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Sex Matters: Gender Bias in the Mutual Fund Industry

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Abstract. We document significantly lower inflows in female-managed funds than in male-managed funds. This result is obtained with field data and with data from a laboratory experiment. We find 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 in 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.

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Keywords: mutual funds • investor behavior • gender bias • implicit association test

1. Introduction

Why are there so few women in the financial industry? Pointing out the low fraction of female mutual fund managers, the *New York Times* recently called this question a "trillion dollar question" (Dunleavey 2017). Indeed, our data show that the fraction of women in charge of a single-managed U.S. equity fund has hovered around a very low level of about 10% over a 20-year period. Attempts to correct the underrepresentation of women in the asset management industry have not been successful so far (Newlands and Ram 2016). Given that the mutual fund industry, as a result of its steady growth and enormous size, is a very important employer, a better understanding of customer behavior and the eventual implications for female workforce participation in this industry is of great importance.

While various reasons such as hiring discrimination against women (Goldin and Rouse 2000), self-selection of women into other professions (Polachek 1981) or into less competitive environments (Niederle and Vesterlund 2007, Sutter and Gätzle-Rützler 2014), and career interruptions (Bertrand et al. 2010) can help to explain 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 at least some customers in the mutual fund industry (i.e., mutual fund 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. Using a new mixed-methods approach, this paper presents results from an empirical study, from an experimental investment task, and from an implicit association test (IAT) that collectively support the idea that a significant fraction of 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 more than one-third lower than those of male-managed funds.

There are two main reasons why investors might shy away from female fund managers: (rational) statistical discrimination (e.g., Phelps 1972) and (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 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, 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 also 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 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, by prejudice against foreign managers, 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 managed funds *would* underperform if they *would* grow larger because of diseconomies of scale and that the low inflows in 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 et al. (2011). Specifically, subjects 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 subjects can infer their gender. If subjects 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 a given index fund if the manager name provided indicates a female manager. The effect is mainly driven by male subjects, while female subjects do not seem to be biased in either direction.

Finally, to test directly whether there is a gender bias in finance, we conduct an IAT with the same subjects who participated 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" versus "Female") based on reaction times. External validations of IATs show that they are able to reliably capture prejudice and predict behavior (e.g., Greenwald et al. 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 they 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 in funds from companies that employ female fund managers (e.g., because of diversity policies). Our results show that the male-managed funds of companies that employ at least one female manager experience higher inflows; that is, there is a positive spillover effect of employing female fund managers on the other funds in the fund company.

Our paper relates to several strands of literature. First, we relate to the general literature on gender issues in finance. Several papers have pointed out the low fraction of women working in the finance industry (see, e.g., Adams and Kirchmaier 2016). However, most of the work on gender differences among managers has been conducted in corporate finance. For example, Adams and Funk (2012) examine gender differences in the boardroom and find that female directors are more benevolent and universally concerned but less power oriented than male directors. Furthermore, Adams and Ferreira (2009) show that female directors have better attendance records than male directors and are more likely to join monitoring committees. In spite of these potential benefits to the functioning of the board, shareholders seem to dislike the appointment of additional women to the board of directors (Ahern and Dittmar 2012). Evidence consistent with gender bias among investors is also presented in Bigelow et al. (2014). In an experimental study, they show that initial public offerings led by female founders were considered as less attractive investments by a group of experimental subjects. Another strand of this literature examines the impact of gender on portfolio choice, highlighting that female retail investors tend to be more risk averse and less overconfident than male investors (e.g., Barber and Odean 2001, Agnew et al. 2003). However, to the best of our knowledge, no one has studied in detail how customers perceive gender in the mutual fund industry. Given the vast amounts of money concentrated in this industry, this is surprising. According to the Investment Company Institute, of the $16 trillion invested in U.S. mutual funds in 2016, $7.13 trillion are held in retirement accounts.[3] Results from our experiment suggest that investors subject to gender bias would be willing to buy a more expensive index fund to avoid a female fund manager. Thus, any bias in this particular industry, such as a gender bias, may have severe long-term consequences for many investors.

Second, our study also 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 (Sirri and Tufano 1998, among many others). Atkinson et al. (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 fund flows.

Third, our findings are also relevant for the literature on biased behavior in finance in general and of mutual fund investors in particular. The idea that mutual fund investors are subject to behavioral biases is examined in Bailey et al. (2011). Furthermore, Kumar et al. (2015) find a negative impact of foreign-sounding names on mutual fund flows, consistent with xenophobia driving investor behavior. Our paper is, to our knowledge, the first to show that gender bias of investors can have an important impact on investment decisions, too. Thus, our paper is one of the first to highlight that not only individual behavioral biases but also social biases—such as gender bias—play an important role in explaining behavior. 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.

Finally, our paper contributes to the finance literature methodologically by presenting a mixed-methods approach. We first investigate gender bias based on field data from the U.S. mutual fund industry and document that female-managed funds generate significantly lower inflows. To isolate the proposed gender bias from any cofounding effects, we then run a lab investment experiment to augment our empirical results and cross-check whether they are replicable in an artificial environment. Specifically, we design an investment task where results, if any, must be driven by gender bias of subjects. As a third ingredient of our analysis, we introduce the IAT method to the finance literature to directly show gender bias in finance among subjects and to link it to investment behavior.[4] Results based on all methods come to the same conclusions and—from a methodological point of view—show how field and lab experiments can fruitfully complement each other to establish a new finding.

2. Data and Summary Statistics

Our primary data sources are the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund database as well as yearly releases of the Morningstar Principia database and the Morningstar Direct mutual fund database. While the first and the latter database are survivorship bias free, each release of the Principia database only provides a snapshot of the cross section of funds alive at that point in time. However, by combining yearly releases of the Principia database, we construct a longitudinal data set that is then also free of survivorship bias. We combine data from CRSP and Morningstar, as the first database contains high-quality data on fund performance while Morningstar is considered to be more precise with respect to manager identities and manager information (Massa et al. 2010). The CRSP database covers virtually all U.S. open-end mutual funds and provides information on fund returns, total net assets, investment objectives, and other fund characteristics. The Morningstar databases provide additional information on fund management structures and individual fund managers, including their age and education.

We focus on actively managed equity funds that invest more than 50% of their assets in stocks and exclude bond funds, money market funds, and index funds. This allows us to focus on a homogeneous group of funds for which we can easily compare performance. We aggregate the Strategic Insight and Lipper objective codes contained in the CRSP database to define the market segment in which a fund operates. This leaves us with 12 different equity fund segments.[5] Following Daniel et al. (1997), we aggregate all share classes of the same fund to avoid multiple counting. Our study covers the time period from January 1992—the year from which detailed fund information data are available in the CRSP mutual fund database—to December 2009.

We concentrate on single-managed funds and exclude all team-managed funds and funds for which Morningstar gives multiple manager names from our analysis. Interestingly, the fraction of female fund managers in (nonanonymous) teams is clearly larger (more than 20%) than among single-managed funds, possibly because this would be a way for fund management companies to fulfill diversity requirements without making their female managers too salient to investors (see Section 6.3). However, including teams in the analysis would be problematic for at least three reasons: First, for teams, the characteristics of each individual team member are less important for team outcomes and for how investors perceive that characteristic. Thus, including gender-diverse teams does not help to precisely identify potential gender bias. We could include all-male and all-female teams, but the fraction of the latter in particular is extremely small, at 0.7%. Second, if fund companies really "hide" women in teams, these companies are also less likely to make the identities of the members of the management team salient, for example, in their marketing material. Third, Baer et al. (2011) show that team-managed funds and single-managed funds behave very differently, and Massa et al. (2010) find that management structures can have a direct impact on flows. Thus, to obtain a clean set of comparable funds, we decided to exclude team-managed funds and focus on single-managed equity funds only.

We identify fund managers' genders based on their first names as given in the Morningstar databases. Managers' first names are matched with a list of the most popular first names by gender for the last 10 decades published by the U.S. Social Security Administration.[6] Remaining names are those we could not clearly identify as male or female (i.e., foreign names or ambiguous names). These names were manually classified by asking foreign exchange students or using internet sources such as fund prospectuses or press releases that include photographs or verbal descriptions of the managers that disclose their gender. Overall, we are able to identify the gender of 99.39% of the fund managers in our sample.

