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

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ABSTRACT

We suggest investor prejudice against women in finance as one potential explanation for the low fraction of women in the U.S. mutual fund industry. Our empirical and experimental results show that female-managed funds experience lower inflows than male-managed funds. This finding can not be explained by rational statistical discrimination: female fund managers follow more persistent investment styles than male fund managers, and performances are virtually identical. To test directly for prejudice against women in finance we conduct an implicit association test (IAT). Most subjects are strongly prejudiced. Higher prejudice scores in the IAT result in significantly lower inflows into female-managed funds in an experimental investment task.

JEL-Classification Codes: G23, J71

Keywords: Gender Differences; Mutual Funds; Customer-Based Discrimination; Prejudice; Implicit Association Test

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We suggest investor prejudice against women in finance as one potential explanation for the low fraction of women in the U.S. mutual fund industry. Our empirical and experimental results show that female-managed funds experience lower inflows than male-managed funds. This finding can not be explained by rational statistical discrimination: female fund managers follow more persistent investment styles than male fund managers, and performances are virtually identical. To test directly for prejudice against women in finance we conduct an implicit association test (IAT). Most subjects are strongly prejudiced. Higher prejudice scores in the IAT result in significantly lower inflows into female-managed funds in an experimental investment task.

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1 Introduction

Why are there so few women in the financial industry? The fraction of female fund managers in the U.S. equity mutual fund industry has hovered around a very low level of about 10% for the last 20 years. While various reasons like hiring discrimination against women (Goldin and Rouse (2000)), self selection of women into other professions (Polachek (1981), Niederle and Vesterlund (2007)), or career interruptions (Bertrand, Goldin, and Katz (2010)) can contribute explaining the low fraction of women in this industry, we suggest customer-based discrimination as an alternative explanation for this phenomenon (Becker (1971)). Our starting point is the conjecture that investors are prejudiced against women in finance, which eventually leads to lower inflows into female-managed funds.[1] Consequently, hiring women as fund managers would be less attractive for fund companies, as they generate their profits from fees charged on assets under management. This paper presents results from an empirical study, from an experimental investment task, and from an implicit association test (IAT) that support this notion.

Our empirical investigation using field data from all single-managed U.S. equity mutual funds from 1992 to 2009 shows that female-managed funds experience significantly lower inflows than male-managed funds. The growth rates of female-managed funds are about one third lower than those of male-managed funds. This effect is not driven by differences in past performance, fund or fund company characteristics, or differences in characteristics of the fund manager other than the manager's gender. Furthermore, the effect is stable across stock market cycles and over time. We also observe lower inflows into female-managed funds based on propensity score matching. We can reject several alternative explanations for our finding of lower inflows into female-managed funds: to address the concern that fund companies might assign female managers to funds that are less attractive to fund investors for reasons

[1] Anecdotal evidence from interviews with fund managers suggests that this is indeed the case: asked 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 (2009)).

that we can not explicitly control for, we look at manager changes. We find that fund flows only decrease significantly if a male manager is replaced by a female manager. Additional analysis show that our results can not be explained by a potentially better access of male managers to male-dominated institutional investor networks, by potential 'macho-ism' of brokers who steer investors away from female-managed funds, or by differences in marketing expenses or media coverage.

There are two main reasons that investors might shy away from female fund managers: (rational) statistical discrimination (e.g., Phelps (1972)) or (irrational) prejudice (e.g., Becker (1971)). If female fund managers underperform or show other undesirable investment behavior, it would be rational for investors to use the manager's gender as a determinant of their investment decision; eventually they would statistically discriminate against female fund managers. We find no evidence supporting this view: the investment styles of female fund managers are more persistent over time than those of male fund managers, while average performance is virtually identical and male fund managers exhibit less performance persistence. Thus, if anything, fund investors should prefer female fund managers.

While we can exclude several alternative explanations using field data, there might be other confounding variables that drive the lower inflows into female-managed funds that we document. Thus, we conduct a controlled laboratory experiment that allows us to isolate the impact of the fund manager's gender from the impact of any confounding effects on money inflows that might play a role in the real world. The experiment consists of a simple investment task where subjects have to decide how to split a certain amount of money between two funds. We keep all information about these funds constant except for the gender of the fund manager, which is manipulated between two randomly assigned groups. We find that subjects in our experiment invest significantly less into female managed funds than into male-managed funds. The experimental evidence supports the notion that our empirical results can indeed be explained by investors avoiding female fund managers because of their gender.

Finally, to test directly whether there is prejudice against women in finance, we conduct an implicit association test (IAT) with the same subjects who participate in the investment task.[2] IATs are an established experimental method regularly employed by social psychologists to uncover prejudice. IATs are based on computerized sorting tasks and allow researchers to measure implicit associations between concepts (e.g., 'Good' and 'Bad') and group affiliation (e.g., 'African-American' vs. 'White') based on reaction times. External validations of IATs show that they are able to reliably capture prejudice (e.g., Greenwald, Poehlman, Uhlmann, and Banaji (2009)). We develop an IAT to test for prejudice against women in finance. Results show strong negative prejudice against women in finance for most of the subjects in our experiment. The effect is robust against variations of the experimental procedure and can be observed among male and female subjects. It is weaker, but still clearly significant, even among female finance students. Linking the results from the IAT to subjects' investment behavior, we find that prejudiced subjects do indeed invest significantly less in female-managed funds in the experimental investment task, while subjects with no prejudice do not invest less in these funds. To the best of our knowledge, our paper is the first to show that prejudice can have a strong impact on investment decisions.

Overall, the results from our empirical study as well as from the experimental investment task and the IAT offer a customer-based explanation of why we see so few women in the fund industry.

Our study contributes to the large literature on the determinants of mutual fund performance and inflows and to previous research that analyzes the impact of fund managers attributes on these variables: Chevalier and Ellison (1999) and Baks (2003) examine the impact of fund manager characteristics on fund performance. Papers on the determinants of fund flows mainly focus on the impact of past performance (e.g., Ippolito (1992), Sirri

[2] A short introductory note on the IAT is Carney, Nosek, Greenwald, and Banaji (2007). The IAT is described in more detail in Section 2.

and Tufano (1998), among many others).[3] Kumar, Niessen-Ruenzi, and Spalt (2011) find a negative impact of foreign sounding names on mutual fund flows.

On a general level, our study contributes to the large sociopolitical debate on stereotyping and gender discrimination (e.g., Neumark (1996), Francois (1998), Bertrand and Hallock (2001), Wolfers (2006), Fryer, Levitt, and List (2008)) by showing that prejudice against women is also an issue in the financial industry. Furthermore, we relate to the broad literature on gender differences in general (e.g., Feingold (1994), Byrnes, Miller, and Schafer (1999), Barber and Odean (2001), Gneezy, Niederle, and Rustichini (2003), Croson and Gneezy (2009)) and to the literature on the influence of manager characteristics on economic outcomes (e.g., Betrand and Schoar (2003)). Our evidence also complements the earlier literature on customer-based discrimination, which mainly focuses on racial discrimination (e.g., Nardinelli and Simon (1990), Holzer and Ihlanfeldt (1998), and Ayres, Banaji, and Jolls (2011)). To the best of our knowledge, our paper is the first that analyzes customer-based gender discrimination.

Finally, our paper also contributes to the finance literature methodologically by introducing the IAT method to the field, which has not been used in finance before. There are only two papers we are aware of that use IATs in the economics literature: Bertrand, Chugh, and Mullainathan (2005) use an IAT to show that hiring discrimination against African-Americans often occurs unconsciously and Beaman, Chattopadhyay, Duflo, Pande, and Topalova (2009) apply an IAT to measure attitudes towards female leaders.

The paper proceeds as follows. Section 2 contains a description of our data. Section 3 contains the results from our empirical study on determinants of fund flows, while Section 4 investigates whether behavior and performance differ between male and female managers. Section 5 presents results from the experimental investment task as well as from the IAT, and Section 6 concludes.

[3] Looking at a small sample of bond funds, Atkinson, Baird, and Frye (2003) find – with the exception of the first year a female manages a fund – no impact of gender on flows after controlling for fund characteristics.

2 Data and Summary Statistics

1 Principal Data Sources

Our primary data source is the CRSP Survivor-Bias-Free Mutual Fund Database. 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. This allows us to focus on a homogenous group of funds for which we can easily compare performance. 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 eleven different equity fund segments.[4] 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. Our study covers the time period from January 1992 – the year from which detailed fund information data are available in the CRSP mutual fund database – to December 2009.

We identify fund managers' gender based on their first names which are usually given in the CRSP database. Overall, we are able to identify the gender of the fund manager in 99.39% of all cases.[5] Information on the age of a fund manager, whether a fund manager obtained a Bachelor, MBA, or PhD degree, and whether a fund manager obtained a professional qualification (mainly Chartered Financial Analyst, CFA, but also others,

[4]Specifically, we use the following eleven 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), RE (Regional Funds), SE (Sector Funds), UT (Utility Funds), and TR (Total Return).

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

e.g., Chartered Financial Planner, CFP, or Certified Public Accountant, CPA) are collected from fund manager biographies in Morningstar Principia and Morningstar Direct, Capital IQ, and from internet searches. Data on the media coverage of fund managers based on the number of newspaper articles in which a manager appears are obtained from the LexisNexis database.

A detailed description of all variables used in our later analysis is contained in Appendix B. Appendix C contains a description of the media coverage data collection process.

2 Summary Statistics

Our final sample contains 24,789 fund year observations, out of which 22,237 (89.71%) have a male manager and 2,552 (10.29%) have a female manager.[6] Figure 1 plots the total number of male and female-managed funds as well as the fraction of female-managed funds between 1992 and 2009.

— Please insert FIGURE 1 approximately here —

The figure shows that the fraction of female-managed funds is low and constant at around 10% over our whole sample period.

Panel A of Table 1 reports summary statistics for various fund and manager characteristics for the sample of funds that we use later in our regression analysis. In Panel B of Table 1, we report differences in fund characteristics between female and male-managed funds in our sample for selected variables.

— Please insert TABLE 1 approximately here —

Female-managed funds get significantly lower money inflows than male-managed funds and female managers are responsible for significantly smaller funds, while the mean age of

[6] The fraction of female managers among team-managed funds is similarly low at about 10.69%.

female-managed funds is slightly higher than the mean age of male-managed funds. With respect to fees, we find that 12b1 fees are significantly higher for female-managed funds than for male-managed funds. We also find that female managers trade significantly less than male managers. There is no difference in average performance and average risk, but female-managed funds have a significantly lower tenure with a particular fund. Female fund managers are significantly less likely than male fund managers to hold a PhD degree. Finally, the media coverage of female fund managers is significantly lower than that of male fund managers.

3 Do Investors Care About the Manager's Gender? - Empirical Evidence

1 Fund Flows and Manager Gender

We start our empirical analysis by examining aggregate investor behavior at the fund level to answer the question whether female-managed funds attract lower inflows than male-managed funds. We relate relative net-inflows into a fund, $FundFlows_{i,t}$ to a female dummy variable, $Female_{i,t}$, 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, $FundRet_{i,t-1}$. We also include lagged fund size, $FundSize_{i,t-1}$, defined as the logarithm of a fund's total net-assets (TNA) in million USD, $TORatio_{i,t-1}$, defined as the fund's annual turnover ratio, $FundAge_{i,t-1}$, defined as the logarithm of fund i's age in years, lagged fund risk, $FundRisk_{i,t-1}$, defined as the total return standard deviation, as well as a fund's lagged expense ratio in percent, $ExpRatio_{i,t-1}$, in our regression. To account for the impact of the characteristics of the fund company on inflows, we additionally include percentage flows in the respective fund's management company c in year t, $CompanyFlow_{c,t}$. Factors affecting flows of new money into the whole segment of the fund are considered by adding the percentage of flows in the respective market segment k in year t, $SegmentFlow_{k,t}$.[7]

We estimate our empirical models by applying a pooled regression approach with standard errors clustered at the fund level and time, segment, and fund company 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 into male-managed funds. The impact of the female dummy is negative and always statistically significant at the 1% level in all model specifications. The effect is also economically significant: depending on the model specification, the estimate for the influence of the female dummy shows that a female-managed fund grows by about 10% to 16% 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 28% p.a. (see Table 1), this means that a female-managed fund grows by 35% to 50% less than a comparable fund that is managed by a male fund manager.

