linearities of the influence of size on fund flows that might have been reflected by the influence of the female dummy (which could possibly just capture a 'small-fund effect'). Thus, we rerun our regression introducing fund size to the power of two and three as explanatory variables. Results (not reported) on the influence of the female dummy remain very similar. Hypothesis 8 is still strongly supported. Although female managed funds offer more stable and less extreme style and performance characteristics than male managed funds, which might be preferable from an investor's point of view, our results suggest that this potential positive effect is more than compensated by the negative attitude of investor's towards female fund managers.

We shortly sum up our findings on consequences of fund manager's gender on performance and inflows from this section: Although average performance is very similar, male managed funds are much more likely to achieve extreme performance ranks. This is in line with the finding of more extreme style bets of fund managers, that obviously lead to more extreme performance outcomes. Furthermore, the more extreme style bets of male managers seem to work out well in some years, but not in others. This leads to a significantly higher performance persistence of female managers as compared to male managers. As a fund management company is ultimately interested in net-inflows of new money, our last finding of lower inflows into female managed funds provides a possible explanation why the proportion of female fund managers remains low over our whole sample period: female fund managers are not hired as regularly because they seem to generate significantly lower inflows.

6 Who Employs Women?

Based on the previous results on significantly lower inflows into female managed funds, one could argue that even the small share of about 10% female fund managers is still surprisingly high. Why should a fund management company employ women at all, if they do not generate superior returns but have profoundly lower inflows?

Based on Hypothesis 9, we expect that women are mainly employed by families that are large and well-established, because these are more likely to be sued in anti-discrimination lawsuits and also have a higher reputational capital at stake. Furthermore, these families have to cater to institutional investors that often require workforce-diversity from the firms they do business with. Using a fund family's total assets under management in all equity funds offered by the family as a proxy for its size and its age as proxy for its reputation, we expect a positive influence of both measures on the likelihood that this family employs women.[30] We examine the determinants of the share of female fund managers within a fund family j in year t, $Share(FemMger)_{j,t}$, by estimating the following multivariate model:

$$\begin{aligned} Share(FemMger)_{j,t} &= \beta_1(FamTNA)_{j,t-1} + \beta_2(FamAge)_{j,t-1} \\ &\quad + \beta_3(AvrgeFundSize)_{j,t-1} + \beta_4(AvrgeFundAge)_{j,t-1} \end{aligned}$$

[30] Alternatively, we also use the number of equity funds offered by the family as a proxy for its size. Results (not reported) are very similar.

$$+\sum_k \beta_k (FamSegment)^k_{j,t} + \sum_{y=1994}^{2003} \alpha_y \cdot D_y + \varepsilon_{i,t} \qquad (19)$$

In this regression, $FamTNA_{j,t-1}$ and $FamAge_{j,t-1}$ denote the size of the family, measured by the logarithm of the total assets under management of all equity funds within the family, and the logarithm of the age of the family in years, respectively. As there are significant differences in the characteristics of funds managed by men and women, we add average fund characteristics of the funds within the family as additional independent variables: $AvrgeFundSize_{j,t-1}$ and $AvrgeFundAge_{j,t-1}$ denote the logarithm of the mean size in millions of assets under management and of the mean age in years of all equity funds in the family. We control for the segments the fund family is doing business in by adding $FamSegment^k_{j,t}$, the share of funds family j offers in segment k. Finally, we add a set of yearly dummies, D_y, to control for year-specific effects. Panel A in Table 13 summarizes the results of an OLS estimation of (19).[31]

— Please insert TABLE 13 approximately here —

We find a significantly positive influence of the size of the family on the likelihood of women being employed in this family (Columns 2–5). The influence of the age of the family is also positive, but not significant at conventional levels.[32] This lends some support to our Hypothesis 9 that large and well-established families are more likely to employ women.

In a final step, we examine whether socio-demographic characteristics of the population of the fund company's location matter for the employment of women. According to Hypothesis 10, we expect fund families located in regions whose population is less favorable of the employment of women to be less likely to employ female fund managers. Therefore,

[31] Since our dependent variable is constrained to values between 0 and 1, we also employ a censored regression approach (tobit-estimation). Results (not reported) are very similar.

