Gender Disparities in Mutual Fund Industry: Investor Flows, Selection Bias, and Managerial Skill

Li-Ting Chiu[*] **Hsuan Fu**[†]

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[*]Bentley University, E-mail: lchiu@bentley.edu (L. Chiu).
[†]Université Laval, E-mail: hsuan.fu@fsa.ulaval.ca (H. Fu).
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Abstract

This paper examines the structural barriers that contribute to the underrepresentation of women in the US equity mutual fund industry. Using data from 1992 to 2022, we identify two primary frictions: a supply-side selection bias, where female managers are disproportionately assigned to funds with poor historical performance, and a demand-side investor bias characterized by asymmetric flow-to-performance sensitivity. Despite these disadvantageous conditions and subsequent capital flight, female managers demonstrate post-appointment performance comparable to their male peers. These findings suggest that observed performance gaps are artifacts of endogenous assignment and investor behavior rather than differences in managerial skill.

Keywords: Women in Finance; Fund Managers; Investor Behaviors; Mutual Fund Industry
JEL Classification: G23, J71, M51

1 Introduction

Despite a decade of increased attention to diversity and inclusion within the financial sector (Edmans, 2023; Sherman and Tookes, 2022), the mutual fund industry remains characterized by persistent gender disparities. Female representation among US equity active mutual fund managers has stagnated, hovering between 8% and 10% for three decades (see Figure 1;2). While the absolute number of newly appointed female managers has seen marginal growth, women seem to remain underrepresented in capital allocation roles, a disparity that unconditional empirical models might seemingly justify based on lower raw average performance[1]. In this paper, we demonstrate that career outcomes for these managers are heavily influenced by a selection bias at the point of assignment, compounded by detrimental systemic investor reactions. We investigate the dual structural barriers female managers face: the "Glass Cliff" imposed by fund families (supply-side) and asymmetric capital flight driven by investors (demand-side).

The persistence of this disparity is particularly puzzling because the mutual fund industry should, in principle, be where gender gaps are hardest to sustain. Unlike most professional settings, fund management produces a homogeneous output (a managed portfolio) evaluated by a standardized, objective metric (risk-adjusted alpha), which ought to let talent surface regardless of gender. Yet the gap not only persists but appears robust to formal interventions[2]. The puzzle deepens once one looks at human capital: female managers in our sample are at least as well credentialed as their male peers on every dimension we observe, yet their tenure in fund management is markedly shorter. Equal or stronger human capital inputs, paired with truncated career trajectories, suggest that the unconditional performance gap reflects something other than skill. The remainder of this paper explores what.

This paper investigates three structural mechanisms that may jointly explain the puzzle. First, on the *supply side*, what types of funds do fund families assign to female managers, and is this assignment driven by performance, risk profile, or gendered preferences? Second, on the *demand side*, how do investors respond to fund performance and to managerial transitions when the manager is female, and are capital flows gender-dependent? Third, once these structural frictions are properly accounted for, does any measurable gender gap in managerial skill remain? A central methodological challenge we explicitly address is that female assignment is not random (it is endogenous to

[1] See Patel and Sarkissian (2017), Csiky and Pichler (2025) and our Appendix Figure A.1, that all document lower average performance for female managers in unconditional models.

[2] The stagnation persists despite federal affirmative action policies in place since 1970 and more recent state-level mandates such as California's 2019 board-diversity requirement.

past performance), rendering unconditional performance comparisons invalid as a measure of skill.

Our analysis yields four interrelated findings. *First*, on the supply side, we document a "Glass Cliff" phenomenon introduced by Ryan and Haslam (2005, 2007): fund families systematically assign female managers to funds with deteriorating historical performance and low within-style rankings. *Second*, on the demand side, we uncover a "convexity gap" in capital flows. Consistent with Niessen-Ruenzi and Ruenzi (2019), funds with female representation experience outflows. We extend that finding by showing that female managers face a significantly flatter flow-to-performance curve, attracting smaller inflows even when achieving high performance rankings. *Third*, we identify a mechanism linking the demand- and supply-side biases. The "Glass Cliff" appears almost entirely in families with high flow volatility and is statistically insignificant in low-volatility families. This pattern is consistent with fund families internalizing investor bias as a form of flow risk and using assignment decisions as a defensive risk-management tool. *Fourth*, after accounting for endogenous assignment using a difference-in-differences design, we find that post-appointment managerial skill is statistically indistinguishable across genders, yet the demand-side penalty persists.

By exposing these structural frictions, this research builds upon a growing literature exploring the intersection of gender, corporate governance, institutional structure, and financial markets. While recent studies emphasize the importance of robust managerial structures (Patel and Sarkissian, 2017, 2021) and advocate for policy solutions to enhance diversity (Edmans, 2023), these efforts are frequently undermined by entrenched structural inequities (Sherman and Tookes, 2022). Evidence of these inequities extends across the broader financial ecosystem, with the nascent and emerging literature documenting precarious leadership appointments for women in adjacent sectors, ranging from the selection of government Finance Ministers during fiscal crises (Armstrong et al., 2024) to promotions among mortgage lenders (Huang et al., 2024). Narrowing the focus to the asset management industry, the mutual fund literature establishes that gender significantly influences career outcomes and tenure (Barber et al., 2018) and that female managers face systemic constraints on capital allocation by investors (Niessen-Ruenzi and Ruenzi, 2019). This demand-side friction reflects a broader, cross-market pattern of bias; for instance, in venture capital and entrepreneurship, female founders similarly raise substantially less equity financing than their male peers (Guzman and Kacperczyk, 2019; Hebert, 2025; Hebert et al., 2026). We extend these theoretical frameworks by modeling both the supply-side assignment mechanisms and demand-side investor behaviors to explain the persistent performance gaps observed in unconditional settings. The mutual fund industry provides an ideal laboratory for this analysis because the underlying products (funds) are highly homogeneous and the primary performance metric (alpha) is standardized, allowing for precise, objective comparisons.

To unpack these dynamics, we first present summary statistics for our sample at both the manager and fund levels (Table 1 and 2). Notably, female managers possess highly competitive credentials, often holding slightly higher rates of advanced degrees and Ivy League education than their male counterparts. Despite these qualifications, their career trajectories within fund families are markedly different from the outset, such as shorter tenure in the funds they managed and in the whole industry. We then uncover strong evidence of the Glass Cliff phenomenon in the assignment of mutual fund managers. In Tables 3 and 4, we analyze the selection mechanism and find that funds experiencing deteriorating historical performance, up to one year prior to a managerial transition, are significantly more likely to appoint a female manager. This finding holds robustly when adjusting for investment style and when utilizing Morningstar's 1-to-5 star rating metrics, which rank performance within style categories. This pattern persists in within-investment-objective comparisons that rule out gendered style preferences (as shown in Appendix Table A.1). Furthermore, we rule out the alternative explanation that women are simply matched with different risk profile portfolios due to gendered risk-aversion stereotypes (Croson and Gneezy, 2009). As shown in Table 5, a fund's past risk loading does not influence the probability of a female manager's assignment. The primary predictor of female appointment is poor past performance, not risk profile.

Once appointed to these challenging roles, female managers encounter our hypothesized demand-side barrier: systemic investor bias. In Figure 3 and Table 6, we document distinct asymmetries in flow-to-performance sensitivity between male and female managers. While male managers enjoy a highly convex flow-performance relationship—reaping outsized capital inflows for top performance—female managers face a significantly flatter curve. They attract lower inflows when highly ranked by alpha and face greater outflows when poorly ranked; yet their outflows are less sensitive to low performance. We hypothesize that the fund families' non-random assignment is due to the investors' flow bias.

We hypothesize that supply- and demand-side frictions are closely linked: the systemic inability to attract proportional capital inflows (i.e., a flatter flow–performance relationship) serves as a key mechanism reinforcing the Glass Cliff. If female managers cannot efficiently attract capital despite strong performance, fund families have weaker incentives to assign them to high-performing flagship funds. To test this mechanism, we partition the sample by fund-family flow volatility in Table 7. The result shows that the Glass Cliff effect appears only in high–flow-volatility families and is insignificant in low-volatility families, supporting the idea that families internalize investor bias under flow risk.

The structural frictions documented above may account for the raw performance deficit associated with female managers (Table 8 and Appendix Figure A.1), rather than differences in skill. Building on the longstanding debate on gender and mutual fund performance initiated by (Bliss and Potter, 2002), we disentangle selection from ability by conducting a difference-in-differences analysis that compares post-appointment performance and flows between female- and male-appointed managers, as reported in Tables 9 and 10.

Given that female managers are systematically assigned to worse-performing funds (*supply-side bias*) and face more severe and prolonged capital outflows (*demand-side bias*), one would expect their subsequent performance to deteriorate significantly. However, the result in Table 9 shows that although these portfolios were already underperforming prior to the female manager's arrival, post-appointment alphas are statistically indistinguishable from those of male peers in the difference-in-difference framework. This resilience suggests that female managers may enhance governance and stability, consistent with (Li and Zeng, 2019), who find that female executives reduce stock price crash risk. Moreover, such stabilization may be supported by stronger liquidity management among female managers (Sehrish et al., 2024), which helps mitigate the payoff complementarities and financial fragility underlying run-like outflows (Chen et al., 2010).

Despite comparable performance, Table 10 shows that investors continue to penalize female managers by withdrawing capital. Among funds that underperformed prior to the transition, post-appointment outflows are larger and more persistent following female appointments than male appointments. This residual outflow, unexplained by skill differences, is consistent with taste-based discrimination in the sense of Gary Becker (1957).

A natural alternative, that male managers benefit from stronger informal networks ("the old boys' club"), is unlikely to be the primary driver of our findings. Although educational and social networks have been shown to generate higher returns on connected holdings in mutual funds (Cohen et al., 2008; Pool et al., 2015), our difference-in-differences estimates show that post-appointment alpha is statistically indistinguishable across genders. Whatever role networks play in shaping connected-stock returns, they do not appear to translate into a gender gap in fund-level managerial skill once endogenous assignment is accounted for.