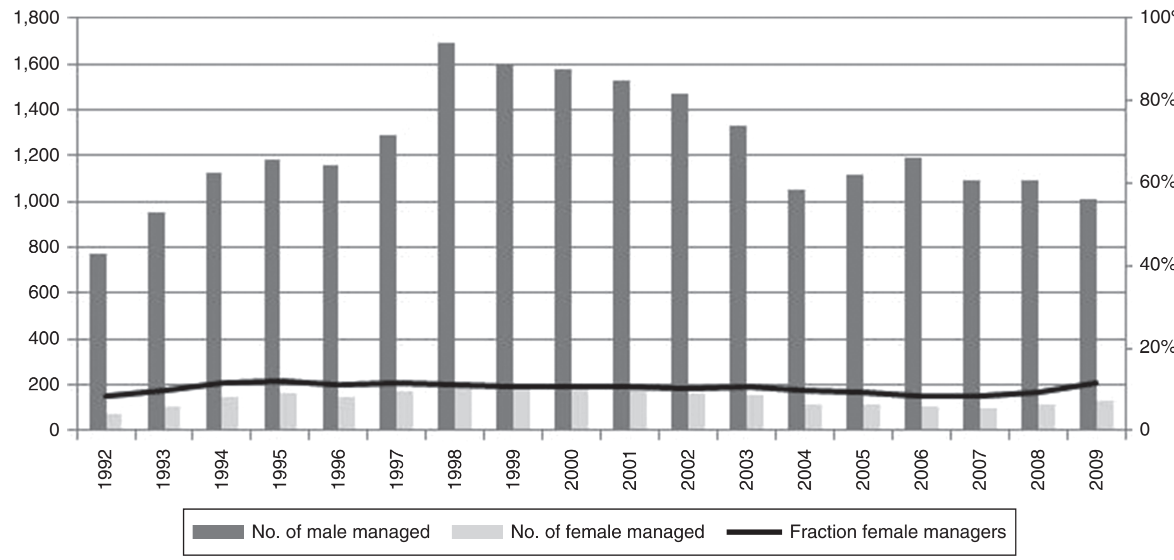
Information on the age of a fund manager; whether a fund manager holds a bachelor's, MBA, or PhD degree; and whether a fund manager obtained a professional qualification (mainly chartered financial analyst (CFA)) are collected from fund manager biographies in the Morningstar Principia and Morningstar Direct databases, from the Capital IQ database, and from internet searches. Data on the media coverage of fund managers based on the number of newspaper articles in which a manager appears in a given year are obtained from the LexisNexis database. Manager ethnicity is determined as in Kumar et al. (2015). A detailed description of all variables used in our later analysis is contained in the appendix.

Our final sample contains 16,509 fund-year observations, of which 14,804 (89.67%) have a male manager and 1,705 (10.33%) have a female manager. There are 545 (13.83%) unique female-managed funds and 3,397 (86.17%) unique male-managed funds. On the manager level, there are 3,182 different managers: 2,818 (89.06%) of them are male, and 364 (10.94%) of them are female. The average number of unique male (female) managers per year is 630 (70), and the mean (median) number of female managers per year and fund company is 4.4 (3), conditional on the fund company offering at least one single-managed fund any time during our sample period. Unconditionally, the mean (median) number of female managers per fund company and year is 2.3 (0). These numbers show that female managers are not equally distributed across fund companies. Female managers are present in 171 out of the 747 fund companies in our sample and tend to be concentrated in larger fund companies. The number of unique female managers per investment style and year ranges between 0 and 48, with a mean (median) of 13 (18).

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 shows that the fraction of female-managed funds is low and constant at about 10% over our whole sample period. At the same time, data reported by the National Center for Education Statistics show that the fraction of female graduates receiving a bachelor's (master's) degree with a major in finance was 40% (38%) during the period 1998–2009.[7] These numbers show that the fraction of women among finance degree holders that are potentially interested in a career in finance is much higher than the actual fraction of female fund managers. While our sample ends in December 2009, more recent descriptive statistics provided by Morningstar show that the fraction of female fund managers in the United States did not increase in more recent years and is still low, at about 9.4%.[8]

In Table 1, we report means and differences in fund characteristics between female- and male-managed funds in the sample used in our baseline flow regression model (column (1) in Table 2) for the most important variables.[9] The univariate comparison shows that female-managed funds get significantly lower money inflows than male-managed funds. Female managers 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. They 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, but there is no significant gender difference in average fund risk. Female fund managers have a significantly lower tenure with a particular fund and 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

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 are taken from the CRSP Survivor-Bias-Free U.S. Mutual Fund database and from Morningstar.

Table 1. Descriptive Statistics

	Sample mean (N = 12,301) (1)	Female managers (N = 1,318) (2)	Male managers (N = 10,983) (3)	Difference (female – male) (4)
Fund flows$_{i,t}$	0.289	0.187	0.301	−0.114***
Fund return$_{i,t}$	0.042	0.050	0.041	0.009
CAPM alpha$^{net}_{i,t}$ (in %)	−0.057	−0.057	−0.057	0.000
Three-factor alpha$^{net}_{i,t}$ (in %)	−0.063	−0.062	−0.063	0.001
Four-factor alpha$^{net}_{i,t}$ (in %)	−0.063	−0.063	−0.063	0.000
Sharpe ratio$_{i,t}$	0.193	0.277	0.183	0.094**
Fund size$_{i,t}$ (in millions)	969.58	779.36	992.40	−213.04**
Fund age$_{i,t}$ (in years)	12.79	13.56	12.70	0.86**
Expense ratio$_{i,t}$	0.014	0.015	0.014	0.001
12b-1 fees$_{i,t}$	0.003	0.004	0.003	0.001***
Turnover ratio$_{i,t}$	1.016	0.914	1.028	−0.049**
Fund risk$_{i,t}$	0.050	0.049	0.050	−0.001
Systematic risk$_{i,t}$	0.995	0.989	0.996	−0.006
Unsystematic risk$_{i,t}$	0.062	0.062	0.062	−0.000
Manager has bachelor's$_{i,t}$	0.998	0.996	0.999	−0.003*
Manager has MBA$_{i,t}$	0.556	0.572	0.554	0.018
Professional qualification$_{i,t}$	0.515	0.507	0.516	−0.009
Manager has PhD$_{i,t}$	0.053	0.007	0.059	−0.052***
Manager tenure$_{i,t}$ (in years)	5.836	4.926	5.945	−1.019***
Manager age$_{i,t}$ (in years)	46.83	44.49	47.11	−2.62***
Foreign manager$_{i,t}$	0.045	0.054	0.044	0.010
Manager's media coverage$_{i,t}$	2.088	0.995	2.219	−1.224***

Notes. This table shows average fund and manager characteristics for all observations entering our main flow regression (column (1) in Table 2). Descriptive statistics for all pooled observations (column (1)), for female-managed funds (column (2)), and for male-managed funds (column (3)) are presented. The difference between the average characteristics of female- and male-managed funds is reported in column (4). All variables are in decimals unless indicated otherwise. The respective number of fund-year observations is displayed in the column header. All variables are defined in detail in the appendix. Significance is calculated based on a two-sided t-test.