[32] Naturally, the age and size of a family are highly positively correlated, which leads to potential problems of multi-collinearity. Even in this case one still gets consistent and unbiased estimators. However, standard errors will be high and it is therefore harder to find significant results.

we add $MDCons_j$ and $MDWomLib_j$ as measures for the conservatism and the attitude towards women liberation in the state fund family j is located in to (19).[33] Results are presented in Columns 3–5 of Table 13. Irrespective of whether we include only one of the proxies (Columns 3 and 4) or both of them simultaneously (Column 5), we always find a highly significant influence in the expected direction: $MDCons_j$ influences the likelihood of the employment of women negatively, while $MDWomLib_j$ has a positive influence. Fund companies located in conservative states and states with a negative attitude towards women liberation employ less women. This is strong evidence in support of our last Hypothesis 10.

Instead of using OLS analysis, we also relate the probability of a fund family employing any female managers at all to the same explanatory variables as in (19) using a Logit model. Results are presented in Panel B of Table 13. They confirm our earlier findings. Using this methodology, the influence of family age becomes significant, too. This delivers further evidence supporting our Hypothesis 9 and 10.

Taken together, women are mainly employed by those fund families most likely to be sued for discrimination and those families whose customers might ask for workforce diversity among fund managers. Furthermore, the location of the fund family matters for the employment of women. Fund families located in less conservative states and in states with a more positive attitude towards the employment of women are considerably more likely to employ women than fund families in other states of the U.S.

7 Implications and Conclusion

While we can not confirm whether women are from Venus, and men are from Mars, our study at least shows that male and female fund managers are not identical. We document several important differences in the way they manage their portfolios and analyze consequences for fund performance and inflows.

[33] These proxies are described in more detail in Section 3 and in the appendix.

Firstly, women seem to take moderately less risk. Specifically, we find that women take less unsystematic risk and less small firm risk, while overall return risk does not differ systematically. This finding differs from findings for individual investors, where much more pronounced differences in risk taking are documented (Barber and Odean (2001)). This provides support for the hypothesis of Johnson and Powell (1994) who argue that women in a managerial sub-population often behave very similar to men.

The significantly higher idiosyncratic risk of male fund managers we document hints at more active trading strategies as compared to female fund managers. This reasoning is confirmed by our examination of investment styles. Woman follow significantly less extreme investment styles, as reflected by factor loadings closer to the average fund in their respective segment than those of male managers. Furthermore, their styles are more stable over time. Finally, we find that male managers trade more actively, which is reflected in a significantly higher turnover ratio as compared to female managers. A higher turnover ratio is regularly interpreted as an indication of overconfidence (Barber and Odean (2001)).

Overall, our findings on behavioral differences between male and female managers suggest, that investors preferring moderate and stable investment styles should invest in female managed funds, while more daring investors interested in funds that take more active bets should choose male managed funds.

However, fund investors are ultimately mainly concerned about performance. We do not find any significant differences in abnormal returns between female- and male-managed funds. This indicates that the market for fund managers is efficient in the sense that it is not possible to find superior managers by just looking at an obvious characteristic like the manager's gender. Furthermore, male managers are much more likely to achieve an extreme (good or bad) rank position than female managers and the performance of the latter is more persistent over time. This effect can be explained by the more extreme style bets of male managers.

While investors are directly interested in performance, fund management companies care more about inflows of money. Our examination of the influence of gender on inflows shows that female-managed funds grow by a surprisingly large 18% p.a. less (on an absolute basis) than comparable male-managed funds. A possible reason for this strong effect is that many investors consider women as less able to manage money. Our finding of significant lower inflows of female managed funds is also a likely explanation why we only see about 10% female-managed funds at all.

Given the comparable performance of female and male managers, the strong negative flow effect raises the provocative question, why fund families employ women at all for the management of their funds? We argue that not employing women entails the threat of being sued for discrimination. We do indeed find that those firms most likely to be sued, i.e. large and well-established fund companies, are also most likely to employ women. These are also the firms who often cater to large institutional investors who regularly require workforce diversity from the investment companies they do business with. Finally, we also show that location matters for the employment of women. Fund families located in states of the U.S. with a generally less favorable attitude towards the employment of women are also less likely to employ women as fund managers.