These findings make three contributions to the literature. First, we contribute to the literature on managerial characteristics and asset management performance (Patel and Sarkissian, 2017; Csiky and Pichler, 2025) by proving that the unconditional gender performance gap is an artifact of endogenous assignment rather than evidence of a skill deficit. Our use of an expanded sample that accounts for varied team compositions — female-only, mixed-gender, and male-only — also allows for cleaner identification than designs restricted to single managers. Second, we contribute to the literature on mutual fund flows and financial fragility (Chen et al., 2010; Niessen-Ruenzi and Ruenzi, 2019) by documenting structural gender asymmetries in flow-performance sensitivity and by showing that post-transition capital flight is not symmetric across gender. Third, we contribute to the broader literature on the "Glass Cliff" and on women's leadership in finance and adjacent settings (Ryan and Haslam, 2005; Cook and Glass, 2014) by, to our knowledge, being the first to document the Glass Cliff within the mutual fund industry. By linking supply-side assignment mechanisms to demand-side investor penalties, we map broader leadership inequities (Armstrong et al., 2024; Huang et al., 2024) directly to capital allocation, highlighting the profound systemic barriers that continue to distort meritocracy in institutional finance.

The remainder of the paper is organized as follows. Section 2 describes the data and provides summary statistics. Section 3 explores the supply-side selection bias by establishing the Glass Cliff effect, and ruling out risk-loading channels. Section 5 presents the evaluation of post-appointment managerial skill. Section 4 examines demand-side investor behavior, detailing flow sensitivity and post-appointment capital flight. Section 6 concludes.

2 Data and preliminary findings

2.1 Sources and variable definition

Our data comes from several sources. First, the manager's characteristics are sourced from Morningstar Direct, including their names, gender, tenures, among others. Although gender is a variable provided by the database, there are many missing values in this variable. In this case, we use given names (first and middle) to *manually* identify the genders. If a name is identified by other managers as female, we treat the whole group of managers who share this name as female, regardless of their surname. In some cases, the manager's gender is not immediately obvious from their given names; we also verify their gender using LinkedIn and/or their fund family website.

We also scrape the short biography of each fund manager from the Morningstar's website, which contains educational and professional background. From the educational background, we can quantify different levels of education based on the type of degrees, including BA, MBA, PhD, etc. The professional background includes the certificates such as CFA, CPA, among others. Since Morningstar removes webpages for inactive funds, we cannot directly scrape data for those funds. We instead assign manager biographical information from active funds managed by the same managers to their inactive funds, allowing the sample to include both active and inactive funds and thereby mitigating survivorship bias.

Throughout our analysis, we measure female representation using $Female_{i,t}$, defined as the percentage of female managers in fund i at month t, rather than a binary indicator for whether a fund has any female manager. This continuous measure is motivated by the prevalence of team management in our sample.[3] A binary *Has Female* dummy would obscure meaningful variation in team composition, treating a fund with one female manager out of five identically to one with four female managers out of five. The percentage measure preserves this variation and allows us to estimate how appointment patterns and investor flows respond to changes in the *degree* of female representation, which is the economically relevant object given heterogeneous team structures.

To map the manager's characteristics with the fund's data, we rely on the International Securities Identification Number (ISIN) from Morningstar and extract the CUSIP by removing the first two-letter country code and the last digit of verification code. Then, we use the link table by CRSP Mutual Fund dataset to link fund CUSIP to Wharton Financial Institution Center Number (WFICN). The fund return, total net asset, investment objective category, expense ratio, age, family size, and other fund- and fund family- characteristics are sourced from the CRSP Mutual Fund dataset.

Flow is calculated by the total asset under management (TNA) and the fund's return (ret) in the following equation

$$Flow_t = \frac{TNA_t - TNA_{t-1}(1 + ret_t)}{TNA_{t-1}}. \tag{1}$$

Flow sensitivity is the beta constructed by regressing flow on the past returns after fees for the past 36 months. The risk adjusted returns (Alphas) are estimated based on the four-factor model in Carhart (1997) or the three-factor model in Fama and French (1993). We source the time series of four factors: Market (MKT), Size (SMB), Value (HML), and Momentum (UMD) from Kenneth R. French's Data Library. The factor loading, reported as betas, of all four factors are estimated based on the same model. Our sample spans January 1992 to December 2022.

[3]approximately 65% of funds are managed by a team rather than a single individual

2.2 Summary statistics

Table 1 reports summary statistics at the fund-manager level. The sample comprises 325,370 female and 2,733,275 male manager-month observations over the period 1992–2022.

Table 1 about here

Panel A shows that educational attainment is broadly comparable across gender. Approximately 4–5% of managers hold a PhD, while female managers are slightly less likely to hold an MBA (42% versus 48%). Professional certifications (e.g., CFA, CPA) are similarly distributed across genders, indicating comparable formal qualifications. Notably, female managers are more likely to have attended Ivy League institutions (26% versus 22%), suggesting comparable, if not higher, educational quality.

In contrast, female managers exhibit shorter tenure than their male peers, both at the current fund (4.51 versus 5.28 years, a 0.77-year gap) and across the industry as a whole (7.48 versus 8.94 years, a 1.46-year gap), a pattern consistent with Barber et al. (2018). The fraction of managers with experience at funds that became inactive during the sample is similar across gender (42% versus 41%). Overall, the evidence suggests that observable qualifications are broadly comparable across gender, while tenure differences likely reflect disparities in career progression rather than managerial ability.

A further feature of the industry that bears on managerial structure is the prevalence of multi-fund assignments. Managers in our sample run an average of 5 funds simultaneously, with no significant gender difference (mean of 5.15 for females and 5.06 for males; median of 3 funds in both groups). The most prolific male and female managers oversee 63 and 45 funds, respectively. This pattern, combined with team management in roughly 65% of funds, reflects the industry's standardized, process-driven nature, in which a manager applies a common investment framework across many mandates. This contrasts with venture capital or private equity, where each portfolio company typically requires individualized, board-level engagement.

Table 2 reports the summary statistics at the fund level. Female managers' representation in our sample averages 9.68% of observations, consistent with prior studies Niessen-Ruenzi and Ruenzi (2019); Csiky and Pichler (2025). As shown in Figure 1, this representation has remained remarkably stable between 8% and 10% throughout the 1992–2022 sample period, despite a more than tenfold increase in the number of active funds and the introduction of federal and state-level diversity policies[4] in the past decades. The 9.68% figure reflects $Female_{i,t}$, our continuous measure of female representation. When measured instead as a binary indicator for the presence of any female manager (*Has Female*), approximately 21% of fund-month observations contain at least one female manager. The gap between these two statistics underscores the importance of distinguishing degree from incidence: while one in five funds has a woman on the management team, women on average account for less than one in ten manager seats, reflecting their concentration in mixed-gender teams rather than equal representation across the industry.

Table 2 and Figure 1 about here

Managerial turnover is relatively infrequent: positive changes in female representation occur in only 0.51% of fund-month observations. While such changes may reflect either new female appointments or the departure of male managers, we further distinguish these channels by tracking changes in the number of female and male managers within each fund. On average, female appointments (0.51%) are less frequent than male appointments (1.32%).

Consistent with Patel and Sarkissian (2017), team management is prevalent in our sample, with approximately 65% of funds managed by multiple managers. Figure 2 decomposes the team structure further, distinguishing all-male, mixed-gender, and all-female teams over the sample period. The vast majority of team-managed funds are all-male, while all-female teams remain rare throughout the sample. Mixed-gender teams have grown in absolute numbers, reflecting the broader expansion of the industry, but their share has not meaningfully increased over time. This decomposition underscores the importance of accounting for team composition when evaluating managerial outcomes, and motivates our empirical strategy of treating female representation as a continuous measure that captures all four configurations: female single managers, female-only teams, mixed-gender teams, and male-only configurations.

Figure 2 about here

The average fund size is $1,714 million, with substantial dispersion (standard deviation of $6,600 million), reflecting the presence of both small and very large funds. The average fund family size

[4] for example: California's 2019 board-diversity mandate.

is \$ 141 trillion. Other fund-level characteristics remain comparable to the broader mutual fund universe. For instance, the average monthly gross return is 0.75%, and the mean expense ratio is 1.19%, both in line with existing datasets. In terms of performance, the average Carhart alpha (-0.02%) and Fama-French alpha (-0.03%) are slightly negative, consistent with the mutual fund literature documenting limited evidence of abnormal performance.

Appendix Table A.1 reports the distribution of female managers across investment styles based on Lipper investment objective codes. Female representation exhibits substantial cross-category variation in our sample, which we exploit to sort investment styles by the share of female managers. In natural resources funds (code: NR), the share of female managers is as low as 1%, whereas in utility funds (code: UT) it reaches 22%. This pattern is not systematically related to fund size. Similarly, among team-managed funds, there is no clear relationship between team management and female representation. Overall, female representation varies markedly across styles, motivating our empirical design, which relies on within-category comparisons throughout the paper.

Appendix Table A.1 about here

3 Supply-Side Selection: The Glass Cliff Effect

3.1 Underperformed Funds and Female Appointments

We begin by examining the supply-side determinants of female manager appointments from the perspective of fund families. Specifically, we ask: what factors drive the decision to appoint a female manager? To answer this, we estimate the following cross-sectional regression:

$$\text{Appointed Female}_{i,t} = \alpha + \beta \text{PastPerformance}_{i,t-j} + \gamma' X_{i,t-1} + \lambda_j + \theta_t + \varepsilon_{i,t}, \tag{2}$$

where Appointed $\text{Female}_{i,t}$ is an indicator equal to one if the female share of managers in fund i increases at time t. This increase may arise from the appointment of a female manager, or the departure of a male manager.[5] $X_{i,t-1}$ is a vector of fund-level controls, including lagged return, fund size, expense ratio, age, family size, and aggregated manager characteristics (industry tenure, CFA credentials, graduate-level degrees, and Ivy League education). λ_j denotes fixed effects for

[5] We also examine the results using only female appointments (excluding departures of male managers) and obtain qualitatively similar findings.

investment objective categories. θ_t represents the year-month time fixed-effect. Standard errors are two-way clustered by year-month and investment category.