***1% significance; **5% significance; *10% significance.

Table 2. Manager Gender and Fund Flows

	Full sample (1)	Manager characteristics (2)	Manager changes (3)	Media coverage (4)	Advertising channel (5)	Broker channel (6)	Only retail investors (7)	Only institutional investors (8)
Female manager$_{i,t}$	−0.112	−0.118		−0.109	−0.115	−0.108	−0.164	−0.123
	(−4.00)	(−3.32)		(−3.89)	(−3.21)	(−3.68)	(−4.01)	(−1.22)
Female manager replaces male$_{i,t-1}$			−0.139					
			(−2.13)					
Fund flows$_{i,t-1}$	0.029	0.019	0.029	0.029	0.025	0.032	0.017	0.078
	(3.32)	(1.28)	(3.31)	(3.29)	(2.62)	(3.06)	(1.32)	(3.32)
*Performance quintile*1$_{i,t}$	0.193	0.069	0.188	0.199	0.507	0.038	0.199	−0.910
	(0.68)	(0.20)	(0.66)	(0.70)	(1.44)	(0.10)	(0.58)	(−1.03)
*Performance quintile*2–4$_{i,t}$	0.381	0.359	0.381	0.379	0.434	0.475	0.384	0.382
	(7.53)	(5.37)	(7.50)	(7.49)	(6.47)	(5.02)	(5.48)	(2.93)
*Performance quintile*5$_{i,t}$	2.373	2.693	2.378	2.367	2.859	2.768	2.311	0.636
	(6.65)	(5.33)	(6.65)	(6.64)	(6.21)	(4.85)	(4.54)	(0.75)
Fund size$_{i,t-1}$	−0.145	−0.145	−0.145	−0.148	−0.163	−0.211	−0.151	−0.127
	(−10.52)	(−8.11)	(−10.47)	(−10.63)	(−8.06)	(−8.41)	(−7.09)	(−3.42)
Turnover ratio$_{i,t-1}$	0.061	0.100	0.062	0.060	0.072	0.024	0.061	0.087
	(3.76)	(2.09)	(3.83)	(3.75)	(2.26)	(1.24)	(3.14)	(0.83)
Fund risk$_{i,t-1}$	0.226	1.405	0.244	0.233	0.608	1.390	0.402	−3.088
	(0.34)	(1.47)	(0.36)	(0.35)	(0.66)	(1.05)	(0.52)	(−1.08)
Expense ratio$_{i,t-1}$	3.931	−2.426	4.015	3.830	1.115	−2.901	1.780	2.018
	(1.20)	(−0.44)	(1.23)	(1.16)	(0.19)	(−0.38)	(0.31)	(1.71)
Fund age$_{i,t-1}$	−0.003	−0.028	−0.003	−0.001	0.009	0.010	−0.024	−0.122
	(−0.16)	(−1.31)	(−0.15)	(−0.04)	(0.31)	(0.27)	(−0.70)	(−1.74)
Segment flow$_{i,t}$	0.138	0.113	0.138	0.137	0.156	0.255	0.118	0.068
	(3.13)	(2.31)	(3.13)	(3.11)	(2.33)	(2.63)	(2.13)	(0.79)
Company flow$_{i,t}$	0.000	−0.002	0.000	0.000	−0.003	−0.002	−0.003	0.004
	(0.13)	(−0.90)	(0.09)	(0.07)	(−1.67)	(−0.54)	(−1.54)	(0.78)
Manager has MBA$_{i,t}$		0.020						
		(0.58)						
Professional qualification$_{i,t}$		0.054						
		(1.45)						
Manager has PhD$_{i,t}$		−0.026						
		(−0.51)						
Manager tenure$_{i,t}$		0.013						
		(3.90)						
Manager age$_{i,t}$		−0.004						
		(−1.83)						
Foreign manager$_{i,t}$		−0.188						
		(−3.58)						
Manager change$_{i,t-1}$			−0.022					
			(−0.73)					
Young manager replaces old$_{i,t-1}$			−0.055					
			(−1.51)					
Manager's media coverage$_{i,t-1}$				0.043				
				(2.80)				

mentioned less than once per year in the public press. It is important to note, however, that media coverage of fund managers is highly skewed, with a few managers receiving abnormally high media coverage, while many managers are not covered by the news media at all.

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

3.1. Manager Gender and Fund Flows

We start our empirical analysis by examining whether female-managed funds attract lower inflows than male-managed funds. We relate net inflows in a fund, *Fund flows*$_{i,t}$, to a dummy variable, *Female manager*$_{i,t}$, that equals 1 if the manager of fund i in year t is female and 0 otherwise. As control variables, we add several characteristics that have proven to influence fund flows.

Specifically, we control for fund flows in the previous year, past performance, fund size, the fund's annual turnover ratio, fund risk, the fund's expense ratio, and the fund's age.[10] We control for the nonlinear impact of past performance on fund flows documented in Sirri and Tufano (1998) by following their approach: we estimate a piecewise linear regression using

Table 2. (Continued)

	Full sample (1)	Manager characteristics (2)	Manager changes (3)	Media coverage (4)	Advertising channel (5)	Broker channel (6)	Only retail investors (7)	Only institutional investors (8)
12b-1 fees$_{i,t-1}$					−0.156 (−1.77)			
No load fund$_{i,t-1}$ × *Female manager*$_{i,t}$						0.030 (0.45)		
No load fund$_{i,t-1}$						0.063 (1.50)		
Adjusted R^2	0.178	0.157	0.177	0.179	0.227	0.135	0.173	0.441
Observations	12,301	6,769	12,300	12,301	7,503	10,672	6,973	1,484
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table shows the estimates of percentage fund flows, *Fund flows*$_{i,t}$, regressed on a female fund manager dummy, as well as fund, segment, and fund company characteristics. Fund flows are calculated by subtracting the internal growth of a fund due to returns earned on assets under management from the total growth rate of the fund's total net assets under management. *Female manager*$_{i,t}$ is a dummy variable that takes on the value 1 if a fund i is managed by a female manager in year t and 0 otherwise. All other variables are defined in the appendix. All regressions include year, segment, and fund company fixed effects. In all regressions, we control for the nonlinear impact of past performance on fund flows. We follow Sirri and Tufano (1998) and include performance quintiles based on net return ranks of all funds belonging to the same market segment in a given year. Column (1) reports results of our baseline regression specification. In column (2), we additionally include demographic characteristics of fund managers as additional control variables. In column (3), we replace our female dummy variable with a variable that is equal to 1 if a male manager at fund i is replaced by a female manager in year $t-1$ and 0 otherwise. We also control for manager changes per se and additionally include a dummy variable indicating whether a younger manager replaces a manager who is older. In column (4), we add the logarithm of a manager's media coverage as a control variable. In column (5), we add *12b-1 fees* as a control variable. Results in columns (6)–(8) are estimated on the share class level rather than the portfolio level. In column (6), we include a dummy variable indicating whether a share class charges front-end load and its interaction with the female dummy variable. In columns (7) and (8), we run our baseline regression from column (1) for share classes designated to retail or institutional investors only, respectively. The t-statistics based on robust standard errors clustered at the fund level are in parentheses. FE, fixed effects.

performance quintiles based on net return ranks of all funds belonging to the same market segment in a given year.[11] All control variables are also defined in more detail in the appendix. Sialm and Tham (2015) show that the stock market performance of mutual fund companies can impact flows of affiliated funds. To account for the impact of this effect and other characteristics of the fund company on inflows, we additionally include the value-weighted average of fund flows in the fund company in year t less the fund under consideration. Factors affecting flows of new money in the whole segment of the fund are considered by adding the percentage of flows in the respective market segment k in year t.[12]

We estimate our empirical models by applying a pooled regression approach with standard errors clustered at the fund level. All regressions include time, segment, and fund company fixed effects.[13] Including fund company and segment fixed effects also addresses the concern that female managers might self-select into particular types of segments or fund companies that for some other reason attract lower inflows. Results are presented in Table 2.

Results in column (1) show that flows in female-managed funds are significantly lower than those in male-managed funds. Despite the relatively low fraction of female-managed funds, the impact of the female manager dummy is negative and statistically significant at the 1% level. The effect is also economically meaningful: the estimate for the influence of the female manager dummy shows that, in a given year, a female-managed fund grows by about 11.2 percentage points less than a comparable fund that is managed by a male fund manager. Given that the average fund in our sample grows by about 29% per annum (see Table 1), this means that a female-managed fund grows by about 40% less (in relative terms) than a comparable fund that is managed by a male fund manager.

Our findings confirm the convex performance-flow relationship documented in, for example, Sirri and Tufano (1998). Furthermore, our results regarding the other control variables also generally confirm findings from the literature.

We also conduct an extensive battery of robustness checks, including the following modifications: (i) changing control variables, (ii) using alternative ways to measure fund flows, (iii) using subsample analysis and temporal stability, (iv) using alternative econometric specifications, and (v) using matched sample methods. Additionally, addressing concerns that results based on the relatively small fraction of female managers are not merely driven by some extreme flow observations, instead of winsorizing at the top and bottom 1%, we also winsorize this variable at the top and bottom 5%. The details of these tests and the results are described in Section IA-2.3 of the internet appendix. In all cases we find a statistically significant and economically meaningful negative impact of the female manager dummy, confirming that female-managed funds receive significantly lower inflows than male-managed funds.

3.2. Empirical Analysis of Alternative Explanations

In columns (2)–(8) of Table 2, we refine our analysis and try to empirically disentangle alternative explanations for the documented lower inflows in female-managed funds. One potential explanation for lower inflows in 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. For example, results in Table 1 show that male and female managers indeed differ, for example, with respect to their tenure at a particular fund, their age, and the probability that they hold a PhD degree. Thus, in column (2), we add further control variables that capture the impact of these differences on flows. We did not include these variables in our baseline 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 1 if the manager holds a MBA degree, a PhD, or a professional qualification (e.g., CFA), respectively, and 0 otherwise, as well as a fund manager's age and tenure at the fund currently managed.[14] To rule out that our results are driven by prejudice against fund managers with foreign names (as in Kumar et al. 2015), we also include a dummy variable indicating whether the fund manager has a foreign-sounding name.