One possible implication of our study is that fund companies should be more concerned about investor education. Investors should be taught that female-managed funds do not underperform and that they usually show investment styles and performance characteristics that are less extreme and more stable, characteristics investors might prefer to the more aggressive investment styles of male managers. Furthermore, the much more pronounced style variability of male-managed funds can be a problem many investors might not be aware of. Often, fund investors construct a fund portfolio with specific style characteristics based on the investment styles funds have shown in the past. In the case of male-managed funds they might end up with a fund that shows style characteristics that are quite different from what they were expecting. Consequently, this fund does not fit into the investor's fund portfolio anymore which eventually leads to a suboptimal performance.

Appendix

Gender Classification

To identify a fund manager's gender we first extract the manager's first name from the CRSP database. From a list published by the U.S. Social Security Administration (SSA) that contains the most popular first names by gender for the last 10 decades we get 2,179 different male and 2,515 different female first names that also account for differences in spelling.[34] We then match this list with the first names taken from the CRSP database and thereby classify most of the managers as male or female. Remaining names are those we could not clearly classify as male or female, i.e. foreign names or ambiguous names. We were able to identify most of the foreign names by asking students from the respective country. Finally, we identify fund managers' gender by several internet sources like the fund prospectus, press releases or photographs that reveal their gender. This leaves us with an identification rate of 99,39%.

Construction of Conservatism and Women Liberation Proxies

Our proxy for the degree of conservatism in a certain state of the US is constructed from the American National Election Survey 1948 – 2002 Cumulative Data File.[35] This survey is conducted to get an impression of the public opinion towards different topics and contains two questions that are of interest for our analysis, the degree of conservatism and the attitude towards women liberation. These questions have to be answered with a so called "feeling thermometer". Thermometer questions are introduced as follows:

> "We'd also like to get your feelings about some groups in American society. When I read the name of a group, we'd like you to rate it with what we call

[34] First names that appeared for both sexes have been excluded from the SSA-List. For further information see `http://www.ssa.gov`.

[35] The National Election Studies, Center for Political Studies, University of Michigan. The ANES Guide to Public Opinion and Electoral Behavior (`http://www.electionstudies.org/nesguide/nesguide.htm`). Any opinion, findings and conclusions or recommendations expressed in this paper are those of the authors and do no necessarily reflect those of the funding agencies of the survey.

> a feeling thermometer. Ratings between 50 degrees-100 degrees mean that you feel favorably and warm toward the group; ratings between 0 and 50 degrees mean that you don't feel favorably towards the group and that you don't care too much for that group. If you don't feel particularly warm or cold toward a group you would rate them at 50 degrees. If we come to a group you don't know much about, just tell me and we'll move on to the next one."

We extract answers from the conservatives-thermometer and the women's movement-feeling thermometer that were given during our sample period from $1994 - 2002$.[36] The survey also contains the state where the respective respondent grew up, so that we can construct a table with the median answer to the respective question that was given by all respondents from a certain state of the US during our sample period.

This list is matched with our sample of fund families. To identify the geographical location of a fund family's headquarter, we use a list provided by Jerry Parwada (University of New South Wales, Sydney). Missing addresses of fund families that we did not find in this list have been hand collected from several internet resources.

In the last step we match the degree of conservatism/ attitude towards women movement of the respective state taken from ANES with the fund family's location, by identifying the state where the headquarter of the fund family is located.

[36]We are not able to cover the last year of our sample period, 2003, as no data is available from the survey for this period yet. Furthermore, we excluded answers given to a female interviewer to preclude a potential social desirability bias (see Richman, Kiesler, Weisband, and Drasgow (1999)).