In Column 1 we control for the impact of past performance by just including the past return of the fund, while in Column 2 (and all following specifications) we additionally included lagged fund flows, $FundFlows_{i,t-1}$. Ippolito (1992) shows, that past performance ranks have a nonlinear impact on fund flows. Thus, in Column 3 and 4 we follow Barber, Odean, and Zheng (2005) and estimate a quadratic performance flow relationship based on net return ranks and based on Carhart (1997) four factor alpha ranks.[8] We can confirm the

[7]Company flows and segment flows are computed net of the flows into the fund under consideration.

[8]We use performance ranks as Patel, Zeckhauser, and Hendricks (1991) show, that ordinal performance measures can explain fund flows much better than cardinal measures. Ranks are calculated for each year and segment separately and are evenly distributed between 0 and 1.

convex performance-flow relationship documented in the literature (e.g. Sirri and Tufano (1998)). More importantly, the impact of the female dummy remains stable.

To address concerns that the performance of funds from different segments is not easily comparable, in Column 5 we estimate the same model as in Column 3 but focus on a more homogenous subgroup of funds that exclusively invest in U.S. equities and belong to the segments 'Aggressive Growth', 'Long-term Growth', 'Income', 'Sector', and 'Growth & Income'. Results are very similar.

In Column 6 we conduct Fama-MacBeth (1973) regressions using ranks based on returns and in Columns 7 and 8 we again repeat the standard regression from Column 3 but cluster standard errors by year or by fund and year, respectively. The impact of the female dummy remains highly significant and is of similar magnitude across specifications, indicating lower inflows of female-managed funds in the range of 10% to 11% p.a.

Fund size is one of the main drivers of funds inflows (see Table 2). Although we control for the linear impact of fund size in all our regressions, the difference in size of female and male-managed funds (see Table 1) in combination with a possibly non-linear influence of fund size on fund flows might affect our result. Therefore, in Column 9, we include fund size to the power of two and three as additional explanatory variables. Our findings are not materially affected.[9] Finally, in Columns 10 and 11, we interact our female manager dummy variable with linear lagged fund performance as well as with lagged performance ranks and lagged performance ranks squared, respectively. The female dummy is still significantly negative and of similar magnitude.

Regarding our results on the influence of the control variables, they are very uniform across specifications and confirm findings reported in the literature. Overall, our results so far are consistent with the view that investors dislike female fund managers.

[9] We also model the impact of size by including ten size dummy variables. Each of these takes on the value one if the fund's size is in a specific size decile as compared to the other funds in the same segment and year. Our main result (not reported) is not affected.

2 Alternative Explanations

We now refine and try to empirically disentangle alternative explanations for investors shying away from female-managed funds because of the manager's gender.[10] Results are presented in Table 3.

— Please insert TABLE 3 approximately here —

First, it is possible that investors prefer certain funds for reasons we do not control for and that women are more likely to manage such funds – either because they self-select themselves into those funds or because they are assigned to these funds by the management of the fund company. To separate the impact of such fund characteristics from the impact of gender on fund flows, in Column 1 we look at the impact of manager changes on fund flows. We create a dummy variable, $FemNew_{i,t-1}$ ($MgrChg_{i,t-1}$), which is equal to one if a male fund manager is replaced by a female fund manager (if any manager change occurs), and zero otherwise. The results show that fund flows decrease by about 14% if a male manager is substituted for a female manager, while a manager change per se has no significant impact.

Another possible explanation for the low inflows into female-managed funds could be that female and male fund managers differ with respect to other demographic characteristics that investors might consider in their investment decision. Results from Panel B in Table 1 show that male and female managers indeed differ, for example, with respect to their tenure at a particular fund, their age, and the probability that they hold a PhD degree. Thus, in Column 2 we add further control variables that capture the impact of these differences on flows. We did not include these variables in our base model, because we only have information on the demographic characteristics for a subset of fund managers. We include dummy variables that take on the value one if the manager holds a MBA degree, a PhD, or a professional qualification (e.g. CFA), respectively, and zero otherwise, as well as a

[10] We will later (Section 5) also examine how subjects respond to fund manager gender in a controlled laboratory experiment in order to preclude other explanations that are difficult to check empirically.

fund manager's age and tenure at the fund currently managed in years.[11] We find that a fund manager's tenure has a positive impact on fund flows, while age and education has no significant impact. However, we still find that female managers receive on average nearly 12% lower inflows after adding these additional control variables.

Kaniel, Starks, and Vasudevan (2007) show that media coverage can have a positive impact on fund flows. A similar effect is documented for fund advertising in Jain and Wu (2000), Cronqvist (2006), and Gallaher, Kaniel, and Starks (2008). The results from Panel B in Table 1 show that the press covers male fund managers significantly more often than female managers, while 12b-1 fees (which are explicitly labeled to cover distribution and marketing expenses) are higher for female-managed funds. To control for the impact of these differences, in Column 3 we thus add lagged media coverage, $LN(1 + MedCov)_{i,t-1}$, defined as the natural logarithm of the number of articles on fund i's manager in year $t - 1$ plus one, as an additional control variable. Results show that media coverage does have a significantly positive impact on fund flows. However, including media coverage does not significantly change the coefficient of our female dummy. In Column 4 we include 12b-1 fees as an (imperfect) proxy for advertising and other marketing expenditures which also does not change our main result.

It is also possible that not investors themselves dislike female managers, but that brokers who advise investors steer them away from female-managed funds. There is some indirect evidence suggesting that fund brokers might stereotype women as less competent in financial matters and might thus promote male-managed funds more often than female-managed funds. For example, a survey conducted by Wang (1994) suggests some 'machismo' among brokers: sales representatives at brokerages spend more time advising men than women, offer a wider variety of investments to men and try harder to acquire men as customers. Thus, in Column 5 we investigate whether the negative impact of our female dummy on

[11] We do not include a separate dummy for Bachelor degrees, as virtually all managers hold at least a Bachelor's degree (see Panel A in Table 1). Some fund managers hold Masters degrees other than MBAs. Including controls for non-MBA Masters does not change our findings.

mutual fund flows is driven by funds that are distributed via brokers. As such funds typically charge front-end loads (Christofferson, Evans, and Musto (2011)), 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.

Another concern is that our results are not really due to investors disliking female fund managers, but can be explained by male managers having better access to often male-dominated networks of institutional investors. Thus, we also run our regression separately on a subsample of funds that only offer retail share classes and on a subsample of funds that only offer institutional share classes. Results presented in Columns 6 and 7 show that the effect of the female dummy is of similar economic magnitude and even slightly larger among funds focusing on retail investors exclusively.

Finally, to check whether it is likely that retail investors are aware of the fund manager's gender, we present screenshots of the information investors would get if they search for information on a specific fund in four of the major online information sources in Figure 2.

— Please insert FIGURE 2 approximately here —

As can be seen from these exhibits, information on the gender of the fund manager is salient to investors as it can typically be easily inferred from the first name of the fund manager, which is always prominently presented on the first page that appears.[12]

[12]Other evidence that investors are often directly exposed to manager names are product descriptions on websites investors use to gather information. For example, Kiplinger Magazine – one of the leading personal finance magazines in the U.S. – features a Top 25 list (KIP25) of funds on its webpage. For many funds, a short feature article appears if investors click on the fund name. When checked in November 2011, there were articles available for 11 of the 15 U.S. equity funds contained in the list. Eight of those mentioned the name of the fund manager in the very first sentence.

3 Robustness

We now analyze whether our results are robust to further variations of our empirical strategy. In Panel B of Table 3 we present results for modifications of our base model (Column 3 in Panel A of Table 3). The same controls are included in the estimation but suppressed in the table. We start by using alternative measures of fund flows as described in Appendix B. First, in Column 1 we use dollar flows, $AbsFlow_{i,t}$, instead of relative flows as dependent variable. We still find a significantly negative impact of the female dummy variable on fund flows that is also economically meaningful: a female-managed fund on average gets about 14.3 million USD less money inflows p.a. than a comparable male-managed fund. This translates into female-managed funds growing by about 19.5% less than male-managed funds. Second, in Column 2, we closely follow Spiegel and Zhang (2010) and use the change of a fund's market share, $ChgMktShr_{i,t}$, as dependent variable, exclude the lagged dependent variable from our regression and estimate the model using quantile regressions.[13] As in Spiegel and Zhang (2010), we now 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. Third, in Column 3 we use monthly instead of yearly relative flows as dependent variable and run our regressions on a monthly basis. In this regression, we only include those controls that also change on a monthly basis.[14] We again find a highly statistically significant negative coefficient indicating that female-managed funds grow by about 5% p.a. less than male-managed funds.

In our previous analysis, we use a quadratic specification to model the impact of past performance on inflows. As an alternative specification, we now follow Sirri and Tufano (1998) and estimate a piecewise linear relationship. Specifically, we estimate distinct slope

[13] In Spiegel and Zhang (2010) the authors use vigintiles in their analysis. However, there are not always observations for female managers in each vigintile and year. Thus, we use quintiles instead of vigintiles.

[14] Results are very similar if we also include the controls that change on a yearly basis.

coefficients for different performance quintiles.[15] Results based on return ranks and Carhart (1997) four factor alpha ranks are shown in Columns 4 and 5. Consistent with our earlier approach, we can confirm the convex performance-flow relationship and still find that our main result of the negative impact of the female dummy is not affected. We also obtain the same results (not reported) if we include ten dummy variables for each decile of past performance instead of the piecewise linear coefficients.

To assess the temporal stability of our findings, we split up our sample into two time periods, up to 2001 and after 2001, as well as into years with negative market returns (2000, 2001, 2002, and 2008) and years with positive market returns (all other sample years). Results presented in Columns 6 to 9 show that a significantly negative impact of a female fund manager can be observed in all cases. The effect is somewhat stronger in later years, but there is no notable difference between good and bad market years.

Finally, in Panel C of Table 3, we present results from a propensity score matching analysis. For each fund managed by a female manager we try to find a match among the male-managed funds that belongs to the same segment and has a similar size and a similar past return. We match based on these variables, because past returns, fund size and segment flows have the strongest and most consistent influence on flows in Table 2. Results based on the nearest neighbor, the radius, the kernel, as well as the stratification method show a very uniform picture: the impact of the female dummy is always significantly negative and economically meaningful.

Overall, our results strongly suggest that investors prefer male-managed funds to female-managed funds. We propose investor prejudice against female managers as an explanation for this finding. However, our findings could be driven by statistical discrimination rather than by prejudice. In that case, investors invest less in female-managed funds because they expect them to behave in an undesirable way or to deliver inferior performance. However,

[15] 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 separately instead of grouping the three middle quintiles together.

this would only be rational, if male fund managers indeed showed more desirable investment behavior and better performance outcomes than female managers. We will examine this issue in the next section.

4 Prejudice vs. Statistical Discrimination

To disentangle the two explanations–that prejudice leads to lower inflows into female-managed funds or that rational statistical discrimination drives this result–we now investigate whether there is any evidence of undesirable investment behavior (Section 1) or inferior fund performance (Section 2) of female fund managers as compared to male fund managers.

1 Investment Styles

It is sometimes argued that gender differences are of little importance in a professional management setting, because the similar environment and educational background of professionals overrides potential gender differences. However, there is also evidence that gender differences exist in professional management settings (e.g. Graham, Harvey, and Puri (2010) and Adams and Funk (2011)).

To examine gender differences between male and female fund managers, we relate various measures of investment behavior to the fund manager's gender and other potentially relevant fund characteristics. We focus on risk-taking behavior, trading activity, and the variability of investment styles over time.