We find that manager tenure has a positive impact on fund flows, while age and education have no notable impact and foreign managers receive significantly lower inflows. Most importantly, we still find that female managers receive on average nearly 12% lower inflows after adding these additional control variables.[15]

It is also possible that investors dislike 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 (3) we look at the impact of manager changes on fund flows. We create a dummy variable that is equal to 1 if a male fund manager is replaced by a female fund manager and 0 otherwise. There are 192 such cases. We also control for manager changes in general and for whether a senior manager is replaced by a junior manager to address concerns that differences in manager age lead to a seniority effect, which we falsely attribute to manager gender. Results show that fund flows decrease by about 14% if a male manager is replaced by a female manager, while a manager change per se has no significant impact. We also find a negative flow reaction to young managers replacing older managers, but the coefficient is not significant at conventional levels.

Kaniel et al. (2007) show that media coverage has a positive impact on fund flows. A similar effect is documented for fund advertising in Jain and Wu (2000), Cronqvist (2006), and Gallaher et al. (2015). Results 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 columns (4) and (5), we add lagged media coverage and a fund's 12b-1 fees, respectively, as additional control variables. We define media coverage as the log of 1 plus the number of articles on a given manager per year to account for the skewed nature of this variable (see Table IA-I in the internet appendix). Results show that gender differences in media coverage or advertising do not affect our main result. In line with earlier work, we also observe a significantly positive impact of media coverage on fund flows.

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. As broker-advised funds typically charge front-end loads, while no-load funds are usually directly distributed (Christoffersen et al. 2013), we use the fee structure of the fund as a proxy for the distribution channel. Most funds offer multiple share classes that differ with respect to their fee structure (and other characteristics). Thus, unlike the rest of our regressions, we conduct this analysis on the share class level rather than on the fund level. We use the same regression setup but additionally interact our female manager dummy with a dummy variable that is equal to 1 if the share class charges no front-end load and 0 otherwise.[16] This setup helps us to rule out that brokers, rather than mutual fund investors, drive our main result. Results in column (6) show no significant impact of the interaction term, suggesting that the negative impact of our female manager 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 share classes only open to retail investors or only open to institutional investors, respectively. Regressions are restricted to these share classes only. Results presented in columns (7) and (8) show that the effect of the female manager dummy is of similar economic magnitude and even slightly larger among funds focusing on retail investors exclusively. It is insignificant among institutional share classes (probably because of the small number of observations) but significant at the 1% level among retail share classes. These findings show that our main result is not due to institutional investor networks.

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 (see Section 4.1) or inferior fund performance (see Section 4.2) of female fund managers compared with male fund managers that could justify investors rationally discriminating against female 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 still relevant in professional management settings (e.g., Adams and Funk 2012, Graham et al. 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.

As dependent variables, we either use one of three risk measures for fund i in year t—total fund return risk ($Fund\ risk_{i,t}$), systematic return risk ($Systematic\ risk_{i,t}$), or unsystematic return risk ($Unsystematic\ risk_{i,t}$)—or use the fund's turnover ratio ($Turnover\ ratio_{i,t}$), all as defined in the appendix. Besides the female manager dummy, we include lagged fund size, the expense ratio, and fund age as control variables. Furthermore, we include a fund's previous year return, the fund manager's tenure, as well as time, segment, and fund company fixed effects. Standard errors are clustered at the fund level. Panel A of Table 3 summarizes our findings.

Regarding the various dimensions of risk-taking behavior, we find negative coefficients for female-managed funds, which is consistent with the widely documented fact that women tend to be more risk averse than men (e.g., Byrnes et al. 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. This result is consistent with earlier work (see, e.g., Adams and Ragunathan 2017) showing that, in contrast to population gender differences, gender differences in a professional setting might be less pronounced. Thus, female managers need not be more risk averse than their male counterparts. However, the insignificant impact of gender in this setting could also be driven by the fact that risk can only be measured with noise and the number of female-managed funds is relatively low. Thus, we also report the 95% confidence intervals for the coefficient estimate of the female manager dummy. They show that any potential gender differences are economically relatively small with a high degree of confidence.

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, SV_i (see the appendix).[17] We conduct only 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 of Table 3 show that style variability is significantly lower for female-managed funds; that is, 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 based on a fund's loadings on the size, value, and momentum factor (columns (2), (3), and (4), respectively).[18]

Overall, we only find 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.

4.2. Fund Performance and Performance Persistence

We now examine whether the behavioral differences documented in the previous section lead to differences in fund performance or performance persistence between male- and female-managed funds. As individual fund performance can only be estimated with noise, we first analyze performance differences on the

Table 3. Gender Differences in Investment Behavior

Panel A: Risk-taking and trading activity

	Fund risk$_{i,t}$ (1)	*Systematic risk*$_{i,t}$ (2)	*Unsystematic risk*$_{i,t}$ (3)	*Turnover ratio*$_{i,t}$ (4)
Female manager$_{i,t}$	−0.000	−0.004	−0.004	−0.020
	(−0.44)	(−0.31)	(−1.16)	(−0.62)
Fund size$_{i,t-1}$	0.001	0.023	−0.002	−0.078
	(5.35)	(5.30)	(−1.24)	(−6.31)
Expense ratio$_{i,t-1}$	0.072	1.163	0.970	−0.004
	(1.85)	(2.59)	(1.36)	(−0.00)
Fund age$_{i,t-1}$	−0.001	−0.015	0.001	0.030
	(−3.20)	(−1.87)	(0.23)	(1.29)
Fund return$_{i,t-1}$	0.009	0.163	0.039	0.113
	(5.65)	(6.54)	(2.58)	(1.03)
Manager tenure$_{i,t-1}$	−0.000	−0.006	0.000	−0.019
	(−4.75)	(−5.24)	(0.59)	(−4.42)
Adjusted R^2	0.609	0.334	0.319	0.490
Observations	15,153	15,122	15,122	15,048
Year FE	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes
Fund company FE	Yes	Yes	Yes	Yes
95% confidence interval for female manager$_{i,t}$	[−0.00, 0.00]	[−0.03, 0.02]	[−1.14, 0.29]	[−0.08, 0.04]

Panel B: Style variability (SV_i)

	SV_i^{Total}	SV_i^{SMB}	SV_i^{HML}	SV_i^{MOM}
Female manager	0.8748	0.8789	0.8750	0.8706
Male manager	1.0059	1.0057	1.0059	1.0061
Difference (female − male)	−0.1311***	−0.1268***	−0.1309***	−0.1355***

Notes. In panel A, the dependent variable is one of the following: fund i's total risk in year t, measured by its return time-series standard deviation (column (1)); the fund's systematic risk, defined as the factor loading on the market factor from the Jensen (1968) one-factor model (column (2)); the fund's unsystematic risk, defined as the standard deviation of the residuals from the Jensen (1968) one-factor model (column (3)); and the fund's annual turnover ratio (column (4)). *Female manager*$_{i,t}$ is a dummy variable that takes on the value 1 if fund i is managed by a female manager in year t and 0 otherwise. All other variables are defined in the appendix. All regressions include year, segment, and fund company fixed effects. The t-statistics based on robust standard errors clustered at the fund level are in parentheses. Panel B shows the average style variability of female-managed and male-managed funds for the aggregate style variability measure (column (1)), as well as for the factor individual style variability measures (columns (2)–(4)). The factor individual style variability measures are defined as the rescaled time-series standard deviations of a fund's yearly 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. FE, fixed effects.

***1% significance; **5% significance; *10% significance.

portfolio level. We evaluate the performance of a hypothetical equal-weighted difference portfolio that is long in all female-managed funds and short in all male-managed funds. Results based on net performance are presented in columns (1)–(3) of panel A in Table 4; results based on gross performance are presented in columns (4)–(6). Irrespective of whether we focus on Jensen (1968) alphas, Fama and French (1993) three-factor alphas, or Carhart (1997) four-factor alphas, the difference portfolio never delivers any statistically significant abnormal returns. In the last line of panel A, we display the 95% confidence interval for the respective alphas. They are relatively tight around zero, suggesting that significant performance differences between female and male managers are indeed unlikely. We conduct a large number of robustness tests and never find any statistically or economically significant performance difference between male- and female-managed funds (see Section IA-2.4 in the internet appendix).

These 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.