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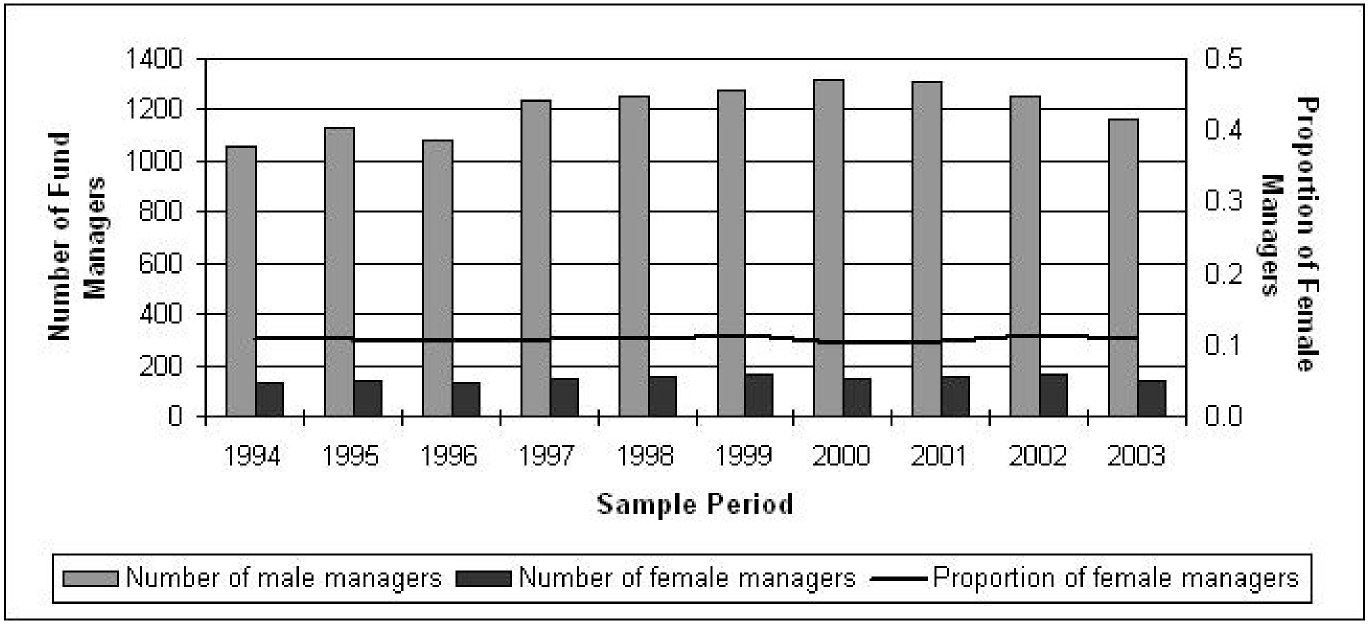
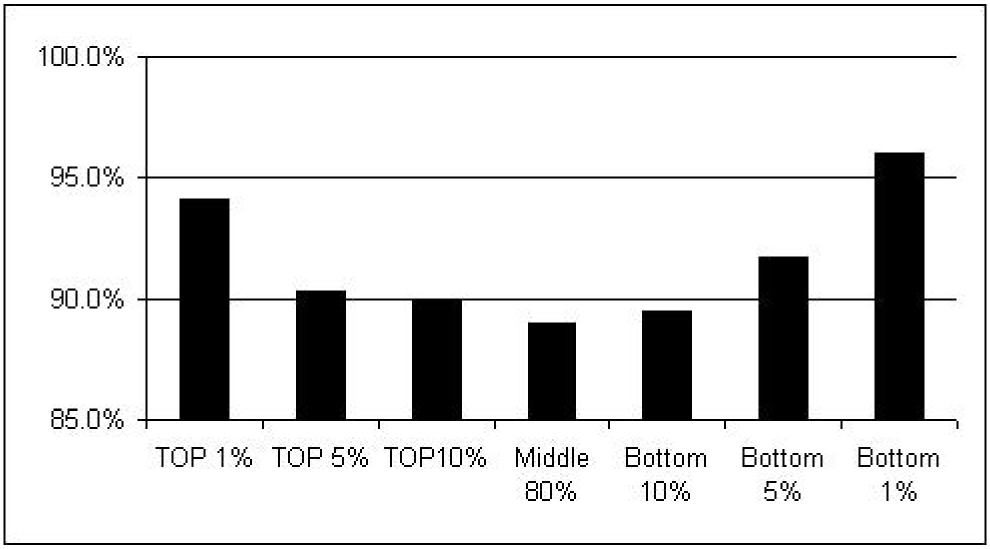
Figure 1: Distribution of Managers by Gender



This figure shows the percentage of female managers and the total number of male and female managers for each year of our sample.

Figure 2: Dispersion of Performance



This figure shows the percentage of male managers within different performance percentiles. Performance for each fund in each year is measured by its Jensen's Alpha.