We measure PastPerformance$_{i,t-j}$ using multiple specifications. First, we employ risk-adjusted returns (alphas) estimated using the Carhart (1997) four-factor model, calculated on gross returns. Second, we examine average performance over rolling windows of 1, 6, 9, and 12 months prior to the appointment decision. The use of multiple horizons reflects the notion that managerial replacement decisions are unlikely to respond to short-term performance fluctuations.

Table 3 about here - appointed female

The results are reported in Table 3. The coefficients on past performance are consistently negative and statistically significant across all specifications, indicating that female managers are significantly more likely to be appointed to funds experiencing poor relative performance. This pattern is robust across alternative risk-adjusted performance measures, including Carhart alpha and Fama-French alpha. Importantly, the Glass Cliff effect persists across all performance windows examined (1, 6, 9, and 12 months), suggesting that fund families systematically assign female managers to underperforming funds regardless of the time horizon used to assess historical performance.

However, one might worry that female managers are simply being matched to particular investment styles that happen to perform worse. To rule out this alternative explanation, we further re-examines the selection mechanism within investment styles in the following section.

3.2 Style-Adjusted Performance and Female Appointments

A natural concern is that the selection effect documented in Section 3.1 could be driven by a "style" or "preference" effect rather than deliberate assignment to underperformed funds. Female representation varies substantially across investment objectives, ranging from 1% in natural resources funds to 35% in industrials (Table A.1), with female managers more concentrated in larger funds and industry-specific categories. If certain styles systematically underperform and also attract more female managers, the appointment-performance relationship could reflect style sorting rather than within-style selection bias.

We address this concern by restricting comparisons to within investment objective. Within-category identification rests on three sources of comparability. First, funds within a category share similar characteristics including size, past flows, and performance. Second, all regressions absorb investment-style heterogeneity through Lipper Class fixed effects. Third, time-fixed effects ensure that comparisons are made across funds at the same point in the business cycle. Together, these restrictions isolate variation in female appointment that cannot be attributed to systematic differences across investment styles.

Within each investment objective, we rank funds into performance quintiles, where Group 1 represents the worst-performing funds and Group 5 represents the best-performing funds within each style, a ranking approach similar to Morningstar ratings. We then substitute these style-relative performance quintiles (based on both our calculations and Morningstar star ratings) for the continuous past performance measure in Equation (2) and re-estimate using panel regression. Under the null that female appointments simply reflect style-driven differences in performance, appointment probability should be independent of style-relative performance. If the Glass Cliff effect is real, female managers should be disproportionately appointed to the lowest-performing funds within each investment style.

Table 4 reports the results. Consistent with the previous analysis, we examine performance quintiles over the past 1, 6, 9, and 12 months. The coefficients are uniformly negative and statistically significant, indicating that female managers are more likely to be appointed to funds in the lowest performance quintile within a given investment objective. These findings are robust to alternative ranking measures, including Morningstar star ratings and performance-based fractional ranks computed strictly within each investment category. [6]

This exercise also addresses the concern that female appointments may reflect heterogeneous skill requirements across investment styles. Since all rankings are constructed within investment objectives, our results cannot be driven by cross-style differences in skill demand. Female managers are appointed to the worst-performing funds within each style, not to particular styles that happen to require different skills.

TABLE 4 ABOUT HERE - APPOINTED FEMALE STYLE ADJUSTED

[6] To obtain a more granular measure of relative performance, we follow Patel and Sarkissian (2021) to construct a continuous performance rank ranging from 0 to 1, defined as the fund's fractional rank relative to peers within the same investment objective. Untabulated results yield conclusions consistent with those based on performance quintiles and Morningstar ratings.

3.3 Risk-aversion stereotype

A common stereotype, supported by some experimental evidence (Croson and Gneezy, 2009), is that women are more risk-averse than men. If fund families internalize this stereotype, they may systematically assign female managers to lower-risk portfolios, potentially confounding our interpretation of the Glass Cliff effect. Under this alternative explanation, female appointments would be predicted by a fund's risk profile rather than its past performance. We test this by replacing past performance with the fund's lagged risk loadings and re-estimating the appointment regression:

$$\text{Appointed Female}_{i,t} = \alpha + \beta \text{FactorLoading}_{i,t-1} + \gamma' X_{i,t-1} + \lambda_j + \theta_t + \varepsilon_{i,t}, \tag{3}$$

where $\text{FactorLoading}_{i,t-1}$ denotes the loading of the four factors used in Carhart (1997), including Market, Size, Value and Momentum. The regression includes year-month and investment-category fixed effects. The controls from the previous tables are also included in this regression, although the coefficients are not tabulated in Table 5 to conserve space. Standard errors are two-way clustered by time and investment category.

Table 5 about here - risk loading

The results are presented in Table 5. None of the four risk factors, in either univariate or multivariate specifications, significantly predicts female appointments. The estimated coefficients are small in magnitude and statistically indistinguishable from zero, with t-statistics ranging from -0.39 to 1.25. This result is robust to alternative measures of female representation. By maintaining within-category comparisons, year-month fixed effects further absorb time-varying risk characteristics, isolating the selection effect from style-specific risk profiles.Taken together, these findings indicate that portfolio risk profiles do not explain the assignment gap. The primary predictor of female appointment is poor past performance, not risk profile, ruling out the risk-aversion stereotype as the mechanism driving the Glass Cliff effect documented in 3.1 and 3.2.

In summary, we document a key supply-side finding: fund families are significantly more likely to appoint female managers to funds with poor performance relative to peers within the same investment objective. These assignments are systematically disadvantageous, as such funds typically experience investor outflows—making female appointments riskier than comparable male manager assignments.

4 Demand Side Bias: Investors' Flows

4.1 Flow Sensitivity: Convexity Gap

To rationalize the Glass Cliff pattern in 3, we examine whether investors respond differently to female managers' performance. We hypothesize that if investors systematically fail to reward female managers' superior performance through proportional capital inflows, fund families face a perverse incentive: assigning female managers to high-performing funds yields diminishing profits. This provides an economic explanation for the supply-side bias.

To visualize this relationship, we present Figure 3, which plots flows against past Carhart alpha rankings, where rankings are computed strictly within each fund's investment category. The figure presents four panels: the whole sample (with versus without female managers), single-manager funds (male versus female), and funds with varying degrees of female representation in teams on the right-hand side.

Figure 3. about here - Flow-Sensitivity by gender

Two patterns emerge. First, the gender-driven flow convexity gap is universal: across both single-manager and team-managed funds, male-managed funds enjoy a more convex flow-to-performance relationship, attracting outsized inflows for top-tier performance, while funds with female representation face a flatter curve. Second, the penalty is most severe in single-manager funds. As shown in the bottom-left panel, female single managers attract systematically lower flows than male single managers across all performance percentiles, including the highest-rated funds where female-managed funds still receive positive but markedly smaller inflows. By contrast, team structures appear to mitigate this gap only at the top of the performance distribution, suggesting that the presence of male co-managers partially shields female managers from investor bias.

To formally test this asymmetry, we estimate the following equation with both Fama and MacBeth's (1973) and cross-section regressions.

$$\text{Flow Sensitivity}_{i,t+36} = \alpha + \beta \text{Female}_{i,t} + \gamma' X_{i,t-1} + \lambda_j + \varepsilon_{i,t}, \tag{4}$$

where $Female_{i,t}$ is our variable of interest, denoting the female representative in fund i at month t, by calculating. We compute *Flow Sensitivity* 36 months ahead to avoid overlapping windows, since the measure is constructed using a 36-month rolling regression of flows on past returns.

Second, to identify where in the performance distribution the gender penalty appears, we directly regress monthly flows on female representation interacted with relative performance, following the piecewise specification of Sirri and Tufano (1998):

$$\text{Flow}_{i,t} = \alpha + \sum_{k} \beta_k \, \text{Perf}^k_{i,t-1} \times \text{Female}_{i,t-1} + \delta \text{FemaleRep}_{i,t-1} + \gamma' X_{i,t-1} + \lambda_j + \varepsilon_{i,t}, \tag{5}$$

where $Perf^k_{i,t-1}$ denotes performance segments at the bottom (LowPerf), middle (MidPerf), and top (HighPerf) of the fractional rank distribution. We estimate this specification separately for team-managed and single-managed funds to test whether the penalty operates differently across managerial structures.

Table 6 reports the results. Columns (1) to (3), which estimate Equation 4, confirm the convexity gap: the coefficient on *Female* is negative and statistically significant in both panel (-0.0270, $t = -2.53$) and Fama-MacBeth (-0.0244, $t = -6.51$) specifications, indicating that female-managed funds exhibit a flatter flow-to-performance curve than male-managed funds.

Table 6 about here - flow sensitivity

Columns (4) to (6) decompose this finding by managerial structure and reveal that the convexity gap operates through different channels in team-managed versus single-managed funds. In team-managed funds (column 5), the interaction *HighPerf* $\times$ *Female* is negative and significant (-0.0173, $t = -2.66$), while *LowPerf* $\times$ *Female* is positive and significant ($+0.0201$, $t = 2.45$). This pattern indicates that female-managed team funds attract smaller inflows at the top of the performance distribution and experience smaller outflows at the bottom, consistent with a genuinely flatter flow sensitivity curve to performance in Figure 3. In single-managed funds (column 6), by contrast, the gender penalty is concentrated at the bottom of the performance distribution: *LowPerf* $\times$ *Female* is negative and significant (-0.0177, $t = -2.81$), while the high-performance interaction is statistically indistinguishable from zero.

The decomposition clarifies the economic mechanism behind the convexity gap. In team settings, the presence of male co-managers buffers female-led funds from severe punishment for poor performance but does not extend to a comparable reward for strong performance. In single-managed settings, female managers face the opposite asymmetry: they are punished more severely for underperformance with no corresponding offset elsewhere in the distribution. Both patterns are inconsistent with rational, performance-based capital allocation and are instead consistent with taste-based investor bias (Becker, 1957).

4.2 Family Flow Volatility: The Mechanism Linking Demand-Side and Supply-Side Biases

The previous sections document two facts that, on their own, could be independent: fund families systematically assign female managers to underperforming funds (the Glass Cliff), and investors penalize female-managed funds with weaker capital inflows (the convexity gap). In this section, we test whether these two patterns are linked. Specifically, we hypothesize that fund families internalize investor bias as a form of flow risk and use the appointment decision as a defensive risk-management tool, generating the Glass Cliff as an endogenous response to demand-side frictions.