In panel B we analyze gender differences in performance persistence. Performance persistence is defined as the standard deviation of a manager's performance ranks over time.[19] We investigate performance persistence based on the six net and gross performance measures analyzed above. Results show that performance

Table 4. Performance and Performance Persistence

Panel A: Fund performance—Portfolio evidence

	Net performance			Gross performance		
	$CAPM_t^{f-m}$ (1)	$Three\text{-}factor_t^{f-m}$ (2)	$Four\text{-}factor_t^{f-m}$ (3)	$CAPM_t^{f-m}$ (4)	$Three\text{-}factor_t^{f-m}$ (5)	$Four\text{-}factor_t^{f-m}$ (6)
Performance alpha$_t$	0.0000	0.0002	0.0000	0.0002	0.0003	0.0001
	(0.05)	(0.71)	(0.08)	(0.83)	(1.11)	(0.37)
Adjusted R^2	0.047	0.165	0.225	0.030	0.190	0.134
Observations	216	216	216	216	216	216
95% confidence interval for performance alpha$_t$	[−0.0005, 0.0005]	[−0.0003, 0.0007]	[−0.0005, 0.0005]	[−0.0003, 0.0008]	[−0.0003, 0.0010]	[−0.0005, 0.0007]

Panel B: Performance persistence

	Female manager	Male manager	Difference (female – male)
CAPM alpha$_{i,t}^{net}$	0.2509	0.2663	−0.0154
Three-factor alpha$_{i,t}^{net}$	0.2486	0.2649	−0.0163*
Four-factor alpha$_{i,t}^{net}$	0.2323	0.2581	−0.0258**
CAPM alpha$_{i,t}$	0.2445	0.2591	−0.0146**
Three-factor alpha$_{i,t}^{gross}$	0.2327	0.2565	−0.0238***
Four-factor alpha$_{i,t}^{gross}$	0.2327	0.2553	−0.0226***

Notes. In panel A, we show results from a regression with the equal-weighted return of a difference portfolio that is long in all female-managed funds and short in all male-managed funds as the dependent variable. Columns (1)–(3) report net difference returns; columns (4)–(6) report gross difference returns. To obtain performance alphas, difference returns are regressed on the capital asset pricing model (CAPM) market factor in columns (1) and (4), on the three factors of Fama and French (1993) in columns (2) and (5), and on the four factors of Carhart (1997) in columns (3) and (6). Panel B contains the average time-series standard deviation of yearly performance ranks of female- and male-managed funds for various performance measures and the difference between female and male fund managers. The *t*-statistics based on robust standard errors are in parentheses.

***1% significance; **5% significance; *10% significance.

ranks of male-managed funds are more variable over time than those of female-managed funds. The effect is statistically significant for five of the six performance measures. These findings provide 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 does not support the idea of investors rationally avoiding female fund managers. Rather, it suggests that investors might 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 flows in 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 of whether investors really care about manager gender, we conduct a controlled laboratory experiment to better identify a causal impact of fund manager gender on fund flows. This procedure also has the advantage that we can examine the impact of investor characteristics on investment decisions, while the previous empirical analysis focuses 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 (see Section 5.1) and an IAT (see Section 5.2). The investment task 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 the subject level. We then link back IAT scores to investment decisions to test whether gender bias predicts investment behavior (see Section 5.3).[20]

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 tracking the same index barely differ from each other and deliver virtually identical gross performance, they offer the cleanest setting to examine the impact of specific variables on investment decisions

(Choi et al. 2011). Furthermore, as index funds are not subject to decreasing returns to scale (see Chen et al. 2004), any observed flow difference cannot be rationalized by optimal behavior in the sense of Berk and Green (2004) (see also Section 6).

In each investment round, the complete amount of 100 experimental units has to be invested in either one or both of the funds. 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 allocate their money to one or both of them. To incentivize subjects to carefully think about their investment decision, we made part of their compensation depend on the performance of the portfolio they chose based on the actual returns earned by the underlying real-world funds in the previous year (see Section IA-3.1 in the internet appendix). Specifically, subjects were told that all funds they could choose from in the experiment are real-world funds but anonymized for the purpose of the experiment. They were told that, on top of a performance-unrelated show-up fee of USD 4, their remuneration is based on the annual returns that the underlying real-world funds had experienced in the previous year. On average, subjects earned USD 24.27 in the experiment.

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. Table 5 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 managers: 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.[21] This procedure allows us to attribute any differences in investment behavior between the two groups solely to the fund manager's gender. However, Table 5 shows that the manager name provided is only one piece of information among others presented to subjects, and it is not made particularly salient. We also did not tell subjects that the experiment is about gender issues to avoid any influence on their behavior.

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, 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 Table 5). 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.

We recruited 121 students as subjects in our experiment. Because of the recruiting procedure (about 50% of the announcements were made in finance classes), most subjects (i.e., 44%) indicated "finance" as their main field of study, followed by 12% majoring in "accounting," 10% majoring in "marketing," and 9% majoring in "management information systems." A smaller fraction of subjects indicated "economics," "engineering," or other fields as their main field of study. The mean age of subjects is 21.4, and the gender distribution is roughly balanced, with 63 male and 58 female subjects. More details on subject characteristics are provided in Table IA-IV in the internet appendix. Results from the investment task are reported in Table 6.

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 presents pooled results based on all four rounds in the first row. Strictly speaking, only the first round of investment decisions can be considered to be completely independent in an experiment such as ours, where subsequent rounds involve investment choices regarding the same pair of funds. Thus, in the second row we focus on the first round of the experiment only.

In both cases, results show that subjects generally invest less in fund A compared with 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 Table 5). 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 et al. (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 units, or roughly 15%, and is significant at the 5% level if we pool observations from all rounds and cluster standard errors at the subject level. It is even larger (8.51 experimental units) and still significant at the 5% level if we only focus on the first round of investment decisions.

In the following panels, we split up observations by various subject characteristics. To prevent samples from getting too small, we focus on results based on observations from all rounds and again cluster

Table 5. Investment Task

	Panel A: Group X	
	Fund A	Fund B
Fund segment	S&P 500 index fund	S&P 500 index fund
Fund manager	Linda Williams	James Davis
About the fund		
Size	$77.49 million	$75.35 million
Inception date	10/2/1998	2/18/2005
Annual expense ratio	0.70%	0.64%
Trading activity (annual turnover ratio)	1.98%	2.03%
Fund facts	The investment seeks to replicate the total return of the S&P 500 index, before fees and expenses. The fund invests primarily in common stocks issued by companies in the S&P 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 S&P 500 Composite Stock Price index.
Top five stock holdings		
1	Exxon Mobil Corporation	Exxon Mobil Corporation
2	General Electric	General Electric
3	Microsoft Corporation	Microsoft Corporation
4	Chevron Corporation	Chevron Corporation
5	AT&T Inc.	AT&T Inc.
	Panel B: Group Y	
	Fund A	Fund B
Fund segment	S&P 500 index fund	S&P 500 index fund
Fund manager	James Williams	Linda Davis
About the fund		
Size	$77.49 million	$75.35 million
Inception date	10/2/1998	2/18/2005
Annual expense ratio	0.70%	0.64%
Trading activity (annual turnover ratio)	1.98%	2.03%
Fund facts	The investment seeks to replicate the total return of the S&P 500 index before fees and expenses. The fund invests primarily in common stocks issued by companies in the S&P 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 S&P 500 Composite Stock Price index.
Top five stock holdings		
1	Exxon Mobil Corporation	Exxon Mobil Corporation
2	General Electric	General Electric
3	Microsoft Corporation	Microsoft Corporation
4	Chevron Corporation	Chevron Corporation
5	AT&T Inc.	AT&T Inc.

Notes. This table displays the information about each fund provided to group X (panel A) and group Y (panel B). 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.

standard errors at the subject level. 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 toward male-managed funds is independent of subjects' main field of study. Panel D splits the subject pool by financial literacy. We observe significantly less money directed toward the female-managed fund in both groups, but the effect is stronger among the more financially literate. Furthermore, as one would hope, more financial literate subjects seem to be more sensitive to fund fees.

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 IAT to directly test for gender bias in the laboratory.

Table 6. Investment Decisions

	% invested in fund A if		Difference	
	Female manager (1)	Male manager (2)	(female – male) (3)	Observations (4)
	Panel A: All subjects			
All rounds	41.43	48.85	−7.42**	484
First round only	34.34	42.85	−8.51**	121
	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/economics	36.74	46.48	−9.74**	240
Marketing/management	44.36	53.98	−9.62*	84
	Panel D: Financial literacy			
Financial literacy ≥ 4	36.19	44.63	−8.43*	220
Financial literacy < 4	47.42	52.33	−4.92	116

Notes. This table shows the fraction of money invested in fund A if it is female managed (column (1)) or male managed (column (2)) 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 experimental subjects pooled over all investment rounds ("All rounds" row) and only for the first round ("First round only" row). 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. Results in panels B–D are based on all investment rounds. In all regressions where multiple rounds of choices per subject are included, standard errors are clustered at the subject level.

***1% significance; **5% significance; *10% significance.

To avoid the IAT's obvious focus on gender issues possibly biasing subjects' investment decisions, we let subjects do the IAT after the investment task.

