Sex Matters: Gender and Prejudice in the Mutual Fund Industry*

Alexandra Niessen-Ruenzi and Stefan Ruenzi

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Abstract

We suggest customer based discrimination as one potential explanation for the low fraction of females in the mutual fund industry. Consistent with investors being prejudiced and stereotyping female fund managers as less skilled, we find that female managed funds experience significantly lower inflows. This result is obtained using market data as well as experimental data. While we document some behavioral differences between male and female fund managers, performance is virtually identical. This shows that rational statistical discrimination can not explain the lower inflows into female managed funds. Evidence based on an implicit association test conducted in a laboratory setting supports the notion that there is prejudice against females in finance.

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*University of Mannheim, L9, 1-2, 68131 Mannheim (e-mail: ruenzi@bwl.uni-mannheim.de, niessen@bwl.uni-mannheim.de). We have benefited from comments by Vikas Agarwal, Brad Barber, Michael Cavanaugh, John Chalmers, Werner DeBondt, Elroy Dimson, John Griffin, Mark Hulbert, Jayant Kale, Shmuel Kandel, Alok Kumar, Camelia Kuhnen, Jerry Parwada, Andrei Simonov, Laura Starks, Russ Wermers, participants at the EEA Annual Meeting 2007, FMA European Meeting 2006, the FMA Annual Meeting 2006, the EFMA Annual Meeting 2006 and the EFM Symposium on Behavioral Finance 2006 as well as seminar participants at Georgia State University, University of Austin (Texas), University of New South Wales, University of Sydney, Australian National University, Maastricht University, Erasmus University of Rotterdam, University of Copenhagen and University of Cologne. All errors are our own.

1 Introduction

Our study is motivated by the observation of a very low fraction of female managers in the US mutual fund industry. Similar to the low fraction of females among CEOs and among analysts (Wolfers (2006) and Adams and Ferreira (2009)), the fraction of female mutual fund managers is consistently low at about 10 percent.

While various reasons like hiring discrimination against females or self selection of females into other professions can contribute in explaining the low fraction of females, we suggest a new customer based explanation for this phenomenon. Our starting point is the conjecture that investors might be prejudiced against female fund managers.[1] Their preference for male managed funds leads to lower inflows into female managed funds and might eventually induce firms to hire less females, because mutual fund companies generate their profit from fees charged on assets under management.

Our empirical investigation of all single managed U.S. equity mutual funds from 1992 to 2009 shows that female managed funds indeed experience significantly lower inflows than male managed funds. The growth rates due to inflows of female managed funds are about one third lower than those of male managed funds. This result is obtained after controlling for the impact of past performance and other fund characteristics. Looking at manager changes, we find that fund flows decrease significantly if a male manager is replaced by a female manager, but not if a female is replaced by a male manager.

While this result is consistent with fund investors shying away from female managed funds, there can be several other explanations. For example, female fund managers might be assigned to less attractive funds, their funds might get advertised less, or they might receive lower media coverage all of which could ultimately lead to lower inflows. These explanations are empirically difficult to disentangle. Thus, we conduct a controlled laboratory experiment

[1] Anecdotal evidence from interviews with fund managers suggests that this is indeed the case: Asked about why female managed funds attract less capital, one fund manager stated: "There's something that prevents people from being totally comfortable about signing their money over to a woman...a lot of negatives are applied." (NCRW-Report (2009)).

that allows us to isolate the impact of the fund manager's gender from the impact of any such confounding effects on money inflows. The experiment consists of an investment task where subjects have to decide on how they would split a certain amount of money between two funds. We keep all information about these funds constant except for the gender of the fund managers which is manipulated between treatment and control group. We find that subjects in our experiment invest significantly less into a fund if the manager's first name is female. The experimental evidence supports the notion that our empirical results of lower inflows into female managed funds can indeed be explained by investors avoiding female fund managers.

There are two main reasons why investors might shy away from female fund managers: rational statistical discrimination or irrational negative prejudice against females in finance. In the first case, investors might expect that female fund managers on average show investment behavior which is undesirable or deliver inferior fund performance as compared to male managers. In that case, our results could be driven by statistical discrimination. However, that kind of behavior would only be rational if female fund managers indeed show undesirable characteristics in reality. Thus, we examine whether gender differences exist along three broad dimensions that are important for fund management: Risk taking, investment styles, and trading activity. Higher risk aversion of females in general (Byrnes, Miller, and Schafer (1999)) and among female retail investors in particular (Jianakoplos and Bernasek (1998), Sunden and Surette (1998), and Barber and Odean (2001)) is widely documented. With respect to management styles, experimental evidence from Cadsby and Maynes (2005) suggests that womens' decisions tend to be more in line with the decisions of others, while mens' decisions are more individually oriented. Furthermore, Barber and Odean (2001) and Dorn and Huberman (2005) show that female retail investors trade less than their male counterparts which they interpret as a gender difference in overconfidence. While it is unclear ex-ante whether these results can be transferred to a setting of professional money managers, we document similar albeit weaker patterns among mutual fund managers. We find that female fund managers are moderately more risk averse than male fund managers.

Furthermore, they follow significantly less extreme and more stable investment styles and trade less than male fund managers. These findings provide evidence that behavioral gender differences that have been documented for the general population can also be observed in a professional setting. We also analyze whether the behavioral differences we document lead to differences in performance. Using various risk-adjusted performance measures, we do not find any significant difference in the average performance of female and male managed funds. However, the more extreme style bets taken by male fund managers lead to more extreme performance outcomes of their funds as compared to female managed funds. Furthermore, we find that female managed funds exhibit higher performance persistence than male managed funds.

Taken together, the results on behavioral differences and performance suggest that female fund managers show no undesirable characteristics. Rather, they should be preferable for fund investors that like a stable performance and reliable investment styles. Thus, female managed funds should receive higher money inflows than male managed funds rather than lower money inflows. Consequently, lower inflows into female managed funds can not be explained by rational statistical discrimination.

This leaves us with the explanation that investors might have some negative prejudice against female fund managers.[2] To take a closer look at the question whether there is really prejudice against female in finance, we conduct an implicit association test (IAT) in a laboratory setting.[3]

The IAT has not been applied in a finance context before. However, it is an established experimental method which is now widely used by social psychologists to uncover attitudes like prejudice and stereotypes that subjects might not be willing to reveal or that they might

[2]There is a large body of evidence suggesting that female managers in upper levels of organizations are stereotyped as less skilled than male managers (Heilman, Martell, and Simon (1989), Oakley (2000)).

[3]A short introductory note on the IAT is Carney, Nosek, Greenwald, and Banaji (2007). The IAT is described in more detail in Section 5.

not even be aware of themselves.[4] This test has been validated internally and externally. It is based on a computerized sorting task where subjects have to simultaneously classify items in one of two concept categories (here: "finance" and, as contrasting concept, "marketing") and two attribute categories (here: "male" and "female"). Items representing one of the four categories at a time (e.g. "boy" for "male" or "stock" for "finance") have to be rapidly categorized by subjects. The relative reaction times provide an estimate of the strength of the association between concepts and attributes. Differences in implicit associations are evidence for the existence of prejudice (Greenwald and Banaji (1995)). Results from our IAT experiment show strong negative implicit prejudice against females in finance. The effect is robust against variations of the experimental procedure and can be observed among male and female participants in the experiment. It is weaker, but still clearly significant even among female finance students. We also find that participants with the strongest implicit prejudice according to the IAT invest less into female managed funds in the experimental investment task, while participants with no implicit prejudice do not invest less into female managed funds. Overall, these results offer an explanation why investors - consciously or unconsciously - direct less money to female managed mutual funds and why we eventually see so few women in the fund industry.

Our paper contributes to several strands of the literature. First, we contribute to the broad literature on gender differences (Feingold (1994), Byrnes, Miller, and Schafer (1999), Bertrand and Hallock (2001), Barber and Odean (2001), Croson and Gneezy (2009a)) by showing that behavioral gender differences also exist in a professional setting of fund managers.

Second, we contribute to the literature on the influence of manager characteristics on managerial outcomes in general (Rajagopalan and Datta (1996), Betrand and Schoar (2003), and Nelson (2005)) and to the recent literature on the influence of fund managers' charac-

[4] For the purpose of this paper, 'implicit attitude', 'implicit prejudice', and 'implicit stereotypes' can be used synonymously. For a detailed discussion of the differences between those concepts from a psychology point of view, see Greenwald and Banaji (1995).

teristics on the success of funds in particular (Chevalier and Ellison (1997) and Baks (2003)) by examining the influence of gender on fund performance.[5]

Our paper also contributes to the finance literature methodologically by introducing the IAT method to the field. IATs are regularly used in social psychology, but we are not aware of any applications in finance. So far, there are also only very few papers using the method in economics. For example, Bertrand, Chugh, and Mullainathan (2005) use an IAT to show that discrimination against females in hiring could be unintended by the discriminating party and Beaman, Chattopadhyay, Duflo, Pande, and Topalova (2009) measure attitudes towards female leaders based on IATs.

Finally, we contribute to the large sociopolitical debate on stereotyping and gender discrimination (Blau and Kahn (1992) and (2000), Francois (1998), and Croson and Gneezy (2009b)) by showing that stereotyping against females might also be an issue in the financial industry. Although the gender differences we find do not support the view that female fund managers are less qualified to manage a fund, there seems to be a prejudice (at least among certain investor groups) that they are. On a broader level, the strong prejudice against females in finance might also offer one potential explanation for the generally low fraction of females in finance in academia as well as in the industry.

The paper proceeds as follows. Section 2 contains a description of our data and the construction of our main variables. Section 3 investigates flows into female and male managed funds using market as well as experimental data. Our empirical results on behavioral differences and differences in performance between female and male fund managers are presented in Section 4. Results from the implicit association test (IAT) are presented in Section 5. Section 6 concludes.

[5] The impact of gender among fund managers is also examined in Atkinson, Baird, and Frye (2003) who investigate gender differences for a small sample of fixed-income fund managers. Consistent with our results, in their univariate analysis they find no gender differences in performance and lower inflows into female managed funds.

2 Data and Summary Statistics

2.1 Principal Data Sources

Our primary data source is the CRSP Survivor Bias Free Mutual Fund Database.[6] It covers virtually all U.S. open-end mutual funds and provides information on fund returns, fund management structures, total net-assets, investment objectives, fund managers' identity, and other fund characteristics.

We focus on actively managed equity funds that invest more than 50% of their assets in stocks and exclude bond and money market funds. We aggregate the SI and Lipper objective codes contained in the CRSP database to define the market segment in which a fund operates. This leaves us with 10 different equity fund segments.[7] Our study covers the time period from January 1992 to December 2009.

Following Daniel, Grinblatt, Titman, and Wermers (1997), we aggregate all share classes of the same fund to avoid multiple counting. Baer, Kempf, and Ruenzi (2011) show that team managed funds and single managed funds behave differently. Thus, we concentrate on single managed funds and exclude all team managed funds and funds for which CRSP gives multiple manager names from our analysis.

To identify the gender of the fund managers in our sample we use the first name of the manager which is usually given in the CRSP database. Overall, we are able to identify the gender of the fund manager in 99.39% of all cases.[8]

[6]Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved.

[7]Specifically, we use the following ten equity fund segments: AG (Aggressive Growth), BAL (Balanced Funds), GE (Global Equity), GI (Growth and Income), IE (International Equity), IN (Income), LG (Long-term Growth), SE (Sector Funds), UT (Utility Funds) and TR (Total Return).

[8]Appendix A provides further details pertaining to the gender identification process.