In our regressions, we either use one of the three risk measures for fund i in year t, $FundRisk_{i,t}$, $SysRisk_{i,t}$, or $UnsysRisk_{i,t}$, or the fund's turnover ratio, $TORatio_{i,t}$, all as defined in Appendix B, as dependent variable. Besides the female manager dummy, we include fund size and age as defined above as independent variables. Furthermore, we include a fund's previous year return, $FundRet_{i,t-1}$, the fund manager's tenure, $MgrTenure_{i,t-1}$, as well as time, segment, and fund company fixed effects. We include segment and fund company fixed effects because some segments are more risky than others and because management companies often have specific guidelines or cultures in place that can have a strong impact on behavior. Standard errors are clustered at the fund level. Panel A of Table 4 summarizes our findings.

— Please insert TABLE 4 approximately here —

Regarding the various dimensions of risk taking behavior and trading activity, we find negative coefficients for the impact of a female manager, which is consistent with the widely documented fact that women tend to be more risk-averse (e.g., Byrnes, Miller, and Schafer (1999)) and that women tend to trade less (Barber and Odean (2001)). However, the coefficients are not statistically significant.

Finally, we want to examine whether there are any differences in style variability as defined in Appendix B based on the variability of a fund's factor loadings over time.[16] We only conduct a univariate comparison between the style variability measures of female- and male-managed funds, because we calculate one style variability measure based on the time span in which a specific manager manages a fund. 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 1) as well as for the three factor individual style variability measures (Columns 2 to 4).[17]

Overall, these results show that there are only minor differences with respect to the investment behavior of female and male fund managers. However, if anything, these differ-

[16] In unreported tests we also compare average factor loadings and find that women tend to have significantly lower (higher) loadings on the HML (MOM) factor, while there is no significant difference with respect to SMB loadings.

[17] Estimates of standard deviations can be biased if they are based on a small number of observations. Thus, we repeat our analysis using the variance of factor loadings over time. Results (not reported) are qualitatively similar, but significance slightly decreases.

ences are in favor of female fund managers: although we do not know investors' preferences for certain investment styles, female fund managers' investment behavior should be more desirable for mutual fund investors as female fund managers follow more stable and thus reliable investment styles than male fund managers.

2 Fund Performance

Findings from earlier studies suggest that the behavioral differences between fund managers we document above can have consequences for fund performance. For example, Brown, Harlow, and Zhang (2011) document a positive influence of stable investment styles on performance. We now examine whether the behavioral differences documented in the previous section have an impact on fund performance and performance persistence.

We start by relating various performance measures of fund i in year t to a female dummy, the fund's lagged size, age, expense ratio, and fund manager tenure as defined in the previous regressions. As performance measures we use a fund's yearly net return, its one-, three- and four-factor Alpha, its Sharpe-Ratio, and an extended version of the Appraisal Ratio of Treynor and Black (1973), all as defined in Appendix B. Results based on panel regressions with time, segment, and fund company fixed effects as well as standard errors clustered at the fund level are presented in Panel A of Table 5.

— Please insert TABLE 5 approximately here —

The main message from this table is that there is no significant difference between the performance of female- and male-managed funds.[18] This result holds irrespective of the specific performance measure we use. Panel B presents results of various further robustness tests. We only present the coefficient estimate for the impact of the female dummy, but the same controls as above are included. In line B.1 we add additional fund characteristics

[18] Atkinson, Baird, and Frye (2003) also report no impact of gender on bond fund performance in a univariate comparison.

as controls. Specifically, we include the fund's lagged turnover ratio, lagged inflows, lagged performance, and lagged fund risk. In line B.2 we include variables capturing the influence of the manager's age and dummy variables reflecting the manager's education (MBA, PhD, Professional Qualification). In both cases and for all performance measures we still can confirm that there is no significant performance difference between male and female fund managers. Furthermore, we also estimate the same models as in Panel A, but additionally cluster standard errors by year (B.3), by fund and year (B.4), and run Fama and MacBeth (1973) regressions (B.5). Again, there is no significant influence of the female dummy on any of the performance measures in all cases.

As individual fund performance can only be estimated with noise we also analyze the performance of (equal and value weighted) portfolios consisting of female- and male-managed funds, respectively, as an alternative to the multivariate regression approach. We evaluate the performance of a hypothetical difference portfolio that is long in all female-managed funds and short in all male-managed funds. Results are presented in Panel C. Columns 1 to 3 (4 to 6) contain results from equal weighted (value weighted) portfolios. Irrespective of whether we focus on Jensen (1968) one-factor Alphas, Fama and French (1993) three-factor Alphas, or Carhart (1997) four-factor Alphas, the difference portfolio never delivers any statistically significant abnormal returns.

Taken together, our results suggest that the market for mutual fund managers is efficient in the sense that it is not possible to generate abnormal returns by following an investment strategy based on a manager characteristic as easily observable as the manager's gender. Although female and male fund managers differ in terms of investment behavior, these differences are not reflected in differences in average fund performance.

In Panel D we analyze gender differences in performance persistence. Performance persistence is defined as the standard deviation of a manager's performance ranks over time.[19] We investigate performance persistence based on the five performance measures analyzed

[19]Analyzing a variance based measure of performance persistence delivers qualitatively identical results.

above. Results show that the performance ranks of male-managed funds are more variable over time than those of female-managed funds. The effect is statistically significant for all performance measures except for the Sharpe ratio. This provides at least some evidence that the performance of female-managed funds is more persistent than the performance of male-managed funds.

Overall, we find no evidence for gender differences in behavior or performance that would support the idea that female fund managers receive lower inflows due to rational statistical discrimination. In contrast, our previous analysis shows that female-managed funds might even 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. These results support the view that prejudice against female fund managers might indeed drive our empirical finding in Section 3 of lower money inflows into female-managed funds.

5 Do Investors Care About the Manager's Gender? - Experimental Evidence

Although rational statistical discrimination and several other alternative explanations for lower inflows into female-managed funds have been rejected, it is still possible that factors other than prejudice against female fund managers drive our results. It is not possible to observe and control for all potential drivers of fund flows. Thus, to investigate whether investors indeed have negative preconceptions about the abilities of female fund managers, we conduct a controlled laboratory experiment. The experiment was conducted at the University of Texas at Austin and consists of two main parts, an investment task (Section 1) and an implicit association test (see Section 2). Details of the experimental procedure are described in Appendix D.

1 Investment Task

First, we develop a simple investment task in which subjects have to decide how to split 100 experimental units between two funds from the same market segment that we randomly chose from the CRSP fund database beforehand. In each investment round, the complete amount of 100 experimental units has to be invested. Instead of providing the funds' real names, we labeled them "Fund A" and "Fund B". At the beginning of each investment round, information about both funds was displayed to subjects and they subsequently decided how to split their money between those funds. Subjects were randomly assigned to one of two groups, group X or group Y. Both groups observed the same set of funds. However, we switched the gender of the fund manager between these groups, while keeping all other information constant. Figure 3 exemplifies the information given to the two groups of subjects.

— Please insert FIGURE 3 approximately here —

As can be seen from Figure 3, the only difference between both groups of subjects is the first name of the fund manager. Group X observes a female fund manager for fund A and a male fund manager for fund B, while group Y observes a male fund manager for fund A and a female fund manager for fund B, respectively.[20] This procedure allows us to offer investment choices that not only differ with respect to gender (in order to make gender not too salient) but to still attribute any differences in investment behavior between the two groups to the fund manager's gender.

The experiment was played over four rounds and for four pairs of funds per round. Investment rounds differed by the amount of information provided about the fund pairs. In the first round, information about the fund segment, the name of the fund manager, fund size, inception date, expense ratio, trading activity, and top five stock holdings was

[20]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 and we use common last names.

provided. In addition, we added a short text labeled “Fund Facts” with a description of the fund’s investment strategy (see Figure 3). In the following rounds we added additional information: an ethical rating of the fund, a classification indicating the fund’s riskiness, and the fund’s return over the past 12 and 24 months. The four pairs of funds were chosen to be either index funds, growth and income funds, aggressive growth funds, or regional funds.

We recruited 100 students as subjects in our experiment. Table 6 provides information on the demographic characteristics of the subjects.

— Please insert TABLE 6 approximately here —

Due to the recruiting procedure (about 50% of the announcements were made in finance classes) the clear majority of 43 subjects indicated “Finance” as their main field of study, followed by 13 subjects 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. The mean age of subjects is 21.3 years and ranges from a minimum of 18 years to a maximum of 40 years. Virtually all subjects were single and the gender distribution is roughly balanced, with 51 male and 49 female subjects. Results from the investment task are reported in Table 7.

— Please insert TABLE 7 approximately here —

We first focus our analysis on the investment decision in index funds. Since index funds barely differ from each other, they offer the cleanest setting in which to examine the impact of specific variables on investment decisions (Choi, Laibson, and Madrian (2011)). In our setting, we compare differences in the amount invested in fund A between group X (which observed a female manager of fund A) and group Y (which observed a male manager of fund A) to isolate the impact of the fund manager’s gender on investment behavior. Panel A of

Table 7 shows that subjects generally invest less into fund A as compared to fund B (i.e., in both groups the fraction invested is below 50%) which might be because fund A has a higher expense ratio (see Figure 3). However, although fees should be the only consideration in choosing between index funds and the whole amount should be invested in the cheaper fund, we find that subjects invest significant amounts in both funds. This confirms results from a similar experiment reported in Choi, Laibson, and Madrian (2011).

More importantly in our context, subjects invest significantly less in fund A if it is managed by a female fund manager than they invest in fund A if it is managed by a male fund manager. The difference is 7.42 experimental units or roughly 15% and is significant at the 1% level. This result is consistent with our previous empirical findings.[21]

In Panel B, we split up subjects by gender. Results show that the difference in investing in 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. Panel C shows that the bias towards male-managed funds is independent of the main field of study of the subjects. Panel D splits the subject pool by financial literacy.[22] We observe significantly less money directed towards the female-managed fund in both groups, but the effect seems to be even slightly stronger among the more financially literate. In Panel E, we investigate investment decisions for the other types of funds. If we pool all investment decisions, we find that female-managed funds receive 2.04 experimental units or nearly 4% less than male-managed funds. This effect is mainly driven by the investment decisions in index funds and growth and income funds.[23] As only the first round of investment decisions can be considered to be completely independent in an experiment like ours, where subsequent rounds involve investment choices regarding the same pairs of funds, in Panel F we focus on the first round of the experiment only. The results show

[21] A discussion of multivariate results is deferred to Section 2.

[22] 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.

[23] The relationship is even (insignificantly) reverse among regional funds. Interestingly, this is also the category where we observe the highest fraction of female managers (18%) in our empirical data.

that subjects invest less in female-managed funds across all types of funds. The effect is statistically significant for all funds grouped together as well as for index funds and growth and income funds.

Overall, our experimental evidence confirms the empirical evidence from Section 3. As all other potential drivers of fund flows are controlled for in this setting, these results suggest that our previous empirical findings are indeed due to the managers' gender and support our conjecture of investor prejudice against women in the financial industry.

2 Implicit Association Test: A Direct Test of Gender Prejudice

Last, in the second part of the experiment, we want to test explicitly for gender prejudice against women in finance in an implicit association test (IAT). This also allows us to analyze later whether the extent of prejudice has any impact on investment behavior. The IAT has gained enormous popularity among social psychologists in recent years as they can uncover prejudice. According to Lane, Banaji, Nosek, and Greenwald (2007), there are now well over 200 papers that use this method. In previous applications, the IAT has been used to uncover prejudice towards, for example, race, religion, gender, or sexual orientation. The test's popularity is based on the fact that it can be easily administered and that it allows us to uncover implicit prejudice that subjects are often not willing to admit openly because of social desirability concerns. 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 prejudice based on automatically operating implicit associations that can not be easily manipulated and might even operate completely unconsciously (Greenwald, Banaji, Rudman, Farnham, Nosek, and Mellott (2002)). Its reliability and validity as a way to measure implicit prejudice is widely confirmed (Cunningham, Preacher, and Banaji (2001), Greenwald, Poehlman, Uhlmann, and Banaji (2009)).