The IAT has gained enormous popularity among social psychologists in recent years and is said to uncover prejudice based on simple associations. According to Lane et al. (2007), there are now well over 200 papers that use this method. In previous applications, the IAT is used to uncover various social biases such as 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 one 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 questions on, for example, racism or sexism, truthfully in standard surveys. 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 et al. 2002). Its reliability and validity has been confirmed by showing that IAT scores predict biased behavior in many contexts, such as voting behavior or brand choices (Cunningham et al. 2001, Greenwald et al. 2009).[24]

As IAT tests are not used in the finance literature so far, we first 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; 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 be displayed on the same side). Subjects have to rapidly sort items appearing in the middle of the screen that clearly belong to one of the four categories 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. By contrast, if there is a biased perception that, for example, 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" versus

Table 7. 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" and "Male"). Panel B contains all items used in the field categories ("Finance" and "Marketing").

"Female." The words belonging to the gender categories are taken from typical gender IATs similar to the one described above. They are all easily recognizable as belonging to the female or male category—for example, "father," "uncle," "mother," or "aunt." The full list of items is presented in panel A of Table 7. 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 7. 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- or right-hand side of the screen. An example is provided in Figure 2.

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. By contrast, panel B displays the incompatible configuration. In the first (second) case of the example shown in Figure 2, subjects had to sort the item "stocks" into the left (right) category as fast as possible. If their average 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 started measuring their reaction times.

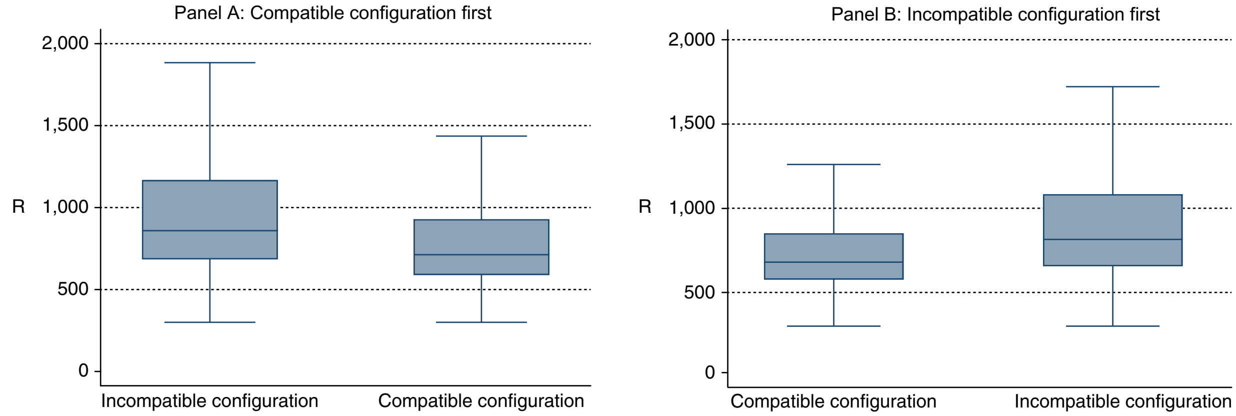
The simplest way to compute IAT scores is to just compare reaction times in milliseconds, which we denote by R. The reaction times for both groups in the compatible and the incompatible configurations are summarized in box plots presented in Figure 3.[25] Panel A (panel B) reports results for subjects 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 (panel B), the mean reaction time for the compatible configuration is 758.97 ms (832.71 ms), while it is 925.77 ms (1,002.70 ms) in the incompatible configuration. To examine reaction times more formally, we aggregate data on the subject level and calculate the average reaction time R in millseconds. We then compute the IAT score as the difference in the mean reaction time between the compatible and the incompatible configuration based on R for each subject j, which we denote by $d(R)_j$.[26] 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. 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 8. The mean of $d(R)$ across all

Figure 2. (Color online) IAT Screen

Note. This figure displays the compatible configuration of the IAT (panel A) and the incompatible configuration (panel B).

Figure 3. (Color online) Reaction Times in IAT



Notes. This figure shows box plots for the reaction times, *R*, in milliseconds for the group playing the compatible configuration first (panel A) and the group playing the incompatible configuration first (panel B). The horizontal line in the box indicates the median level, and the upper and lower hinges represent the 75th and 25th percentiles, 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).

subjects is 174.66 ms—that is, the average of the subject mean reaction times in the incompatible configuration is about 20% 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 > 11). The 95% confidence interval for $d(R)$ is shown in column (3). 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. Nearly 62% of the subjects show a significantly positive d even on an individual level. Only about 4% exhibit a significantly negative d. When we focus on subjects that played the compatible (incompatible) configuration first, results presented in row 2 (row 3) are very similar. These findings 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. Results are presented in panel A of Table 9 and show significant reaction time differences among both groups. Tajfel (1970) provides evidence for an in-group bias of individuals, and we thus except prejudice against women in finance to be less pronounced or absent among female finance students. In panel B, we find that the 31 male subjects that study finance show an average difference in reaction times of 242 ms, which is clearly larger than the typically observed effect of about 175 ms in the overall subject population. By contrast, among the 22 female subjects who study finance, the difference amounts to only 127 ms. Interestingly, this effect is still significant at the 5% level, but it 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 = 2.18).

Finally, in panel C 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 193 ms versus 159 ms in the low

Table 8. IAT Reaction Time Differences

	Mean $d(R)$ (1)	t-stat. (2)	95% CI (3)	sign. <0 (4)	<0 (5)	>0 (6)	sign. >0 (7)
All subjects	174.66	11.06	[143.40; 205.93]	5 (4.13%)	12 (9.92%)	29 (23.97%)	75 (61.98%)
Compatible configuration first	172.10	7.75	[127.69; 216.51]	5 (8.48%)	3 (5.08%)	13 (22.03%)	38 (64.41%)
Incompatible configuration first	177.10	7.82	[131.87; 222.33]	0 (0.00%)	9 (15.25%)	16 (27.12%)	37 (62.71%)

Notes. This table displays differences in reaction times from the IAT. The first row contains results for all subjects in our experiment. The second (third) row contains results for the group that played the compatible configuration (incompatible configuration) first. The implicit prejudice score is denoted by $d(R)$, which is the difference in the average reaction times R between the incompatible and the compatible configuration in milliseconds. Columns (2) and (3) present t-statistics and the 95% confidence intervals (CI) of the average d measures aggregated at the subject level. Columns (4)–(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) than in the compatible configuration on the individual subject level.

Table 9. Impact of Subject Characteristics on IAT Score

	Observations (1)	Mean $d(R)$ (2)	Standard deviation (3)	Minimum (4)	Maximum (5)	t-stat. (6)	p-value (7)
			Panel A: Gender				
Female subjects	58	172.75	193.19	−215.35	760.15	6.81	0.0000
Male subjects	63	176.42	155.15	−107.85	661.38	9.03	0.0000
			Panel B: Female and male finance students				
Female finance students	22	127.02	234.02	−215.35	760.15	2.55	0.0188
Male finance students	31	242.05	149.89	−66.80	661.38	8.99	0.0000
			Panel C: Financial literacy				
High literacy	55	193.23	194.15	−203.30	760.15	7.38	0.0000
Low literacy	66	159.20	154.42	−107.85	485.90	8.38	0.0000

Notes. This table displays differences in reaction times from the 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. Panel C contains results for subjects with high and low financial literacy. Note that $d(R)$ denotes the difference in the average reaction times R between the incompatible and the compatible configuration in milliseconds.

financial literacy group, but the difference is not statistically significant.

Results in experiments often crucially depend on the experimental procedure. Thus, we also test whether the results are stable against variations of the experimental parameters. In Table IA-VI in the internet appendix we check whether results depend on 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 et al. 1976). Our results are unaffected by differences in 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 flows in 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 to subjects with no or even a reverse gender bias according to their respective IAT scores. Results are presented in Table 10.

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 ($d(R) > 0$) invest significantly less in female-managed funds. By 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 manager and 0 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 1 if subject j has an above-median IAT score, is female, studies finance or economics, or has above-median financial literacy. Regressions are estimated with session fixed effects. Standard errors are clustered at the subject level.

Results in column (1) confirm our earlier empirical results from Table 6 and show that fund A receives 9.5 experimental units or nearly 20% less if a female manager is displayed to the subject. In column (2) we interact the female manager dummy with a dummy equal to 1 if a subject showed above-median IAT scores and 0 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 compared with the base case. The linear impact of the female manager dummy itself is now insignificant. This result confirms our 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 positive and nearly as large as the impact of the female manager dummy itself. This confirms our earlier findings from panel B in Table 6 and shows that the negative impact of a female manager is neutralized if the subject making the investment decision is female. In columns (4) and (5) we interact the female manager dummy with a dummy for finance/economics students and with a dummy for high financial literacy, respectively. None of these interaction terms is significant.