2.2 Variable Construction

Measures of Investment Behavior

We compute three measures of *risk taking*: (i) $TotalRisk_{i,t}$, is computed as fund i's monthly return standard deviation in year t. (ii) The fund's systematic risk, $SystematicRisk_{i,t}$, is defined as fund $i's$ factor loading on the market factor from a one factor model in year t (Chevalier and Ellison (1999a)). (iii) Unsystematic risk, $UnsystematicRisk_{i,t}$, is measured by the standard deviation of fund i's residual fund return from the same model in year t.[9]

To capture the style of a fund, we follow Baer, Kempf, and Ruenzi (2011) and compute *style extremity* measures, $EM_{i,t}^{f}$, for each fund i in each year t. These measures are defined as the yearly absolute differences between a fund's factor weighting f, and the corresponding average factor weighting of a fund's market segment in the same year.

$$EM_{i,t}^{f} = \frac{|(FactorWeighting_f)_{i,t} - (AverageFactorWeighting_f)_{i,t}^{k}|}{\frac{1}{N_t^k}\sum_{i=1}^{N_t^k}|(FactorWeighting_f)_{i,t} - (AverageFactorWeighting_f)_{i,t}^{k}|}, \tag{1}$$

where k defines the market segment fund i belongs to, N_t^k is the number of funds in this segment in year t and f represents the SMB, HML, and MOM factor from a Carhart (1997) four factor model. A higher value of $EM_{i,t}^{f}$ of fund i corresponds to a more extreme factor weighting on factor f, i.e. to a more extreme style of this fund as compared to the average fund in its segment in year t. A fund with average style extremity has, by construction, an extremity measure of one for each of the factors. To get an aggregate measure of the style extremity for each fund, $EM_{i,t}$, we average the three individual factor extremity measures as defined in (1) on the fund level.

[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 of a fund, respectively. Results (not reported) are not affected.

We also calculate a *style variability* measure for each style factor f of fund i:

$$SVM_i^f = \frac{STD(FactorWeighting_f)_i}{\frac{1}{N_t^k}\sum_{i=1}^{N_t^k} STD(FactorWeighting_f)_i}. \tag{2}$$

SVM_i^f represents the style variability of fund i with respect to a specific factor f. It is calculated as the rescaled standard deviation STD of its factor loading f over time. Standard deviations are rescaled by the average factor weighting standard deviation of all funds in the corresponding market segment.[10] In a last step, we compute the average of the individual factor style variability measures to get a measure for the overall stability of a fund's style over time, SVM_i. A higher value of the factor-individual as well as aggregate style variability measures indicates a less stable investment style over time. A fund with average style variability has, by construction, a variability measure of one.

We follow Cremers and Pfleiderer (2009) in defining a fund's *active share* and *tracking error*. Active share of a fund i in year t, $ActiveShare_{i,t}$ is computed as

$$ActiveShare_{i,t} = \frac{1}{2}\sum_{j=1}^{N} |w_{i,j,t} - w_{benchmark(i),j,t}| \tag{3}$$

where $w_{i,j,t}$ is the weight of stock j in fund is portfolio in year t and $w_{benchmark(i),j,t}$ is the weight of stock j in the benchmark of fund i in year t.

A fund's tracking error, $TrackingError_{i,t}$, is computed as the standard deviation of the residual obtained from a one factor market model.

Measures of Performance and Performance Persistence

We investigate the performance of a fund based on its risk-adjusted abnormal returns. Specifically, we calculate Jensen (1968) Alphas, Fama and French (1993) three-factor Al-

[10]To calculate this measure, we first compute the standard deviations of a fund's yearly factor weightings over time. We exclude funds that have less than three years of data and funds with a manager change during the observation period.

phas, and Carhart (1997) four-factor Alphas on an annual basis using monthly returns.[11] We also compute a modified version of the Treynor and 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, thereby taking into account possible differences in idiosyncratic risk.

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 following way: First, we calculate the performance rank for each fund i in each year t, $PerfRank_{i,t}$. Ranks are based on one of the performance measures introduced above. They are calculated for each segment and each year separately and normalized so that they are evenly distributed between zero and one. The best fund gets assigned a rank of one. Second, we calculate the performance persistence of a fund i, $PerformancePersistence_i$, as the variation of its yearly performance ranks over time measured by the time series standard deviation of ranks.[12] The less a fund's performance rank varies over time, i.e. the lower PP_i, the more persistent is the fund's performance.

2.3 Summary Statistics

Our final sample contains 24,789 fund year observations, out of which 22,237 have a male manager and 2,552 have a female manager. Figure 1 plots the total number of male and female managed funds as well as the fraction of female managed funds over our sample period.

— Please insert FIGURE 1 approximately here —

[11] These estimates can be quite noisy since they are from a regression with only twelve observations. However, this should not affect our results since we use a large cross-section of data and are only interested in the difference between the female and male subsamples.

[12] We only calculate $PerformancePersistence_i$ 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.

It shows that the share of female managed funds is low and constant at around 10% in each year. This is in line with findings from other management jobs such as CEOs and analysts (Wolfers (2006) and Adams and Ferreira (2009)).

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

— Please insert TABLE 1 approximately here —

Female managers are responsible for significantly smaller funds, while the mean age of female managed funds is slightly higher than the mean age of male managed funds. With respect to fees, we find no clear pattern. While expense ratios are insignificantly higher for female managed funds than for male managed funds, 12b1 fees are significantly lower for male managed funds than for female managed funds. We also find that female managers trade significantly less than male managers and that female managed funds get significantly lower money inflows than male managed funds. There is no difference in average performance and average risk, while female managed funds have less active share and a lower tracking error. Finally, the mean tenure of a female fund manager in years is significantly lower than the mean tenure of a male fund manager.

3 Do Investors Care About the Manager's Gender?

We start our analysis by examining whether investors shy away from female managed funds. In Section 3.1 we conduct an empirical study where we examine differences in mutual fund flows between male and female managed funds. This allows us to analyze actual investor behavior. However, it is difficult to identify whether any difference we might find is really due to the fund managers' gender or other confounding effects like, e.g., allocation of female fund managers to less attractive funds. Thus, in Section 3.2, we report results from an experiment where subjects were asked to split a fixed investment amount between female and a male managed funds in a controlled setting.

3.1 Empirical Results

To answer the question whether investors shy away from female managed funds, we relate relative net-inflows (=inflows-outflows) of new money into a fund, $Flow_{i,t}$, as defined in Sirri and Tufano (1998), to a female dummy variable, $FemaleDummy_{i,t}$, that equals one if the manager of fund i in year t is female, and zero otherwise. As control variables, we add several characteristics that have proven to influence fund flows. Specifically, we have to control for the influence of past performance on fund flows. Ippolito (1992) shows, that past performance has a nonlinear impact on fund flows. Thus, we use two alternative models suggested in the literature to capture this non-linearity. First, we follow Barber, Odean, and Zheng (2005) and estimate a quadratic performance flow relationship.[13] Second, we use a piecewise linear regression approach as suggested by Sirri and Tufano (1998) and estimate distinct slope coefficients for different performance quintiles.[14] We also include the lagged flows of a fund as control variable. Furthermore, we include $FundSize_{i,t-1}$, defined as the logarithm of a fund's total net-assets in million USD (TNA), $Turnover_{i,t-1}$, and $FundAge_{i,t-1}$, defined as the logarithm of fund i's age in years in our regression since Chevalier and Ellison (1997) suggest that risk taking of fund managers depends on age and size of a fund. We also include fund risk measured by the total return standard deviation as well as a fund's expense ratio. To account for the impact of the characteristics of the fund

[13] We use ranks based on raw returns as Patel, Zeckhauser, and Hendricks (1991) show, that ordinal performance measures can explain fund flows much better than cardinal measures. Ranks are calculated based on raw returns for each year and segment separately and are evenly 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.

[14] 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 $Quintile5_{i,t-1} = PerfRank_{i,t-1} - (Quintile1_{i,t-1} + Quintile2-4_{i,t-1})$. We follow Sirri and Tufano (1998) by grouping the three middle quintiles together. Results (not reported) do not change if we model a distinct slope coefficient for each of the five performance quintiles instead of grouping the three middle quintiles together.

company on inflows, we additionally include percentage flows into the respective fund's company. Factors affecting flows of new money into the whole segment of the fund are considered by adding the percentage of flows into the respective market segment.[15]

We estimate the model by applying a pooled regression approach with standard errors clustered at the fund level and including different combinations of fixed effects as well as Fama and MacBeth (1973) regressions. Estimation results are presented in Table 2.

— Please insert TABLE 2 approximately here —

Our findings show that flows into female managed funds are significantly lower than those of male managed funds. The impact of the female dummy is negative and always statistically significant at the 1% level. The effect is also economically significant: depending on the model specification, the estimate for the influence of the female dummy suggests that a female managed fund grows by about 7% to 11% p.a. less than a comparable fund that is managed by a male fund manager. Given that the average fund in our sample grows by 25% p.a., this means that a female managed fund grows by about 28-44% slower than a comparable fund that is managed by a male fund manager. This result is very stable, irrespective of whether we only use pooled regressions with year and segment fixed effects (Columns 1 and 3), pooled regressions with year, family, and segment fixed effects (Columns 2 and 4), or Fama and MacBeth (1973) regressions (Columns 5 and 6). Regarding our results on the influence of the control variables, they are consistent with findings reported in the literature.

We now try to shed more light on the question why female managed funds receive lower inflows. Results in Table 3 are presented to refine our analysis and to disentangle different explanations.

— Please insert TABLE 3 approximately here —

[15] Company flows and segment flows are always computed without flows into the fund under consideration.

To analyze whether investors react differently upon past performance of male and female managers, in Columns 1 and 2 of Table 3, we interact our dummy variable indicating a female manager with lagged fund performance. The interaction term is significantly negative both for the level of lagged performance (Column 1) as well as the squared performance rank (Column 2). This indicates that a fund profits less from good past performance if it is managed by a woman. Additionally, the female dummy is still significantly negative and of similar magnitude.

In Column 3, we investigate whether the negative impact of our female dummy on mutual fund flows is driven by funds that are distributed by brokers. Fund brokers might stereotype female fund managers as less able and thus promote male managed funds more often than female managed funds. A survey conducted by Wang (1994) suggests some machismo among brokers: 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. As funds that are distributed by brokers usually charge front-end loads (Christofferson, Evans, and Musto (2010)), we interact our female dummy with a dummy variable which is equal to one if a fund has no front-end loads, and zero otherwise. We do not find a significant difference between no-load funds and load-funds suggesting that the negative impact of our female dummy on mutual fund flows is not driven by brokers.

To separate fund characteristics from the impact of gender on fund flows, we look at the impact of manager changes on fund flows (Column 4). We create a dummy variable, $FemNew_{i,t-1}$ ($MaleNew_{i,t-1}$), which is equal to one if the fund manager's gender changes from male to female (female to male), and zero otherwise. The result shows that fund flows decrease by about 14% if a male manager is substituted by a female manager, while a change from female to male manager has a positive but insignificant coefficient.

Since female fund managers on average manage smaller funds (see Table 1), it is possible that a non-linear influence of fund size on fund flows affects our result. Therefore, in Column

5, we include fund size to the power of two and three as additional explanatory variables. Our results are not affected.

Finally, in Column 6 and 7 we use alternative measure of fund flows. We follow Spiegel and Zhang (2010) and use the change of a fund's market share as dependent variable in Column 6. The change of a fund's market share, $\Delta MS_{i,t}$, is computed as $\Delta MS_{i,t} = \frac{n_{i,t}}{N_t} - \frac{n_{i,t-1}}{N_t-1}$ with $n_{i,t-1}$, $n_{i,t}$, N_{t-1}, and N_t representing the lagged and concurrent assets under management of the fund n and of all funds N. As in Spiegel and Zhang (2010), we do not find much evidence for a significantly convex performance-flow relationship anymore (the squared performance rank is only marginally significant). However, the female dummy variable is still significantly negative. In Column 7, we use dollar flows ($AbsFlow_{i,t}$), computed as the annual change of a fund's total net assets (TNA) adjusted by the annual fund return (ret_t), $AbsFlow_{i,t} = TNA_t - TNA_{t-1} \cdot (1 + ret_t)$, as dependent variable. We still find a significantly negative impact of the female dummy variable on fund flows that is also economically important: a female managed fund on average gets about 12.2 million USD less money inflows than a comparable male managed fund. This translates into female managed funds growing by about 19.5% less than male managed funds.

