Sex Matters: Gender Bias in the Mutual Fund Industry *

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ABSTRACT

We document significantly lower inflows in female-managed mutual funds than in male-managed funds. This result is obtained with field data and with data from a laboratory experiment. There are no gender differences in performance. Thus, rational statistical discrimination is unlikely to explain the fund flow effect. We conduct an implicit association test and find that subjects with stronger gender bias according to this test invest significantly less into female-managed funds. Our results suggest that gender bias affects investment decisions and thus offer a new potential explanation for the low fraction of women in the mutual fund industry.

JEL-Classification Codes: G23, J71

Keywords: Mutual Funds; Investor Behavior; Gender Bias; Implicit Association Test

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1 Introduction

Why are there so few women in the financial industry? The fraction of female fund managers in charge of a single managed U.S. equity fund 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)), less competitive environments (Niederle and Vesterlund (2007) and Sutter and Gätzle-Rützler (2014)), 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 some investors might be subject to gender bias, which eventually leads to lower money flows in 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 the idea that investors are subject to such a gender bias.

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 money inflows than male-managed funds. The growth rates of female-managed funds are about one third lower than those of male-managed funds. Furthermore, interactions of manager gender with fund performance indicate that a fund profits less from good past performance in terms of inflows if it is managed by a woman.

There are two main reasons why investors might shy away from female fund managers: (rational) statistical discrimination (e.g., Phelps (1972)) or (irrational) prejudice against female fund managers due to gender bias (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 signal of their investment skills; eventually they would statistically discriminate against female fund managers by investing less in their funds. However, we find no evidence for gender differences among fund managers that would support the view that shying away from female managers could be rational: their investment styles are more persistent over time than those of male fund managers, while average

[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." (National Council for Research on Women (2009)).

performance is virtually identical and male fund managers exhibit less performance persistence. Thus, if anything, fund investors should prefer female fund managers.

In our regressions, we control for differences in past fund performance, fund and fund company characteristics such as size, and differences in characteristics of the fund manager other than the manager's gender. Furthermore, we conduct a matched sample analysis and obtain similar results. To address the concern that fund companies might assign female managers to funds that are less attractive to fund investors for reasons that we cannot explicitly control for, we look at manager changes. We find that fund flows decrease significantly if a male manager is replaced by a female manager, but not if a female manager is replaced by a male manager. Additional analysis shows that our results also cannot 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 the extent of media coverage.

There are two possible concerns regarding our results. First, one might wonder whether fund investors are even aware of who is managing their fund. Second, according to the equilibrium arguments made in Berk and Green (2004), one could argue that female fund managers *would* underperform if they *would* grow larger because of diseconomies of scale and that the low inflows into female-managed funds could thus be a rational equilibrium outcome. In our later discussion we address these concerns and present supporting evidence for our postulated gender bias channel and against alternative explanations.

To further investigate gender bias in investment decisions, we conduct a controlled laboratory experiment similar to Choi, Laibson, and Madrian (2011). Specifically, participants in the experiment have to decide how to split a certain amount of money between two index funds. We chose index funds because the ability of a fund manager to outperform the market is irrelevant for this type of fund. In the experiment, we keep all information about the fund constant, except for the managers' names based on which participants can infer their gender. If participants ignore the manager's name, as they should in this setting, we should not find any impact of gender on the chosen investment amount. However, we observe that subjects in our experiment invest significantly less in the same index fund if the manager name provided indicates a female manager. The effect is mainly driven by male subjects, while female subject do not seem to be biased.

Finally, to test directly whether there is a gender bias 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 based on associations. IATs consist of computerized sorting tasks and allow researchers to measure implicit associations between concepts (e.g., 'Science' and 'Liberal Arts') and group affiliation (e.g., 'Male' vs. 'Female') based on reaction times. External validations of IATs show that they are able to reliably capture prejudice and predict behavior (e.g., Greenwald, Poehlman, Uhlmann, and Banaji (2009)). We develop a new IAT to test for a potential gender bias in finance. Results indicate a bias against women in finance for most of the subjects in our experiment. Linking the results from the IAT back to subjects' investment behavior, we find that subjects with high IAT prejudice scores do indeed invest significantly less in female-managed funds in the experimental investment task, while subjects for which the IAT does not indicate any gender bias do not invest less in these funds.

While we cannot provide direct evidence that fund companies consider the lower flows that have to be expected when hiring a female fund manager, the results from our empirical study as well as from the experimental investment task and the IAT suggest that this would be a plausible reaction and thus offer a new customer-based explanation of why we see so few women in the fund industry.

We also discuss why we then see any women in this industry at all. We provide evidence consistent with the notion that some investor groups are not biased against women or have a preference to invest with funds from companies that employ female fund managers, e.g., due to diversity policies. Our results show that the male-managed funds of companies that employ at least one female manager experience higher inflows, i.e., there is a positive spill-over effect of employing female fund managers on the other funds in the family.

Our study contributes to the large literature on the determinants of mutual fund performance and inflows. Chevalier and Ellison (1999) and Baks (2003) examine the impact of fund manager characteristics on fund performance (without a focus on gender). Papers on the determinants of fund flows mainly focus on the impact of past performance (e.g., Sirri and Tufano (1998), among many others). Atkinson, Baird, and Frye (2003) look at a small sample of bond funds, but generally find—with the exception of the first year a female manager manages a fund—no impact of gender on flows.

The idea that mutual fund investors are subject to behavioral biases is examined in Bailey, Kumar, and Ng (2011). Kumar, Niessen-Ruenzi, and Spalt (2015) find a negative impact of foreign sounding

[2] A short introductory note on the IAT is Carney, Nosek, Greenwald, and Banaji (2007).

names on mutual fund flows, consistent with xenophobia driving investor behavior. Our paper is the first to show that gender bias of investors has an important impact on investment decisions, too. Thereby, it contributes to the large sociopolitical debate on gender stereotyping (e.g., Neumark (1996), Bertrand and Hallock (2001), Newton and Simutin (2014)) by showing that gender bias is also an issue in the financial industry. Gender issues in a financial context are not widely researched, but at least three important related papers exist: Wolfers (2006) examines stock market returns of firms with female CEOs and male CEOs and finds them to be identical, Kumar (2010) analyzes financial analysts and finds that female analysts provide better estimates and that markets react stronger upon their reports, while Green, Jegadeesh, and Tang (2009) find that the forecast precision of female analysts is lower than that of male analysts.