The subjects in an IAT are required to classify items like words or pictures into one of four categories (for example 'African-American' or 'White' and 'Good' or 'Bad') in a computerized double-sorting task. 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. In the 'stereotypical' or compatible configuration, 'White' and 'Good' would be displayed together and 'African-American' and 'Bad' would be displayed together, while in the incompatible configuration one of the categories is switched from one side of the screen to the other (e.g. 'White' and 'Bad' would show up on the same side). Subjects have 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 the two configurations. The test relies on the fact that stronger associations (e.g., 'African-American' with 'Bad') result in faster reaction times than weaker associations (e.g., 'African-American' with 'Good'). If there is no implicit prejudice average reaction times should be identical.

To examine whether there is any implicit prejudice against women in finance, we adapt the IAT to the context of finance. The first category we use is 'male' vs. 'female'. The words belonging to the gender categories are taken 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 category we use is 'finance' and 'marketing'. We chose 'marketing' as the 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 'stocks', 'mutual funds', 'advertising', and 'logo'. The full list of items is presented in Panel B of Table 8. In our IAT, subjects have to categorize items by hitting the 'E' or 'I' 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 4.

— Please insert FIGURE 4 approximately here —

Panel A displays the stereotypical or compatible configuration where the categories 'finance' and 'male' are on one side of the screen and 'marketing' and 'female' on the other side. In contrast, Panel B displays the incompatible configuration. In both cases of the example shown in the figure, subjects had to sort the item "stocks" into the right category as fast as possible. If there is implicit prejudice against women in finance, the reaction time will be significantly higher in the incompatible configuration than in the compatible configuration. The test was administered in two versions and subjects were randomly assigned to one of the versions. Subjects assigned to the first version of the test started with the compatible configuration followed by the incompatible configuration, and vice versa for subjects assigned to the second version. After several practice rounds, in which subjects could get familiar with the sorting task, we start measuring their reaction times.

The simplest way to measure implicit attitudes is just to compare reaction times in milliseconds (ms), which we denote by R. The reaction times for both groups in the compatible and the incompatible configuration are summarized in box-plots presented in Figure 5.[24]

— Please insert FIGURE 5 approximately here —

In both cases reaction times are lower in the compatible than in the incompatible configuration. In Panel A (B), the mean reaction time for the compatible configuration is 753.99 ms (833.13 ms), while it is 914.15 ms (994.79 ms) in the incompatible configuration. To examine reaction times more formally we aggregate data on the subject level and calculate the average reaction time using three alternative methods. First, we compute 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

[24]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.

variable defined as $S = \frac{1{,}000}{R}$. Speed also has desirable distributional characteristics that stabilize variances and 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 the compatible and the incompatible configuration based on R, $log(R)$, and S for each subject j. These implicit prejudice measures are suggested in Greenwald, McGhee, and Schwartz (1998) and are denoted by $d(R)_j$, $d(log(R))_j$, and $d(S)_j$, respectively. Independent of the configuration a subject plays first, we always subtract the mean reaction time in the compatible configuration from the reaction time in the incompatible configuration for R and $log(R)$, and vice versa for S. Thus, a d significantly larger than zero always indicates that there is implicit prejudice against women in finance. The magnitude of these simple d measures can be directly interpreted.[25]

Results for a pooled examination of all subjects are presented in Panel A of Table 9.

— Please insert TABLE 9 approximately here —

The mean of $d(R)$ across all subjects is 160.96 ms, i.e., the average of the subject individual mean reaction times in the incompatible configuration is 160.96 ms or about 18% higher than in the compatible configuration. The hypothesis that the implicit prejudice score is not different from zero can be rejected at the 1% level (t-statistic > 10). This also holds for the other prejudice measures $d(log(R))$ and $d(S)$. In the last four columns, we present the number and percentage of subjects for which the respective d measure is (at least at the 10% level) significantly negative, negative, positive, and (at least at the 10% level) significantly positive, respectively, on an individual level. 62% of the subjects show a significantly positive d even on an individual level. Only 4% exhibit a significantly negative

[25] Alternatively, we use the pooled standard deviation from both configurations as effect size unit to get subject-individual adjusted measures d^{adj} for implicit prejudice. For example, $d^{adj}(R)$ is defined as $d^{adj}(R) = \frac{\bar{R}^I - \bar{R}^C}{std(R)}$, where $\bar{R}^C$ ($\bar{R}^I$) denotes mean trial reaction times from the compatible (incompatible) configuration, and $std(R)$ denotes the pooled standard deviation of reaction times from both configurations. These measures, for which the variance is more stable, allow us to detect statistical effects more precisely. Results (not reported) using these adjusted measures are very similar.

d. These results provide corroborating evidence for pronounced prejudice against women in finance for most of our subjects.

In Panels B and C, we present results separately for the group that played the compatible configuration first and for the group that played the incompatible configuration first, respectively. The mean difference in average response times, $d(R)$, is about 161 ms in both cases. The differences between both groups are not statistically significant. Thus, we will again pool them together in our further analysis.

— Please insert TABLE 10 approximately here —

We now investigate which subject characteristics are related to the strength of the implicit prejudice effect. We first compare male and female subjects as well as finance and marketing students. Results are presented in Panel A and B of Table 10 and show significant prejudice effects among all groups. The differences between the groups are not statistically significant. Tajfel (1970) provides strong evidence for an in-group bias of individuals. This effect should lead to less pronounced or no implicit prejudice against women in finance among female finance student subjects because we would expect them to have less prejudice about their own group than men in finance or men and women from other disciplines might have. In Panel C, 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. Interestingly, 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, based on $d(R)$). Finally, in Panel D we check whether there is 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 and the difference is not statistically significant.

Results in experiments often crucially depend upon the experimental procedure. Thus, we also test whether the results are stable against variations of the experimental parameters. Specifically, in Panels E to G we check whether results depend upon the gender of the instructor in the experiment, on the time of the day (Folkard (1976)), or on differences in the number of subjects per session, i.e., the crowdedness of the sessions (Paulus, Annis, Seta, Schkade, and Matthews (1976)). Our results are unaffected by these parameters.

Overall, the results of this section provide direct evidence that there is prejudice against women in finance. However, it is unclear whether this prejudice is strong enough to affect investment behavior and eventually result in lower inflows into female-managed funds. Thus, we now compare the fraction invested in female-managed funds in the first part of the experiment between subjects that exhibit implicit prejudice in the IAT to the (minority of) subjects that show no or even reverse implicit prejudice. Results are presented in Table 11.

— Please insert TABLE 11 approximately here —

Panel A shows the mean amounts invested in the male- and female-managed index funds over all rounds. They clearly show that subjects that exhibit implicit prejudice ($d(R) > 0$, $d(log(R)) > 0$, $d(S) > 0$) invest significantly less in female-managed funds. In contrast, we find (insignificantly) larger investments in female-managed funds of those subjects that exhibit no implicit prejudice, showing that prejudice has an impact on investment decisions.

In Panel B, we present results from a multivariate censored Tobit regression with the fraction of experimental units invested in index fund A –which can either have a male manager (group X) or female manager (group Y)– by subject j as dependent variable. As independent variables we include a female manager dummy, that takes on the value 1 if fund A as presented to subject j is managed by a female, and zero otherwise, as well as controls. We include (but do not explicitly report in the Table for the sake of brevity) dummies that take on the value one, if the subject j has above median prejudice in the IAT, ($SubjPrej_j$), is female ($SubjGen_j$), studies finance or economics ($FinEcon_j$), has above median financial literacy ($HighFinLit_j$), faced a female instructor explaining the experiment ($InstrGen_j$), is married ($SubjMarital_j$), and has investment experience ($EverInvest_j$), respectively, and zero otherwise, as well as the age of the subject in years ($SubjAge_j$). Regressions are estimated with session fixed effects.

Results in Column 1 confirm our earlier results from Table 7 and show that fund A receives 9.3 experimental units or nearly 20% less if it has a female manager. In Column 2, we interact the female manager dummy with a dummy that takes on a value of one if a subject showed above median prejudice values in the IAT. The interaction term is significantly negative. The coefficient indicates that subjects with above median prejudice on average allocate 17.3% less to fund A if it is managed by a female manager as compared to the base case. The linear impact of the female manager dummy itself is insignificant. This result confirms our earlier univariate finding from Panel A that the negative impact of a female fund manager on investment decisions is driven by subjects with high implicit prejudice scores.

In Column 3, we add an interaction term between the female manager dummy and the female subject dummy. The coefficient on the interaction term is significantly positive and nearly as large as the impact of the female manager dummy itself, showing that the negative impact of a female manager is neutralized if the subject is female. In Columns 4 to 6 we interact the female dummy with a dummy for finance/economics students, with a dummy for high financial literacy, and with a female instructor dummy, respectively. None of these interaction terms is significant.

Overall, our results from the IAT show pronounced implicit prejudice against women in finance and our findings from Table 11 show that implicit prejudice does have implications for actual investment behavior, thereby confirming the predictive validity of the IAT in our setting, too.

6 Conclusion

This paper examines the conjecture that investors are prejudiced against women in finance and thus eventually prefer to invest in male-managed funds. 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 and can reject several alternative explanations for lower inflows into female-managed funds. Furthermore, we find that female fund managers follow more reliable investment styles and we document that performance is identical between male and female fund managers. These results provide no support for the notion that the lower inflows into female-managed funds might be due to rational statistical discrimination. Rather, our results from an implicit association test show that prejudice against women in finance exists among most of the subjects participating in our experiment. Finally, we find that prejudiced subjects according to the IAT invest less in female-managed funds in our experiment.

Overall, our findings help to clarify why female-managed funds receive much lower inflows than male-managed funds. Furthermore, as managers generating low inflows are not attractive for fund companies to hire, our results also provide an explanation for low fraction of female managers in the mutual fund industry. This does of course not preclude other explanations. Particularly, our results from the IAT can also help to explain why the fraction of women is so low in the financial industry (and also in finance in academia) via two additional channels: first, prejudice against women often leads to implicit discrimination in hiring (Bertrand, Chugh, and Mullainathan (2005)). Second, the prejudice against women in finance that exists even among female finance students can lead them to eventually self-select into other fields.

One provocative question that one may ask based on our findings is why we observe any female fund managers at all if investors prefer male fund managers? As results from the IAT show that there is a minority of subjects (typically women) that do not discriminate against female managers; it can still make sense from the fund company's point of view to hire female fund managers to specifically cater to this group of investors.[26] Furthermore, in recent years many institutional investors require their business partners to report explicitly on their diversity policy. In a similar vein, the new Dodd-Frank Act explicitly requires federal agencies to do business only with firms that ”ensure the fair inclusion of women” and to ”give consideration to the diversity of the applicant” (Dodd-Frank Financial Regulation Bill Section 342(c)). For mutual fund companies to win mandates from such clients, it is necessary to employ at least some female fund managers.

[26]There are some niche funds like the Pax World Global Women’s Equality Fund that specifically cater to female investors.

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.[27] First names that appear for both sexes are excluded from the SSA-List. 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%.

[27]For further information see `http://www.ssa.gov`.

Appendix B: Brief Definitions and Data Sources of Main Variables

This table briefly defines the main variables used in the empirical analysis. The data sources are: (i) CRSP: CRSP Survivor-Bias-Free Mutual Fund Database, (ii) CIQ: Capital IQ, (iii) EST: Estimated or computed by the authors, (iv) EX: Experimental data, (v) KF: Kenneth French Data Library, (vi) LN: Lexis Nexis, (vii) MSD: Morningstar Direct, (viii) MSP: Morningstar Principia.