The much lower flows into female managed funds might be one reason why the proportion of female fund managers in our sample remains low at around 10% and does not rise over time (see Figure 1): since fund management companies are ultimately interested in maximizing profits from fee income, they might employ female fund managers less because of the lower inflows they generate. This suggests an important role for a customer based explanation of the low fraction of females among mutual fund managers.

The finding of lower flows into female managed funds than into male managed funds is puzzling. One potential explanation for this finding is that investors might have some negative preconception about the abilities of female fund managers. However, it could also be the case that female managed funds receive, for example, lower media coverage or are advertised less. Due to lack of data, these explanations are hard to disentangle empirically.

Therefore, we also conduct a laboratory experiment to identify the impact of gender on fund flows in an environment that allows us to control for any such confounding factors.

3.2 Experimental Results

To investigate whether investors indeed have negative preconceptions about the abilities of female fund managers, we conduct a laboratory experiment that consists of two main parts, an investment task and the implicit association test (IAT, see Section 5).

The investment task is similar to a recent experimental study by Bigelow, McLean Parks, Lundmark, and Wuebker (2006) and Wuebker and Bigelow (2010) who provide evidence that investors in a hypothetical IPO invest less in a company managed by a female CEO than in an otherwise identical company with a male CEO. Subjects in our experiment have to decide how to split 100 experimental units (where one experimental unit corresponds to 5.5 USD) between two funds. The complete amount of 100 experimental units has to be invested. We randomly picked two funds from the CRSP mutual fund database, and labeled these funds as "fund A" and "fund B". Information about both funds was displayed to subjects at the same time and subjects decided how to split up their money after observing the fund information. Subjects were randomly assigned to either treatment or control group. Both groups observed the same set of funds. However, we switched the gender of the fund manager between these groups keeping all other information constant. This allows us to investigate whether the lower money inflows that we observe into female managed funds are indeed due to the fund managers gender. Figure 2 exemplifies the information given to treatment and control group, respectively.

— Please insert FIGURE 2 approximately here —

As can be seen from Figure 2, the only difference between treatment and control group is the first name of the fund manager. The treatment group observes a female fund manager for fund A and a male fund manager for fund B, while the control group observes a male fund manager for fund A and a female fund manager for fund B, respectively.[16] Thus, any differences in investment behavior between treatment and control group can be attributed to the fund managers' gender. Remuneration in our experiment depends on the actual return of the two funds and the relative investment made into these funds.

The experiment was played over four rounds. They differed by the amount of information provided about the funds. In the first round, information about the fund segment, the name of the fund manager, fund size, inception date, expense ratio, turnover activity, and top five stock holdings was provided. In addition, we added a short text labeled "Fund Facts" with a description of the fund's investment strategy (see Figure 2). In the second round, an ethical rating of the fund was added, while the third round also contained a rank indicating the fund's riskiness. Finally, we added the fund's return over the past 12 and 24 months in round four. In each round, the investment decision had to be made for four different fund types: index funds, growth and income funds, aggressive growth funds, and international funds.

The experiment took place in 11 individual sessions with a total of 100 students at the McCombs School of Business Behavioral Lab of the University of Texas at Austin. Table 4 provides information on the demographic characteristics of the participants.

— Please insert TABLE 4 approximately here —

Due to the recruiting procedure, which mainly focused on announcements in finance classes, the clear majority of 43 participants indicated "Finance" as their main field of study, followed by 13 participants in "Accounting", 10 in "Marketing", and 9 in "Management Information Systems". A smaller number of subjects indicated "Economics", "Engineering", or other fields as their main field of study.[17] The mean age of participants is 21.3 years and

[16] We took the most common US first names according to the US Social Security Administration to ensure that subjects perceive these names as very common for each gender category.

[17] The "Other Business" category in Table 4 mainly includes students in "International Business" or "Supply Chain Management", while the "Other" category contains students from non-business fields that have such diverse backgrounds as "Geography", "Literature", or "Physical Therapy".

ranges from a minimum of 18 years to a maximum of 40 years. However, more than 80% of all participants were between 22 and 24 years of age. Regarding marital status, virtually all participants were single. The sex distribution of participants is roughly balanced, with 51 male and 49 female participants. Results of the investment task are reported in Table 5.

— Please insert TABLE 5 approximately here —

We start our analysis by focusing on index funds only. Since index funds do not differ much from each other, they offer the cleanest setting to examine the impact of gender on investment decisions. Panel A of Table 5 shows that subjects in our experiment invested significantly less into the female managed fund. The difference is 7.42 experimental units and is significant at the 1% level. This result is consistent with our previous empirical findings.

Results in Panel B suggest that the difference in investing into female and male managed funds is mainly driven by male subjects. We find no significant difference in the fraction of money invested between male and female managed funds among female subjects. The bias towards male managed funds is independent of the main field of study of the subjects (Panel C). Panel D splits the subject pool by financial literacy according to a short financial literacy test we conducted at the end of the experiment.[18] We observe significantly less money directed towards the female managed fund in both groups, but the effects seems to be stronger among the less financially literate.[19]

In Panel E, we investigate investment decisions for different types of funds, separately. As one could argue that only the first round of investment decisions can be considered as independent, we start by focusing on the first round of the experiment only.[20] The results

[18] The test consists of six questions typically used in financial literacy tests like those in van Rooij, Lusardi, and Alessie (2011) or Chen and Volpe (2002).

[19] As financial literacy is also closely related to the main field of study - finance students typically achieve better scores on this test - we also split the subject pool according to 'field-of-study'-adjusted financial literacy. Results (not reported) are similar.

[20] In the second to the fourth round of the experiment, the investment task was repeated for the same set of funds, but participants obtained more information about the funds.

show that participants invested less into female managed funds across all types of funds. However, statistical significance is obtained for index funds and growth and income funds only. The results are similar if we include all rounds into the analysis.[21]

Overall, our results suggest that investors prefer male managed funds to female managed funds. One explanation for this finding is that investors are prejudiced against female fund managers. However, it could also be the case that our findings are driven by statistical discrimination. In that case, subjects invest less into female managed funds because they expect them to behave in an undesirable way or deliver inferior performance. This would only be rational, if male fund managers indeed showed more desirable investment behavior and better performance outcomes. To disentangle between the irrational prejudice and the rational statistical discrimination explanations, we now investigate whether there is any evidence of undesirable investment behavior or inferior fund performance of female managed funds in reality that might explain our result of lower money inflows into these funds.

4 Gender Differences between Female and Male Fund Managers

4.1 Investment Styles

To examine gender differences in investment behavior, we relate various measures of investment behavior to the fund manager's gender and other potentially relevant fund characteristics:

$$\begin{aligned} IB_{i,t} &= \beta_1 \cdot FemaleDummy_{i,t} + \beta_2 \cdot FundSize_{i,t-1} + \beta_3 \cdot FundAge_{i,t-1} \\ &\quad + \beta_4 \cdot Ret_{i,t-1} + \beta_5 \cdot Tenure_{i,t-1} + Segment_j + Year_t + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

[21] For the sake of brevity, we do not report more cross-sectional results from our experiment in this paper.

In this equation, the dependent variable is a fund manager's investment behavior, $IB_{i,t}$. This variable is either one of the three risk measures for fund i in year t, $TotalRisk_{i,t}$, $SystematicRisk_{i,t}$, or $UnsystematicRisk_{i,t}$ as defined in Section 2.2, the funds turnover ratio, $TurnoverRatio_{i,t}$, its active share, $ActiveShare_{i,t}$, its tracking error, $TrackingError_{i,t}$, or its style extremity, $EM_{i,t}$, defined as in section 2. Fund size and fund age are defined as in the previous regressions. We also include a fund's previous year return, $Ret_{i,t-1}$ as well as the fund manager's tenure, $Tenure_{i,t-1}$.[22] We estimate Model (4) with time and segment fixed effects.[23] Including segment fixed effects controls for the average investment behavior of funds in a specific segment. It is possible that women work in specific segments either because they choose to do so or because their employer wants them to do so. For example, if women are allocated to funds in less risky segments, this would result in a seemingly less risky behavior of female fund managers if we would not estimate our model with segment fixed effects. Standard errors are clustered at the fund level. Panel A of Table 6 summarizes our findings.

— Please insert TABLE 6 approximately here —

Regarding total and systematic risk, we do not find any significant differences between female and male managed funds. However, our results clearly indicate that female managed funds have significantly less unsystematic risk. Furthermore, female fund managers trade less than male fund managers. The estimate for the influence of the female dummy is statistically significant at the 1% level. The coefficient of -0.116 indicates that female managed funds have a turnover ratio that is by an economically meaningful 12% p.a lower than that of comparable male managed funds. We also find that female managed funds have significantly lower active shares and a lower tracking error. These effects are statistically significant on

[22] Chevalier and Ellison (1999b) suggest that manager characteristics like age and education might influence managerial behavior. However, this data is available for a small subset of managers only. In unreported results, we include the manager's age in years and dummy variables equal to one if a manager holds an undergraduate (master, PhD) degree, and zero otherwise. Our results are very similar.

[23] Ideally, we would like to estimate our models with fund fixed effects. However, given the very small number of cases in which a female manager is replaced by a male manager - or vice versa - this is not feasible.

the 5% and 1% level, respectively. Our findings suggest that male fund managers pursue more active investment styles by taking more active bets while female managers avoid active risk and herd closer towards the market.

In Panel B, we analyze whether female fund managers follow less extreme investment styles than male fund managers. We find a highly significant negative influence of the female dummy on our extremity measures. Female fund managers follow less extreme investment styles than male fund managers. This finding holds for the aggregate style extremity measure, $EM_{i,t}$, (Column 2) as well as for the three factor-individual style extremity measures, $EM^f_{i,t}$, (Columns 3 to 5).

In Panel C, we examine the *style variability* of male and female managed funds over time as defined in section 2. Results show that style variability is significantly lower for female managed funds, i.e. female fund managers follow more stable investment styles over time than male fund managers. This finding holds for the overall style variability measure (Column 2) as well as for the three factor individual style variability measures (Columns 3 to 5).

Overall, these results show that there are clear differences with respect to the investment styles female and male fund managers follow. Our results support earlier findings from retail investors (Barber and Odean (2000)) suggesting that female investors are more risk averse and trade less than their male counterparts. This suggests that gender differences are also observable in a professional setting. More important in our context is that female fund managers' investment behavior, however, should rather be desirable for mutual fund investors as they deliver more stable investment styles and performance than male fund managers.

4.2 Fund Performance

We now examine whether the behavioral differences documented in the previous section have an impact on average fund performance, the dispersion of performance ranks, i.e. performance extremity, and performance persistence of female and male fund managers.

Findings from earlier studies suggest that our result of behavioral differences between fund managers has consequences for fund performance. For example, Barber and Odean (2000) show that high trading activity hurts performance while Brown, Harlow, and Zhang (2010) document a positive influence of stable investment styles on performance. Furthermore, Cremers and Pfleiderer (2009) show that funds with the highest active share significantly outperform their benchmarks. Thus, based on our findings from the previous section it is an open empirical question whether female managers outperform male managers.