Overall, the results from the experiment suggest that many individuals are subject to gender bias against women in finance based on their IAT scores and

Table 10. Investment Decision Depending on IAT Score

Panel A: % invested in fund A—Univariate evidence					
	Female manager (1)	Male manager (2)	Difference (female – male) (3)	t-stat. (4)	Observations (5)
$d(R) > 0$	41.51	49.58	−8.06	−2.23	428
$d(R) < 0$	49.04	43.90	5.13	0.08	56

Panel B: % invested in fund A—Multivariate evidence					
	(1)	(2)	(3)	(4)	(5)
Female manager$_{\text{fund A}}$	−9.464	4.370	−15.894	−8.743	−7.454
	(−2.24)	(0.47)	(−2.21)	(−1.81)	(−1.46)
Female manager$_{\text{fund A}}$ × *Subject IAT score*$_j$		−17.283			
		(−1.94)			
Female manager$_{\text{fund A}}$ × *Female subject*$_j$			13.376		
			(1.82)		
Female manager$_{\text{fund A}}$ × *FinEcon*$_j$				−1.862	
				(−0.24)	
Female manager$_{\text{fund A}}$ × *High literacy*$_j$					−4.492
					(−0.52)
Control variables	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.018	0.019	0.019	0.018	0.018
Observations	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 the IAT. If $d(R) > 0$, 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 is the dependent variable. *Female manager*$_{\text{fund A}}$ is a dummy variable that takes on the value 1 if fund A is managed by a female fund manager and 0 otherwise. All other control variables are described in the appendix. The t-statistics are in parentheses. Standard errors are clustered at the subject level. FE, fixed effects.

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 (see 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 of why we see any women in the mutual fund industry at all, given that they attract significantly lower inflows (see 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 funds 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 50 largest fund companies in our sample. Of these funds, 98% report the fund manager's name online on their web page as well as in the official prospectus.[27] Furthermore, besides prospectuses and fund company websites, many investors rely on financial websites such as, for example, Yahoo Finance to gather fund information. Information on the gender of the fund manager is salient to investors on these pages, as it can typically be easily inferred from the first name of the fund manager, which is usually prominently presented on the first page that appears.[28]

Additional evidence that investors are often directly exposed to manager names comes from product descriptions in personal finance magazines. For example, *Kiplinger*—one of the leading personal finance magazines in the United States—featured a top 25 list of funds, the KIP 25, on its web page. 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). Of those 11 articles, 8 mentioned the name of the fund manager in the very first sentence.

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 et al. (2010) show that funds have greater inflows if the name of the fund manager is declared compared with funds where the manager name is kept anonymous. They also show that departures of named managers reduce inflows. Furthermore, Kumar et al. (2015) show that fund investors shy away from funds with managers with foreign-sounding names. 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 2015). 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 et al. (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).[29]

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.

Results from the experimental investment task show that there is indeed 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.[30] Furthermore, many institutional investors require their business partners to report explicitly on their diversity policy. In a similar vein, the Dodd–Frank Wall Street Reform and Consumer Protection Act requires federal agencies to do business only with firms that "ensure . . . the fair inclusion of women" and that give "consideration to the diversity of the applicant" (Dodd–Frank Financial Regulation Bill Section 342(c)(2)). 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 directly 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 in their own funds, but their presence in the company would lead to positive spillover effects for the other funds of the company.

To test this idea, we adapt the flow regression from column (1) in Table 2 to capture such potential spillover effects and run the regression for male-managed funds only. Results are presented in Table 11. In column (1),

Table 11. Spillover Effects of Female Managers

	Any female (1)	Number of females (2)	Both variables (3)
Any female manager in company$_{i,t}$	0.079 (3.34)		0.068 (2.59)
Number of female managers in company$_{i,t}$		0.006 (2.48)	0.002 (0.79)
Control variables	Yes	Yes	Yes
Adjusted R^2	0.098	0.097	0.098
Observations	11,002	11,002	11,002

Notes. In this table, we use the same baseline specification as in column (1) of Table 2. In column (1), we replace our female dummy, *Female manager$_{i,t}$*, with a variable that is equal to 1 if there is any female fund manager working in the fund company of fund i in year t and 0 otherwise. In column (2), we replace our female dummy, *Female manager$_{i,t}$*, with a variable that is equal to the number of female fund managers in the fund company of fund i in year t. In column (3), we include both variables 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.

we replace the female manager dummy by a dummy variable taking on the value 1 if there is any female-managed fund among the single-managed funds of the same fund company and 0 otherwise.[31] In column (2), instead of the dummy variable, we use the number of female-managed funds in the same company as the independent variable.[32] In both cases, we find a highly significant positive impact of the spillover variable. For example, the coefficient in column (1) indicates that male-managed funds grow by nearly eight percentage points per annum more if the fund company also employs at least one female manager. This seems like a large impact and gives rise to the question of 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 spillover 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; that is, 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 11 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 from 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 spillover effects on flows in other funds offered by the fund company.

7. Conclusion

This paper uses a novel mixed-methods approach to examine 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 in 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 in female-managed funds. Furthermore, we find that female fund managers follow more reliable investment styles, and we document that average 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 in female-managed funds might be due to rational statistical discrimination of investors. Rather, our results from an implicit association test suggest 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 suggest customer-based discrimination as a possible new explanation for the low fraction of female managers in the mutual fund industry.

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Appendix. Brief Definitions and Data Sources of Main Variables

Variable name	Description	Source
	Panel A: Fund characteristics	
Fund flows$_{i,t}$	Computed as $(TNA_{i,t} - TNA_{i,t-1} \cdot (1 + \text{Fund return}_{i,t}))/TNA_{i,t-1}$, where $TNA_{i,t}$ denotes fund i's total net assets in year t and *Fund return*$_{i,t}$ denotes fund i's return in year t. Flows are winsorized at the top 99% and bottom 1%.	CRSP, EST
Female manager$_{i,t}$	Dummy variable equal to 1 if fund i is managed by a woman in year t and 0 otherwise.	MSD
Fund return$_{i,t}$	A fund's annual raw net return.	CRSP
CAPM alpha$^{\text{net}}_{i,t}$	Jensen (1968) one-factor alpha. We use three years of monthly returns after fees 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
Three-factor alpha$^{\text{net}}_{i,t}$	Fama and French (1993) three-factor alpha. We use three years of monthly returns after fees 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
Four-factor alpha$^{\text{net}}_{i,t}$	Carhart (1997) four-factor alpha. We use three years of monthly returns after fees 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
CAPM alpha$^{\text{gross}}_{i,t}$	Jensen (1968) one-factor alpha. We use three years of monthly returns before fees 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
Three-factor alpha$^{\text{gross}}_{i,t}$	Fama and French (1993) three-factor alpha. We use three years of monthly returns before fees 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
Four-factor alpha$^{\text{gross}}_{i,t}$	Carhart (1997) four-factor alpha. We use three years of monthly returns before fees 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
Sharpe ratio$_{i,t}$	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
Performance rank$_{i,t}$	Performance rank of a fund based on its annual return relative to the other funds in its market segment in a given year. This variable is normalized to be between 0 and 1. The best fund is assigned a rank of 1.	CRSP, EST
Performance quintile1$_{i,t}$	Piecewise linear regression (PLR) variable, computed as min(*Performance rank*$_{i,t}$; 0.2).	CRSP, EST
Performance quintile2–4$_{i,t}$	PLR variable, computed as min(*Performance rank*$_{i,t}$ – *Performance quintile1*$_{i,t}$; 0.8).	CRSP, EST
Performance quintile5$_{i,t}$	PLR variable, computed as min(*Performance rank*$_{i,t}$ – (*Performance quintile1*$_{i,t}$ + *Performance quintile2–4*$_{i,t}$)).	CRSP, EST
Fund size$_{i,t}$	Logarithm of a fund's total net assets (plus 1), ln($TNA_{i,t}$+1).	CRSP, EST
Fund age$_{i,t}$	Logarithm of fund i's age in years (plus 1) computed based on the date a fund was first offered (CRSP variable *first_offer_dt*).	CRSP, EST
Expense ratio$_{i,t}$	Fund i's annual expense ratio.	CRSP
12b-1 fees$_{i,t}$	Fund i's actual 12b-1 fees.	CRSP
Turnover ratio$_{i,t}$	Fund i's annual turnover ratio.	CRSP
Fund risk$_{i,t}$	Fund i's monthly return standard deviation in year t.	CRSP, EST
Systematic risk$_{i,t}$	Fund i's factor loading on the market factor from a one-factor model in year t.	CRSP, EST
Unsystematic risk$_{i,t}$	Standard deviation of fund i's residual return from a one-factor model in year t.	CRSP, EST
$SV^{f}_{i,m}$	Style variability of fund i with respect to a specific factor f while manager m is managing this fund. It is calculated as the standard deviation of a fund's yearly factor loadings on factor f over time. The Carhart (1997) SMB, HML, and MOM factors are considered. 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 three years of consecutive data are required.	CRSP, EST
$SV^{\text{Total}}_{i,m}$	Average style variability of fund i calculated as the average of the factor individual style variability measures, $SVM^{f}_{i,m}$.	CRSP, EST