Panel A: Measures of Fund Flows

Variable Name	Description	Source
$FundFlows_{i,t}$	Computed as $\frac{TNA_{i,t}-TNA_{i,t-1}\cdot(1+Ret_{i,t})}{TNA_{i,t-1}}$ where $TNA_{i,t}$ denotes fund i's total net assets in year t and $Ret_{i,t}$ denotes fund i's return in year t.	CRSP, EST
$AbsFlow_{i,t}$	Computed as $TNA_{i,t} - TNA_{i,t-1} \cdot (1 + Ret_{i,t})$.	CRSP, EST
$ChgMktShr_{i,t}$	Computed as $\frac{TNA_{i,t}}{AggTNA_{i,t}} - \frac{TNA_{i,t-1}}{AggTNA_{i,t-1}}$ where $AggTNA_{i,t}$ denotes the aggregate assets under management of all funds in the same year and market segment as fund i.	CRSP, EST

Panel B: Measures of Fund Performance

$FundRet_{i,t}$	A fund's annual raw net return.	CRSP
$CAPM_{i,t}$	Jensen (1968) performance Alpha. We use three years of monthly return data first to compute factor loadings and then use the last 12 months of realized fund and factor return data in this period to compute Alphas.	CRSP, KF, EST
$FF_{i,t}$	Fama and French (1993) performance Alpha. We use three years of monthly return data first to compute factor loadings and then use the last 12 months of realized fund and factor return data in this period to compute Alphas.	CRSP, KF, EST
$Car_{i,t}$	Carhart (1997) performance Alpha. We use three years of monthly return data first to compute factor loadings and then use the last 12 months of realized fund and factor return data in this period to compute Alphas.	CRSP, KF, EST
$ShaR_{i,t}$	Sharpe Ratio computed as a fund's annual excess return over the risk free rate divided by the annualized return standard deviation.	CRSP, EST
$AppR_{i,t}$	Appraisal Ratio computed as a fund's four factor abnormal return, $Car_{i,t}$ divided by the standard deviation of the residuals of the four-factor regression.	CRSP, EST
$PerfRank_{i,t}$	Performance rank of a fund based on its annual return relative to its market segment in a given year. This variable is normalized to be between zero and one. The best fund is assigned a rank of one.	CRSP, EST
$PerfPers_{i,m}$	Performance persistence measured as the time series standard deviation of manager m's performance ranks at fund i. At least three years of performance ranks are required.	CRSP, EST
$Quintile1_{i,t}$	Piecewise linear regression (PLR) variable, computed as $\min(PerfRank; 0.2)$.	CRSP, EST
$Quintiles2-4_{i,t}$	PLR variable, computed as $\min(PerfRank - Quintile1; 0.8)$.	CRSP, EST
$Quintile5_{i,t}$	PLR variable, computed as $\min(PerfRank - (Quintile1 + Quintiles2-4))$.	CRSP, EST

Panel C: Measures of Investment Behavior		
Variable Name	Description	Source
$FundRisk_{i,t}$	Fund i's monthly return standard deviation in year t.	CRSP, EST
$SysRisk_{i,t}$	Fund i's factor loading on the market factor from a one factor model in year t.	CRSP, EST
$UnsysRisk_{i,t}$	Standard deviation of fund i's residual return from a one factor model in year t.	CRSP, EST
$TORatio_{i,t}$	A fund's annual turnover ratio in %.	CRSP
$SVM^{f}_{i,m}$	Style variability of fund i with respect to a specific factor loading f while manager m is managing this fund. It is calculated as the rescaled standard deviation of a fund's yearly factor loadings f over time. Standard deviations are rescaled by the average factor weighting standard deviation of all funds in the corresponding market segment over the same period. At least 3 years of data are required.	CRSP, EST
SVM_{i}	Average style variability of fund i calculated as the average of the factor individual style variability measures, $SVM^{f}_{i,m}$.	CRSP, EST

Panel D: Main Independent Variables		
$Female_{i,t}$	Dummy variable equal to one if fund i is managed by a woman in year t, and zero otherwise.	CRSP
$FemNew_{i,t}$	Dummy variable equal to one if a male manager at fund i is replaced by a female manager in year t, and zero otherwise.	CRSP
$MgrChg_{i,t}$	Dummy variable equal to one if there is a manager change at fund i in year t, and zero otherwise.	CRSP
$FundSize_{i,t}$	Logarithm of a fund's total net assets, $ln(tna + 1)$.	CRSP, EST
$ExpRatio_{i,t}$	A fund's annual expense ratio in %.	CRSP
$Act12b1_{i,t}$	A fund's actual 12b1 fees in %.	CRSP
$MgrTenure_{i,t}$	Tenure of fund manager, computed as difference between year t and the year in which the manager started working for fund i.	CRSP, EST
$FundAge_{i,t}$	Logarithm of a fund's age (plus one) computed based on the date a fund was first offered (variable $first\_offer\_dt$).	CRSP, EST
$SegmentFlow_{k,t}$	Average of $FundFlows_{i,t}$ over all funds i belonging to the same segment k in year t.	CRSP, EST
$CompanyFlow_{c,t}$	Average of $FundFlows_{i,t}$ over all funds i belonging to the same fund company c in year t.	CRSP, EST
$MgrAge_{i,t}$	Logarithm of a fund manager's age in years (plus one). Data are manually collected from manager biographies.	MSP, MSD, CIQ
$MBA_{i,t}$	Dummy variable equal to one if a fund manager has obtained a Master of Business Administration (MBA) degree, and zero otherwise. Data are manually collected from manager biographies.	MSP, MSD, CIQ
$PhD_{i,t}$	Dummy variable equal to one if a fund manager has obtained a PhD degree, and zero otherwise. Data are manually collected from manager biographies.	MSP, MSD, CIQ
$ProfQual_{i,t}$	Dummy variable equal to one if a fund manager has obtained a professional qualification (mainly CFA, but also others such as CFP or CPA), and zero otherwise. Data are manually collected from manager biographies.	MSP, MSD, CIQ
$LN(1+MedCov)_{i,t}$	Logarithm of the number of articles on fund i's manager in year t. Details on the media data collection process are described in Appendix C.	LN

Panel E: Experimental Variables		
Variable Name	Description	Source
$FinLit_j$	Financial literacy of subject j, computed as the number of right answers that are given to the 6 financial literacy questions (see Appendix D).	EXP
$d(R)$	Difference in mean reaction times in milliseconds between the incompatible and the compatible configuration in the IAT.	EXP, EST
$d(log(R))$	Difference in mean log reaction times in milliseconds between the incompatible and the compatible configuration in the IAT.	EXP, EST
$d(S)$	Difference in mean speed between the compatible and the incompatible configuration. The speed variable is defined as $S = \frac{1{,}000}{R}$.	EXP, EST
$Female_A$	Dummy variable equal to one if fund A is managed by a female manager, and zero otherwise.	EXP, EST
$FinEcon_j$	Dummy variable equal to one if subject j studies finance or economics, and zero otherwise.	EXP, EST
$HighFinLit_j$	Dummy variable equal to one if subject j answered at least 3 out of 6 financial literacy questions correctly, and zero otherwise.	EXP, EST
$SubjPrej_j$	Dummy if IAT score of subject j is positive, and zero otherwise.	EXP, EST
$SubjGen_j$	Dummy variable equal to one if subject j is female, and zero otherwise.	EXP, EST
$SubjAge_j$	Subject j's age at time of experiment.	EXP, EST
$SubjMarital_j$	Dummy variable equal to one if subject j is married, and zero otherwise.	EXP, EST
$EverInvest_j$	Dummy variable equal to one if subject j ever invested into a mutual fund, and zero otherwise.	EXP, EST
$InstrGen_j$	Dummy variable equal to one if the instructor subject j faced was female, and zero otherwise.	EXP, EST

Appendix C: Media Coverage

We use LexisNexis to collect newspaper articles that mention mutual fund managers. Out of all newspapers covered by LexisNexis we only include a subset in our search strategy to keep the data collection process manageable. We focus on newspapers belonging to the top 50 U.S. newspapers according to their print run. Furthermore, we require LexisNexis to have covered the newspaper since at least the mid 1990s. Additionally, to ensure a regionally balanced panel, we include all regional papers used in Engelberg and Parsons (2011) that are also covered in LexisNexis. Table C.1 shows the list of newspapers finally included in our search and the period for which articles are contained in LexisNexis.

Table C.1: Newspapers Covered in LexisNexis Search

Newspaper	Coverage	Newspaper	Coverage
Atlanta Journal	Jan 1991-Dec 2009	Atlanta Constitution	Jan 1991-Dec 2009
Denver Post	Dec 1993-Dec 2009	Houston Chronicle	Sep 1991-Dec 2009
Las Vegas Review	Sep 1996-Dec 2009[a]	Wisconsin State Journal	Jan 1992-Dec 2009
Minneapolis Star Tribune	Sep 1991-Dec 2009	New York Times	Jun 1980-Dec 2009
Pittsburgh Post-Gazette	Mar 1993-Dec 2009	Sacramento Bee	Jan 2002-Dec 2009
San Antonio Express-News	Jan 1996-Dec 2009	San Francisco Chronicle	Oct 1989-Dec 2009
Seattle Post-Intelligencer	Jan 1986-Mar 2009	St. Louis Post-Dispatch	Feb 1981-Dec 2009
St. Petersburg Time	Jan 1987-Dec 2009	Washington D.C. Post	Jan 1977-Dec 2009
USA Today	Jan 1989-Dec 2009	Wall Street Journal	May 1973-Dec 2009
San Jose Mercury News	Jan 1994-Dec 2009	Daily News (New York)	Mar 1995-Dec 2009
Philadelphia Inquirer	Jan 1994-Dec 2009	New York Post	Dec 1997-Dec 2009
Dallas Morning News	Oct 1992-Dec 2009	Chicago Sun-Times	Jan 1992-Dec 2009[b]
Arkansas Democrat-Gazette	Oct 1984-Dec 2009[c]	Augusta Chronicle	Jan 1992-Dec 2009[d]
Austin American-Statesman	Jan 1994-Dec 2009	Buffalo News	Nov 1992-Dec 2009
Christian Science Monitor	Jan 1980-Dec 2009	Dayton Daily News	Jan 1994-Dec 2009
Fresno Bee	Jan 1994-Dec 2009	Oklahoman	Jan 1992-Dec 2009
Palm Beach Post	Aug 1988-Dec 2009	Phoenix New Times	Jan 1989-Dec 2009
Providence Journal-Bulletin	Jan 1994-Dec 2009	Record (Bergen County, NJ)	Jan 1996-Dec 2009
Richmond Times Dispatch	Nov 1995-Dec 2009	Salt Lake Tribune	Jan 1994-Dec 2009
Santa Fe New Mexican	Jan 1994-Oct 2011	Tulsa World	Dec 1995-Dec 2009
Virginian-Pilot	Jan 1994-Dec 2009		

[a] Stories not available for October 9, 2001.

[b] Stories not available for November 1992.

[c] Incomplete coverage for 1992 and 1993.

[d] Incomplete coverage for June 2000

In our search query we search for all articles that mention the last name as well as the first name of a fund manager and require that the first name appears before the last name with a maximum distance of two letters (to allow for middle initials). To make sure that we capture fund managers, we only count articles that additionally contain the word 'equity' or 'stock' and 'portfolio' or 'investment' or 'fund'. Checking a small sample of the articles that were identified using this search strategy confirmed that most articles found were related to the fund manager. Using this approach, we do not distinguish between cases in which fund managers were interviewed and are quoted with their comments on, e.g., some recent market trends and cases in which an article features the success of a fund manager explicitly.

Appendix D: Details of the Experimental Procedure

The experiment took place in 11 individual sessions with a total of 100 students in the McCombs School of Business Behavioral Laboratory at the University of Texas at Austin. Subjects were recruited via flyers and announcements made in undergraduate business classes and on Blackboard (a class management and student communication system used at McCombs). Subjects participated in the experiment while sitting in front of PC screens that were separated from each other. After all subjects were seated, a female or male instructor briefly explained the experiment to them. They were told that the experiment would consist of two parts, a simple investment task (as described in detail in the main text) and a concentration task (the IAT). Afterwards, a short survey was conducted. Pay consisted of two parts. The first part was a show-up fee of 4 USD, the second part was a payoff that depended on the return of their investment decision in one randomly drawn round. The return was determined based on the actual annual return from CRSP of the funds they could choose from in that specific round. One experimental unit in the investment task was equivalent to 5.50 USD. Subjects earned on average 24 USD, with a maximum (minium) of 38 (4) USD.