To examine this question, we relate the performance of fund i in year t, measured by the one-, three- and four-factor Alphas as defined in Section 2.2, to a female dummy and the same control variables as in Model (4). Additionally, we include the fund's lagged expense ratio. To take into account the effect of gender differences in unsystematic risk (see Section 4.1), we also analyze an extended version of the Appraisal Ratio of Treynor and Black (1973), $AppraisalRatio_{i,t}$, as defined in Section 2.2. Results are presented in Panel A of Table 7.

— Please insert TABLE 7 approximately here —

There is no significant difference between the performance of female and male managed funds. The influence of the female dummy is not significant at conventional levels for the abnormal return measures (Columns 1–3) as well as the Appraisal Ratio (Column 4).[24] Our result suggests that the market for mutual fund managers is efficient in the sense

[24] As an alternative to the multivariate regression approach, we also analyze the performance of (equal and value weighted) portfolios consisting of female and male managed funds, respectively. Results (not reported) using various performance measures indicate that there is no significant difference between these two portfolios.

that it is not possible to generate abnormal returns by following an investment strategy based on a manager characteristic as easily observable as gender. Although female and male fund managers differ in terms of investment behavior, these differences are not reflected in differences in average fund performance.

However, it might still be the case that the dispersion of performance ranks differs between female and male managed funds. We expect the more extreme style bets of male managed funds to be reflected in more extreme performance outcomes of these funds if we do not adjust performance for the investment styles of fund managers. To test this conjecture, we relate the probability of a fund to achieve a specific performance percentile to a female dummy and various fund characteristics by estimating the following logit model:

$$\begin{aligned} Prob(Percentile)_{i,t} \quad = \quad & \beta_1 \cdot FemaleDummy_{i,t} + \beta_2 \cdot FundSize_{i,t-1} + \beta_3 \cdot FundAge_{i,t-1} \\ & + \beta_4 \cdot Ret_{i,t-1} + \beta_5 \cdot Tenure_{i,t-1} + Segment_j + Year_t + \varepsilon_{i,t}, \quad (5) \end{aligned}$$

where $Prob(Percentile)_{i,t}$ is the probability that the performance of fund i is in the indicated percentile, $Percentile$, in year t. The control variables are defined as in Model (4). We test the probability of a fund being among the top or bottom 1% and 5%, respectively, for all funds in a given year t. Results are presented in Panels B and C of Table 7.[25]

Panel B presents results for the probability of a female managed fund to achieve a performance rank among the best or worst 1% of all funds. We find that female managed funds are significantly less likely than male managed funds to end up among the best or worst 1% of all funds when performance ranks are based on Jensen (1968) Alphas. Results are similar if we look at the probability of a fund achieving a performance among the 5% most extreme outcomes (Panel C). This finding only holds if we examine Jensen (1968) Alphas and vanishes if we control for the fund manager's investment styles analyzing the three- or four-factor Alphas. This confirms our reasoning that more extreme performance

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

outcomes of male fund managers are driven by the more extreme style bets they take as compared to female fund managers.

Thus, in Panel D we analyze gender differences in performance persistence. Results show that the performance ranks of male managed funds are more variable over time than those of female managed funds. This suggests that the performance of female managed funds is more persistent than that of male managed funds. This result holds irrespective of the specific performance measure analyzed. These findings show that past performance is a better indicator of future performance for female managed funds than for male managed funds.

Overall, we find no evidence for gender differences in behavior or performance that would support statistical discrimination against female fund managers. In contrast, our previous analysis shows that female managed funds might have some desirable characteristics from an investor's point of view: Female fund managers follow more stable and thus more reliable investment styles and their funds show a higher performance persistence and less extreme performance outcomes. These results support the view that unjustifiable prejudice against female fund managers might indeed drive our empirical and experimental finding of lower money inflows into female managed funds. We test this conjecture in the next section by conducting an implicit association test.

5 Implicit Association Test

Implicit Association tests (IAT) allow to uncover prejudice. They have gained enormous popularity among social psychologist in recent years. According to Lane, Banaji, Nosek, and Greenwald (2007), there are now well over 200 papers that use this method. Its popularity is based on the fact that it can be easily administered and that it allows to uncover implicit attitudes like negative prejudice or stereotypes that participants are often not willing to openly admit. Even if complete anonymity is credibly guaranteed, respondents often do not answer truthfully in standard surveys. In contrast, the IAT provides a simple way to measure implicit attitudes based on automatically operating implicit associations that can not be easily manipulated (Greenwald and Banaji (1995)). It also allows to uncover implicit attitudes based on implicit associations that the subjects might not even be aware of themselves (Greenwald, Banaji, Rudman, Farnham, Nosek, and Mellott (2002)). Its reliability and validity as a way to measure implicit prejudice has been widely tested and is now generally accepted (Cunningham, Preacher, and Banaji (2001)). Appendix B contains an explanation on how a typical IAT works. Basically, participants have to rapidly sort items into different categories. Their reaction times are then used to uncover prejudice.

To examine whether there is any gender bias against females in finance, we adapt the IAT to the context of finance. The first categorization we look at is gender, i.e. a male vs. female category. The words belonging to the gender categories are similar to those from typical gender discrimination IATs and are all easily recognizable as belonging to the female or male category like 'father', 'uncle', 'mother', or 'aunt'. The full list of items is presented in Panel A of Table 8.

— Please insert TABLE 8 approximately here —

The second categorization we use is the field in which an individual might work. The first category is 'finance', while we chose 'marketing' as the second category. We chose 'marketing' as a contrasting category, because finance and marketing are two of the most prominent majors among US undergraduate students. The items that have to be sorted into these categories are again easily recognizable and include, e.g., 'stocks', 'mutual funds', 'advertising', or 'logo'. The full list of items is presented in Panel B of Table 8.

In the IAT, subjects have to categorize items by hitting the 'I' or 'E' key on their keyboards, depending on whether the specific item displayed on the center of the screen belongs to a category displayed on the left-hand or right-hand side of the screen. An example is provided in Figure 3.

— Please insert FIGURE 3 approximately here —

Panel A displays the *incompatible configuration* where the categories 'finance' and 'female' are used together on one side and 'marketing' and 'male' on the other side. In contrast, Panel B displays the *compatible configuration* where categories 'finance' and 'male' together on one side of the screen and 'marketing' and 'female' on the other side. In both cases of this example, participants had to sort the item "stocks" into the right category as fast as possible. The main idea of IAT is that the reaction time will take longer for the incompatible condition as compared to the compatible condition.

Following Greenwald, McGhee, and Schwartz (1998), the IAT is played in seven rounds and two versions. Out of the seven rounds, two rounds are test rounds that will be evaluated, while the other five rounds are practice rounds. First, two practice rounds 1 and 2 with 20 trials each are played to familiarize subjects with the tasks. In the first round, only items belonging to the categories 'female' and 'male' had to be sorted. In the second round, only items belonging to the categories 'marketing' and 'finance' had to be sorted. As items, we chose the words as presented in Table 8. Then, another practice round with 20 trials was administered in which subjects were asked to categorize items in a combined task, i.e. they had to categorize items into the 'male/female' and 'marketing/finance' categories. After these three practice rounds, a test round with 40 trials which was otherwise identical to the third practice round was played. Then, two more test rounds 5 and 6 with 20 trials each follow that are similar to the test rounds 1 and 3. However, one of the categories is exchanged from the left to the right side of the screen. Finally, round 7 is another test round with 40 trials, which is identical to the last practice round.

The test was administered in two versions. The treatment group first played the compatible configuration, and then the incompatible configuration. The second version is played by the control group and starts with the incompatible configuration followed by the compatible configuration. We separate participants in treatment and control group to ensure that the ordering of the configurations (compatible vs. incompatible first) does not affect our results.

The simplest way to measure implicit attitudes is to just compare reaction times in milliseconds (ms), which we denote by R. To prevent outliers from driving the results we follow Greenwald, McGhee, and Schwartz (1998) and set all unrealistically long reactions times over 3 seconds equal to 3 seconds and all unrealistically short reaction times below 300 ms equal to 300 ms. This method makes sure that no potentially valuable observations are lost but also prevents them from having an undue impact on average reaction times.

The reaction times for the treatment and the control group in the test rounds 4 and 7 as well as in the respective practice rounds 3 and 6 are summarized in the box-plots presented in Figure 4.

— Please insert FIGURE 4 approximately here —

In both, the combined practice rounds (3 and 6) as well as the combined test rounds (4 and 7), reaction times are much faster in the compatible than in the incompatible configuration. For the treatment group, the mean reaction time for the compatible test round 4 is 753.99 ms, while it is 914.15 ms in the incompatible test round 7. Similarly, for the control group, the mean reaction time in the compatible test round 7 is 833.13 ms, while it is 994.79 ms in the incompatible test round. These differences in reaction times suggest that the implicit association of males with finance is much stronger than that of females with finance, which is consistent with negative prejudice against females in finance.

The above results are based on a sample where all trials per round are pooled across individuals. To examine reaction times more formally and to be able to relate reaction times to personal characteristics, we now aggregate data on the subject level. To do so, we calculate the average reaction time per round and subject using three alternative methods. First, we calculate the simple average of the reaction times R in ms. This approach has the advantage that effects can be directly interpreted. Second, we calculate log-transformed reaction times, $\log(R)$. This approach has the additional advantage that the distribution of log-transformed reaction times has a more stable variance and is thus more suitable for analysis. Third, we calculate a speed variable defined as $S = \frac{1{,}000}{R}$. Speed also has desirable distributional characteristics that stabilize variances. It can be directly interpreted as items per second.

To get a measure for the extent of implicit prejudice, we then calculate the difference in the mean reaction time between rounds 4 and 7 based on R, $log(R)$, and S. These implicit prejudice measures are denoted by $d(R)$, $d(log(R))$, and $d(S)$, respectively. For the treatment group, the mean reaction time from round 4 is subtracted from the mean reaction time in round 7, and vice versa for the control group, because the latter plays the incompatible configuration first. In this way, the sign of d has the same interpretation in both cases. A d significantly larger than zero indicates that there is implicit prejudice against females in finance. The magnitude of these simple d measures can be directly interpreted. However, to run statistical tests we use the pooled standard deviation from rounds 4 and 7 as effect size unit to get subject-individual adjusted measures d^{adj} for implicit prejudice. Using simple reaction times R, the implicit prejudice measures $d^{adj}(R)$ for the treatment group is defined as:

$$d^{adj}(R) = \frac{\bar{R}^7 - \bar{R}^4}{std(R)}, \tag{6}$$

where $\bar{R}^4$ ($\bar{R}^7$) denotes mean trial reaction times from round 4 (7), and $std(R)$ denotes the pooled standard deviation of reaction times from round 4 and 7. Similarly, implicit prejudice measures based on $log(R)$, $d^{adj}(log(R))$, and S, $d^{adj}(S)$, are computed accordingly.

The results on the unadjusted and adjusted d measures are presented in Table 9. Results for a pooled examination of all subjects from the treatment and control group are presented in Panel A.

— Please insert TABLE 9 approximately here —

The first three columns show the mean, standard deviation, minimum and maximum value of all subject-individual d-measures. The first three rows show results for the unadjusted d-measures, while the fourth to sixth row show results for the adjusted d measures.[26]

The mean of $d(R)$ is 160.96, i.e. the average of the subject individual mean reaction times in the incompatible configuration is 160.96 ms slower than in the compatible configuration. The standard deviation adjusted measures are between 0.45 for $d^{adj}(R)$ and $d^{adj}(S)$, and 0.48 for $d^{adj}(log(R))$. The last four columns present results from a simple t-test. We test whether the implicit prejudice effect is significantly different from zero. No matter which specific d measure we use, the hypothesis that the implicit prejudice effect is not different from zero can be rejected in all cases. The t-statistic is between 10 and 11 and the respective p-values are all below 0.00005. This confirms our preliminary results from the comparison of simple reaction times in Figure 4. The implicit prejudice measure results provide corroborating evidence for strong and highly significant negative prejudice against females in finance.