Appendix. (Continued)

Variable name	Description	Source
	Panel A: Fund characteristics (continued)	
Segment flow$_{i,t}$	Average of *Fund flows*$_{i,t}$ over all funds i belonging to the same segment as fund i in year t, net of flows in fund i.	CRSP, EST
Company flow$_{i,t}$	Value weighted average of *Fund flows*$_{i,t}$ over all funds i belonging to the same fund company as fund i in year t, net of flows in fund i.	CRSP, EST
Manager change$_{i,t}$	Dummy variable equal to 1 if there is a manager change at fund i in year t and 0 otherwise.	EST
Female manager replaces male$_{i,t}$	Dummy variable equal to 1 if a male manager at fund i is replaced by a female manager in year t and 0 otherwise.	MSD
Young manager replaces old$_{i,t}$	Dummy variable equal to 1 if a manager at fund i is replaced by a younger manager in year t and 0 otherwise.	EST
No-load fund$_{i,t}$	Dummy variable equal to 1 if a fund's share class does not charge a front-end load in year t and 0 otherwise.	CRSP, EST
Any female manager in company$_{i,t}$	Dummy variable equal to 1 if the fund company fund i belongs to employs at least one female fund manager in year t and 0 otherwise.	MSD, CRSP
Number of female managers in company$_{i,t}$	Number of female fund managers that the fund company fund i belongs to employs in year t.	MSD, CRSP
	Panel B: Manager characteristics	
Manager tenure$_{i,t}$	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.	MSP, EST
Manager age$_{i,t}$	Logarithm of a fund manager's age in years (plus 1). Data are manually collected from manager biographies.	MSP, MSD, CIQ
Manager has bachelor's$_{i,t}$	Dummy variable equal to 1 if a fund manager has obtained a bachelor's degree and 0 otherwise. Data are manually collected from manager biographies.	MSP, MSD, CIQ
Manager has MBA$_{i,t}$	Dummy variable equal to 1 if a fund manager has obtained a Master of Business Administration (MBA) degree and 0 otherwise. Data are manually collected from manager biographies.	MSP, MSD, CIQ
Manager has PhD$_{i,t}$	Dummy variable equal to 1 if a fund manager has obtained a PhD degree and 0 otherwise. Data are manually collected from manager biographies.	MSP, MSD, CIQ
Professional qualification$_{i,t}$	Dummy variable equal to 1if a fund manager has obtained a professional qualification (mainly CFA, but also others such as certified financial planner or certified public accountant) and 0 otherwise. Data are manually collected from manager biographies.	MSP, MSD, CIQ
Foreign manager$_{i,t}$	Dummy variable equal to 1 if at least 75% of respondents on Amazon Mechanical Turk indicated that the fund manager's name sounds foreign and 0 otherwise. Data are obtained from Kumar et al. (2015).	MSD, AMT
Manager's media coverage$_{i,t}$	Logarithm of the number of articles on fund i's manager in year t. Details on the media data collection process are described in Section IA-2.2 in the internet appendix.	LN
	Panel C: Experimental variables	
$d(R)$	Difference in mean reaction times in milliseconds between the incompatible and the compatible configurations in the IAT.	EXP, EST
Female manager$_{\text{fund }A}$	Dummy variable equal to 1 if fund A is managed by a female manager and 0 otherwise.	EXP, EST
Subject IAT score$_j$	Dummy variable equal to 1 if the IAT score of subject j is above the median and 0 otherwise.	EXP
Female subject$_j$	Dummy variable equal to 1 if subject j is female and 0 otherwise.	EXP
FinEcon$_j$	Dummy variable equal to 1 if subject j studies finance or economics and 0 otherwise.	EXP, EST
High literacy$_j$	Dummy variable equal to 1 if subject j answered at least four of six financial literacy questions correctly and 0 otherwise.	EXP

Notes. This table briefly defines the main variables used in the empirical analysis. The data sources are (i) CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP), (ii) Capital IQ (CIQ), (iii) estimated or computed by the authors (EST), (iv) experimental data (EXP), (v) Kenneth French's data library (KF; http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, accessed September 27, 2010), (vi) LexisNexis (LN), (vii) Morningstar Direct (MSD), (viii) Morningstar Principia (MSP), and (ix) Amazon Mechanical Turk (AMT).

Endnotes

[1] Anecdotal evidence from interviews with fund managers suggests that this is indeed the case: when asked why female-managed funds might 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" (quoted in National Council for Research on Women 2009, p. 10, ellipses in original).

[2] A short introductory note on the IAT is Carney et al. (2007).

[3] See https://www.ici.org/pdf/2017_factbook.pdf (accessed April 11, 2018).

[4] There are only two papers we are aware of that use IATs in the economics literature: Bertrand et al. (2005) use an IAT to examine hiring discrimination against African Americans, and Beaman et al. (2009) apply an IAT to measure attitudes toward female leaders.

[5] Specifically, we use the following 12 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).

[6] For further information, see https://www.ssa.gov/oact/babynames/decades/index.html (accessed April 11, 2018).

[7] Data can be obtained from https://nces.ed.gov/datatools/.

[8] As of March 31, 2015; see Lutton and Davis (2015).

[9] More detailed summary statistics are provided in Table IA-I in the internet appendix.

[10] Fund flows are winsorized at the top and bottom 1%. Winsorizing them at the top and bottom 5% does not change the results (see panel A, column (7) of Table IA-II in the internet appendix).

[11] As in Sirri and Tufano (1998), we pool together the three middle performance quintiles—that is, slope coefficients are estimated separately for the lowest, the three middle, and the top quintiles of past performance. We use performance ranks because Patel et al. (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.

[12] Company flows and segment flows are computed net of the flows in the fund under consideration.

[13] In an alternative specification, we include combined fund company-year fixed effects to control for the possibly time-varying nature of these fund company-level characteristics. Results (reported in panel C, column (2) in Table IA-II in the internet appendix) remain largely unaffected.

[14] We do not include a separate dummy for bachelor's degrees, as virtually all managers hold at least a bachelor's degree. Some fund managers hold master's degrees other than MBAs. Including controls for non-MBA master's does not change our findings.

[15] 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 manager 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.

[16] We drop all observations for share classes where information on the load fee is missing from our data.

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

[18] 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.

[19] Analyzing a variance-based measure of performance persistence delivers very similar results.

[20] More details on the experimental procedure are provided in Section IA-3.1 of the internet appendix.

[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).

[23] Note that we only compare investments in fund A between subjects conditional on the fund manager's gender. Thus, the amounts shown in columns (1) and (2) in Table 6 do not add up to 100. By definition, our conclusions would remain unchanged if we compared investments in fund B instead.

[24] More recently, there has been some controversy in the psychological literature about the power of the IAT. Specifically, the IAT has been criticized for producing noisy prejudice scores that might not perform better than explicit measures of prejudice (for a meta-analysis of IAT studies, see Oswald et al. 2013).

[25] To prevent outliers from driving the results, we follow Greenwald et al. (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.

[26] Alternatively, we use two other ways to compute IAT scores that are also suggested in the literature (see Section IA-3.3 in the internet appendix). Our results are virtually identical.

[27] The only two companies that did not report the manager's name on their web page are Dimensional Fund Advisors and Capital Growth Management. However, even these companies reported the manager's name in the prospectus. For 74% of the funds, the manager's 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).

[28] To illustrate this point, in Figure IA-I in the internet appendix we present screenshots of the information investors would get if they search for a specific fund in four of the major online financial information sources.

[29] Of course, field data on index fund investment behavior would also be a clean test setting in our context. Unfortunately, given the relatively small number of index funds and the resulting tiny number of female index fund managers, such a test would lack statistical power.

[30] Consistent with this argument, there are indeed some niche funds such as the Pax Ellevate Global Women's Index Fund that specifically cater to female investors.

[31] Alternatively, we define this dummy as being 1 if there is any other female manager in the same fund company in a single- or team-managed fund. Hiding female managers in teams to avoid the negative direct flow consequences while still fulfilling diversity goals could be in the interest of fund companies. Results using this alternative definition are very similar.

[32] As these variables 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 the control variable. This variable captures the impact of the size of the fund company (and of all other fund company characteristics) on individual-level flows.

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