The economic mechanism operates as follows. Investors do not reward female managers proportionally for strong performance (Section 4.1). Fund families act as rational but risk-averse agents: they do not necessarily share investor bias, but they internalize it as a constraint on their profit-maximization problem because investor flows directly affect family revenue. Families highly exposed to flow volatility cannot easily absorb additional outflows and therefore incorporate this anticipated investor reaction into their managerial assignments. To protect flagship products and stabilize family-level flows, these families avoid appointing women to high-flow funds, instead concentrating female appointments in funds where the downside flow risk has already been realized, namely, underperforming funds (Sections 3.1 and 3.2). By contrast, families with stable flows face no comparable incentive, so the Glass Cliff should be muted or absent in this subsample.

To test this prediction, we partition the sample by fund family flow volatility and re-estimate the appointment regression:

$$\text{Appointed Female}_{i,t} = \alpha + \beta\,\text{Morningstar Rating}_{i,t-j} + \gamma' X_{i,t-1} + \lambda_j + \theta_t + \varepsilon_{i,t}, \tag{6}$$

where Morningstar Rating$_{i,t-j}$ is the average rating over the past j months ($j = 1, 6, 12$). Family flow volatility is measured as the standard deviation of monthly flows at the fund-family level over the 24 months preceding the appointment. We define high- (low-) volatility families as the top (bottom) 50% of the family-level distribution in each month.

Table 7 reports the results. In high-volatility families (columns 1–3), the coefficient on past Morningstar rating is negative and statistically significant across all horizons (-0.0004, $t = -2.80$ for the 1-month rating; -0.0004, $t = -2.76$ for 6 months; -0.0003, $t = -2.64$ for 12 months), confirming that female managers are disproportionately appointed to underperforming funds within this subsample. In low-volatility families (columns 4–6), by contrast, the coefficients are uniformly small and statistically indistinguishable from zero. The Glass Cliff is therefore concentrated in families that are most exposed to flow risk and disappears in families with stable flows.

TABLE 7 ABOUT HERE - FAMILY FLOW VOLATILITY

This pattern is consistent with the mechanism we propose: the Glass Cliff is not an independent supply-side phenomenon but a strategic, risk-management response by fund families to anticipated demand-side frictions. When flow volatility is low, families face no incentive to internalize investor bias, and the appointment-performance relationship becomes gender-neutral. When flow volatility is high, families ration female appointments toward funds where the downside risk is already realized, generating the asymmetric assignment patterns documented in Section 3. This finding closes the analytical loop: demand-side investor bias and supply-side family bias are not parallel frictions but causally connected through the family's flow-risk management.

5 Managerial skills: The Illusion of the Unconditional Gap

5.1 The Methodological Challenge

We document two structural barriers that female managers face: endogenous assignment to underperforming funds and disproportionate investor capital flight. These structural frictions raise a fundamental measurement problem: any unconditional comparison of fund performance across gender confounds true managerial skill with the pre-existing portfolio characteristics that female managers inherit at the moment of appointment. We refer to this confounded performance metric as "dirty alpha," a misleading signal generated by two correlated channels: inherited "sinking ship" portfolios (pre-existing underperformance) and the disproportionate capital flight that follows female appointments.

Table 8 illustrates the unconditional pattern. In standard panel specifications with category and year-month fixed effects, the coefficient on *Female* representation is consistently negative and statistically significant across both Carhart and Fama-French alphas, suggesting that funds with female managers underperform by 4–5 basis points monthly. This pattern is consistent with prior studies, including Patel and Sarkissian (2017), Sehrish et al. (2024), and Csiky and Pichler (2025).[7]

Table 8 about here - Unconditional Performance Gap

These unconditional estimates, however, are not informative about managerial skill. Because female assignment is systematically endogenous to poor past performance (Reuben et al., 2014; Armstrong et al., 2024), unconditional models cannot disentangle skill from inherited disadvantage. To recover a clean estimate of managerial skill, we must isolate the differential effect of female appointment from the pre-existing trajectory of the funds to which women are assigned.

5.2 Difference-in-Differences Framework

To address endogeneity in female assignment, we adopt a quasi-Difference-in-Differences (DiD) design that compares post-appointment performance and flows between female- and male-appointed managers, using male-appointed funds as a control group for the inherited portfolio trajectory. Figure 4 illustrates the event structure. For each manager appointment, we define a 12-month pre-appointment window ($t-12$ to $t-1$) that captures baseline performance and flows, an event window ($t-3$ to $t+3$) that brackets the appointment month, and a 12-month post-appointment window ($t+1$ to $t+12$) over which treatment effects are observed.

Figure 4 about here - DiD Timeline

Several sample restrictions ensure clean identification. If we observe both female and male appointments within the inner event window, we drop both events because the gender-specific effect cannot

[7] Earlier work yielded mixed results. Bliss and Potter (2002) report a modest positive relationship between female representation and performance in a sample of equity mutual funds during the 1990s, while Niessen-Ruenzi and Ruenzi (2019) find no significant performance difference in their sample restricted to single-managed funds. Barber et al. (2018) similarly find no significant performance difference between male and female managers, although they document that female managers, particularly those co-managing in teams, face worse career outcomes in terms of promotion and tenure. Our unconditional results, which use a broader sample including both single- and team-managed funds, align with more recent findings of an apparent negative performance gap.

be isolated. If we observe multiple same-gender appointments in the inner window, we combine them by relabeling the median month as the event date. We also exclude any events occurring in the outer windows ($t \pm 3$ to $t \pm 9$) to avoid staggered treatment.[8] After trimming, we obtain 7,989 appointment events, of which 654 (approximately 8.19%) involve female appointments.

We estimate the following standard 2×2 DiD specification:

$$Y_{i,t} = \alpha + \beta_1 \text{Post}_{i,t} + \beta_2 \text{FemaleAppoint}_i + \beta_3 \, \text{Post}_{i,t} \times \text{FemaleAppoint}_i + \gamma' X_{i,t-1} + \lambda_j + \theta_t + \varepsilon_{i,t}, \quad (7)$$

where $Y_{i,t}$ is either monthly fund performance (Carhart alpha) or monthly fund flow, $Post_{i,t}$ equals one for the 12-month post-appointment window, and $FemaleAppoint_i$ equals one if the appointment involves at least one female manager. Our coefficient of interest is β_3, which captures the differential change in performance (or flows) for female-appointed funds relative to male-appointed funds after the event. A statistically insignificant β_3 for performance would imply that, once endogenous assignment is properly controlled for, female and male managers exhibit equal skill.

5.3 Post-Appointment Performance: Indistinguishable Skill

Table 9 reports the DiD results for post-appointment performance. In the full sample (column 1), the interaction term Post × Female is statistically insignificant (-0.0292, $t = -0.61$), indicating that the apparent gender performance gap from unconditional models disappears once selection is properly accounted for. This result holds in both subsamples partitioned by pre-appointment performance. Among funds that were underperforming prior to the appointment (column 2, average Morningstar rating below 3 over the prior 12 months), β_3 remains insignificant (-0.0868, $t = -1.11$). The same holds in non-underperforming funds (column 3, $\beta_3 = 0.0213$, $t = 0.34$).

Table 9 about here - post-appointment performance

Although β_3 is statistically insignificant across all three specifications, the *Post* coefficient (β_1) reveals an interesting asymmetry by fund type: post-appointment performance improves substantially in underperforming funds ($+0.144$, $t = 7.31$) and deteriorates in non-underperforming funds (-0.068, $t = -3.79$). Manager appointments thus have heterogeneous effects on subsequent perfor-

[8] The maximum number of appointments observed within any inner window in our sample is three.

mance, but these effects are not gender-specific. The unconditional underperformance documented in Table 8 therefore reflects endogenous assignment, not differences in managerial skill.

5.4 Post-Appointment Flows: The Persistent Penalty

Having established that managerial skill is statistically indistinguishable across genders, we next examine whether investor capital flows respond to the appointment in a similarly gender-neutral way. Using the same DiD framework, we replace performance with monthly fund flows as the dependent variable and re-estimate Equation 7.

TABLE 10 ABOUT HERE - POST-APPOINTMENT FLOWS

Table 10 reveals a striking asymmetry between skill and flow responses. In the full sample (column 1), the interaction Post × Female is negative but statistically marginal (-0.173, $t = -1.65$). The decisive result emerges in the underperforming-fund subsample (column 2), where β_3 is large, negative, and significant at the 5% level (-0.468, $t = -2.59$). In non-underperforming funds (column 3), the effect is essentially zero (-0.002, $t = -0.01$). Thus, when a female manager is appointed to a previously underperforming fund, investors withdraw substantially more capital than they would for a comparable male appointment, even though, as Table 9 establishes, post-appointment skill is the same.

The juxtaposition of these two findings collectively suggests that female managers inherit underperforming funds as a result of supply-side selection, are penalized by disproportionate capital outflows from investors, yet deliver post-appointment alphas indistinguishable from their male peers (Table 9). The persistent flow penalty (Table 10) cannot, therefore, be rationalized by skill differences. It is consistent with the taste-based discrimination framework of Becker (1957), in which investors are willing to forgo expected returns in order to allocate capital away from female-managed funds.[9]

[9]The resilience of female managers' post-appointment performance, despite inheriting weaker portfolios and facing severe outflows, is also consistent with Li and Zeng (2019), who find that female executives reduce stock price crash risk, and with Sehrish et al. (2024), who document stronger liquidity management among female managers. Both channels may help mitigate the financial fragility associated with run-like outflows.