In Panels B and C, we present results based on subjects from the treatment group and the control group separately. The mean difference in average response times, $d(R)$, is about 161 ms in both cases and the adjusted implicit prejudice measures are all between 0.43 and 0.50. The differences between the treatment and control group are not statistically significant. This shows, that observations from subjects playing the incompatible configuration first and from subjects playing the compatible configuration first can be (and will be) pooled in further analysis.

Tajfel (1970) provides strong evidence for an in-group bias of individuals. Such a bias should lead to less pronounced or no implicit prejudice against females in finance among female finance student subjects. To examine whether there is any effect along those lines in our setting, we first investigate whether there is any difference in implicit prejudice between male and female subjects. Results on the implicit prejudice effect based on the unadjusted

[26]The results for the adjusted d-measure based on simple reaction times R and the measure based on speeds S are identical, because S is a simple linear transformation of R.

and adjusted version of $d(R)$ for subsamples of female and male subjects are presented in Panel A of Table 10.

— Please insert TABLE 10 approximately here —

Our findings suggest that implicit prejudice against females in finance does not seem to depend on the subject's sex. The implicit prejudice effect is 164 ms among male participants. It is somewhat lower with 158 ms among female participants, but the difference is not statistically significant.

However, the impact of any in-group bias as described in Tajfel (1970) is more likely to be found among subjects whose main field of study is finance. The reason for this is that females in finance should have less prejudice about females in finance than males in finance or males and females from other disciplines might have. To investigate this possibility, we now explicitly examine differences between female and male subjects that study finance. Results are presented in Panel B of Table 10. We find that the 25 male subjects that study finance show an implicit prejudice effect of 224 ms, which is clearly larger than the typically observed effect of about 160 ms in the overall subject population. In contrast, among the 18 female subjects that study finance the implicit prejudice effect amounts to only 118 ms. This effect is still significant at the 5% level, but is only about half the size of the effect observed among male finance students. Moreover, the difference in the implicit prejudice effect between male and female finance students is also statistically significant (t-statistic: 2.05; p-value: 0.0467, both based on unadjusted $d(R)$).[27]

Regarding the field of study, results in Panel C show that the implicit prejudice effect is a little bit stronger among finance students (180 ms) as compared to all subjects (161 ms, Table 9). However, the difference is not statistically significant.

[27]A similar difference can be observed for the adjusted implicit prejudice measures, for which the variance is more stable and statistical effects can be detected more precisely. Again, the effect is about twice as strong for male subjects ($d(R)^{adj} = 0.61$) than for female subjects ($d(R)^{adj} = 0.34$) and the difference is statistically significant (t-statistic: 2.20; p-value: 0.0338).

Finally, results from Agnew, Szykman, Utkus, and Young (2008) and Kaustia, Alho, and Puttonen (2008) suggest that behavioral biases and investment mistakes are weaker if investors are financially literate. Thus, in Panel D we check whether there is also any relation between the level of financial literacy and implicit prejudice. The implicit prejudice measure in the high financial literacy group is 177 ms vs. 150 ms in the low financial literacy group. However, the difference is not statistically significant (p-value of 0.33 based on adjusted $d(R)$).

The analysis of the impact of subject characteristics on implicit prejudice delivers several additional results: implicit prejudice seems to be equally strong among male and female subjects. However, it is much more pronounced among male finance students than among female finance students. Nevertheless, implicit prejudice is still significant even among the latter. Finally, field of study and financial literacy have no significant relation to the extent subjects are prone to implicit prejudice.[28]

Overall, the results of this section suggest that there is prejudice against females in the financial industry. However, it is still unclear whether this prejudice is strong enough to result in lower inflows into female managed funds. To check whether there is any correlation between implicit prejudice as revealed by the IAT and the actual investment behavior of subjects in the experimental investment task, we now compare the fraction invested in the female managed fund between participants that exhibit implicit prejudice to the (minority of) subjects that show no signs of implicit prejudice. Results are presented in Table 11.

— Please insert TABLE 11 approximately here —

They clearly show that subjects that exhibit implicit prejudice ($d(R) > 0$, $d(log(R)) > 0$, $d(S) > 0$) invest significantly less in the female managed fund. In contrast, we find even

[28] Results in experiments often crucially depend upon the experimental procedure. In unreported results that we skipped for brevity, we test whether the results are stable against variations of the experimental parameters. Specifically, we checked whether results depend upon the sex of the instructor in the experiment, on the time of the day (Cajochen, Kruchi, and Wirz-Justice (1997)), and on differences in the number of participants per session, i.e. on the crowdedness of the sessions (Bruins and Barber (2006)). Our results are robust to these consistency checks.

slightly (but statistically not significant) larger investments in the female managed fund of those participants that exhibit no implicit prejudice. This shows that implicit prejudice has implications for investment behavior and confirms the external validity of the IAT in our setting, too.

6 Conclusion

This paper examines the conjecture that investors might have negative prejudice about female fund managers and eventually invest less into their funds. As fund companies generate their profit from fees charged on assets under management, customer based discrimination might cause the low fraction of female fund managers in the mutual fund industry. Consistent with this conjecture, we find strong evidence that mutual fund investors direct significantly less money into female managed funds. We are able to replicate this finding under the controlled conditions of a laboratory experiment.

We show that investors' preconception on female fund managers is not supported by underperformance of female managed funds. We further find that female fund managers are more risk averse and follow less extreme and more stable investment styles than male fund managers. In addition, male managers trade more and deviate more from benchmarks than female managers. Although we find no significant differences in average performance between female and male managed funds, the performance of the latter is less persistent over time. These results show that female managers exhibit characteristics that should actually be preferable from an investor's point of view.

Finally, we explicitly investigate potential prejudice against females in finance by conducting an implicit association test (IAT). The results from this test show that the implicit association of males with finance is much stronger than that of females with finance. As implicit associations are a strong psychological predictor of implicit attitudes, we can interpret these results as evidence for prejudice against females in finance.

Overall, our findings help to understand, why female managed funds receive much lower inflows than male managed funds: If investors have negative prejudices about women in finance, they would automatically shy away from investing with them. While our argument is based on prejudice among investors which can lead to customer demand driven hiring of more men, this is of course only one possible channel that helps in explaining the low fraction of female mutual fund managers.

Our results from the IAT can also help to explain why the fraction of females in finance is so low in the industry, but also in academia, via two other channels: First, implicit prejudice against females typically leads to implicit discrimination in hiring (Bertrand, Chugh, and Mullainathan (2005)). Second, the implicit prejudice against females in finance that we observe even among female finance students can lead to female finance students being underconfident with respect to their abilities in finance. Thus, they might eventually self-select into other fields.

Appendix A

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 United States 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.[29] We then match this list with the first names obtained 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 foreign exchange students from the respective country. For the remaining cases, we try to 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%.

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

Appendix B

Example of Implicit Association Test

In the following, we describe an IAT that is used to reveal prejudice against gay people.[30] The subjects in such a test are required to classify items (typically words, symbols, or pictures) into four categories. In the example, two of the categories would be 'gay' and 'straight', which describe the 'target concept discrimination'. The other two categories would be 'good' and 'bad', which describe the 'attribute discrimination'. The IAT is conducted with the help of a computer. Participants sit in front of a screen and two of the four categories are displayed on the left side of the screen, while the other two are displayed on the right side of the screen. On each side, one concept and one attribute (e.g. 'straight' and 'good' on the left side and 'gay' and 'bad' on the left side) are displayed. The connection of the negative attribute ('bad') with the concept that subjects are expected to have prejudice about ('gay') is called the compatible configuration. Then, in the first test round, items belonging to one of the categories show up in the middle of the screen and subjects are asked to respond rapidly by pressing a left-hand (right-hand) key if the item belongs to the categories displayed on the left side (right side) of the screen. In the incompatible configuration one of the categories is switched from one side of the screen to the other (e.g. 'straight' and 'bad' on the left side and 'gay' and 'good' on the right side). Again, subjects are asked to rapidly sort items appearing in the middle of the screen by hitting a left- or right-hand key. The IAT measures reaction times in these two tasks. If subjects have stronger associations of 'gay' with 'bad' than with 'good', this shows up in slower reaction times in the incompatible configuration, i.e. they find it more difficult to sort items along the 'bad/straight' vs. 'good/gay' dimensions than along the 'bad/gay' vs. 'good/straight' dimensions. If there is no implicit prejudice among subjects, then the average reaction times should be the same in both tasks.

[30] This example is taken from https://implicit.harvard.edu, where more information on IATs can be found and demo versions of various IATs can be tried out.

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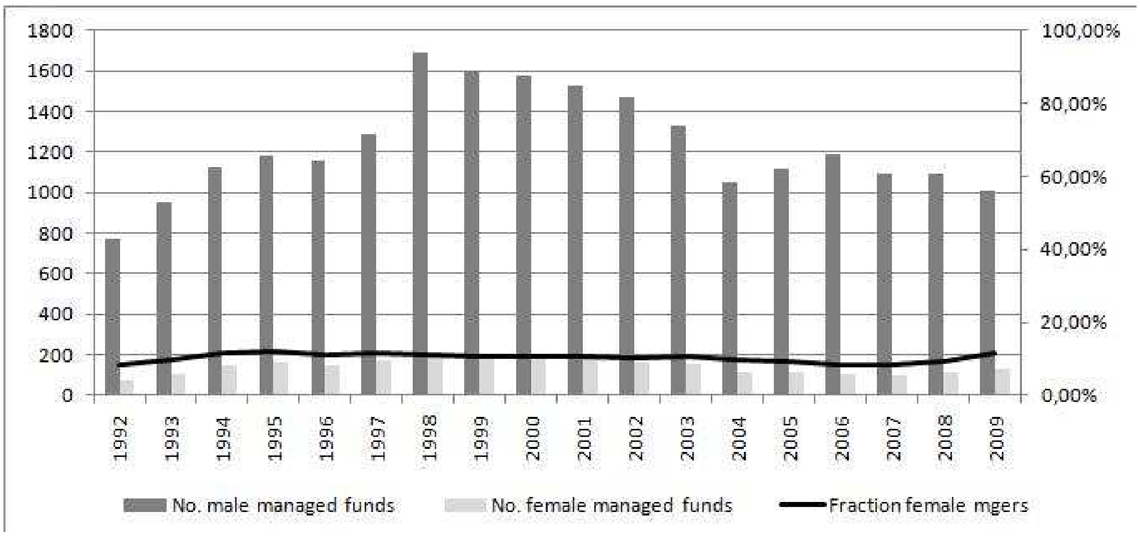
Figure 1: Distribution of Funds by Manager Gender



Notes: This figure displays the total number of female and male managed funds (bars) and the share of female managed funds (line). The sample consists of all female and male fund managers responsible for at least one single managed equity fund from January 1992 to December 2009. Data is taken from the CRSP Survivor Bias Free Mutual Fund Database.

Figure 2: Investment Task

Panel A: Treatment group

	Fund A	Fund B
Fund Segment	S&P 500 Index Fund	S&P 500 Index Fund
Fund Manager	Linda Williams	James Davis
About the Fund		
Size	$77.49 Million	$75.35 Million
Inception Date	10/2/1998	2/18/2005
Annual Expense Ratio	0.70%	0.64%
Trading Activity (Annual Turnover Ratio)	1.98%	2.03%
Fund Facts	The investment seeks to replicate the total return of the S&P 500 index, before fees and expenses. The fund invests primarily in common stocks issued by companies in the Standard & Poor's 500 Composite Stock Price index.	The investment seeks to replicate the total return of the S&P 500 index, before fees and expenses. The fund invests primarily in common stocks issued by companies in the Standard & Poor's 500 Composite Stock Price index.
Top Five Stock Holdings		
1	Exxon Mobil CP	Exxon Mobil CP
2	General Electric CO	General Electric CO
3	Microsoft Corporation	Microsoft Corporation
4	Chevron Corp	Chevron Corp
5	AT&T Inc.	AT&T Inc.