Furthermore, we relate to the broad literature on gender differences in general (e.g., Barber and Odean (2001), Croson and Gneezy (2009), and Adams and Funk (2012)) and to the general 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), and Holzer and Ihlanfeldt (1998)) in non-financial contexts. To the best of our knowledge, our paper is the first that analyzes customer-based gender discrimination.

Finally, our paper contributes to the finance literature methodologically by introducing the IAT method to the field, which has not been used in finance before.[3]

2 Data and summary statistics

Our primary data sources are the CRSP Survivor-Bias-Free Mutual Fund Database as well as the Morningstar Direct and Morningstar Principia mutual fund databases. While the former contains high quality data on fund performance, the latter is more precise with respect to manager identities and manager information (Massa, Reuter, and Zitzewitz (2010)). The CRSP database 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. The Morningstar databases provide information on fund managers including their age and education.

[3] 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 examine hiring discrimination against African-Americans and Beaman, Chattopadhyay, Duflo, Pande, and Topalova (2009) apply an IAT to measure attitudes towards female leaders.

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 twelve 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 Morningstar gives multiple manager names from our analysis. Our study covers the time period from January 1992—the year from which on 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 as given in the Morningstar databases. Massa, Reuter, and Zitzewitz (2010) show that information on fund managers as reported by Morningstar much better match the content of official regulatory filings, i.e., it is more reliable than fund manager information as provided by the CRSP database. Therefore, we use fund manager names from Morningstar to identify the fund manager's gender. Overall, we are able to identify the gender of the fund manager in 99.39% of all cases based on the procedure described in detail in Appendix A. 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, 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.

Our final sample contains 16,509 fund year observations, out of which 14,804 (89.67%) have a male manager and 1,705 (10.33%) have a female manager. Figure 1 plots the total number of male and female-managed funds as well as the fraction of female-managed funds over our sample period. It

[4] Specifically, we use the following twelve equity fund segments: AG (Aggressive Growth), BAL (Balanced Funds), EM (Emerging Markets), 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).

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 later use 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 the most important variables.

The univariate comparison shows that 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 female-managed funds is slightly higher than the mean age of male-managed funds. With respect to fees, we find that 12b-1 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. Female manager have a slightly better average performance based on Sharpe Ratios, but there is no difference in average performance based on factor alphas or raw returns and no significant difference in average risk. Female fund managers have a significantly lower tenure with a particular fund and they 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. While male fund managers are covered more than twice per year on average, female managers are mentioned less than once per year in the public press.

3 Do investors care about the manager's gender? - Empirical evidence

3.1 Fund flows and manager gender

We start our empirical analysis by examining whether female-managed funds attract lower inflows than male-managed funds. We relate 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 control for the influence of past performance, $FundRet_{i,t-1}$, on fund flows. We also include lagged fund size, $FundSize_{i,t-1}$, the fund's annual turnover ratio, $TORatio_{i,t-1}$, the fund's age, $FundAge_{i,t-1}$, lagged fund risk, $FundRisk_{i,t-1}$, as well as a fund's lagged expense ratio in percent, $ExpRatio_{i,t-1}$, in our regression.[5] All variables are defined in more detail in Appendix B. Sialm and Tham (2015) show that the stock market performance of mutual fund companies can impact the flows of the affiliated funds. To account for the impact of this effect and other 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, $SegmentFlow_{k,t}$.[6] 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.

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 statistically significant at the 1% level in all model specifications. The effect is also economically meaningful: 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 (in relative terms) 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,[7] while in Column 2 (and all following specifications) we additionally include lagged fund flows, $FundFlows_{i,t-1}$. Sirri and Tufano (1998) show 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 convex performance-flow relationship documented in the literature. 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

[5]To control for further differences in investment styles, in unreported tests we also include the loadings of fund returns on the Carhart (1997) style factors as explanatory variables. Our results remain unaffected.

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

[7]Fund returns are winsorized at the top 1%. Not winsorizing returns does not change the results.

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

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.

Results in this table show that fund size is one of the main drivers of funds inflows. 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 lagged fund returns as well as with lagged performance ranks and squared lagged performance ranks, respectively. In Column 10, we find a significantly negative impact of the interaction term, suggesting that flows to female-managed funds are generally less performance sensitive. In Column 11, the interaction term of the female dummy with squared past performance is highly significant and positive, while the interaction term with linear past performance ranks is significantly negative, but smaller in absolute size. This indicates that a fund profits less from good past performance if it is managed by a woman, while the punishment for bad performance does not differ much between female and male managers. Irrespective of the inclusion of the performance interaction terms, the female dummy itself is still significantly negative and of similar magnitude as before, showing a strong negative level effect.

Regarding our results on the influence of the control variables, they are very uniform across specifications and generally confirm findings reported in the literature. Overall, our results so far support the notion that investors exhibit gender bias and prefer male-managed funds.

3.2 Alternative explanations

We now refine our analysis and try to empirically disentangle alternative explanations for the documented lower inflows into female-managed funds. Results are presented in Table 3.

[9]We also control for the impact of size by including dummies based on size deciles. Our main result (not reported) is not affected.

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 to manage those funds or because they are assigned to these funds by 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 13% if a male manager is replaced by 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, e.g., 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 fund manager's age and tenure at the fund currently managed.[10] We find that manager tenure has a positive impact on fund flows, while age and education have no significant impact. Irrespective of this, we still find that female managers receive on average nearly 12% lower inflows after adding these additional control variables.[11]

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 (2015). 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,

[10]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.

[11]To test whether the negative impact of gender might be weakened if the fund manager has a good education or a long tenure, in unreported tests, we also interact the impact of the female dummy with the education dummies and an above median tenure dummy. In all cases, we find no significant impact of the interaction terms, while our main results remain unaffected.

$LN(1+MedCov)_{i,t-1}$, defined as the natural logarithm of the number of articles on fund i's manager in year $t-1$, 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.[12] In Column 4, we include 12b-1 fees as a proxy for advertising and other marketing expenditures which again does not change our main result.