The concentration task consists of an IAT which we designed to uncover prejudice against women in finance. 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 are evaluated, while the other five rounds are practice rounds. First, two practice rounds with 20 trials each are played to familiarize subjects with the tasks. In the first (second) round, only items belonging to the categories 'female' and 'male' ('marketing' and 'finance') have to be sorted (see Table 8). Then, another practice round with 20 trials was administered in which subjects are asked to categorize items in a combined task, i.e., 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 is 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. Our main results in the paper are based on the reaction times subjects achieve in the two test rounds 4 and 7. Results are very similar if we also include results from the two practice rounds 3 and 6.

The final survey consisted of questions on subjects' demographic characteristics, a question whether they had any investment experience, and a short financial literacy test. This test consists of six questions that are also used in van Rooij, Lusardi, and Alessie (2011).

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Table 1: Descriptive Statistics

Panel A	Mean (1)	Median (2)	SD (3)	p1 (4)	p99 (5)	Obs. (6)
$Female_{i,t}$	0.108	0.000	0.310	0.000	1.000	13302
$FundFlows_{i,t}$ (in percent)	0.280	0.052	1.094	-0.561	1.441	13302
$AbsFlow_{i,t}$	64.653	2.774	258.085	-411.027	1330.419	12974
$ChgMktShr_{i,t}$	-0.001	0.000	6.621	-8.362	8.462	13302
$FundReturn_{i,t}$	0.040	0.047	0.278	-0.524	0.720	13302
$CAPM_{i,t}$	-0.063	-0.074	1.165	-3.370	3.316	13278
$FF_{i,t}$	-0.134	-0.096	1.134	-3.690	2.989	13278
$Car_{i,t}$	-0.157	-0.103	1.177	-4.091	2.938	13278
$ShaR_{i,t}$	0.184	0.041	1.398	-2.199	3.957	12916
$AppR_{i,t}$	-0.001	-0.000	0.008	-0.027	0.017	13278
$FundSize_{i,t}$ (in Millions)	980.8	172.1	2987	1.251	13565	13302
$ExpRatio_{i,t}$ (in percent)	0.014	0.013	0.014	0.002	0.036	13291
$Act12b1_{i,t}$ (in percent)	0.003	0.003	0.003	0.000	0.010	8090
$TORatio_{i,t}$	1.009	0.661	1.626	0.030	6.520	13243
$FundRisk_{i,t}$	0.050	0.044	0.027	0.014	0.145	13296
$SysRisk_{i,t}$	0.994	0.949	0.417	0.179	2.435	13278
$UnsysRisk_{i,t}$	6.180	2.458	15.464	0.093	53.726	13278
SVM_i	1.000	0.851	0.613	0.237	3.519	2272
$FundAge_{i,t}$(in years)	13.102	9.000	12.622	3.000	68.000	13302
$MgrAge_{i,t}$ (in years)	45.658	45.000	8.703	28.000	68.000	10630
$MgrTenure_{i,t}$ (in years)	5.863	5.000	4.617	0.000	13.000	13298
$Bachelor_{i,t}$	0.998	1.000	0.039	1.000	1.000	10630
$MBA_{i,t}$	0.556	1.000	0.497	0.000	1.000	10630
$PhD_{i,t}$	0.056	0.000	0.231	0.000	1.000	10630
$ProfQual_{i,t}$	0.521	1.000	0.500	0.000	1.000	10630
$MedCov_{i,t}$	2.021	0.000	7.306	0.000	33.000	13302

Table 1: continued

Panel B	Female Manager (1)	Male Manager (2)	Difference (3)
$FundFlows_{i,t}$	0.19	0.29	-0.10^{***}
$FundReturn_{i,t}$	0.05	0.06	0.01
$CAPM_{i,t}$	-0.09	0.05	-0.04
$FF_{i,t}$	-0.06	-0.06	0.00
$Car_{i,t}$	-0.06	-0.07	0.01
$ShaR_{i,t}$	0.27	0.20	0.07^{*}
$AppR_{i,t}$	-0.00	-0.00	0.00
$FundSize_{i,t}$	573.07	711.01	-137.94^{***}
$ExpRatio_{i,t}$	1.46	1.44	0.02
$Act12b1_{i,t}$	0.32	0.28	0.04^{***}
$TORatio_{i,t}$	0.95	1.07	-0.12^{**}
$FundRisk_{i,t}$	0.05	0.05	0.00
$SysRisk_{i,t}$	0.98	0.99	-0.01
$UnsysRisk_{i,t}$	6.31	6.27	0.04
$FundAge_{i,t}$	10.89	10.33	0.55^{**}
$MgrAge_{i,t}$	43.06	45.28	-2.22^{***}
$MgrTenure_{i,t}$	4.90	5.99	-1.09^{***}
$Bachelor_{i,t}$	99.59	99.90	-0.31^{**}
$MBA_{i,t}$	56.08	55.04	1.04
$PhD_{i,t}$	1.78	6.53	-4.75^{***}
$ProfQual_{i,t}$	0.53	0.53	0.00
$MedCov_{i,t}$	0.96	2.15	-1.19^{***}

Notes: Panel A of this table shows fund characteristics based on our sample of all single-managed U.S. equity funds from January 1993 to December 2009. Means, medians, standard deviations (SD), bottom percentile ($p1$), upper percentile ($p99$), and the number of observations (*Obs.*) are reported. The detailed description of the variables listed in the first column is contained in Appendix B. Panel B of this table shows average characteristics for female-managed funds, average characteristics for male-managed funds, and 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

	NLD	WLD	RankRet	RankCar	USE	FMB	YC	FYC	NLS	Perf. Interactions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$Female_{i,t}$	–0.120	–0.121	–0.111	–0.104	–0.116	–0.106	–0.111	–0.107	–0.096	–0.123	–0.163
	(–4.32)	(–4.23)	(–3.95)	(–3.74)	(–3.37)	(–4.03)	(–4.18)	(–3.47)	(–3.58)	(–4.32)	(–2.64)
$FundFlows_{i,t-1}$		0.046	0.032	0.042	0.024	0.064	0.032	0.043	0.055	0.046	0.050
		(5.12)	(3.67)	(4.79)	(2.02)	(3.72)	(3.69)	(3.46)	(6.43)	(5.12)	(6.04)
$FundRet_{i,t-1}$	0.329	0.294								0.324	
	(4.47)	(3.37)								(4.33)	
$PerfRank_{i,t-1}$			–0.243	–0.061	–0.266	–0.218	–0.243	–0.249	–0.465		–1.056
			(–1.58)	(–0.40)	(–1.42)	(–1.47)	(–1.35)	(–1.74)	(–3.45)		(–6.33)
$PerfRank^2_{i,t-1}$			0.812	0.559	0.938	0.740	0.812	0.809	1.139		1.754
			(5.07)	(3.40)	(4.63)	(4.01)	(3.73)	(4.45)	(7.44)		(9.10)
$FundSize_{i,t-1}$	–0.134	–0.139	–0.144	–0.141	–0.146	–0.158	–0.144	–0.158	–0.497	–0.139	–0.121
	(–10.07)	(–10.09)	(–10.48)	(–10.33)	(–8.40)	(–12.51)	(–11.40)	(–12.90)	(–3.48)	(–10.10)	(–9.25)
$TORatio_{i,t-1}$	0.059	0.058	0.061	0.056	0.091	0.065	0.061	0.059	0.054	0.058	0.058
	(3.61)	(3.65)	(3.72)	(3.44)	(2.81)	(4.36)	(8.50)	(5.93)	(3.60)	(3.65)	(3.70)
$FundRisk_{i,t-1}$	–0.571	–0.455	0.291	–0.938	0.306	1.443	0.291	0.598	–0.553	–0.453	–0.480
	(–0.87)	(–0.67)	(0.43)	(–1.40)	(0.34)	(1.31)	(0.48)	(0.81)	(–0.84)	(–0.66)	(–0.72)
$ExpRatio_{i,t-1}$	3.980	4.621	3.987	4.887	4.367	–3.897	3.987	0.863	4.863	4.603	4.342
	(1.21)	(1.45)	(1.23)	(1.47)	(1.21)	(–1.53)	(0.91)	(0.23	(1.56)	(1.45)	(1.35)
$FundAge_{i,t-1}$	–0.067	–0.025	–0.002	–0.022	0.013	–0.014	–0.002	–0.014	–0.035	–0.025	–0.021
	(–3.74)	(–1.29)	(–0.13)	(–1.19)	(0.68)	(–0.74)	(–0.12)	(–0.69)	(–1.99)	(–1.28)	(–1.13)
$SegmentFlow_{k,t}$	0.152	0.128	0.138	0.139	–0.071	0.065	0.138	0.129	0.141	0.128	0.144
	(3.20)	(2.85)	(3.13)	(3.09)	(–1.47)	(0.23)	(1.60)	(1.33)	(3.20)	(2.85)	(3.27)
$CompanyFlow_{c,t}$	0.002	0.000	0.000	0.000	0.001	0.022	0.000	0.004	–0.000	0.000	0.000
	(1.03)	(0.03)	(0.08)	(0.14)	(0.51)	(3.04)	(0.07)	(2.12)	(–0.02)	(0.03)	(0.29)
$FundSize^2_{i,t-1}$									0.049		
									(1.96)		
$FundSize^3_{i,t-1}$									–0.002		
									(–1.11)		
$FundRet \cdot Female_{i,t-1}$										0.083	
										(0.98)	
$PerfRank \cdot Female_{i,t-1}$											0.790
											(2.25)
$PerfRank^2 \cdot Female_{i,t-1}$											–1.043
											(–2.59)
(adj./avg.) R^2	0.146	0.157	0.176	0.169	0.204	0.143	0.176	0.095	0.197	0.146	0.194
Observations	13265	12301	12301	12232	8223	12334	12301	12334	12279	13265	12301

Table 2: continued

Notes: This table shows the estimates of percentage fund flows, $FundFlows_{i,t}$, regressed on a female fund manager dummy, 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. $Female_{i,t}$ 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. $FundRet_{i,t-1}$ denotes fund i's lagged net return. $FundSize_{i,t-1}$ is the lagged natural logarithm of the fund's size in million USD and $TORatio_{i,t-1}$ 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 the fund's lagged total expense ratio. $FundAge_{i,t-1}$ is the lagged natural logarithm of fund i's age in years. $SegmentFlow_{k,t}$ is the average growth rate of all funds in fund i's market segment k due to flows in year t. $CompanyFlow_{c,t}$ is the average growth rate of all funds in fund i's fund company c due to flows in year t. $SegmentFlow_{k,t}$ and $CompanyFlow_{c,t}$ are calculated net of the flows into fund i. Column (1) reports results without the lagged dependent variable (NLD), while Column (2) presents results including the lagged dependent variable (WLD). In Columns (3) to (9) and (11), 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 to capture the non-linearity of the performance-flow relationship. In Columns (3) and (4), performance ranks are computed based on raw returns (RankRet) or based on Carhart (1997) four factor Alphas (RankCar), respectively. Results in Column (5) are obtained from a subsample of funds investing in U.S. equities (USE) only. Results in Column (6) are based on Fama and MacBeth (1973) regressions (FMB). In Columns (7) and (8), standard errors are clustered at the year level (YC) and at the fund and year level (FYC), respectively. In Column (9), we include fund size to the power of two and three to capture a non-linear impact of size (NLS). In Columns (10) and (11), we interact the female dummy variable with lagged performance. Regressions are estimated with time (except in Column (6)), segment and fund company fixed effects. t-statistics are in parentheses. In Columns (1) to (5) and (9) to (11), standard errors are clustered at the fund level.