5.5 Robustness and discussions

The gender literature (Sehrish et al., 2024) documents differences in risk-taking behavior between female and male decision makers. To examine whether such differences extend to manager's asset allocation, we collect fund-level portfolio composition data from Morningstar, including the shares of equity, bonds, cash, and other asset classes. Given that equity allocations are the most consistently reported, we use the equity share as a proxy for portfolio risk and test whether female managers hold less risky portfolios than their male counterparts. We further examine liquidity risk by constructing the Amihud (2002) illiquidity measure and incorporating fund turnover as an additional proxy. We did not find evidence of risk-taking behavior nor liquidity risk in our analysis of female manager appointments.[10]

A separate concern is whether male managers' superior unconditional performance and capital flows reflect access to informal professional networks, such as connections with CEOs, sell-side analysts, or institutional brokers, rather than the structural frictions we document. We do not argue that networks are irrelevant in mutual funds. (Cohen et al., 2008) shows that managers earn higher returns on holdings of firms whose board members share their educational background, and (Pool et al., 2015) finds that information is transmitted through neighborhood-based peer networks. What our analysis shows is more specific: while such network channels may operate at the level of individual holdings, they do not produce a measurable gender gap in fund-level post-appointment alpha after controlling for non-random assignments. [11]

Two features of the industry may further moderate the role of individual relationships in driving gender disparities. First, active equity mutual funds hold diversified portfolios of 50 to 150+ stocks, which mechanically dilutes the contribution of any single connection to overall fund returns. This contrasts with more concentrated vehicles such as venture capital, where networks have been shown to substantially shape fund-level performance (Hochberg et al., 2007). Second, fund families typically separate portfolio management from capital-raising through dedicated internal sales divisions, limiting the extent to which a manager's personal broker relationships translate into fund-level flows.

[10] See results in Appendix Table A.2.

[11] See the difference-in-difference results in Table 9.

6 Conclusion

This paper provides a comprehensive analysis of the systemic barriers facing female managers in the US equity mutual fund industry from 1992 to 2022. While raw performance data might initially suggest a gender gap in managerial ability, our study reveals that this gap is entirely driven by two significant structural frictions: a supply-side selection bias and a demand-side investor penalty.

First, we document a persistent "Glass Cliff" phenomenon, where female managers are systematically assigned to funds with deteriorating historical performance and poor relative rankings. We rule out the possibility that this is a result of matching women to less risky portfolios; rather, it is the "sinking ship" status of the fund that predicts a female appointment. Second, we uncover a pronounced demand-side barrier in the form of investor bias. Female managers face a significantly flatter flow-performance relationship than their male counterparts, attracting less capital for top-tier performance while suffering larger and more persistent outflows during transition periods. Crucially, our analysis of post-assignment performance reveals that despite inheriting underperforming funds and facing severe capital flight, female managers demonstrate skill levels indistinguishable from their male peers.

These findings have significant implications for fund families and regulators. For fund families, the systematic assignment of women to high-failure-risk roles may inadvertently shorten their career tenures and reinforce unfounded stereotypes regarding female performance. For investors and regulators, our results highlight the need for greater transparency and a reassessment of how managerial transitions are communicated to mitigate the "gender penalty" in capital flows. Ultimately, by disentangling selection effects from ability, this paper underscores that achieving true meritocracy in institutional finance requires addressing the structural inequities that continue to mask the true skill of female fund managers.

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Figure 1. Female managers representation in mutual fund industry

This figure presents the female percentage as mutual fund managers in the US industry. The bars show the numbers of funds, which naturally grow over time. The blue line exhibits the average female percentage over time.

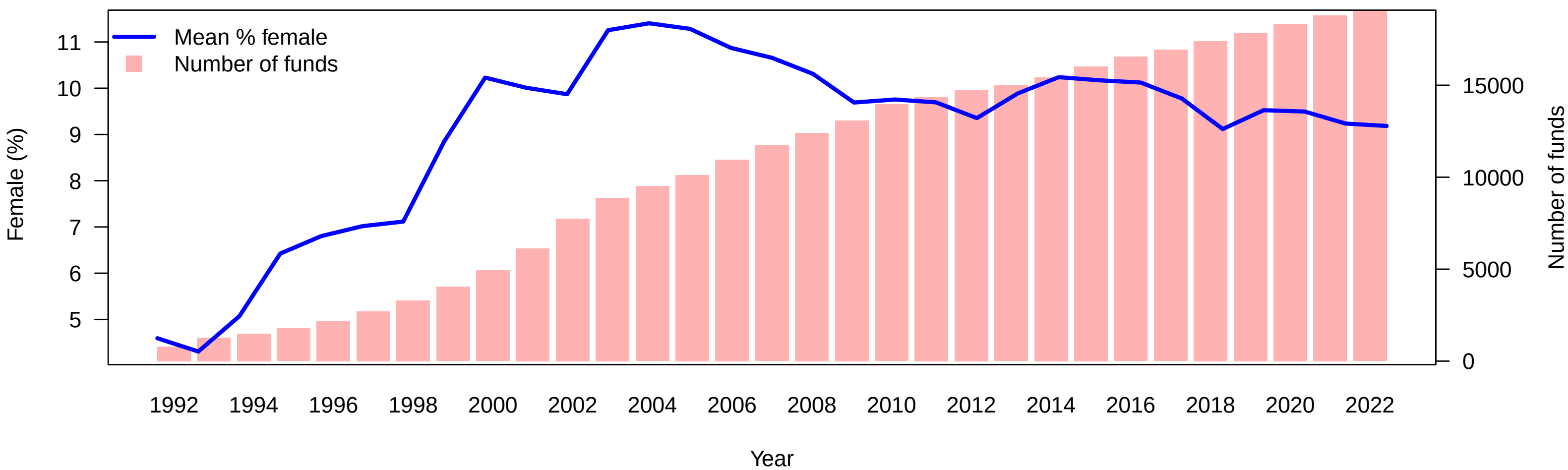

Figure 2. Team composition

This figure depicts the team composition in non single-manager funds from 1992 to 2022. There are three types of team composition: Female only (black bars), Mixed-gender team (dark gray bars), and Male only (light gray bars).

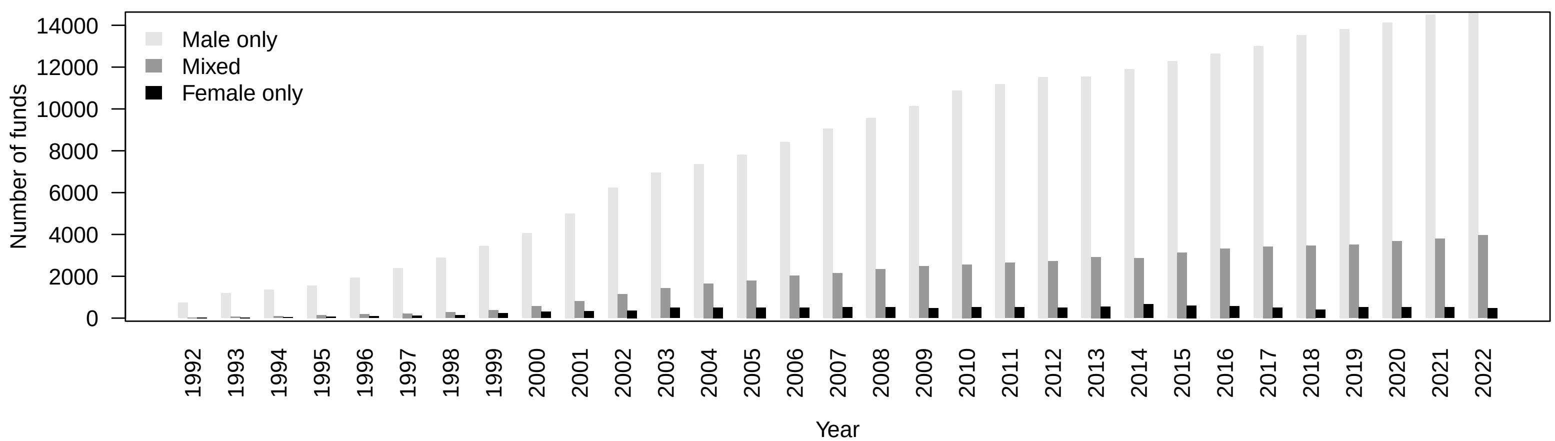

Figure 3. Flow-performance relation by gender

This figure depicts the relation between the flows (expressed in percentage) and the lagged performance based on Carhart alpha ranking within investment objective. The lagged fund performance is sorted into quintiles (1, the worst; 5, the best). The dashed blue lines represent funds with male only managers. The black solid lines in left plots indicate funds with female manager(s). In the upper-right plot, the black solid line represents funds managed by a team of mixed gender managers. In the lower-right plot, the black solid (red dotted) line represents funds managed by a team with less than (larger than or equal to) 25% of female managers. The sample covers the period between January 1992 and December 2022.

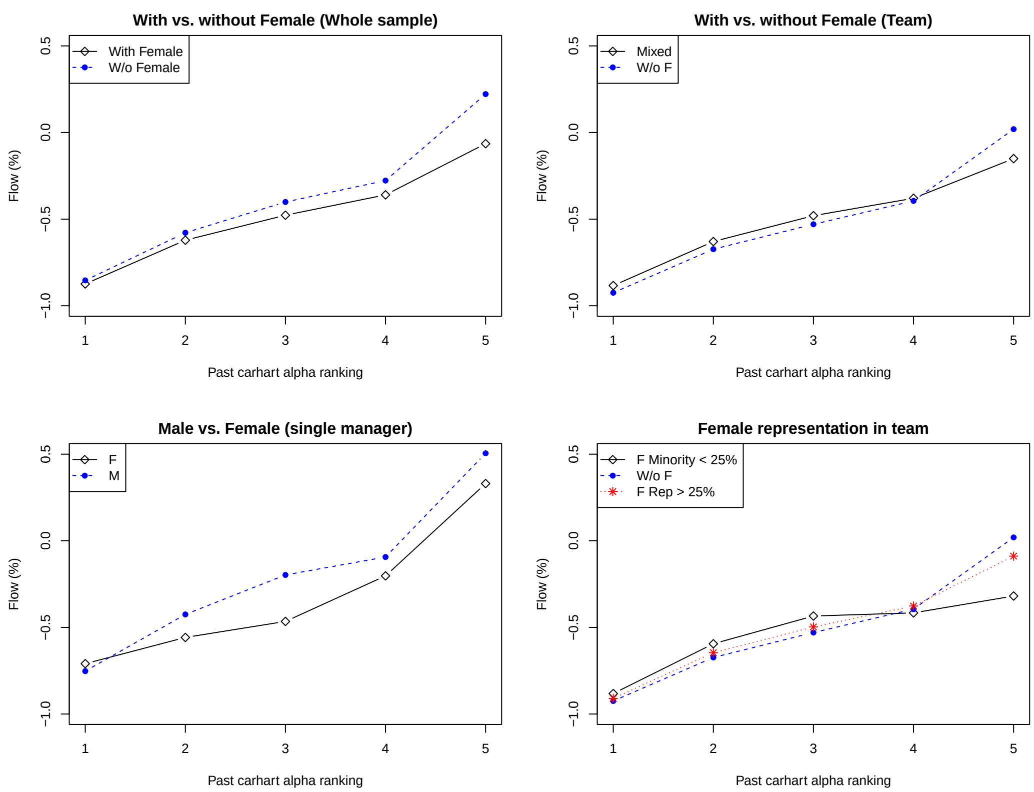

Figure 4. Event study timeline

This figure demonstrates the sample constructions of Difference-in-Differences design.