It is also possible that it is not gender bias of investors themselves that drives our results, 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 mutual fund flows is driven by funds that are distributed via brokers. As such funds typically charge front-end loads (Christoffersen, Evans, and Musto (2013)), we interact our female dummy with a dummy variable which is equal to one if none of the fund's share classes charges a front-end load, 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 preferring male 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. It is insignificant among institutional funds (probably due to the small number of observations), but significant at the 1% level among retail funds.

[12]In unreported tests, we also add an interaction term between media coverage and the female manager dummy. The interaction term is not significant (indicating that press coverage on females is neither more positive nor particularly negative as compared to that of male managers). Again, our main result remain unaffected.

3.3 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 follow Spiegel and Zhang (2013) 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 (2013), 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. 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 estimate a piecewise linear relationship in Columns 4 and 5. Specifically, we estimate distinct slope coefficients for different performance quintiles.[14] Results based on return ranks and Carhart (1997) four factor alpha ranks confirm the convex performance-flow relationship and we still find a negative impact of the female dummy.

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 a significantly negative impact of the female fund manager variable in all cases. The effect is even somewhat stronger in later years, but there is no big difference between good and bad market years.

[13]In Spiegel and Zhang (2013) 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]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.

Finally, in panel C of Table 3, we present results from a matched sample analysis. For each observation with a female manager we try to find male-managed twin funds with similar characteristics. We use different combinations of matching criteria. In all cases, we require the matching observations to be from the same year and segment and to be in the same size decile in the respective year. We always match based on fund size because this variable has the strongest and most consistent influence on flows in Table 2. Then, we re-run the same regression as in Column 3 in panel A of Table 2 based on our matched sample. Results in Column 1 of Table 3 show a highly significant negative impact of the female dummy on flows which amounts to 7.5% p.a. In Columns 2 to 6 we additionally require the matching funds to be in the same fund-age decile, manager-age decile, lagged return rank decile, have a manager with the same level of eduction, and to be in the same manager fund tenure decile, respectively. The results show a very uniform picture: the impact of the female dummy is always significantly negative and economically meaningful, ranging from -8% to -10% p.a.

4 Gender bias vs. rational statistical discrimination

Results in the previous section suggest that investors prefer male-managed funds to female-managed funds. We propose gender bias as one possible explanation for this finding. However, our findings could also be driven by statistical discrimination rather than by a gender bias. To disentangle these two explanations, we now investigate whether there is any evidence of undesirable investment behavior (Section 4.1) or inferior fund performance (Section 4.2) of female fund managers as compared to male fund managers.

4.1 Investment styles

It is sometimes argued that gender differences are of little importance among professionals, because the similar environment and educational background of professionals overrides potential gender differences. However, there is also evidence that gender differences are relevant in professional management settings (e.g., Adams and Funk (2012) and Graham, Harvey, and Puri (2013)).

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 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 control 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 a fund manager's investment behavior. Including fund company fixed effects also addresses the concern that female managers might self-select into low-risk fund companies. Standard errors are clustered at the fund level. Panel A of Table 4 summarizes our findings.

Regarding the various dimensions of risk taking behavior, 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)). We also find that women tend to trade less, which is often interpreted as evidence for less overconfidence (Barber and Odean (2001)). However, both effects are not statistically significant.

Finally, we want to examine whether there are any differences in style variability defined as the variability of a fund's factor loadings over time (see Appendix B).[15] We only conduct a univariate comparison between the style variability measures of female- and male-managed funds, because we only calculate one style variability measure based on the entire time span over which a specific manager manages a fund. Results in panel B 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).[16]

Overall, we find only minor differences with respect to the investment behavior of female and male fund managers: female fund managers' investment behavior should be, ceteris paribus, more desirable for mutual fund investors as they follow more stable and thus reliable investment styles than male fund managers.

[15] 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.

[16] 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.

4.2 Fund performance

We now examine whether the behavioral differences documented in the previous section have an impact on fund performance and performance persistence.[17] We start by relating various performance measures of fund i in year t to a female dummy and controls. 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.

There is no significant difference between the performance of female- and male-managed funds. 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 as controls. Specifically, we include the fund's lagged inflows to control for the effect that it might be more difficult for male managers to perform well because they face larger inflows. Other additional fund characteristics we include are the fund's lagged turnover ratio, 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. This also holds if we estimate the same models as in panel A, but run Fama and MacBeth (1973) regressions (B.3). Finally, we conduct a matched sample analysis, where each female-managed fund year observation is matched with male-managed fund year observations from the same segment, the same year, and the same size decile (B.4). We specifically match based on size to control for the potential impact of diseconomies of scale. Again, there is no significant influence of the female dummy on any of the performance measures.[18]

As individual fund performance can only be estimated with noise we also analyze the performance of equal-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

[17]e.g., Brown, Harlow, and Zhang (2014) document a positive influence of stable investment styles on performance.

[18]Glode (2011) argues that investors particularly value good performance during bad states of the economy. Thus, we also check whether males might deliver better returns than females during market downturns. In unreported tests we find no difference in the impact of the female dummy on various performance measures across market states.

presented in panel C. 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.[19]

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.[20] We investigate performance persistence based on the five performance measures analyzed 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 most performance measures. This provides some evidence that the performance of female-managed funds is more persistent than the performance of male-managed funds. A more stable performance as well as the more stable investment styles of female managers documented above should, if anything, be preferable from an investor's point of view.

Overall, the evidence provided in this section is not consistent with the idea of investors rationally avoiding female fund managers. Rather, it suggests that investors exhibit taste-based irrational behavior leading to gender bias.

5 Do investors care about the manager's gender? - Experimental evidence

Although the previous sections suggest that rational statistical discrimination and several other alternative explanations for lower inflows into female-managed funds are unlikely to be the main driver of our results, it is of course not possible to empirically observe and control for all other potential drivers of fund flows. Thus, to shed further light on the question whether investors really care about manager gender, we conduct a controlled laboratory experiment to better identify a causal impact of fund manager gender on flows. This procedure also has the advantage that we can examine the impact

[19]In unreported tests, we also analyze value-weighted portfolios. Results are again insignificant.
[20]Analyzing a variance based measure of performance persistence delivers qualitatively identical results.

of investor characteristics on investment decisions, while the previous empirical analysis focusses on aggregate investor behavior at the fund level.