Table 3: Fund Flows: Alternative Explanations and Robustness

Panel A: Alternative Explanations

	Manager Change (1)	Manager Char. (2)	Media Coverage (3)	Adver-tising (4)	Broker Channel (5)	Retail Fund (6)	Instl. Fund (7)
$FemNew_{i,t-1}$	–0.127						
	(–1.93)						
$MgrChg_{i,t-1}$	–0.011						
	(–0.40)						
$Female_{i,t}$		–0.119	–0.108	–0.120	–0.120	–0.155	–0.138
		(–3.99)	(–3.91)	(–3.35)	(–3.68)	(–3.84)	(–1.34)
$MBA_{i,t}$		0.001					
		(0.04)					
$PhD_{i,t}$		–0.056					
		(–1.59)					
$ProfQual_{i,t}$		0.014					
		(0.50)					
$MgrAge_{i,t}$		–0.003					
		(–1.50)					
$MgrTenure_{i,t-1}$		0.011					
		(3.86)					
$LN(1+MedCov)_{i,t-1}$			0.046				
			(3.04)				
$NoLoad \cdot Fem_{i,t}$					0.024		
					(0.47)		
$NoLoad_{i,t}$					0.028		
					(1.04)		
$Act12b1_{i,t}$				–16.210			
				(–1.90)			
Controls	yes	yes	yes	yes	yes	yes	yes
adj./Pseudo R^2	0.193	0.169	0.194	0.236	0.194	0.187	0.445
Observations	12300	9787	12301	7503	12299	6973	1484

Panel B: Robustness

	Alternative Flow Measures			PLRet	PLCar	Year $\leq$ 2001	Year >2001	Good Market	Bad Market
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Female_{i,t}$	–14.270	–0.009	–0.004	–0.112	–0.108	–0.085	–0.201	–0.124	–0.097
	(–1.99)	(–3.02)	(–4.33)	(–4.00)	(–3.87)	(–2.09)	(–4.72)	(–3.62)	(–2.20)
$Quintile1_{i,t-1}$				0.193	0.748				
				(0.68)	(3.17)				
$Quintile2-4_{i,t-1}$				0.381	0.229				
				(7.53)	(4.56)				
$Quintile5_{i,t-1}$				2.373	2.474				
				(6.65)	(5.72)				
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
adj./Pseudo R^2	0.299	0.007	0.123	0.178	0.172	0.104	0.238	0.177	0.339
Observations	11890	15376	247630	12301	12232	6614	5687	8759	3542

Panel C: Propensity Score Matching Analysis

	Nearest Neighbor (1)	Radius (2)	Kernel (3)	Strati-fication (4)
$Female_{i,t}$	–0.070	–0.051	–0.094	–0.115
	(–2.04)	(–2.32)	(–4.71)	(–4.79)
Number of matches	1332	1332	1332	1226

Table 3: continued

Notes: In this table, we use the same baseline specification as in Column (3) of Table 2. In Column (1) of Panel A, we replace our female indicator variable, $Female_{i,t}$, with a variable that is equal to one if a male manager at fund i is replaced by a female manager in year $t-1$, $FemNew_{i,t-1}$, and zero otherwise. $MgrChg_{i,t-1}$ is a dummy variable equal to one if a manager change occurred at fund i in year $t-1$. In Column (3), we add the logarithm of a manager's media coverage, $LN(1 + MedCov)_{i,t-1}$, as a control variable. In Column (4), we add 12b1 fees ($Act12b1_{i,t}$) as a control variable. In Column (5), we interact our female indicator variable with a dummy variable equal to one, if a fund charges no load fees, $NoLoad_{i,t}$, and zero otherwise. In Columns (6) and (7), we restrict our sample to funds that are declared as retail (institutional) funds, respectively. In Panel B, we use absolute fund flows, $AbsFlows_{i,t}$, (Column (1)), the change of a fund's market share, $ChgMktShr_{i,t}$, (Column (2)), both as defined in Appendix B, and monthly instead of yearly fund flows (Column (3)) as alterative dependent variables. In Columns (4) and (5) we capture the nonlinear performance flow relationship by a piecewise linear regression approach instead of squared performance ranks. Ranks are based on returns (PLRet) and Carhart (1997) four factor Alphas (PLCar), respectively. Results in the last four columns of Panel B are based on subsamples of funds till 2001 (Column (6)), after 2001 (Column (7)), in years following positive market returns (Column (8)) and in years following negative market returns (Column (9)), respectively. Panel C reports results from a propensity score matching analysis where we match based on segment, size, and past fund returns. t-statistics are in parentheses.

Table 4: Gender Differences in Investment Behavior

Panel A: Risk Taking and Trading Activity	$FundRisk_{i,t}$	$SysRisk_{i,t}$	$UnsysRisk_{i,t}$	$TORatio_{i,t}$
	(1)	(2)	(3)	(4)
$Female_{i,t}$	–0.000	–0.004	–0.424	–0.020
	(–0.44)	(–0.31)	(–1.16)	(–0.62)
$FundSize_{i,t-1}$	0.001	0.023	–0.188	–0.078
	(5.35)	(5.30)	(–1.24)	(–6.31)
$ExpRatio_{i,t-1}$	0.072	1.163	96.950	–0.004
	(1.85)	(2.59)	(1.36)	(–0.00)
$FundAge_{i,t-1}$	–0.001	–0.015	0.082	0.030
	(–3.20)	(–1.87)	(0.23)	(1.29)
$FundRet_{i,t-1}$	0.009	0.163	3.891	0.113
	(5.65)	(6.54)	(2.58)	(1.03)
$MgrTenure_{i,t-1}$	–0.000	–0.006	0.026	–0.019
	(–4.75)	(–5.24)	(0.59)	(–4.42)
adj. R^2	0.609	0.334	0.319	0.490
Observations	15153	15122	15122	15048
Panel B: 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***

Notes: In Panel A of this table, the dependent variable is one of the following: the fund's total risk measured by its return time series standard deviation, $FundRisk_{i,t}$, the fund's systematic risk, $SysRisk_{i,t}$, defined as the factor loading on the market factor from the Jensen (1968) one-factor model, the fund's unsystematic risk, $UnsysRisk_{i,t}$, defined as the standard deviation of the residuals from the Jensen (1968) one-factor model, and the fund's turnover ratio, $TORatio_{i,t}$. $Female_{i,t}$ is a dummy variable that takes on the value one, if 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. $ExpRatio_{i,t-1}$ is a fund's lagged total expense ratio. $FundAge_{i,t-1}$ is the lagged natural logarithm of fund i's age in years. $FundRet_{i,t-1}$ is a fund's lagged raw return. $MgrTenure_{i,t}$ is the fund manager's tenure with the fund in years. The regressions are estimated with time, segment, and fund company fixed effects. t-statistics are in parentheses. Standard errors are clustered at the fund level. Panel B shows the average style variability of female and male-managed funds for the aggregate style variability measure (Column 1) as well as for the factor individual style variability measures (Columns 2 to 4). 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. Significance is calculated based on a two-sided t-test. *** 1% significance, ** 5% significance, * 10% significance.

Table 5: Gender and Fund Performance

Panel A: Fund Performance - Multivariate Evidence						
	$FundRet_{i,t}$	$CAPM_{i,t}$	$FF_{i,t}$	$Car_{i,t}$	$ShaR_{i,t}$	$AppR_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_{i,t}$	–0.003	–0.006	–0.001	–0.001	–0.005	–0.000
	(–0.80)	(–0.92)	(–0.20)	(–0.18)	(–0.18)	(–0.46)
$FundSize_{i,t-1}$	–0.013	–0.011	–0.005	–0.006	–0.068	–0.000
	(–12.65)	(–7.80)	(–3.65)	(–4.51)	(–10.89)	(–2.83)
$ExpRatio_{i,t-1}$	–0.329	–0.579	–0.466	–0.396	–1.065	0.010
	(–1.56)	(–2.53)	(–1.55)	(–0.87)	(–0.87)	(1.16)
$FundAge_{i,t-1}$	0.002	0.001	–0.007	–0.007	–0.016	–0.000
	(1.20)	(0.42)	(–2.68)	(–2.42)	(–1.33)	(–0.69)
$MgrTenure_{i,t-1}$	0.001	0.000	–0.000	0.000	0.009	0.000
	(3.68)	(0.69)	(–0.08)	(0.96)	(3.61)	(1.41)
R^2	0.611	0.167	0.154	0.163	0.606	0.004
Observations	16509	9804	9804	9803	16116	18181
Panel B: Robustness						
	$FundRet_{i,t}$	$CAPM_{i,t}$	$FF_{i,t}$	$Car_{i,t}$	$ShaR_{i,t}$	$AppR_{i,t}$
$Female_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)
B.1 Fund Chars.	–0.002	–0.008	–0.001	–0.002	0.006	–0.000
	(–0.41)	(–1.10)	(–0.18)	(–0.27)	(0.17)	(–0.99)
R^2	0.621	0.178	0.163	0.176	0.624	0.050
Observations	12483	9000	9000	8999	12165	13765
B.2 Manager Chars.	–0.004	–0.006	0.001	0.001	–0.020	–0.000
	(–0.82)	(–0.77)	(0.16)	(0.10)	(–0.63)	(–0.41)
R^2	0.630	0.171	0.159	0.168	0.622	0.006
Observations	12990	7811	7811	7810	12677	14348
B.3 YC	–0.003	–0.006	–0.001	–0.001	–0.005	–0.000
	(–0.61)	(–0.98)	(–0.20)	(–0.20)	(–0.13)	(–0.47)
R^2	0.611	0.167	0.154	0.163	0.606	0.004
Observations	16509	9804	9804	9803	16116	18181
B.4 FYC	–0.000	–0.002	0.001	–0.001	0.028	–0.000
	(–0.47)	(–0.32)	(0.16)	(–0.15)	(0.73)	(–0.57)
R^2	0.004	0.109	0.077	0.084	0.591	0.008
Observations	18181	9822	9822	9821	16156	18229
B.5 FMB	0.001	–0.000	0.002	0.000	0.004	–0.000
	(0.17)	(–0.06)	(0.56)	(0.12)	(0.15)	(–0.14)
R^2	0.223	0.185	0.165	0.164	0.210	0.074
Observations	16549	9822	9822	9821	16156	18229

Table 5: continued

Panel C: Fund Performance - Portfolio Evidence						
	Equal-Weighted			Value-Weighted		
	$CAPM_t^{f-m}$	FF_t^{f-m}	Car_t^{f-m}	$CAPM_t^{f-m}$	FF_t^{f-m}	Car_t^{f-m}
	(1)	(2)	(3)	(4)	(5)	(6)
$Alpha_t$	0.000	0.000	0.000	–0.001	–0.000	–0.001
	(0.05)	(0.77)	(0.09)	(–1.61)	(–0.70)	(–1.20)
$MKTRF_t$	0.019	0.010	0.019	0.035	0.017	0.028
	(3.40)	(1.77)	(3.23)	(3.32)	(1.63)	(2.62)
SMB_t		0.011	0.009		0.003	0.000
		(1.60)	(1.33)		(0.26)	(0.03)
HML_t		–0.034	–0.028		–0.084	–0.075
		(–4.62)	(–3.77)		(–6.13)	(–5.45)
MOM_t			0.019			0.025
			(4.16)			(2.94)
R^2	0.047	0.165	0.225	0.045	0.200	0.227
Observations	216	216	216	216	216	216

Panel D: Performance Persistence			
	Female	*Male*	*Difference*
$FundRet_{i,t}$	0.2274	0.2452	−0.0178 (−1.65)
$CAPM_{i,t}$	0.2565	0.2700	−0.0135 (−1.98)
$FF_{i,t}$	0.2542	0.2712	−0.0170 (−1.97)
$Car_{i,t}$	0.2410	0.2637	−0.0227 (−2.46)
$ShaR_{i,t}$	0.2517	0.2524	−0.0007 (−0.95)
$AppR_{i,t}$	0.2360	0.2591	−0.0231 (−2.11)

Notes: In Panel A of this table, the performance of a fund computed as the raw return ($FundRet_{i,t}$), the Jensen (1968) Alpha ($CAPM_{i,t}$), the Fama and French (1993) three-factor Alpha ($FF_{i,t}$), the Carhart (1997) four-factor Alpha ($Car_{i,t}$), the Sharpe (1966) Ratio ($ShaR_{i,t}$), or a modified version of the Treynor and Black (1973) Appraisal Ratio ($AppR_{i,t}$), all as defined in Appendix B, is the dependent variable. $Female_{i,t}$ 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. $MgrTenure_{i,t}$ is the fund manager's tenure with the fund in years. All other controls are defined as in the previous tables. Panel B presents the coefficient and t-statistic on $Female_{i,t}$ in regressions including the same controls as in Panel A from various robustness checks. In B.1, we add $TORatio_{i,t-1}$, $FundFlows_{i,t-1}$, $FundRisk_{i,t-1}$, and the lagged dependent variable as controls. In B.2, we add $MgrAge_{i,t}$, $MBA_{i,t}$, $PhD_{i,t}$, and $ProfQual_{i,t}$ as controls. Results in B.3 (B.4) are obtained by clustering standard errors at the year level (YC) and the year and fund level (FYC). In B.5, results are obtained by estimating Fama and MacBeth (1973) regressions. Panel C shows results from a regression with the equal weighted and value weighted return of a difference portfolio that is long in all female-managed funds and short in all male-managed funds as dependent variable. Difference returns are regressed on the market factor, $MKTRF_t$, the size factor, SMB_t, the value factor, HML_t, and the momentum factor, MOM_t. Panel D contains the average time series standard deviation over performance ranks of female- and male-managed funds for various performance measures and the difference between female and male fund managers. t-statistics are in parentheses. Regressions are estimated with time, segment, and fund company fixed effects. Standard errors are clustered at the fund level.