Table 1: Average Fund Characteristics

	Female Manager	Male Manager	Difference
Fund Size (in Millions)	676.53	806.08	-129.55^{***}
Fund Age (in years)	10.12	10.07	0.05^{***}
Manager Tenure (in years)	4.17	5.22	-1.05^{***}
Expense Ratio (in %)	1.42	1.48	-0.06^{***}
Total Loads (in %)	2.62	2.09	0.53^{***}

*** 1% significance, ** 5% significance, *10% significance

Table 2: Individual Fund Risk

Panel A: Univariate Approach

	Total Risk	Systematic Risk	Small-Firm Risk	Unsystematic Risk
female	0.04979	0.04564	0.18114	0.02497
male	0.05061	0.04669	0.20969	0.02627
difference	-0.00082	-0.00105	-0.02855^{**}	-0.00130^{***}

*** 1% significance, ** 5% significance, *10% significance

Panel B: Multivariate Approach

	Total Risk	Systematic Risk	Small-Firm Risk	Unsystematic Risk
Female Dummy	-0.00031	-0.00016	-0.02426^{*}	-0.00127^{***}
$Age_{i,t-1}$	-0.00077^{**}	-0.00134^{***}	-0.01665^{**}	0.00096^{***}
$Size_{i,t-1}$	-0.00001	0.00044^{***}	-0.01644^{***}	-0.00122^{***}
$Turnover_{i,t-1}$	0.00061^{***}	0.00053^{***}	-0.00166	0.00051^{***}
Time dummies	included	included	included	included
Segment dummies	”	”	”	”
R^2	86.32%	86.03%	28.51	78.63%
Observations	10,533	10,533	10,533	10,533

*** 1% significance, ** 5% significance, *10% significance

Table 3: Average Investment Style

Panel A: Univariate Approach

	SMB	HML	MOM
female	0.17183	0.07504	0.04626
male	0.18289	0.06557	0.02889
difference	-0.01107	0.00947	0.01736^{*}

*** 1% significance, ** 5% significance, *10% significance

Panel B: Portfolio Approach

	SMB	HML	MOM
female	0.13019^{***}	0.11525^{***}	0.03791^{***}
male	0.12938^{***}	0.11238^{***}	0.00506
difference	0.00217	0.00678	0.03275^{***}

*** 1% significance, ** 5% significance, *10% significance

Panel C: Multivariate Approach

	SMB	HML	MOM
Female Dummy	-0.02426^{*}	-0.00846	0.02100^{**}
$Age_{i,t-1}$	-0.01665^{**}	0.03085^{***}	-0.01153^{**}
$Size_{i,t-1}$	-0.01644^{***}	-0.02622^{***}	0.00848^{***}
$Turnover_{i,t-1}$	-0.00166	-0.01718^{***}	0.00373^{***}
Time dummies	included	included	included
Segment Dummies	”	”	”
R^2	28.51%	10.61%	7.79%
Observations	10,533	10,533	10,533

*** 1% significance, ** 5% significance, *10% significance

Table 4: Style Extremity

Panel A: Univariate Approach

	EM	EM^{SMB}	EM^{HML}	EM^{MOM}
Female Manager	0.93375	0.93905	0.93193	0.93026
Male Manager	1.02963	1.03117	1.01898	1.03873
Female-Male Manager	-0.09588^{***}	-0.09212^{***}	-0.08705^{***}	-0.10847^{***}

*** 1% significance, ** 5% significance, *10% significance

Panel B: Multivariate Approach

	EM	EM^{SMB}	EM^{HML}	EM^{MOM}
Female Dummy	-0.09458^{***}	-0.08773^{***}	-0.08448^{***}	-0.11153^{***}
$Age_{i,t-1}$	0.04949^{***}	0.01257	0.07485^{***}	0.06105^{***}
$Size_{i,t-1}$	-0.06008^{***}	-0.05561^{***}	-0.05166^{***}	-0.07297^{***}
$Turnover_{i,t-1}$	0.01503^{***}	0.01489^{***}	0.01180^{***}	0.01841^{***}
Time dummies	included	included	included	included
Segment Dummies	”	”	”	”
R^2	68.39%	56.45%	57.17%	49.21%
Observations	10,533	10,533	10,533	10,533