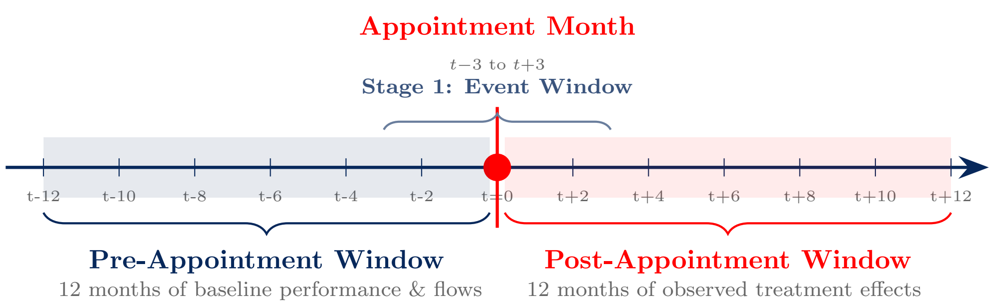

Table 1. Summary Statistics at Manager Level

This table presents summary statistics at the manager level for actively managed equity funds from January 1992 to December 2022.

	Female (obs. = 325,370)				Male (obs. = 2,733,275)			
Variable	Mean	Std	Median	Max	Mean	Std	Median	Max
Panel A: Education & certificates								
PhD	0.05	0.22	0	1	0.04	0.21	0	1
MBA	0.42	0.49	0	1	0.48	0.50	0	1
MA	0.14	0.35	0	1	0.17	0.37	0	1
BAA	0.66	0.47	1	1	0.68	0.47	1	1
CFA	0.32	0.47	0	1	0.33	0.47	0	1
CPA	0.01	0.11	0	1	0.01	0.12	0	1
FRM	0	0	0	0	0.00	0.05	0	1
Foreign education	0.17	0.37	0	1	0.13	0.34	0	1
Ivy league	0.26	0.44	0	1	0.22	0.41	0	1
Panel B: Industry experiences								
Tenure in fund (years)	4.51	4.41	3.20	30	5.28	5.16	3.70	55.70
Tenure in industry (years)	7.48	5.77	6.25	33.52	8.94	6.96	7.36	55.78
Inactive Funds Exp.	0.42	0.49	0	1	0.41	0.49	0	1
Num Funds Managed	5.15	6.69	3	45	5.06	7.14	3	63

Table 2. Summary Statistics at Fund Level

This table presents the summary statistics for actively managed equity funds during the period from January 1992 to December 2022. Female. represents the female percentage. Has Female is a dummy variable indicating any female in each fund. Change of Female Per. is the first difference with respect to the previous month. Appointed Female is a dummy variable indicating at least one female manager is newly appointed. Fund size is the monthly asset under management ($MTNA$). Age is the number of months since find initiation. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1 + Rret_t)]/MTNA_{t-1}$. Monthly Gross Return ($Rret$) is before fees. # of CFA is the number of managers who hold a CFA certificate, and # of MBA is the number of managers who has an MBA degree or above. Team is an indicator for funds managed by a team of managers. MKT, SMB, HML, and UMD Betas are factor loadings recorded from the Carhart 4-factor model.

	N	Mean	Std	Min	p25	Median	p75	Max
Female.	537,972	9.68	22.71	0	0	0	0	100
Has Female	537,972	0.21	0.41	0	0	0	0	1
Monthly Flow (%)	533,347	−0.39	4.70	−48.06	−1.65	−0.59	0.58	54.07
Flow Sensitivity	537,972	69.79	249.44	−1133.67	−35.44	25.90	120.67	3011.95
Change of Female Per.	533,086	0.00	3.35	−100	0	0	0	100
Female Change + (%)	533,086	0.51	7.15	0	0	0	0	100
Appointed Female (%)	537,972	0.27	5.20	0	0	0	0	100
Appointed Memale (%)	537,972	1.32	11.42	0	0	0	0	100
Carhart Alpha (%)	537,972	−0.02	1.73	−12.68	−0.82	−0.02	0.78	13.27
FF Alpha (%)	537,972	−0.03	1.85	−13.59	−0.88	−0.03	0.81	13.87
Fund size (millions)	537,972	1714.56	6600.50	5	86.6	312.2	1119.8	301870
Monthly Gross Return (%)	537,972	0.75	5.31	−26.47	−1.96	1.16	3.81	26.21
Expense Ratio (%)	537,584	1.19	0.44	0	0.93	1.14	1.41	8.89
Age	537,972	202.10	162.90	25	92	158	255	1181
Family size (trillions)	537,972	141.13	452.22	0.01	2.22	16.64	69.92	7260.56
# of CFA	468,866	0.90	1.38	0	0	0	1	19
# of MBA	468,866	1.31	1.53	0	0	1	2	21
# of IVY	468,866	0.63	0.98	0	0	0	1	12
Team	537,972	0.65	0.48	0	0	1	1	1
MKT Beta	537,972	0.99	0.32	−31.86	0.89	0.99	1.08	14.27
SMB Beta	537,972	0.20	0.52	−28.07	−0.09	0.10	0.47	51.65
HML Beta	537,972	0.01	0.66	−61.81	−0.22	0.01	0.23	78.66
UMD Beta	537,972	0.00	0.36	−50.63	−0.10	0.00	0.10	18.86

Table 3. Selection

This table reports the regressions of female managers' appointment. Appointed Female is an indicator of positive change of female percentage in a fund. The past performance has two measures: the Carhart alpha and the Fama-French 3-factor alpha. The past 6-, 9- and 12-month performance is calculated by the average of the Carhart or FF alpha in the past. MTNA is monthly total net assets under management, measured in billions of U.S. dollars. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1 + Rret_t)]/MTNA_{t-1}$. MRET is monthly gross return. Age is the number of decades since fund initiation. Tenure is the industry experience in number of decades of the fund's managers. Expense is the fund's annual expense ratio. FamilySize is the natural log of total asset under management for the fund family to which the equity fund belongs. CFA, MBA, Ivy is the number of female managers who hold a CFA certificate, an MBA degree, and had education from an Ivy league institution. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

	Dependent Variable					
	Positive change of female pct			Appointed Female		
	(1)	(2)	(3)	(4)	(5)	(6)
Past 6m alpha	−0.0290*			−0.0181		
	(−2.02)			(−1.55)		
Past 9m alpha		−0.0550**			−0.0274*	
		(−2.71)			(−1.96)	
Past 12m alpha			−0.0599**			−0.0286*
			(−2.61)			(−1.79)
$MTNA_{t-1}$	0.1268***	0.1288***	0.1306***	0.0112	0.0123	0.0130
	(3.86)	(3.87)	(3.84)	(0.81)	(0.88)	(0.91)
$MRET_{t-1}$	−0.6109*	−0.6195*	−0.6384*	−0.4287	−0.4898*	−0.5172*
	(−1.81)	(−1.80)	(−1.77)	(−1.69)	(−1.91)	(−1.93)
$Flow_{t-1}$	−0.0082***	−0.0080***	−0.0082***	−0.0046*	−0.0046*	−0.0048*
	(−3.11)	(−3.02)	(−2.95)	(−1.95)	(−1.96)	(−1.96)
$Expense_{t-1}$	−0.0101	−0.0125	−0.0092	0.0352*	0.0316	0.0344
	(−0.26)	(−0.32)	(−0.23)	(1.87)	(1.63)	(1.72)
Age_{t-1}	0.0002**	0.0002**	0.0002*	0.0002***	0.0002***	0.0002***
	(2.33)	(2.30)	(2.05)	(4.21)	(4.06)	(3.82)
$FamilySize_{t-1}$	0.0002**	0.0002**	0.0002**	0.0001***	0.0001**	0.0001**
	(2.60)	(2.45)	(2.37)	(2.82)	(2.61)	(2.57)
$Tenure_{t-1}$	−0.0038***	−0.0038***	−0.0039***	−0.0025***	−0.0025***	−0.0026***
	(−14.53)	(−14.61)	(−14.59)	(−14.95)	(−15.06)	(−15.00)
CFA_{t-1}	0.0117***	0.0120***	0.0120***	0.0065***	0.0066***	0.0065***
	(5.27)	(5.29)	(5.18)	(5.30)	(5.44)	(5.37)
MBA_{t-1}	0.0081***	0.0082***	0.0082***	0.0045***	0.0045***	0.0045***
	(4.21)	(4.17)	(4.14)	(3.87)	(3.84)	(3.84)
Ivy_{t-1}	0.0106***	0.0105***	0.0104***	0.0061***	0.0060***	0.0059***
	(6.44)	(6.27)	(6.39)	(4.95)	(4.79)	(4.84)
Constant	0.0049***	0.0050***	0.0051***	0.0025***	0.0026***	0.0026***
	(7.97)	(8.05)	(8.16)	(7.99)	(7.99)	(7.90)
Observations	432,778	424,759	416,906	433,247	425,219	417,355
R-squared	0.013	0.013	0.013	0.008	0.008	0.008
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered STD	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Selection within style