Panel B: Control group

	Fund A	Fund B
Fund Segment	S&P 500 Index Fund	S&P 500 Index Fund
Fund Manager	James Williams	Linda Davis
About the Fund		
Size	$77.49 Million	$75.35 Million
Inception Date	10/2/1998	2/18/2005
Annual Expense Ratio	0.70%	0.64%
Trading Activity (Annual Turnover Ratio)	1.98%	2.03%
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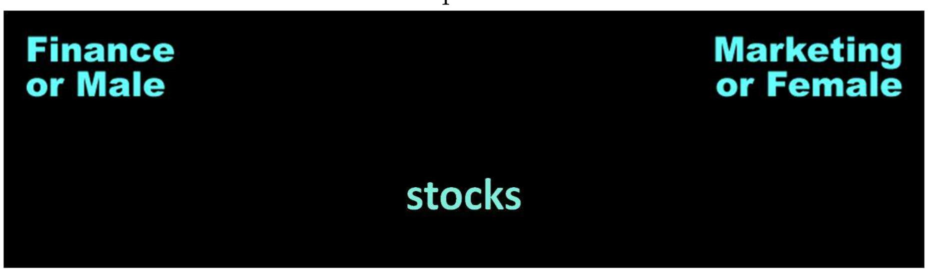
Top Five Stock Holdings		
1	Exxon Mobil CP	Exxon Mobil CP
2	General Electric CO	General Electric CO
3	Microsoft Corporation	Microsoft Corporation
4	Chevron Corp	Chevron Corp
5	AT&T Inc.	AT&T Inc.

Notes: This figure displays the information about each fund provided to the treatment group (Panel A) and the control group (Panel B), respectively. Identical information is provided to both groups except for the gender of the fund manager (indicated by her first name) which is switched between fund A and fund B.

Figure 3: IAT Screen

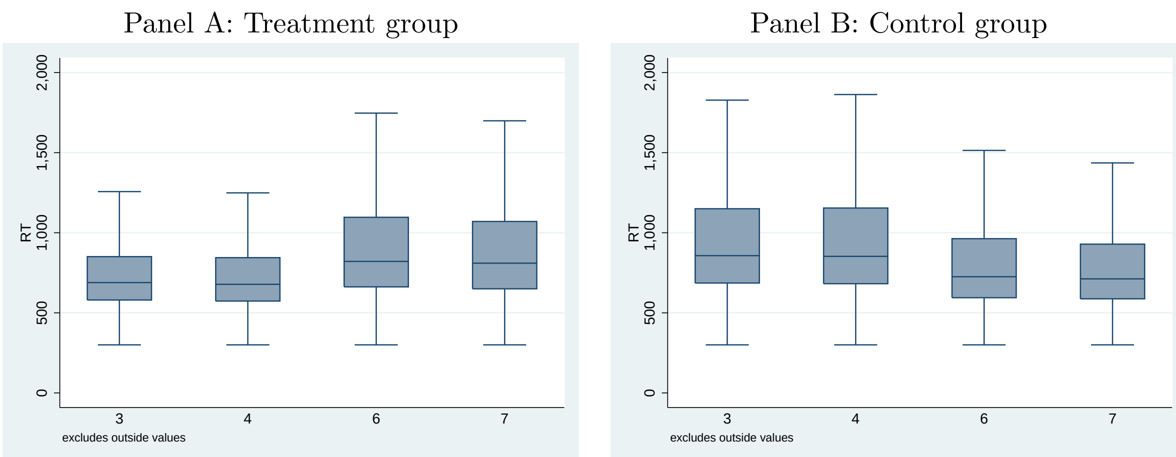
Panel A: Incompatible Condition

Panel B: Compatible Condition



Notes: This figure displays the incompatible condition of the IAT (Panel A) and the compatible condition (Panel B), respectively.

Figure 4: Reaction Times in the Implicit Association Tests (IAT)



Notes: This figure shows boxplots for the reaction times, RT, in milliseconds (ms) from rounds 3, 6 (practice) and 4, 7 (test) for the treatment group (Panel A) and control group (Panel B). For the treatment group, rounds 3 and 4 contain the compatible configuration, while rounds 6 and 7 contain the incompatible configuration. For the control group, the ordering was reverse. The vertical line in the box indicates the median level, and the upper and lower hinge represent the 75th and 25th percentile, respectively. The length of the whiskers are determined by the adjacent value which is still just inside a limit determined by 1.5 times the interquartile range.

Table 1: Descriptive Statistics

	Female Manager	*Male Manager*	*Difference*
Fund Size (in Millions)	573.07	711.01	-137.94^{***}
Fund Age (in years)	10.89	10.33	0.55^{**}
Expense Ratio (in percent)	1.46	1.44	0.02
Max 12b1 (in percent)	0.36	0.33	0.03^{***}
Turnover Ratio	0.95	1.07	-0.12^{**}
Relative Fund Flows	0.32	0.37	-0.05^{**}
Fund Return	0.05	0.06	0.01
Jensen Alpha p.a.	−0.09	0.05	−0.04
Total Risk	0.05	0.05	0.00
Systematic Risk	0.98	0.99	−0.01
Unsystematic Risk	6.31	6.27	0.04
Active Share	0.76	0.78	-0.02^{***}
Tracking Error	0.65	0.74	-0.09^{***}
Manager Tenure (in years)	4.14	4.87	-0.73^{***}

Notes: This table shows the average fund characteristics based on our sample of all single managed U.S. equity funds from January 1993 to December 2009. The detailed description of the variables listed in the first column is contained in the main text. The second column contains average characteristics for female managed funds. The third column contains average characteristics for male managed funds. The last column contains the difference between the average characteristics of female and male fund managers. Significance is calculated based on a two-sided t-test. *** 1% significance, ** 5% significance, * 10% significance.

Table 2: Fund Flows

	(1)	(2)	(3)	(4)	(5)	(6)
$FemaleDummy_{i,t}$	–0.076	–0.103	–0.075	–0.108	–0.076	–0.070
	(–3.36)***	(–3.79)***	(–3.27)***	(–3.87)***	(–3.72)***	(–3.27)***
$Flow_{i,t-1}$	0.075	0.053	0.064	0.040	0.087	0.072
	(8.30)***	(6.16)***	(6.77)***	(4.47)***	(6.32)***	(5.08)***
$PerfRank_{i,t-1}$	–0.348	–0.428			–0.276	
	(–2.67)***	(–3.15)***			(–1.27)	
$PerfRank^2_{i,t-1}$	1.106	1.109			0.981	
	(7.29)***	(7.22)***			(3.94)***	
$Quintile1_{i,t-1}$			0.725	0.748		0.707
			(3.53)***	(3.17)***		(3.16)***
$Quintile2-4_{i,t-1}$			0.222	0.229		0.179
			(4.50)***	(4.56)***		(3.20)***
$Quintile5_{i,t-1}$			2.569	2.474		2.648
			(6.00)***	(5.72)***		(4.65)***
$FundSize_{i,t-1}$	–0.058	–0.124	–0.066	–0.141	–0.059	–0.065
	(–7.43)***	(–9.51)***	(–7.95)***	(–10.32)***	(–7.59)***	(–7.39)***
$Turnover_{i,t-1}$	0.051	0.057	0.049	0.055	0.035	0.036
	(4.19)***	(3.69)***	(3.93)***	(3.47)***	(1.89)*	(2.05)*
$FundRisk_{i,t-1}$	–2.012	–0.505	–2.567	–1.016	–0.257	–0.253
	(–3.16)***	(–0.77)	(–3.99)***	(–1.53)	(–0.24)	(–0.27)
$ExpRatio_{i,t-1}$	0.731	5.608	0.028	4.831	–3.261	–3.836
	(0.32)	(1.89)*	(0.01)	(1.39)	(–1.72)	(–1.56)
$FundAge_{i,t-1}$	–0.096	–0.032	–0.095	–0.022	–0.096	–0.091
	(–7.89)***	(–1.73)*	(–7.41)***	(–1.19)	(–4.99)***	(–4.53)***
$SegmentFlow_{i,t}$	0.178	0.139	0.177	0.135	0.292	0.263
	(4.09)***	(3.13)***	(3.99)***	(2.98)***	(3.67)***	(3.05)***
$CompanyFlow_{i,t}$	0.003	0.000	0.003	0.000	0.096	0.097
	(2.26)**	(0.13)	(2.28)**	(0.12)	(2.33)**	(2.39)**
Year FE	yes	yes	yes	yes	no	no
Segment FE	yes	yes	yes	yes	no	no
Family FE	no	yes	no	yes	no	no
Method	OLS	OLS	OLS	OLS	FMB	FMB
(avg.) R^2	0.113	0.189	0.089	0.172	0.092	0.113
Observations	12312	12279	12265	12232	12312	12265

Table 2: continued

Notes: This table shows the estimates of percentage fund flows regressed on a female fund manager dummy, $FemaleDummy_{i,t}$, as well as fund and segment characteristics. Fund flows are calculated by subtracting the internal growth of a fund due to the returns earned on assets under management from the total growth rate of the fund's total net-assets under management. $FemaleDummy_{i,t}$ is a dummy variable that takes on the value one, if a fund i is managed by a female manager in year t, and zero otherwise. $Flow_{i,t-1}$ is the lagged net-inflow into fund i. To capture the non-linearity of the performance-flow relationship we include the performance rank of fund i in the previous year $t-1$, $PerfRank_{i,t-1}$, as well as the squared performance rank of fund i in the previous year $t-1$, $PerfRank^2_{i,t-1}$ relative to all other funds in the same market segment (Columns 2, 3, and 6). Alternatively, we use a piecewise linear regression approach (Columns 4, 5 and 7) and include piecewise linear regression coefficients 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 $Quintile5_{i,t-1} = PerfRank_{i,t-1} - (Quintile1_{i,t-1} + Quintile2-4_{i,t-1})$. $FundSize_{i,t-1}$ is the lagged natural logarithm of the fund's size in million USD and $Turnover_{i,t-1}$ is the fund's lagged turnover rate. $FundRisk_{i,t-1}$ is the lagged return time series standard deviation of fund i. $ExpRatio_{i,t-1}$ is defined as the fund's yearly total expense ratio. $FundAge_{i,t-1}$ is the lagged natural logarithm of fund i's age in years. $SegmentFlow_{i,t}$ is the growth rate of fund i's market segment due to flows in year t. $CompanyFlow_{i,t}$ is the growth rate of fund i's fund company due to flows in year t. $SegmentFlow_{i,t}$ and $CompanyFlow_{i,t}$ are calculated net of the flows into fund i. The model is estimated by a pooled regression approach (Columns 1 to 4) as well as Fama and MacBeth (1973) regressions (Columns 5 and 6). The sample is from January 1993 to December 2009. Standard errors are clustered at the fund level. *** 1% significance, ** 5% significance, * 10% significance.