*** 1% significance, ** 5% significance, *10% significance

Table 5: Style Variability

Panel A: Absolute Style Variability

	$SVM(abs)$	$SVM^{SMB}(abs)$	$SVM^{HML}(abs)$	$SVM^{MOM}(abs)$
Female Manager	0.79008	0.79161	0.80259	0.77603
Male Manager	1.01444	1.01434	1.01358	1.01541
Female-Male Manager	-0.22437^{***}	-0.22273^{***}	-0.21099^{***}	-0.23938^{***}

*** 1% significance, ** 5% significance, *10% significance

Panel B: Relative Style Variability

	$SVM(rel)$	$SVM^{SMB}(rel)$	$SVM^{HML}(rel)$	$SVM^{MOM}(rel)$
Female Manager	0.85471	0.81976	0.88723	0.85715
Male Manager	1.00920	1.01240	1.00776	1.00983
Female-Male Manager	-0.15528^{**}	-0.19264^{***}	-0.12053^{*}	-0.15268^{*}

*** 1% significance, ** 5% significance, *10% significance

Table 6: Trading Activity

Panel A: Univariate Approach

	Coefficients
female	0.94
male	1.04
difference	-0.09959^{***}

*** 1% significance, ** 5% significance, *10% significance

Panel B: Multivariate Approach

	Coefficients
Female Dummy	-0.08262^{*}
$Age_{i,t-1}$	-0.02295
$Size_{i,t-1}$	-0.07103^{***}
$Perf_{i,t-1}$	0.35748^{**}
$MgerTenure_{i,t}$	-0.19700^{***}
Time-Dummies	included
Segment-Dummies	"
R^2	32.91%
Observations	10,194

*** 1% significance, ** 5% significance, *10% significance

Table 7: Performance: Portfolio Approach

Panel A: Performance Before Expenses

	female	male	difference
Jensen-Alpha	0.00003	−0.00003	0.00006
3-Factor-Alpha	−0.00068	−0.00066	−0.00002
4-Factor-Alpha	−0.00106	−0.00071	−0.00035

*** 1% significance, ** 5% significance, *10% significance

Panel B: Performance After Expenses

	female	male	difference
Jensen-Alpha	−0.00115	−0.00127	0.00011
3-Factor-Alpha	−0.00189**	−0.00187*	0.00002
4-Factor-Alpha	−0.00224**	−0.00194**	−0.00031

*** 1% significance, ** 5% significance, *10% significance

Table 8: Performance: Multivariate Analysis

	Jensen-Alpha	3F-Alpha	4F-Alpha	Appraisal Ratio
Female Dummy	−0.00010	−0.00031	−0.00034	−0.01551
$Perf_{i,t-1}$	0.12085***	0.05797***	0.01782*	0.06193***
$Age_{i,t-1}$	0.00028**	0.00018	0.00026*	0.01564**
$Size_{i,t-1}$	−0.00042***	−0.00025***	−0.00032***	−0.01676***
$Expenses_{i,t-1}$	−0.09911***	−0.07549***	−0.09634***	−2.15479***
Time-Dummies	included	included	included	included
Segment-Dummies	”	”	”	”
R^2	21.05%	13.29%	14.46%	13.41%
Observations	10,191	10,191	10,191	10,191

*** 1% significance, ** 5% significance, *10% significance

Table 9: Concentration of Male-Manager Funds by Alpha Dispersion

	Share of male managed funds
Top 1%	94.1%
Top 5%	90.3%
Top 10%	89.9%
Middle 80%	89.0%
Bottom 10%	89.5%
Bottom 5%	91.8%
Bottom 1%	96.0%

Table 10: Performance: Alpha Dispersion

Panel A: Female Managers Among the Top/Bottom 1%

	Female Dummy		
	Top or Bottom 1%	Top 1%	Bottom 1%
Jensen Alpha	-1.10346^{***}	-0.99310^{*}	-1.16941^{**}
3-Factor Alpha	0.07112	-0.14303	0.22578
4-Factor Alpha	-0.11323	-0.20021	-0.04584

*** 1% significance, ** 5% significance, *10% significance

Panel B: Female Managers Among the Top/Bottom 5%

	Female Dummy		
	Top or Bottom 5%	Top 5%	Bottom 5%
Jensen Alpha	-0.28916^{**}	-0.12357	-0.41484^{**}
3-Factor Alpha	-0.15371	-0.13265	-0.15223
4-Factor Alpha	-0.14546	-0.09813	-0.16691