Table 6: Subject Characteristics

Panel A: Main Field of Study	Number	Percentage
Accounting	13	13.00%
Economics	5	5.00%
Finance	43	43.00%
Management Information Systems	9	9.00%
Marketing	10	10.00%
Other	20	20.00%
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	12	12.00%
Panel C: Marital Status	**Number**	**Percentage**
Single	97	97.00%
Married/Engaged	3	3.00%
Panel D: Gender	**Number**	**Percentage**
Female	49	49.00%
Male	51	51.00%

Notes: This table shows summary statistics of subjects' characteristics in our experiment. Panel A displays the number and percentage of subjects with different main fields of study. The "Other" category mainly includes students in "International Business" or "Supply Chain Management" as well as students from non-business fields like "Geography", "Literature", or "Physical Therapy". Panel B contains the number and percentage of subjects in different age brackets. Panel C provides number and percentage of subjects depending on their marital status and Panel D contains number and percentage of subjects that belong to each gender category.

Table 7: Investment Decisions

	Female Manager	Male Manager	Difference (F-M)	Obs.
	% invested into fund A			
	(1)	(2)	(3)	(4)
Panel A: All subjects	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 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
Regional^{all}	48.77	45.63	3.14	484
	% 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
Regional^{1st}	46.30	49.97	–3.66	121

Notes: This table shows the fraction of money invested in the female-managed (Column (1)) and male-managed (Column (2)) fund in our experiment. The difference between the amounts invested in the female- and male-managed fund is displayed in Column (3). The number of observations is provided in Column (4). Panel A presents results for all subjects in our experiment, while Panel B contains results for female and male subjects separately. In Panel C, we form subsamples of subjects by field of study. In Panel D, we divide subjects based on their financial literacy. Financial literacy is computed based on the number of correct answers in a standard financial literacy test containing six questions on financial issues (see Appendix D). Panel E displays results for different types of funds and for the first round of the experiment separately. *** 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: This table shows the list of items used in 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	t-stat	95% Confidence Interval	sign. < 0	< 0	> 0	sign. > 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All Subjects							
$d(R)$	160.96	10.08	[129.28;192.64]	4 (4%)	8 (8%)	26 (26%)	62 (62%)
$d(log(R))$	0.1724	10.95	[0.1411;0.2036]	4 (4%)	8 (8%)	25 (25%)	63 (63%)
$d(S)$	0.1610	10.08	[0.1293;0.1926]	4 (4%)	10 (10%)	25 (25%)	61 (61%)
Panel B: Compatible Configuration First							
$d(R)$	160.16	6.68	[111.88;208.45]	4 (8.51%)	2 (4.26%)	11 (23.40%)	30 (63.83%)
$d(log(R))$	0.1700	7.06	[0.1234;0.2218]	4 (8.51%)	2 (4.26%)	10 (21.28%)	31 (65.96%)
$d(S)$	0.1602	6.68	[0.1119;0.2084]	4 (8.51%)	2 (4.26%)	11 (23.40%)	30 (63.83%)
Panel C: Incompatible Configuration First							
$d(R)$	161.67	7.50	[118.43;204.90]	0 (0.00%)	6 (11.32%)	16 (30.19%)	31 (58.49%)
$d(log(R))$	0.1721	8.39	[0.1310;0.2133]	0 (0.00%)	6 (11.32%)	15 (28.30%)	32 (60.38%)
$d(S)$	0.1617	7.50	[0.1184;0.2049]	0 (0.00%)	8 (15.09%)	14 (26.42%)	31 (58.49%)

Notes: This table displays differences in reaction times from the implicit association test (IAT). Panel A contains results for all subjects in our experiment. Panel B contains results for the group that played the compatible configuration first. Panel C contains results for the group that played the incompatible configuration first. Implicit prejudice measures are denoted by $d(R)$, $d(log(R))$, and $d(S)$, respectively. $d(R)$ denotes the difference in the average reaction times R between the incompatible and the compatible configuration in milliseconds. $d(log(R))$ denotes the difference in the log-transformed reaction times R between the incompatible and the compatible configuration. $d(S)$ is computed as the difference in the speed variable defined as $S = \frac{1{,}000}{R}$ between the compatible and the incompatible configuration. Columns (2) and (3) present t-statistics and the 95% confidence intervals of the average d-measures aggregated at the subject level. Columns (4) to (7) contain the number and percentage of subjects for which the average reaction time in the incompatible configuration is significantly smaller (sign. < 0), smaller (< 0), larger (> 0), and significantly larger (sign. > 0), respectively, than in the compatible configuration on the individual subject level.

Table 10: Impact of Subject Characteristics and Experimental Parameters on Implicit Prejudice

Measure	Subject Characteristic & Design Parameters	Obs	Mean $d(R)$	Std	Min	Max	t-stat	p
Panel A: Gender								
$d(R)$	Female Subjects	49	158.22	167.79	-203.30	619.93	6.60	0.0000
$d(R)$	Male Subjects	51	163.59	153.07	-107.85	661.38	7.63	0.0000
Panel B: Female and Male Finance Students								
$d(R)$	Female Finance Students	18	118.43	180.58	-203.30	438.85	2.78	0.0128
$d(R)$	Male Finance Students	25	223.59	154.66	-66.80	661.38	7.23	0.0000
Panel C: Field of Study								
$d(R)$	Finance	43	179.57	172.11	-203.30	661.38	6.84	0.0000
$d(R)$	Marketing	10	224.61	139.06	-15.08	485.90	5.11	0.0006
Panel D: Financial Literacy								
$d(R)$	High Literacy	43	176.73	172.30	-203.30	661.38	6.73	0.0000
$d(R)$	Low Literacy	57	149.06	149.88	-107.85	485.90	7.51	0.0000
Panel E: Instructor Sex								
$d(R)$	Female Instructor	53	169.03	148.76	-120.80	619.93	8.27	0.0000
$d(R)$	Male Instructor	47	151.85	172.30	-203.30	661.38	6.04	0.0000
Panel F: Time of Day								
$d(R)$	Morning Session	35	170.65	148.81	-107.85	619.93	6.78	0.0000
$d(R)$	Afternoon Session	65	155.74	166.10	-203.30	661.38	7.56	0.0000
Panel G: Crowdedness								
$d(R)$	Large Sessions	37	170.24	187.51	-203.30	661.38	5.52	0.0000
$d(R)$	Small Sessions	63	155.51	142.15	-120.80	485.90	8.68	0.0000

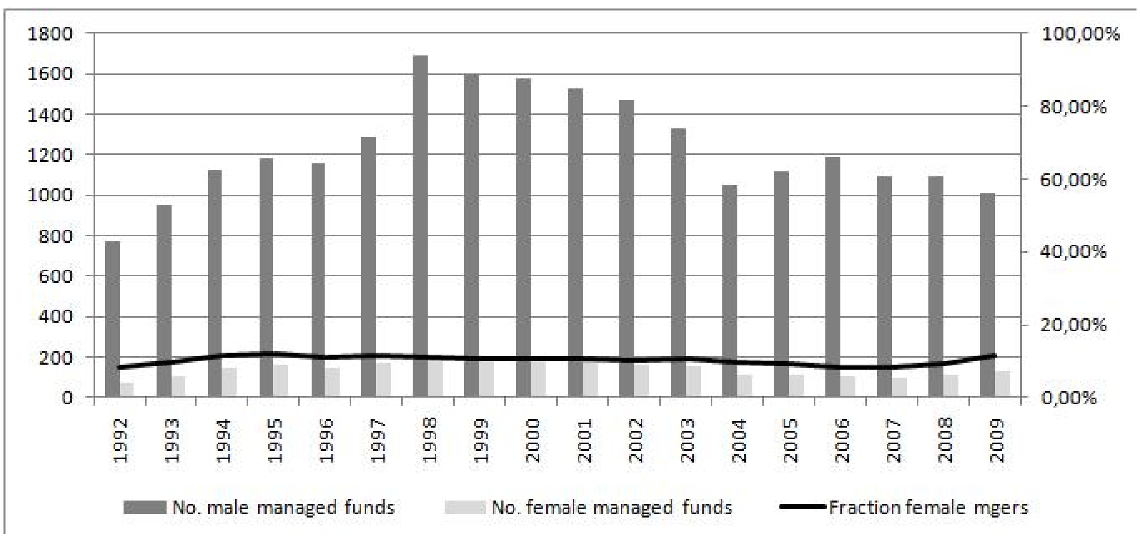
Notes: This table displays differences in reaction times from the implicit association test (IAT) for different subsamples. Panel A contains results for subsamples of female and male subjects in our experiment. Panel B contains results for subsamples of female and male finance students, respectively. In Panel C, we split up our sample by field of study. Panel D contains results for subjects with high and low financial literacy. Panel E contains results depending on whether the instructor in the experiment was female or male. Panel F contains results for experimental sessions that took place in the morning or afternoon, respectively. In Panel G, we split up our sample by number of subjects in each session. $d(R)$ denotes the difference in the average reaction times R between the incompatible and the compatible configuration in milliseconds.

Table 11: Investment Decisions Depending on IAT Result

Panel A: Percentage invested in fund A - Univariate evidence						
	Female Manager	Male Manager	Diff. (F-M)	t-stat	Obs.	
	(1)	(2)	(3)	(4)	(5)	
$d(R) > 0$	41.51	49.58	–8.06	–3.09	428	
$d(R) < 0$	49.04	43.90	5.13	0.77	56	
$d(log(R)) > 0$	41.52	49.56	–8.04	–3.14	436	
$d(log(R)) < 0$	49.04	42.29	6.75	0.88	48	
$d(S) > 0$	41.52	49.59	–8.07	–3.09	428	
$d(S) < 0$	49.04	43.91	5.14	0.77	56	
Panel B: Percentage invested in fund A - Multivariate evidence						
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_A$	–9.464	4.370	–15.894	–8.743	–7.454	–10.388
	(–3.15)	(0.64)	(–3.75)	(–2.33)	(–1.81)	(–2.59)
$Female_A \cdot Prej_j$		–17.283				
		(–2.27)				
$Female_A \cdot SubjGen_j$			13.376			
			(2.15)			
$Female_A \cdot FinEcon_j$				–1.862		
				(–0.32)		
$Female_A \cdot HighFinLit_j$					–4.492	
					(–0.71)	
$Female_A \cdot InstrGen_j$						2.121
						(0.35)
Controls	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.018	0.019	0.019	0.018	0.018	0.018
Observations	484	484	484	484	484	484

Notes: Panel A of this table shows the amount invested in female- and male-managed funds in the investment task depending on whether subjects exhibit (or do not 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, a subject is prejudiced against females in finance, and vice versa. Panel B of this table shows results from a censored tobit regression with session fixed effects, where the fraction of money invested by subject j into index fund A, $investment_{A,j}$ is the dependent variable. $Female_A$ is a dummy variable that takes on the value one, if fund A is managed by a female fund manager, and zero otherwise. All other control variables are described in Appendix B. t-statistics are in parentheses.

Figure 1: Distribution of Funds by Manager Gender



Notes: This figure displays the total number of female- and male-managed funds (bars) and the fraction 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.