This table reports the regressions of female managers' appointment on the past within-style ranking. Appointed Female is an indicator of positive change of female percentage in a fund. The past ranking has two measures: the within-style quintile and the Morningstar rating. Both are estimated based on the fund's performance within investment style. The past 1-, 6-, 9- and 12-month rankings are calculated by the average of the Carhart or FF alpha in the past. MTNA is monthly total net asset under management. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1 + Rret_t)]/MTNA_{t-1}$. MRET is monthly gross return. Age is the number of months since fund initiation. Tenure is the industry experience in number of years of the fund's managers. Expense is the fund's annual expense ratio. FamilySize is the natural log of total asset under management for the fund family to which the equity fund belongs. CFA, MBA, Ivy is the number of female managers who hold a CFA certificate, an MBA degree, and had education from an Ivy league institution. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

Dependent variable: Appointed Female (Positive change of pct_female)								
	Within-style quintile				Morningstar rating			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past 1m ranking	−0.0203*				−0.0593***			
	(−2.00)				(−5.13)			
Past 6m ranking		−0.0828***				−0.0649***		
		(−4.60)				(−4.54)		
Past 9m ranking			−0.1240***				−0.0659***	
			(−4.98)				(−4.48)	
Past 12m ranking				−0.1391***				−0.0632***
				(−4.73)				(−4.30)
$MTNA_{t-1}$	0.1220***	0.1235***	0.1258***	0.1279***	0.1477**	0.1503**	0.1529**	0.1561**
	(3.69)	(3.78)	(3.77)	(3.76)	(2.67)	(2.75)	(2.73)	(2.75)
$MRET_{t-1}$	−0.1112	−0.0835	−0.0983	−0.1028	−0.0587	−0.1111	−0.0981	−0.0728
	(−0.39)	(−0.31)	(−0.36)	(−0.38)	(−0.18)	(−0.33)	(−0.29)	(−0.21)
$Flow_{t-1}$	−0.0112***	−0.0100***	−0.0096***	−0.0094***	−0.0103***	−0.0108***	−0.0116***	−0.0119***
	(−4.82)	(−3.91)	(−3.62)	(−3.37)	(−3.84)	(−3.79)	(−4.15)	(−4.03)
$Expense_{t-1}$	−0.0383	−0.0409	−0.0457	−0.0434	−0.0834	−0.0900	−0.0859	−0.0759
	(−0.93)	(−0.96)	(−1.07)	(−1.01)	(−1.37)	(−1.40)	(−1.37)	(−1.21)
Age_{t-1}	0.0003***	0.0003**	0.0003**	0.0003**	0.0003**	0.0003**	0.0004**	0.0004**
	(2.94)	(2.73)	(2.68)	(2.41)	(2.30)	(2.21)	(2.32)	(2.19)
$FamilySize_{t-1}$	0.0002***	0.0002***	0.0002**	0.0002**	0.0002*	0.0002	0.0001	0.0001
	(2.96)	(2.96)	(2.75)	(2.64)	(1.75)	(1.62)	(1.41)	(1.30)
$Tenure_{t-1}$	−0.0031***	−0.0032***	−0.0032***	−0.0033***	−0.0033***	−0.0033***	−0.0034***	−0.0034***
	(−13.88)	(−14.02)	(−14.02)	(−14.02)	(−12.08)	(−12.38)	(−12.21)	(−12.14)
CFA_{t-1}	0.0116***	0.0118***	0.0121***	0.0121***	0.0108***	0.0109***	0.0111***	0.0109***
	(5.27)	(5.32)	(5.34)	(5.23)	(4.05)	(4.00)	(4.05)	(3.94)
MBA_{t-1}	0.0079***	0.0082***	0.0082***	0.0083***	0.0085***	0.0090***	0.0091***	0.0091***
	(3.99)	(4.25)	(4.21)	(4.18)	(4.61)	(4.90)	(4.89)	(4.86)
Ivy_{t-1}	0.0113***	0.0106***	0.0105***	0.0105***	0.0114***	0.0108***	0.0106***	0.0105***
	(6.32)	(6.36)	(6.22)	(6.34)	(5.78)	(5.53)	(5.46)	(5.49)
Constant	0.0052***	0.0071***	0.0085***	0.0090***	0.0070***	0.0073***	0.0073***	0.0072***
	(7.54)	(7.79)	(7.67)	(7.73)	(7.00)	(6.44)	(6.52)	(6.50)
Observations	445,755	431,536	423,481	415,613	275,491	267,141	262,398	257,746
R-squared	0.011	0.011	0.011	0.011	0.012	0.012	0.012	0.012
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	No	No	No	No	No	No	No	No
Clustered STD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Risk Loading

This table reports the regressions of the past risk loadings. Appointed Female is an indicator of positive change of female percentage in a fund. The risk loading includes the market factor (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD). MTNA is monthly total net asset under management. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1 + Rret_t)]/MTNA_{t-1}$. MRET is monthly gross return. Age is the number of months since fund initiation. Tenure is the industry experience in number of years of the fund's managers. Expense is the fund's annual expense ratio. FamilySize is the natural log of total asset under management for the fund family to which the equity fund belongs. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

Dependent variable: Appointed Female (Positive change of pct_female)						
	(1)	(2)	(3)	(4)	(5)	(6)
MKT_{t-1}	0.0034				0.0543	0.0530
	(0.08)				(1.70)	(1.38)
SMB_{t-1}		0.0450			0.0311	0.0274
		(1.29)			(0.92)	(0.73)
HML_{t-1}			0.0300		0.0251	0.0136
			(1.15)		(0.94)	(0.49)
UMD_{t-1}				−0.0220	−0.0129	−0.0279
				(−0.62)	(−0.42)	(−0.94)
$MTNA_{t-1}$	0.1483***	0.1487***	0.1486***	0.1484***	0.1492***	0.1407***
	(3.64)	(3.66)	(3.65)	(3.65)	(3.66)	(3.37)
$MRET_{t-1}$	−1.0333***	−1.0334***	−1.0439***	−1.0341***	−1.0386***	−0.2136
	(−2.86)	(−2.87)	(−2.88)	(−2.86)	(−2.86)	(−0.77)
$Flow_{t-1}$	−0.0085***	−0.0084***	−0.0085***	−0.0084***	−0.0084***	−0.0124***
	(−3.61)	(−3.60)	(−3.61)	(−3.58)	(−3.58)	(−5.20)
$Expense_{t-1}$	−0.0150	−0.0181	−0.0144	−0.0150	−0.0178	−0.0724
	(−0.37)	(−0.44)	(−0.35)	(−0.37)	(−0.43)	(−1.47)
Age_{t-1}	0.0001	0.0001	0.0001	0.0001	0.0001	0.0002*
	(1.17)	(1.19)	(1.18)	(1.17)	(1.20)	(1.80)
$FamilySize_{t-1}$	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0005***
	(6.41)	(6.43)	(6.41)	(6.43)	(6.34)	(7.13)
$Tenure_{t-1}$	−0.0043***	−0.0043***	−0.0043***	−0.0043***	−0.0043***	−0.0031***
	(−16.02)	(−16.21)	(−16.27)	(−16.03)	(−16.23)	(−15.02)
Constant	0.0073***	0.0073***	0.0073***	0.0073***	0.0068***	0.0061***
	(11.41)	(12.20)	(12.21)	(12.29)	(10.31)	(9.27)
Observations	450,696	450,696	450,696	450,696	450,696	450,696
R-squared	0.003	0.003	0.003	0.003	0.003	0.001
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	No
Clustered STD	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Flow sensitivity

This table reports the regressions of flow sensitivity to performance. Flow Sensitivity is the coefficient of the regression of flows on lagged fund net returns over the past 36 months. Female is the percentage of female managers in each fund. The fund-level controls include lagged MTNA, MRET, flow, Expense, Age, Family-Size, and Tenure. CFA, MBA, Ivy is the number of female managers who hold a CFA certificate, an MBA degree, and had education from an Ivy league institution. $LowPerf_{t-1} = \min(0.25, Rank_{t-1})$, $MidPerf_{t-1} = \min(0.5, Rank_{t-1} - LowPerf_{t-1})$, and $HighPerf_{t-1} = Rank_{t-1} - MidPerf_{t-1} - LowPerf_{t-1}$, where, *Rank*, which ranges between 0 and 1, is the fund's fractional performance rank estimated under the same investment objective within the same period. Two subsamples are constructed for analysis. Team indicates funds managed by a group of managers, while Single consists of funds with one single manager. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

Dependent variable:	$Flow\ Sensitivity_{t+36}$			$Flow_t$		
	Panel		Fama-MacBeth	Full sample	Team	Single
	(1)	(2)	(3)	(4)	(5)	(6)
$Female_t$	-0.0233^{**}	-0.0270^{**}	-0.0244^{***}			
	(−2.61)	(−2.53)	(−6.51)			
$HighPerf \times Female_{t-1}$				−0.0057	-0.0173^{**}	0.0050
				(−1.47)	(−2.66)	(0.81)
$MidPerf \times Female_{t-1}$				0.0054^{*}	0.0117^{*}	−0.0005
				(1.94)	(1.85)	(−0.12)
$LowPerf \times Female_{t-1}$				−0.0001	0.0201^{**}	-0.0177^{**}
				(−0.03)	(2.45)	(−2.81)
$Female_{t-1}$				0.0001	−0.0017	0.0013
				(0.07)	(−0.95)	(0.98)
HighPerf				0.0137^{***}	0.0134^{***}	0.0150^{***}
				(7.87)	(7.10)	(6.28)
MidPerf				-0.0043^{***}	-0.0044^{***}	-0.0044^{***}
				(−5.74)	(−4.29)	(−3.18)
LowPerf				−0.0033	−0.0038	−0.0036
				(−1.41)	(−1.57)	(−0.91)
CFA_{t-1}		0.0055	0.0038	0.0001	0.0002	−0.0002
		(1.08)	(0.86)	(0.67)	(1.08)	(−0.36)
MBA_{t-1}		−0.0032	-0.0146^{***}	−0.0002	−0.0001	−0.0007
		(−1.01)	(−6.59)	(−1.13)	(−0.91)	(−1.28)
Ivy_{t-1}		−0.0000	0.0085^{***}	0.0000	−0.0000	0.0005
		(−0.00)	(3.20)	(0.19)	(−0.05)	(1.12)
Constant	0.0405^{**}	0.0493^{**}	0.3690^{***}	−0.0007	0.0003	−0.0024
	(2.46)	(2.74)	(16.59)	(−0.67)	(0.25)	(−1.61)
Observations	358,332	308,067	108,206	384,092	257,899	126,191
R-squared	0.120	0.124	0.325	0.109	0.102	0.122
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	No	Yes	Yes	Yes
Clustered STD	Yes	Yes	No	Yes	Yes	Yes
Number of groups			337			
Newey-West STD	No	No	Yes	No	No	No