The experiment was conducted with U.S. university students and consists of two main parts, an investment task (Section 5.1) and an Implicit Association Test (IAT, see Section 5.2). The investment task experiment allows us to analyze the impact of manager gender on capital allocations in a controlled laboratory setting and the IAT allows us to get a proxy for gender bias on an individual level. We then link back IAT scores to investment decisions to test whether gender bias and investment behavior are linked (Section 5.3). Details of the experimental procedure are described in Appendix D.

5.1 Investment task

We develop a simple between-subjects design in which 100 experimental currency units have to be split between two S&P 500 index funds that we randomly chose from the CRSP fund database beforehand. 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 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" to avoid any framing or familiarity effects. 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 were shown information on the funds. However, we manipulated the gender of the fund manager between these groups, while keeping all other information constant. Figure 3 shows the information given to the two groups of subjects. 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.[21] This procedure allows us to attribute any differences in investment behavior between the two groups solely to the fund manager's gender.

The experiment consisted of four rounds.[22] Investment rounds only differed with respect to the amount of information provided about the funds. In the first round, information about the fund segment,

[21] We took the most common U.S. first names according to the U.S. Social Security Administration to ensure that subjects perceive these names as very common for each gender category and we use common last names.

[22] The experiment was part of a more extensive investigation where subjects also made additional investment decisions. In this paper we only report the results relevant in our context, i.e., the impact of gender on index fund investments.

the name of the fund manager, fund size, inception date, expense ratio, trading activity, and top five stock holdings was provided. In addition, we added a short text labeled "Fund Facts" with a description of the fund's investment strategy (see Figure 3). In the following three 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, respectively.

We recruited 100 students as subjects in our experiment. Table 6 provides information on the demographic characteristics of the subjects. Due to the recruiting procedure (about 50% of the announcements were made in finance classes) most subjects (i.e., 43 individuals) 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.

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 presents results based on all four rounds in the first line. Strictly speaking, 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 pair of funds. Thus, in the second line we focus on the first round of the experiment only.

In both cases, results show 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 due to fund A's 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 finding confirms results from a similar experiment reported in Choi, Laibson, and Madrian (2011).

More important in our context, subjects invest significantly less in fund A if it is managed by a female fund manager than if it is managed by a male fund manager.[23] The difference is 7.42 experimental

[23]Note, that we only compare investments in fund A between subjects conditional on the fund manager's gender. Thus, the amounts shown in Column 1 and 2 in Table 7 do not add up to 100. By definition, our conclusions would remain unchanged if we compared investments in fund B instead.

units or roughly 15% and is significant at the 1% level if we pool observations from all rounds. It is even larger (8.51 experimental units) and significant at the 5% level if we only focus on the first round investment decisions.

In the following panels, we split up observations by various subject characteristics. In order to prevent samples from getting too small, we focus on results based on observations from all rounds. 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. We observe significantly less money directed towards the female-managed fund in both groups, but the effect seems to be slightly stronger among the more financially literate. Furthermore, as one would hope, the more financial literate subjects seem to be more sensitive to fund expenses. On average, they invest only 35.3 experimental units in the more expensive index fund, as compared to 46.6 experimental units invested in this fund by the less financial literate subjects.

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 investors preferring male-managed funds.

5.2 Implicit Association Test

In the second part of the experiment, we conducted an implicit association test (IAT) to directly examine whether gender bias explains the observed investment behavior in the laboratory. The IAT has gained enormous popularity among social psychologists in recent years as it can uncover prejudice based on simple associations. According to Lane, Banaji, Nosek, and Greenwald (2007), there are now well over 200 papers that use this method. In previous applications, the IAT is used to uncover various social biases like prejudice against different races, religions, genders, or sexual orientations. The test's popularity is based on the fact that it can be easily administered and that it allows to also 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 cannot be easily manipulated and might even operate completely unconsciously (Greenwald, Banaji, Rudman, Farnham, Nosek, and Mellott (2002)). Its reliability and validity is widely confirmed by showing that IAT scores predict biased behavior in many contexts like voting behavior or brand choices (Cunningham, Preacher, and Banaji (2001), Greenwald, Poehlman, Uhlmann, and Banaji (2009)).

As IAT tests are not used in the finance literature so far, we will now shortly describe how a typical gender IAT works: Subjects are required to classify items into one of four categories (e.g., 'Male' or 'Female' and 'Science' or 'Liberal Arts') 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, 'Male' and 'Science' would be displayed together on one side and 'Female' and 'Liberal Arts' would be displayed together on the other side, while in the incompatible configuration one of the categories is switched from one side of the screen to the other (e.g., 'Female' and 'Science' would show up on the same side). Subjects have to rapidly sort items appearing in the middle of the screen by hitting either a left- or a right-hand key. The IAT measures reaction times in the two configurations. The test relies on the fact that stronger associations (e.g., 'Male' with 'Science') result in faster reaction times than weaker associations (e.g., 'Female' with 'Science') and that the strength of associations serves as a proxy for implicit prejudice. If there is no implicit prejudice, average reaction times should be identical. In contrast, if there is a biased perception that, e.g., men are more skilled in science and women are more skilled in liberal arts, reaction times would be higher in the incompatible configuration.

To examine whether there is any evidence of gender bias in our setting, 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 IATs like the one described above. They 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. 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 U.S. undergraduate students in business administration. 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. 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.

Panel A displays the compatible configuration where the categories 'Finance' and 'Male' are on one side of the screen and 'Marketing' and 'Female' are on the other side. In contrast, panel B displays the incompatible configuration. In both cases of the example shown in Figure 4, subjects had to sort the item 'stocks' into the right category as fast as possible. If their reaction time is significantly higher in the incompatible configuration than in the compatible configuration, this indicates that they are more biased. 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 compute IAT scores is to just 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] Panel A (B) reports results for subjects who first played the compatible (incompatible) configuration and then the incompatible (compatible) configuration. 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 advantage that the distribution of log-transformed reaction times has a more stable variance and is thus more suitable for statistical analysis. Third, we calculate a speed variable defined as $S = \frac{1{,}000}{R}$. This variable also has desirable distributional characteristics that stabilize variances and can be directly interpreted as items per second. We then calculate the corresponding IAT score as 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 scores are suggested in Greenwald, McGhee, and Schwartz (1998) and are denoted by $d(R)_j$, $d(log(R))_j$, and $d(S)_j$, respec-

[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.

tively.[25] 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, if d is significantly larger than zero, this suggests the existence of a gender bias.