Table 3: Fund Flows: Interactions and Robustness

	Performance Interactions		Broker Channel	Manager Change	Size	Alternative Flow Measures	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FemaleDummy_{i,t}$	–0.119	–0.147	–0.108		–0.096	–0.007	–12.204
	(–4.31)***	(–2.39)**	(–3.44)***		(–3.58)***	(–3.97)***	(–2.12)**
$FemNew_{i,t-1}$				–0.149			
				(–2.49)**			
$MaleNew_{i,t-1}$				0.022			
				(0.25)			
$Perf * Fem_{i,t-1}$	–0.064						
	(–3.77)***						
$PerfRank * Fem_{i,t-1}$		0.566					
		(1.77)*					
$PerfRank^2 * Fem_{i,t-1}$		–0.738					
		(–2.12)**					
$NoLoad * Fem_{i,t}$			0.011				
			(0.22)				
$Performance_{i,t-1}$	0.103						
	(8.64)***						
$PerfRank_{i,t-1}$	–0.447	–0.485	–0.425	–0.429	–0.465	0.014	90.023
	(–3.31)***	(–3.31)***	(–3.12)***	(–3.16)***	(–3.44)***	(1.65)	(3.38)***
$PerfRank^2_{i,t-1}$	1.114	1.183	1.106	1.112	1.139	0.013	56.045
	(7.31)***	(7.12)***	(7.18)***	(7.23)***	(7.44)***	(1.73)*	(2.05)**
$NoLoad_{i,t}$			0.011				
			(0.22)				
$Flow_{i,t-1}$	0.042	0.053	0.053	0.053	0.055		
	(4.78)***	(6.16)***	(6.16)***	(6.18)***	(6.43)***	(20.47)***	
$MShare_{i,t-1}$						–0.462	
						(–2.56)**	
$AbsFlow_{i,t-1}$							0.498
							(20.47)***
$FundSize_{i,t-1}$	–0.129	–0.124	–0.125	–0.123	–0.497	0.019	14.761
	(–9.80)***	(–9.51)***	(–9.55)***	(–9.48)***	(–3.48)***	(20.45)***	(9.09)***
$FundSize^2_{i,t-1}$					0.049		
					(1.96)*		
$FundSize^3_{i,t-1}$					–0.002		
					(–1.11)		
$Turnover_{i,t-1}$	0.056	0.057	0.057	0.058	0.054	0.000	1.152
	(3.66)***	(3.70)***	(3.69)***	(3.76)***	(3.60)***	(1.92)*	(2.88)***
$FundRisk_{i,t-1}$	–1.061	–0.517	–0.510	–0.498	–0.553	–0.039	–239.459
	(–1.64)	(–0.79)	(–0.78)	(–0.76)	(–0.84)	(–1.22)	(–2.79)***
$ExpRatio_{i,t-1}$	5.878	5.586	5.717	5.689	4.863	0.303	250.644
	(1.83)*	(1.88)*	(1.95)*	(1.93)*	(1.56)	(6.68)***	(1.76)*
$FundAge_{i,t-1}$	–0.032	–0.032	–0.032	–0.033	–0.035	–0.003	–2.299
	(–1.76)*	(–1.73)*	(–1.73)*	(–1.79)*	(–1.99)**	(–1.70)*	(–0.88)
$SegmentFlow_{i,t}$	0.120	0.140	0.139	0.139	0.141	0.006	0.003
	(2.69)***	(3.16)***	(3.14)***	(3.14)***	(3.20)***	(1.86)*	(0.71)
$CompanyFlow_{i,t}$	0.000	0.000	0.000	0.000	–0.000	0.000	0.030
	(0.15)	(0.10)	(0.11)	(0.08)	(–0.02)	(1.85)*	(2.85)***
Year/Segment FE	yes	yes	yes	yes	yes	yes	yes
Family FE	yes	yes	yes	yes	yes	no	yes
adj./Pseudo R^2	0.199	0.189	0.189	0.189	0.197	0.028	0.317
Observations	12266	12279	12277	12278	12279	14539	11870

Table 4: Participant Characteristics

Panel A: Main Field of Study	Number	Percentage
Accounting	13	13.00%
Economics	5	5.00%
Engineering	4	4.00%
Finance	43	43.00%
Management Information Systems	9	9.00%
Marketing	10	10.00%
Other	7	7.00%
Other (business related)	9	9.00%
Panel B: Age in Years	**Number**	**Percentage**
18 to 19	8	8.00%
20	30	30.00%
21	30	30.00%
22	21	21.00%
23 to 25	9	9.00%
26 to 30	1	1.00%
31 to 40	2	2.00%
Panel C: Marital Status	**Number**	**Percentage**
Single	97	97.00%
Married	1	1.00%
Engaged	2	2.00%
Divorced	0	0.00%
Other	0	0.00%
Panel D: Gender	**Number**	**Percentage**
Female	49	49.00%
Male	51	51.00%

Notes: This table shows summary statistics of participants' characteristics in our experiment. Panel A displays the number and percentage of participants with different main fields of study. Panel B contains the number and percentage of participants in different age brackets. Panel C provides number and percentage of participants depending on their marital status and Panel D contains number and percentage of participants that belong to each gender category.

Table 5: Investment Decisions

	Female Manager	Male Manager	Difference (F-M)	Obs.
	% invested into index fund			
Panel A: All participants	41.43	48.85	–7.42***	484
Panel B: Gender				
Males	35.77	46.23	–10.47***	252
Females	50.56	51.31	–0.75	232
Panel C: Field of Study				
Finance/Econ	36.74	46.48	–9.74***	240
Marketing/Mgmt	44.36	53.98	–9.62**	84
Panel D: Financial Literacy				
FinLit ≥ 4	36.19	44.63	–8.43**	220
FinLit<4	47.42	52.33	-4.92*	116
Panel E: Type of Fund				
	% invested first round			
All funds^{1st}	45.71	50.15	–4.43**	484
Index^{1st}	34.34	42.85	–8.51**	121
Growth/Inc.^{1st}	56.17	61.29	–5.12*	121
Aggr. Growth^{1st}	42.77	46.29	–3.52	121
ASIA/EUR^{1st}	46.30	49.97	–3.66	121
	% invested all rounds			
All funds^{all}	45.20	47.23	–2.04**	1,936
Index^{all}	41.43	48.85	–7.42***	484
Growth/Inc.^{all}	51.87	55.33	–3.46**	484
Aggr. Growth^{all}	38.85	38.63	0.22	484
ASIA/EUR^{all}	48.77	45.63	3.14	484

Notes: This table shows the fraction of money invested into the female managed (Column 1) and male managed (Column 2) fund. The difference between the amounts invested in the female and male managed fund is displayed in Column 3. Panel A presents results for all participants of our experiment, while Panel B contains results for female and male participants separately. In Panel C, we form groups of participants by field of study. In Panel D, we divide participants based on their financial literacy, using mean financial literacy as a cut-off. Financial literacy is computed based on the number of correct answers in a standard financial literacy test containing six questions on financial issues. Panel E displays results depending on different types of funds and different rounds of the experiment. *** 1% significance, ** 5% significance, * 10% significance.

Table 6: Gender Differences in Investment Behavior

Panel A: Risk Taking and Trading Activity

	Total $Risk_{i,t}$	*Systematic* $Risk_{i,t}$	*Unsystematic* $Risk_{i,t}$	*Turnover* $Ratio_{i,t}$	*Active* $Share_{i,t}$	*Tracking* $Error_{i,t}$
$FemaleDummy_{i,t}$	–0.000	0.010	–0.948	–0.116	–0.025	–0.009
	(–0.42)	(0.77)	(–2.37)**	(–2.86)***	(–1.98)**	(–4.28)***
$FundSize_{i,t-1}$	0.000	0.012	–0.870	–0.093	–0.022	–0.004
	(0.04)	(3.50)***	(–2.62)***	(–6.03)***	(–8.19)***	(–7.48)***
$FundAge_{i,t-1}$	–0.001	–0.015	0.613	–0.018	–0.000	0.001
	(–1.58)	(–2.07)**	(0.83)	(–0.62)	(–0.04)	(0.58)
$Ret_{i,t-1}$	0.010	0.193	3.539	0.421	0.023	0.015
	(5.71)***	(6.65)***	(2.29)**	(2.24)**	(2.51)**	(4.31)***
$Tenure_{i,t-1}$	–0.000	–0.005	0.074	–0.025	0.003	0.001
	(–2.09)**	(–3.58)***	(2.29)**	(–6.04)***	(3.95)***	(3.58)***
Year FE	yes	yes	yes	yes	yes	yes
Segment FE	yes	yes	yes	yes	yes	yes
R^2	0.507	0.196	0.157	0.065	0.204	0.399
Observations	15264	15233	15233	15158	6219	6086

Panel B: Style Extremity

	$EM_{i,t}$	$EM_{i,t}^{SMB}$	$EM_{i,t}^{HML}$	$EM_{i,t}^{MOM}$
$FemaleDummy_{i,t}$	–0.151	–0.104	–0.183	–0.167
	(–4.10)***	(–2.49)**	(–4.16)***	(–3.82)***
$FundSize_{i,t-1}$	–0.045	–0.046	–0.041	–0.048
	(–2.70)***	(–2.78)***	(–2.28)**	(–2.86)***
$FundAge_{i,t-1}$	0.029	0.035	0.019	0.033
	(1.12)	(1.31)	(0.68)	(1.22)
$Ret_{i,t-1}$	0.215	0.196	0.293	0.156
	(3.03)***	(2.48)**	(3.71)***	(2.08)**
$Tenure_{i,t-1}$	0.009	0.007	0.008	0.011
	(1.45)	(1.12)	(1.32)	(1.77)*
Year FE	yes	yes	yes	yes
Segment FE	yes	yes	yes	yes
R^2	0.207	0.185	0.181	0.181
Observations	15233	15233	15233	15233

Panel C: Style Variability

	SVM_i	SVM_i^{SMB}	SVM_i^{HML}	SVM_i^{MOM}
Female Manager	0.8748	0.8789	0.8750	0.8706
Male Manager	1.0059	1.0057	1.0059	1.0061
Difference	−0.1311**	−0.1268**	−0.1309*	−0.1355**

Table 6: continued

Notes: This table shows the estimates of various investment style measures regressed on a female fund manager dummy, $FemaleDummy_{i,t}$, as well as fund characteristics. In Panel A, the dependent variable is on of the following: the fund's total risk measured by its return time series standard deviation, the fund's systematic risk, defined as the factor loading on the market factor from the Jensen (1968) one-factor model, the fund's unsystematic risk, defined as the standard deviation of the residuals from the Carhart (1997) four-factor model, the fund's turnover ratio, the fund's active share, and the fund's tracking error. In Panel B, the dependend variable is one of the funds' style extremity measures for the aggregate style extremity (Column 2) as well as for the factor individual style extremity (Columns 3 to 5). The factor individual style extremity measures are defined in (1) in the main text as the yearly rescaled absolute differences between a fund i's factor weightings on the SMB, the HML, and the momentum factor from the Carhart (1997) four-factor model and the corresponding average factor weighting of all funds in the same segment and year. The aggregate style extremity measure is defined as the average of the three factor individual style extremity measures. $FemaleDummy_{i,t}$ is a dummy variable that takes on the value one, if a fund i is managed by a female manager in year t, and zero otherwise. $FundSize_{i,t-1}$ is the lagged natural logarithm of the fund's size in million USD and $FundAge_{i,t-1}$ is the lagged natural logarithm of fund i's age in years. $Ret_{i,t-1}$ is the fund's lagged investment return. $Tenure_{i,t}$ is the fund manager's tenure with the fund in years. The sample is from January 1993 to December 2009. The regressions are estimated with time and segment fixed effects. Standard errors are clustered at the fund level. Panel C shows the average style variability of female and male managed funds for the aggregate style variability measure (Column 2) as well as for the factor individual style variability measures (Columns 3 to 5). The factor individual style variability measures are defined as the rescaled time series standard deviations of a fund's factor loading on the SMB, the HML, and the momentum factor from the Carhart (1997) four-factor model. The aggregate style variability measure is defined as the average of the three factor individual style variability measures. Differences in style variability between female and male fund managers are given in the third line. The sample is from January 1993 to December 2009. Significance is calculated based on a two-sided t-test. *** 1% significance, ** 5% significance, * 10% significance.