*** 1% significance, ** 5% significance, *10% significance

Table 11: Performance Persistence

	female	male	difference
Jensen-Alpha	0.23398	0.26119	-0.02721^{***}
3-Factor-Alpha	0.23814	0.27022	-0.03208^{***}
4-Factor-Alpha	0.24249	0.27038	-0.02788^{***}

*** 1% significance, ** 5% significance, *10% significance

Table 12: Fund Flows

Panel A: Univariate Approach

	Coefficient
female	0.1521
male	0.2871
difference	-0.1348^{***}

*** 1% significance, ** 5% significance, *10% significance

Panel B: Multivariate Approach

Variable	FMB-Approach	FMB-Approach	pooled regression	pooled regression
Female Dummy	-0.1782^{**}	-0.18403^{**}	-0.16795^{*}	-0.17172^{*}
$PerfRank_{i,t-1}$	-0.3818		-0.4002	
$PerfRank^2_{i,t-1}$	0.9814^{**}		1.0239^{***}	
$Quintile1_{i,t-1}$		0.67379^{**}		1.04295
$Quintile2-4_{i,t-1}$		0.16859^{*}		0.18943
$Quintile5_{i,t-1}$		3.46456^{**}		3.52468^{***}
$Flow_{i,t-1}$	0.1439^{***}	0.13153^{***}	0.11713^{**}	0.10413^{**}
$FundRisk_{i,t-1}$	1.6622^{**}	1.01434	1.57592	1.7000
$Age_{i,t-1}$	-0.0656^{***}	-0.07062^{***}	-0.05096	-0.04912
$Size_{i,t-1}$	-0.1976^{**}	-0.20114^{**}	-0.21347^{***}	-0.21485^{***}
$Turnover_{i,t-1}$	-0.0021	-0.00627	-0.03091	-0.03134
$Fees_{i,t-1}$	-0.0778	-0.08525	-0.13684	-0.14012
$SegmentFlow_{i,t}$	2.3497	2.32616	1.08779^{**}	1.12776^{**}
$FamilyFlow_{i,t}$	0.9383^{***}	0.92213^{***}	0.96159^{***}	0.95494^{***}
$FamilySize_{i,t-1}$	0.1109^{**}	0.10768^{**}	0.11749^{***}	0.11754^{***}
$FamilyAge_{i,t-1}$	0.0118	0.01116	0.01062^{**}	0.01082^{**}
Time Dummies			included	included
R^2			8.65%	8.77%
Observations			8,376	8,376

*** 1% significance, ** 5% significance, *10% significance

Table 13: Determinants of a fund family employing females

Panel A: OLS Estimation (Proportion of females employed)

Variable	Coefficients			
$FamTNA_{j,t-1}$	0.01722***	0.10822***	0.01797***	0.01869***
$FamAge_{j,t-1}$	0.00607	0.00274	0.00427	0.00399
$AvrgeFundSize_{j,t-1}$	−0.01884***	−0.02026***	−0.01996***	−0.02079***
$AvrgeFundAge_{j,t-1}$	−0.00729	−0.00298	−0.00498	−0.00445
$MDCons_j$		−0.00043***		−0.00034***
$MDWomLib_j$			0.00029***	0.00025***
Segment Dummies	included	included	included	included
Time Dummies	”	”	”	”
Observations	3,658	2,888	2,752	2,707

*** 1% significance, ** 5% significance, *10% significance

Panel B: Logit Estimation

Variable	Coefficients			
$FamTNA_{j,t-1}$	1.66491***	1.69956***	1.72442***	1.73346***
$FamAge_{j,t-1}$	0.34621**	0.32208*	0.38247*	0.37514*
$AvrgeFundSize_{j,t-1}$	−1.66291***	−1.74144***	−1.73058***	−1.73995***
$AvrgeFundAge_{j,t-1}$	−0.52666**	−0.42531*	−0.53503**	−0.51183**
$MDCons_j$		−0.01928***		−0.01369***
$MDWomLib_j$			0.01465***	0.01146***
Segment Dummies	included	included	included	included
Time Dummies	”	”	”	”
$PseudoR^2$	40.69%	41.58%	42.93%	43.43%
Observations	3,658	2,888	2,752	2,707

*** 1% significance, ** 5% significance, *10% significance