Results for a pooled examination of all subjects are presented in Table 9. 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 IAT score is not different from zero can be rejected at the 1% level (t-statistic > 10). This also holds for the other 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 d. These results provide evidence that most of our subjects indeed show signs of gender bias in a financial context.

We also investigate which subject characteristics are related to the strength of gender bias. We first compare male and female subjects as well as finance and marketing students. Results are presented in panels A and B of Table 10 and show significant gender bias among all groups. The differences between the groups are not statistically significant.

Tajfel (1970) provides evidence for an in-group bias of individuals. This effect should lead to less pronounced or no gender bias among female finance students. In panel C, we find that the 25 male subjects that study finance show an average difference in reaction times 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 who study finance, the difference 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 between male and female finance students is also statistically significant (t-statistic: 2.05, based on $d(R)$).

[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.

Finally, in panel D we check whether there is any relation between the level of financial literacy and the IAT score. The average IAT score in the high financial literacy group is 177 ms vs. 150 ms in the low financial literacy group but 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.

5.3 Impact of investor-level IAT scores on investment decisions

Overall, the results from the IAT are consistent with the view that there is gender bias in finance. However, it is unclear whether this bias affects investment behavior and is strong enough to eventually result in lower inflows into female-managed funds. Thus, we now compare the fraction invested in female-managed funds in the investment task of the experiment between subjects with a strong gender bias according to their IAT score to subjects with no or even a reverse gender bias. Results are presented in Table 11.

Panel A shows the mean amounts invested in the male- and female-managed index funds over all rounds separating between subjects with high and low IAT scores. The results show that subjects with high IAT scores ($d(R) > 0$, $d(log(R)) > 0$, $d(S) > 0$) invest significantly less in female-managed funds. In contrast, we find (insignificantly) larger investments in female-managed funds of those subjects with negative IAT scores.

In panel B, we present multivariate evidence from a censored Tobit regression with the fraction of experimental units invested in index fund A—which can either have a male manager (group X) or a 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 a set of control variables. We include (but do not explicitly report for the sake of brevity) dummies that take on the value one, if subject j has an above median IAT score, ($SubjIAT_j$), 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. More interestingly, in Column 2 we interact the female manager dummy with a dummy equal to one if a subject showed above median IAT scores, and zero otherwise. The interaction term is significantly negative. The coefficient indicates that subjects with above median IAT scores on average allocate 17.3 experimental units 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 now insignificant. This result confirms our earlier univariate finding from panel A.

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. This confirms our earlier findings from panel B in Table 10 and shows that the negative impact of a female manager is neutralized if the subject making the investment decision 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, the results from the experiment suggest that many individuals are subject to gender bias as measured by IAT scores and that this bias has a very strong impact on investment decisions.

6 Discussion and equilibrium implications

In this section, we discuss some potential remaining concerns regarding our results as well as the equilibrium implications of our findings. First, we address the concern that investors might not even know who the fund manager is (Section 6.1). Second, in Section 6.2, we discuss whether our results could be consistent with a rational equilibrium as described in Berk and Green (2004). Finally, we turn to the question why we see any women at all in the mutual fund industry, given that they attract significantly lower inflows (Section 6.3).

6.1 Do investors know who manages their fund?

One might be concerned about whether fund investors are aware of who is managing the fund they invest in. First, it is important to note that it does not matter so much for our analysis whether investors remember who manages their fund at a later point in time. It is only important that investors are exposed to the identity of the manager when they make their investment decision. The literature on social categorization processes has shown that social biases are automatically activated by the mere presence of a stimulus. With respect to gender as a social category, several papers have shown that exposure to information about gender, as conveyed through names, pictures, or gender stereotypical words, can exert an unconscious influence on individual decision making (Banaji and Greenwald (1995), Blair and Banaji (1996)). Thus, even if mutual fund investment decisions do not consciously rely on the gender of a fund manager, they can be influenced by investors' perception of the manager's name, particularly if the name evokes any unconscious stereotypes or other emotional responses.

Second, we can show that information on the fund manager is usually easily available to investors: We collect fund information for the largest single-managed fund of the fifty largest fund companies in our sample. Out of these funds, 98% report the fund manager's name online on their webpage as well as in the official prospectus.[26] Furthermore, besides prospectuses and fund company websites, many investors rely on financial websites like, e.g., Yahoo Finance to gather fund information. Figure 2 presents screenshots of the information investors would get if they search for a specific fund in four of the major online financial information sources. 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 prominently presented on the first page that appears.

Additional evidence that investors are often directly exposed to manager names comes from product descriptions in personal finance magazines. 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. For example, there were articles available for 11 of the 15 U.S. equity funds contained in the list (in November 2011). Eight out of those eleven articles mentioned the name of the fund manager in the very first sentence.

[26] The only two companies that did not report the manager's name on their webpage is Dimensional Fund Advisory and Capital Growth Management. However, even these companies reported the manager's name in the prospectus. For 74% of the funds, the manager name was reported on the main website of the fund (instead of only being visible after clicking once more or just being included in the fund prospectus).

Finally, evidence that fund managers' identities matter for investment decisions of mutual fund investors is also provided in earlier empirical papers on mutual fund flows. For example, Massa, Reuter, and Zitzewitz (2010) show that funds have greater inflows if the name of the fund manager is declared as compared to funds where the manager name is kept anonymous. They also show that departures of named managers reduce inflows. Furthermore, Kumar, Niessen-Ruenzi, and Spalt (2015) show that fund investors shy away from funds with managers with foreign sounding names and that this effect got stronger for Middle Eastern sounding names after 9/11. These results suggest that a sufficiently large fraction of investors takes the manager's name into account.

From the evidence provided in this section, we conclude that manager information is generally available to investors and that investors are often exposed to and take into account fund manager names when making investment decisions.