Table 7: Gender and Fund Performance

Panel A: Average Fund Performance

	$CAPM_{i,t}$	$FF_{i,t}$	$CAR_{i,t}$	$AR_{i,t}$
$FemaleDummy_{i,t}$	–0.026	–0.019	–0.029	–0.000
	(–0.97)	(–0.67)	(–1.00)	(–0.54)
$Performance_{i,t}$	0.076	0.066	0.008	0.491
	(7.77)***	(5.87)***	(0.81)	(19.59)***
$FundSize_{i,t-1}$	–0.031	–0.011	–0.021	–0.000
	(–4.58)***	(–1.97)**	(–3.43)***	(–2.72)***
$FundAge_{i,t-1}$	0.040	0.019	0.029	0.000
	(3.67)***	(1.68)*	(2.45)**	(2.16)**
$Tenure_{i,t-1}$	–0.001	–0.001	–0.000	0.000
	(–0.31)	(–0.43)	(–0.18)	(1.79)*
$ExpRatio_{i,t-1}$	–8.616	–5.256	–6.452	–0.003
	(–2.52)**	(–3.36)***	(–3.90)***	(–1.16)
Year FE	yes	yes	yes	yes
Segment FE	yes	yes	yes	yes
R^2	0.127	0.107	0.123	0.702
Observations	17501	17501	17501	17501

Panel B: Female Managers in Top/Bottom 1%

	Top or Bottom 1%	*Top 1%*	*Bottom 1%*
$JensenAlpha_{i,t}$	-0.798^{***}	-0.624^{**}	-1.565^{**}
$ThreeFactorAlpha_{i,t}$	-0.341	-0.224	-0.778
$FourFactorAlpha_{i,t}$	-0.347	-0.240	-0.723

Panel C: Female Managers in Top/Bottom 5%

	Top or Bottom 5%	*Top 5%*	*Bottom 5%*
$JensenAlpha_{i,t}$	-0.423^{***}	-0.400^{***}	-0.408^{**}
$ThreeFactorAlpha_{i,t}$	-0.294^{**}	-0.212	-0.361^{**}
$FourFactorAlpha_{i,t}$	-0.347	-0.240	-0.723

Panel D: Performance Persistence

	Female	*Male*	*Difference*
$JensenAlpha_{i,t}$	0.2565	0.2700	-0.0135^{***}
$ThreeFactorAlpha_{i,t}$	0.2542	0.2712	-0.0170^{***}
$FourFactorAlpha_{i,t}$	0.2410	0.2637	-0.0227^{***}

Table 7: continued

Notes: Panel A of this table shows the estimates of fund performance regressed on a female fund manager dummy, $FemaleDummy_{i,t}$, as well as fund characteristics. The performance of a fund is defined as the Jensen (1968) Alpha (Column 2), the Fama and French (1993) three-factor Alpha (Column 3), its Carhart (1997) four-factor alpha, and a modified version of its Treynor and Black (1973) Appraisal Ratio (Column 4), defined as the alpha from the Carhart (1997) four-factor Alpha divided by the standard deviation of the residuals from the four-factor regression. $FemaleDummy_{i,t}$ is a dummy variable that takes on the value one, if a fund i is managed by a female manager in year t, and zero otherwise. $Performance_{i,t-1}$ is the lagged dependent variable of fund i. $FundSize_{i,t-1}$ is the lagged natural logarithm of the fund's size in million USD. $FundAge_{i,t-1}$ is the lagged natural logarithm of fund i's age in years. $Tenure_{i,t}$ is the fund manager's tenure with the fund in years. $ExpRatio_{i,t-1}$ is the fund's lagged total expense ratio. Panels B and C of this table shows the estimates of the probability of a female managed fund to reach the top or bottom 1% (Panel B) or the top or bottom 5% (Panel C) performance percentile regressed on a female fund manager dummy as well as the same fund characteristics as in Table 6. Only the estimates for the influence of the gender dummy are reported. The model is estimated by a probit regression with time and segment fixed effects. Panel D contains the average time series standard deviation over performance ranks of female and male managed funds. Column 4 of Panel D contains the difference between the average time series standard deviation of performance ranks between female and male managed funds. The sample is from January 1993 to December 2009. The regressions are estimated with time and segment fixed effects. Standard errors are clustered at the fund level. *** 1% significance, ** 5% significance, * 10% significance.

Table 8: Items Used in the IAT

Panel A: Gender Items	
Female	Male
MOTHER	FATHER
DAUGHTER	SON
GIRL	BOY
AUNT	UNCLE
GRANDMA	GRANDPA
SISTER	BROTHER
Panel B: Field Items	
Finance	Marketing
STOCKS	ADVERTISEMENT
DERIVATIVE	PRODUCT PLACEMENT
MUTUAL FUNDS	MERCHANDISING
STOCK EXCHANGE	SALES PROMOTION
CORPORATE BOND	BRANDING
MORTGAGE	CUSTOMER RELATIONSHIP
INTEREST RATE	LOGO
INVESTMENT	CONSUMER BEHAVIOR

Notes: The table shows the list of items used in our categories of the IAT test. Panel A contains all items used in the gender categories (female/male). Panel B contains all items used in the field categories (finance/marketing).

Table 9: Implicit Prejudice Measures

Measure	Mean	Std	Min	Max	t	p	Std Err	95% Confidence Intervall
Panel A: All Subjects								
$d(R)$	160.96	159.66	-203.3	661.38	10.08	0.0000	15.97	[129.28;192.64]
$d(log(R))$	0.1724	0.1574	-0.1653	0.5377	10.95	0.0000	0.0169	[0.1411;0.2036]
$d(S)$	0.1610	0.1597	-0.2033	0.6614	10.08	0.0000	0.0160	[0.1293;0.1926]
$d(R)$ adjusted	0.4452	0.4013	-0.5749	1.2327	11.09	0.0000	0.0401	[0.3656;0.5248]
$d(log(R))$ adjusted	0.4842	0.4302	-0.6194	1.3610	11.26	0.0000	0.0430	[0.3989;0.5696]
$d(S)$ adjusted	0.4452	0.4013	-0.5749	1.2327	11.09	0.0000	0.0401	[0.3656;0.5248]
Panel B: Treatment Group - Compatible Configuration First								
$d(R)$	160.16	164.45	-203.30	661.38	6.68	0.0000	23.99	[111.88;208.45]
$d(log(R))$	0.1700	0.1676	-0.1653	0.5377	7.06	0.0000	0.0245	[0.1234;0.2218]
$d(S)$	0.1602	0.1644	-0.2033	0.6614	6.68	0.0000	0.0240	[0.1119;0.2084]
$d(R)$ adjusted	0.4680	0.4424	-0.5749	1.2327	7.25	0.0000	0.0645	[0.3381;0.5979]
$d(log(R))$ adjusted	0.4977	0.4829	-0.6194	1.3610	7.07	0.0000	0.0704	[0.3559;0.6394]
$d(S)$ adjusted	0.4680	0.4424	-0.5749	1.2327	7.25	0.0000	0.0645	[0.3381;0.5979]
Panel C: Control Group - Incompatible Configuration First								
$d(R)$	161.67	156.87	-120.80	619.93	7.50	0.0000	21.55	[118.43;204.90]
$d(log(R))$	0.1721	0.1494	-0.1137	0.5165	8.39	0.0000	0.0205	[0.1310;0.2133]
$d(S)$	0.1617	0.1569	-0.1208	0.6199	7.50	0.0000	0.0215	[0.1184;0.2049]
$d(R)$ adjusted	0.4250	0.3641	-0.3199	1.0972	8.50	0.0000	0.0500	[0.3246;0.5253]
$d(log(R))$ adjusted	0.4723	0.3818	-0.2799	1.1379	9.00	0.0000	0.0524	[0.3670;0.5776]
$d(S)$ adjusted	0.4250	0.3641	-0.3199	1.0972	8.50	0.0000	0.0500	[0.3246;0.5253]

Notes: This table displays reaction times from the implicit association test (IAT). Panel A contains results for all participants in our experiment. Panel B contains results for the treatment group which played the compatible condition first. Panel C contains results for the control group which played the incompatible condition first. Implicit prejudice measures are denoted by $d(R)$, $d(log(R))$, and $d(S)$, respectively. A d significantly larger than zero (p-values are given in Column 6) indicates that there is implicit prejudice against females in finance. $d(R)$ denotes the difference in the average reaction times R between compatible and incompatible condition in milliseconds. $d(log(R))$ denotes the difference in the log-transformed reaction times R between compatible and incompatible condition. $d(S)$ is computed as the difference in the speed variable defined as $S = \frac{1{,}000}{R}$ between compatible and incompatible condition. The adjusted version of these measures is computed by dividing the unadjusted measure by the pooled standard deviation as described in the main text.

Table 10: Impact of Subject Characteristics on Implicit Prejudice

Measure	Subject Characteristic	Obs	Mean	Std	Min	Max	t	p
Panel A: Gender								
$d(R)$	Female Subjects	49	158.22	167.79	-203.30	619.93	6.60	0.0000
$d(R)$ adjusted	Female Subjects	49	0.4333	0.4015	-0.4733	1.2327	7.55	0.0000
$d(R)$	Male Subjects	51	163.59	153.07	-107.85	661.38	7.63	0.0000
$d(R)$ adjusted	Male Subjects	51	0.4566	0.4047	-0.5749	1.0972	8.06	0.0000
Panel B: Female and Male Finance Students								
$d(R)$	Finance Students Female	18	118.43	180.58	-203.30	438.85	2.78	0.0128
$d(R)$ adjusted	Finance Students Female	18	0.3424	0.4656	-0.4733	1.0920	3.12	0.0062
$d(R)$	Male Finance Students	25	223.59	154.66	-66.80	661.38	7.23	0.0000
$d(R)$ adjusted	Male Finance Students	25	0.6097	0.3338	-0.3761	1.0077	9.13	0.0000
Panel C: Field of Study								
$d(R)$	Finance	43	179.57	172.11	-203.30	661.38	6.84	0.0000
$d(R)$ adjusted	Finance	43	0.4978	0.4114	-0.4733	1.0920	7.93	0.0000
$d(R)$	Marketing	10	224.61	139.06	-15.08	485.90	5.11	0.0006
$d(R)$ adjusted	Marketing	10	0.7046	0.3719	-0.0917	1.2327	5.99	0.0002
Panel D: Financial Literacy								
$d(R)$	High Literacy	43	176.73	172.30	-203.30	661.38	6.73	0.0000
$d(R)$ adjusted	High Literacy	43	0.4896	0.3788	-0.4733	1.0920	8.48	0.0000
$d(R)$	Low Literacy	57	149.06	149.88	-107.85	485.90	7.51	0.0000
$d(R)$ adjusted	Low Literacy	57	0.4117	0.4177	-0.5749	1.2327	7.44	0.0000

Notes: This table displays reaction times from the implicit association test (IAT) for different subsamples. Panel A contains results for female and male participants in our experiment. Panel B contains results for female and male finance students, respectively. In Panel C, we split up our sample by field of study. Panel D contains results for participants with high and low financial literacy. $d(R)$ denotes the difference in the average reaction times R between compatible and incompatible condition in milliseconds.

Table 11: Investment Decisions Depending on IAT Result

	Female Manager	Male Manager	Difference (F-M)	Obs.
	% invested into index fund			
$d(R) > 0$	41.51	49.58	–8.06***	428
$d(R) < 0$	49.04	43.90	5.13	56
$d(log(R)) > 0$	41.52	49.56	–8.04***	436
$d(log(R)) < 0$	49.04	42.29	6.75	48
$d(S) > 0$	41.52	49.59	–8.07***	428
$d(S) < 0$	49.04	43.91	5.14	56

Notes: This table shows results on the investment task depending on whether participants exhibit prejudice against females in finance in an implicit association test (IAT). If $d(R) > 0$, $d(log(R)) > 0$, and $d(S) > 0$, respectively, the subject shows signs of negative prejudice against females, and vice versa. *** 1% significance, ** 5% significance, * 10% significance.