6.2 Lower inflows in a rational equilibrium?

Berk and Green (2004) show theoretically that the observed performance of all fund managers is identical in equilibrium even if their skill levels differ. The reason for this result is that they assume that fund managers' investment skills are subject to decreasing returns to scale. If there is competitive provision of capital by investors in the form of money inflows, this leads to an equilibrium where all funds grew to a size at which they are not able to outperform any longer. In a perfect Berk and Green (2004) world, investors might rationally predict that female fund managers would underperform if they received larger inflows. Thus, they provide less capital to female fund managers. However, recent empirical evidence questions the underlying assumption of the Berk and Green (2004) model that there are strong diseconomies of scale in the fund industry (see Reuter and Zitzewitz (2013)). Furthermore, our results obtained from the controlled laboratory experiment in Section 5.1 clearly cannot be explained by the Berk and Green (2004) model. The findings reported there are based on investment decisions between a female and a male-managed index fund. One reason why we focused on index funds is that the ability of the manager to outperform the market is irrelevant for this type of fund. In addition, Chen, Hong, Huang, and Kubik (2004) argue that diseconomies of scale are not important for index funds. Consequently, the Berk and Green (2004) equilibrium argument is not relevant in this context. We conclude that it is unlikely that the flow effects we document using field data and particularly the experimental evidence can be explained as a rational equilibrium response of investors as described in Berk and Green (2004).

6.3 Why not even fewer female fund managers?

One provocative question that one may ask based on our findings is why we observe any female fund managers at all. One could argue that it is suboptimal for fund management companies to employ female fund managers at all if they attract lower inflows than male managers. However, while our results show that investors *on average* shy away from female-managed funds, this does not mean that all investors behave like this. If there is a significant number of investors who do not display a gender bias (or even actively favor females) it makes sense for fund companies to employ at least some female managers to cater to those investors.

Results from the experimental investment task show that there is a minority of subjects (typically women) who are not biased against female fund managers or even invest more with them. Therefore, 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.[27] Furthermore, many institutional investors require their business partners to report explicitly on their diversity policy. In a similar vein, the Dodd-Frank Act 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.

However, most regulations and diversity policies of institutional investors do not prescribe them to invest in female-managed funds. Rather, they typically only have to make sure that the companies they do business with have some diversity policy in place. Thus, it could be the case that fund companies employ some female managers to formally fulfill the requests of such investors. However, these investors might still not invest in the female-managed funds, but rather in the other funds of the company. Then, female fund managers would not directly attract flows into their own funds, but their presence in the company would lead to positive spill-over effects for the other funds of the company.

To test this idea, we adapt the flow regression from Column 3 in Table 2 to capture such potential spill-over effects and run the regression based on male-managed funds only. Results are presented in Table 12. In Column 1, we replace the female dummy by a dummy variable taking on the value one, if there is another female-managed fund among the single-managed funds of the same fund company, and

[27] Consistent with this argument, there are indeed some niche funds like the Pax World Global Women's Equality Fund that specifically cater to female investors.

zero otherwise.[28] In Column 2, instead of the dummy variable, we use the number of female-managed funds in the same company as independent variable. In both cases, we find a highly significant positive impact of the spill-over variable. For example, the coefficient in Column 1 indicates that male-managed funds grow by more than 6% p.a. more if the fund company also employs at least one female manager. This seems like a very large impact and gives rise to the question whether fund companies should not employ more female managers in order to profit from these large indirect positive flow effects. However, in Column 3, we present results where we include both spill-over variables simultaneously. We find a highly significant impact of the variable indicating the presence of at least one female-managed fund, while the number of female managers now is insignificant, i.e., there seems to be no additional benefit of adding more female managers if there is already at least one female-managed fund in the company.

Overall, our results from Table 12 are consistent with the argument that fund companies should at least employ some female fund managers despite the lower inflows they generate because of the demand of certain investor groups requiring them to document the inclusion of women. The observed fraction of female fund managers in the industry could thus be an equilibrium outcome in the sense that the negative direct flow effect of having a female-managed fund is offset by the positive spill-over effects on flows in other funds offered by the fund company.

7 Conclusion

This paper examines the conjecture that mutual fund investors exhibit gender bias and prefer to invest in male-managed funds. Consistent with this conjecture, we find 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, while the performance of female managers is more stable than that of male 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 suggests

[28] As this variable might also proxy for the size of the fund company (as it is more likely to have at least one female manager if there are simply more other funds), we again include company-level flows as control variable. This captures the impact of the size of the fund company (and of all other fund company characteristics) on individual level flows.

that there is a gender bias among most of the subjects participating in our experiment. Subjects with the strongest gender bias (according to the IAT) invest the least in female-managed funds.

Overall, our findings show that gender bias of investors can have a strong impact on financial markets and 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 a possible new explanation for the low fraction of female managers in the mutual fund industry based on customer-driven discrimination.

Appendix A: Gender classification

To identify a fund manager's gender we first extract the manager's first name from the Morningstar databases. From a list published by the United States Social Security Administration (SSA) that contains the most popular first names by gender for the last 10 decades we get 2,179 different male and 2,515 different female first names that also account for differences in spelling.[29] First names that appear for both sexes are excluded from the SSA-List. We then match this list with the first names and thereby classify most of the managers as male or female. Remaining names are those we could not clearly classify as male or female, i.e., foreign names or ambiguous names. We were able to identify most of the foreign names by asking foreign exchange students from the respective country. For the remaining cases, we try to identify fund managers' gender by several internet sources like the fund prospectus, press releases or photographs that reveal their gender. This leaves us with an identification rate of 99.39%.

[29] 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: LexisNexis, (vii) MSD: Morningstar Direct, (viii) MSP: Morningstar Principia.

Panel A: Measures of fund flows

Variable name	Description	Source
$FundFlows_{i,t}$	Computed as $\frac{TNA_{i,t}-TNA_{i,t-1}\cdot(1+FundRet_{i,t})}{TNA_{i,t-1}}$ where $TNA_{i,t}$ denotes fund i's total net assets in year t and $FundRet_{i,t}$ 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

Variable name	Description	Source
$FundRet_{i,t}$	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 based on monthly return data.	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
$TORatio_{i,t}$	Fund i'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 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 consecutive 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

Variable name	Description	Source
$Female_{i,t}$	Dummy variable equal to one if fund i is managed by a woman in year t, and zero otherwise.	MSD
$FemNew_{i,t}$	Dummy variable equal to one if a male manager at fund i is replaced by a female manager in year t, and zero otherwise.	MSD
$MgrChg_{i,t}$	Dummy variable equal to one if there is a manager change at fund i in year t, and zero otherwise.	MSD
$FundSize_{i,t}$	Logarithm of a fund's total net assets, $ln(TNA+1)$.	CRSP, EST
$ExpRatio_{i,t}$	Fund i's annual expense ratio in %.	CRSP
$Act12b1_{i,t}$	Fund i's actual 12b-1 fees in %.	CRSP
$MgrTenure_{i,t}$	Tenure of fund i's manager in years, computed as difference between year t and the year in which the manager started managing fund i.	CRSP, EST
$FundAge_{i,t}$	Logarithm of fund i's age in years (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
$Bachelor_{i,t}$	Dummy variable equal to one if a fund manager has obtained a Bachelor degree, and zero otherwise. 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
$FemInCompany_{c,t}$	Dummy variable equal to one if the fund company c a fund belongs to employs at least one female fund manager in year t, and zero otherwise.	MSD, CRSP
$NumberFemales_{c,t}$	Number of female fund manager that the fund company c a fund belongs to employs in year t.	MSD, CRSP

Panel E: Reaction time variables from the experiment

Variable name	Description	Source
$d(R)$	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

Panel F: Other variables from the experiment

Variable name	Description	Source
$Female_A$	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
$FinLit_j$	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
$HighFinLit_j$	Dummy variable equal to one if subject j answered at least 3 out of 6 financial literacy questions correctly, and zero otherwise.	EXP
$SubjIAT_j$	Dummy if IAT score of subject j is above the median, and zero otherwise.	EXP
$SubjGen_j$	Dummy variable equal to one if subject j is female, and zero otherwise.	EXP
$SubjAge_j$	Subject j's age in years at the time of the experiment.	EXP
$SubjMarital_j$	Dummy variable equal to one if subject j is married, and zero otherwise.	EXP
$EverInvest_j$	Dummy variable equal to one if subject j ever invested into a mutual fund, and zero otherwise.	EXP
$InstrGen_j$	Dummy variable equal to one if the instructor subject j faced was female, and zero otherwise.	EXP

Appendix C: Media coverage

We use LexisNexis to collect newspaper articles that mention mutual fund managers. We only include a subset of newspapers in our search strategy to keep the data collection process manageable. We focus on 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 covered in LexisNexis. The following table shows the newspapers included in our search and the period for which articles are contained in LexisNexis.

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

We search for all articles that mention a manager's first and last name 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 also 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 of them were indeed related to the fund manager. We do not distinguish between cases in which fund managers were interviewed or are quoted with their comments 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 practice 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 financial literacy questions that are also used in van Rooij, Lusardi, and Alessie (2011).

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Table 1: Descriptive Statistics

Panel A	Mean	Median	SD	p1	p99	Obs.
	(1)	(2)	(3)	(4)	(5)	(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	Male Manager	Difference
	(1)	(2)	(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

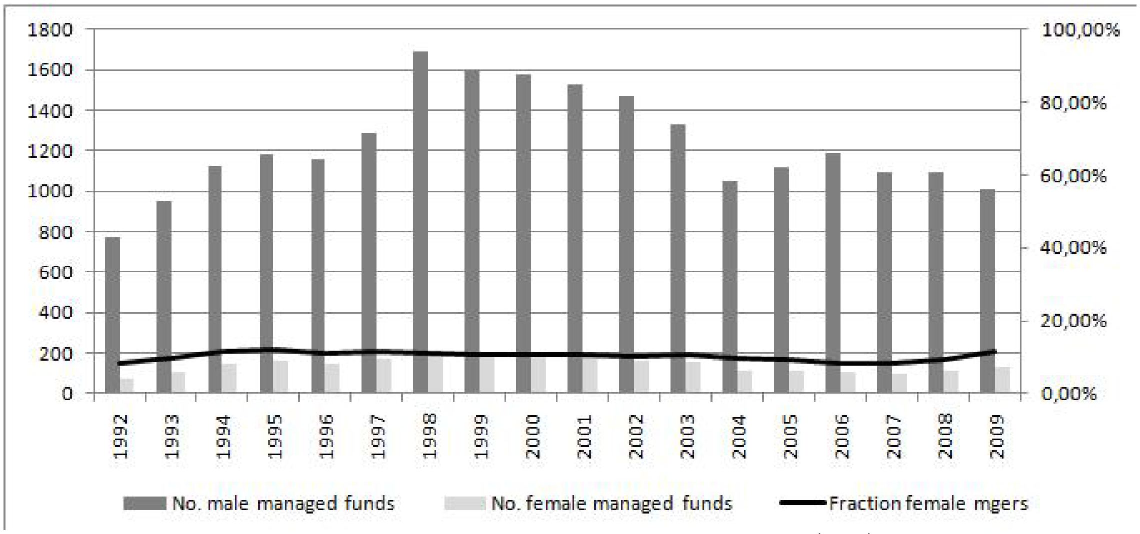
Notes: Panel A of this table shows the amount invested in female- and male-managed funds in the investment task depending on whether subjects exhibit (or do not exhibit) prejudice against females in finance in an implicit association test (IAT). If $d(R) > 0$, $d(log(R)) > 0$, and $d(S) > 0$, respectively, 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.

Table 12: Spillover Effects of Female Managers

	Any Female (1)	Number of Females (2)	Both Variables (3)
$FemInCompany_{c,t}$	0.076		0.066
	(3.22)		(2.52)
$NumberFemales_{c,t}$		0.006	0.002
		(2.35)	(0.69)
Controls	yes	yes	yes
Adj. R^2	0.093	0.092	0.092
Observations	11002	11002	11002

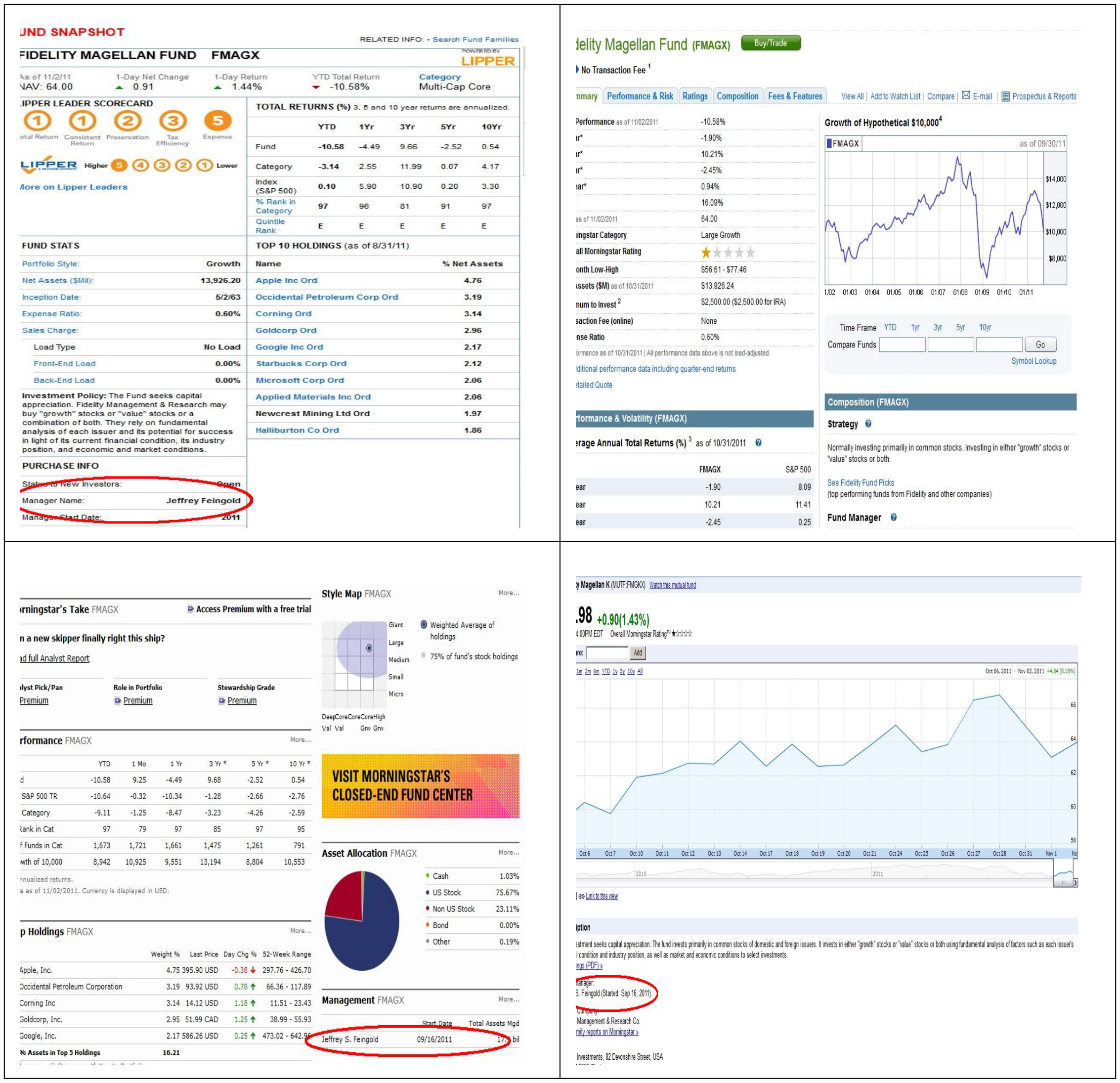
Notes: In this table, we use the same baseline specification as in Column (3) of Table 2. In Column (1), we replace our female dummy, $Female_{i,t}$, with a variable that is equal to one if there is any female fund manager at fund company c in year t, $FemInCompany_{c,t}$, and zero otherwise. In Column (2), we replace our female dummy, $Female_{i,t}$, with a variable that is equal to the number of female fund managers at fund company c in year t, $NumberFemales_{c,t}$. In Column (3), we include both variables, $FemInCompany_{c,t}$, and $NumberFemales_{c,t}$ at the same time. The regressions are based on male-managed funds only. They are estimated with time and segment fixed effects. Standard errors are clustered at the fund level.

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.

Figure 2: Salience of Fund Managers' Gender



Notes: This figure displays four screenshots for fund information on the Fidelity Magellan fund from the websites of the Wall Street Journal, Morningstar, Google Finance, and Yahoo Finance. The manager name is always shown on the first page that appears and is circled in red in the pictures.

Figure 3: Investment Task

Panel A: Group X

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

Panel B: Group Y

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

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

Figure 4: IAT Screen

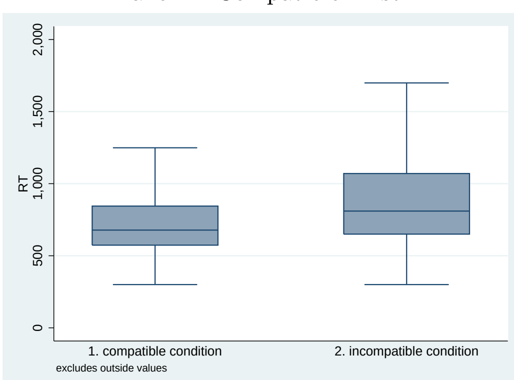
Panel A: Compatible Condition

Panel B: Incompatible Condition

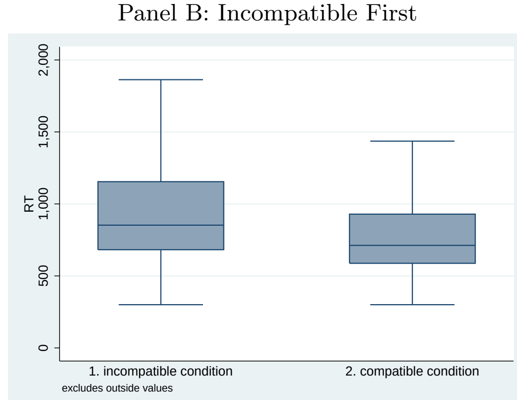
Notes: This figure displays the compatible configuration of the IAT (Panel A) and the incompatible configuration (Panel B), respectively.

Figure 5: Reaction Times in the Implicit Association Tests (IAT)

Panel A: Compatible First



Panel B: Incompatible First



Notes: This figure shows boxplots for the reaction times, RT, in milliseconds (ms) for the group playing the compatible configuration first (Panel A) and the group playing the incompatible configuration first (Panel B). The vertical line in the box indicates the median level, and the upper and lower hinge represent the 75th and 25th percentile, respectively. The length of the whiskers is determined by the adjacent value which is still just inside a limit determined by 1.5 times the interquartile range. Extremely low (high) reaction times of below 300 ms (above 3 seconds) are set equal to 300 ms (3 seconds).