Table 7. Selection and fund family flow volatility

This table reports the determinants of female manager appointments. Fund family flow volatility is measured as the standard deviation of fund flows at the fund-family level over the past 12 months. The time-varying classification into high- and low-volatility groups is defined at the fund-family level. $Rating_{t-1}$ denotes the previous month's Morningstar rating, and $Rating_{t-j}$ denotes the average rating over the past j months. The fund-level controls include lagged MTNA, MRET, flow, Expense, Age, FamilySize, and Tenure. CFA, MBA, Ivy is the number of female managers who hold a CFA certificate, an MBA degree, and had education from an Ivy league institution. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

Dependent variable: Female Appointment						
	Fund family flows					
	High Volatility			Low Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
$Rating_{t-1}$	−0.0004**			−0.0001		
	(−2.80)			(−1.12)		
$Rating_{t-6}$		−0.0004**			−0.0002	
		(−2.76)			(−1.44)	
$Rating_{t-12}$			−0.0003**			−0.0001
			(−2.64)			(−1.11)
CFA_{t-1}	0.0071**	0.0071**	0.0066**	0.0051***	0.0051***	0.0051***
	(2.57)	(2.56)	(2.31)	(5.25)	(5.32)	(5.35)
MBA_{t-1}	0.0022	0.0030	0.0035	0.0043***	0.0046***	0.0045***
	(0.92)	(1.19)	(1.33)	(4.28)	(4.45)	(4.15)
Ivy_{t-1}	0.0067**	0.0057*	0.0047	0.0061***	0.0058***	0.0061***
	(2.36)	(1.96)	(1.63)	(4.02)	(3.84)	(3.90)
Constant	0.0045***	0.0043***	0.0041***	0.0034***	0.0037***	0.0035***
	(6.56)	(5.82)	(5.23)	(4.90)	(4.93)	(4.71)
Observations	93,042	89,398	85,353	182,158	177,664	172,376
R-squared	0.013	0.013	0.013	0.009	0.009	0.009
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered STD	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Unconditional Performance

This table reports the regressions of unconditional performance on female percentage. The horizons of future performance range from 1, 6, 9, to 12 months. We calculate monthly average of future alpha as dependent variables. Fama-French e-factor alpha and Carhart 4-factor alpha are considered together with Gross (pre-fee) and net (post-fee) alphas. MTNA is monthly total net asset under management. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1 + Rret_t)]/MTNA_{t-1}$. MRET is monthly gross return. Age is the number of months since fund initiation. Tenure is the industry experience in number of years of the fund's managers. Expense is the fund's annual expense ratio. FamilySize is the natural log of total asset under management for the fund family to which the equity fund belongs. CFA, MBA, Ivy is the number of female managers who hold a CFA certificate, an MBA degree, and had education from an Ivy league institution. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. *t*-statistics are reported in parentheses. ***, **, and * indicate *p*-values less than 1%, 5%, and 10%, respectively.

	FF alpha		Carhart alpha					
Fees	Gross	Net	Gross	Net				
Horizon			1m			6m	9m	12m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
pct_female	−2.7514**	−0.0472***	−3.9628***	−0.0576***	−0.0460**	−0.0429**	−0.0389**	−0.0359**
	(−2.29)	(−3.40)	(−3.55)	(−4.22)	(−2.54)	(−2.39)	(−2.24)	(−2.17)
$MTNA_{t-1}$	0.0641	0.0001	0.0180	−0.0004	−0.0004	−0.0004	−0.0004	−0.0003
	(1.22)	(0.19)	(0.36)	(−0.51)	(−0.54)	(−0.62)	(−0.57)	(−0.47)
$MRET_{t-1}$	0.0183	0.0002	0.0156	0.0001	0.0001	0.0001***	0.0001***	0.0001***
	(1.31)	(1.13)	(1.57)	(1.18)	(1.18)	(2.93)	(3.47)	(4.11)
$Flow_{t-1}$	0.7227***	0.0080***	0.5781***	0.0067***	0.0067***	0.0052***	0.0045***	0.0039***
	(3.49)	(3.69)	(3.09)	(3.28)	(3.30)	(4.59)	(3.71)	(3.59)
$Expense_{t-1}$	−1.5397	−0.0862***	−1.7114	−0.0885***	−0.0874***	−0.0744***	−0.0679***	−0.0626***
	(−1.14)	(−4.92)	(−1.29)	(−5.34)	(−5.31)	(−4.92)	(−4.49)	(−4.16)
Age_{t-1}	−0.4705	0.0027	−0.3971	0.0037	0.0037	0.0034	0.0027	0.0013
	(−1.39)	(0.34)	(−1.36)	(0.48)	(0.46)	(0.45)	(0.38)	(0.23)
$FamilySize_{t-1}$	0.2273	0.0015	0.1983	0.0007	0.0006	0.0008	0.0011	0.0015
	(1.12)	(0.55)	(1.16)	(0.30)	(0.26)	(0.36)	(0.47)	(0.64)
$Tenure_{t-1}$	0.3925	0.0220	0.7591	0.0261	0.0269	0.0252	0.0232	0.0209
	(0.40)	(1.11)	(0.82)	(1.39)	(1.44)	(1.39)	(1.28)	(1.16)
CFA_{t-1}					0.0002	0.0044	0.0049	0.0062
					(0.01)	(0.41)	(0.47)	(0.60)
MBA_{t-1}					−0.0284**	−0.0294**	−0.0297**	−0.0287**
					(−2.11)	(−2.63)	(−2.71)	(−2.72)
Ivy_{t-1}					0.0422***	0.0454***	0.0459***	0.0456***
					(3.93)	(4.78)	(4.75)	(4.83)
Constant	−0.1781	−0.0249	0.5509	−0.0167	−0.0195	−0.0390	−0.0448	−0.0502
	(−0.09)	(−0.58)	(0.29)	(−0.41)	(−0.48)	(−1.00)	(−1.14)	(−1.35)
Observations	450,765	450,765	450,765	450,765	446,891	430,446	421,085	411,949
R-squared	0.067	0.018	0.070	0.017	0.017	0.018	0.020	0.023
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered STD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. After-selection performance

This table reports the difference-in-differences regressions of performance following fund's appointments of new managers. The performance is measured by Carhart 4-factor alpha. Post indicates the 12 consecutive months following a new manager appointment. FemaleAppoint is a dummy variable that indicates the appointment concerning female manager(s). Regression (3) is estimated on the sample of non-underperforming (NU) funds. Funds are classified as underperforming if their 12-month average of Morningstar rating prior to the appointment is strictly below 3. MTNA is monthly total net asset under management. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1 + Rret_t)]/MTNA_{t-1}$. MRET is monthly gross return. Age is the number of months since fund initiation. Tenure is the industry experience in number of years of the fund's managers. Expense is the fund's annual expense ratio. FamilySize is the natural log of total asset under management for the fund family to which the equity fund belongs. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

	Dependent variable: Carhart Alpha		
	Whole sample	Sub-samples	
	(1)	(2) Underperforming funds	(3) NU funds
Post × FemaleAppoint	−0.0292	−0.0868	0.0213
	(−0.61)	(−1.11)	(0.34)
Post	0.0210	0.1439***	−0.0682***
	(1.63)	(7.31)	(−3.79)
FemaleAppoint	−0.0263	−0.0068	−0.0487
	(−0.78)	(−0.12)	(−1.14)
$MTNA_{t-1}$	−0.4593	−3.9585	−0.7665
	(−0.53)	(−1.07)	(−0.97)
$MRET_{t-1}$	0.0064	0.0068	0.0060
	(0.68)	(0.63)	(0.63)
$Flow_{t-1}$	0.0036	0.0039	0.0013
	(1.30)	(0.91)	(0.52)
$Expense_{t-1}$	−0.1168***	−0.0609	−0.1373***
	(−4.66)	(−1.61)	(−5.04)
Age_{t-1}	−0.0026	−0.0013	−0.0007
	(−0.49)	(−0.16)	(−0.14)
$FamilySize_{t-1}$	0.0003	0.0059	−0.0036
	(0.10)	(1.52)	(−0.86)
$Tenure_{t-1}$	−0.0121	−0.0066	−0.0248
	(−0.78)	(−0.24)	(−1.14)
Constant	0.0298	−0.1651***	0.1490***
	(0.91)	(−2.99)	(3.29)
Observations	84,082	34,036	50,046
R-squared	0.074	0.103	0.074
Category FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Clustered STD	Yes	Yes	Yes

Table 10. After-selection flows

This table reports the difference-in-differences regressions of flows following fund's appointments of new managers. PostAppoint indicates the 12 consecutive months following a new manager appointment. Female is a dummy variable that indicates the appointment concerning female manager(s). Regression (3) is estimated on the sample of non-underperforming (NU) funds. Funds are classified as underperforming if their 12-month average of Morningstar rating prior to the appointment is strictly below 3. MTNA is monthly total net asset under management. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1 + Rret_t)]/MTNA_{t-1}$. MRET is monthly gross return. Age is the number of months since fund initiation. Tenure is the industry experience in number of years of the fund's managers. Expense is the fund's annual expense ratio. FamilySize is the natural log of total asset under management for the fund family to which the equity fund belongs. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

	Dependent variable: $Flow_t$		
	Whole sample	Sub-samples	
	(1)	(2) Underperforming funds	(3) NU funds
PostAppoint × Female	−0.1731	−0.4681**	−0.0016
	(−1.65)	(−2.59)	(−0.01)
PostAppoint	−0.0672*	0.2333***	−0.2590***
	(−1.93)	(4.38)	(−5.51)
Female	0.0076	−0.0312	0.0131
	(0.07)	(−0.28)	(0.09)
$MTNA_{t-1}$	6.8417***	−19.2663	3.5685
	(3.94)	(−1.43)	(1.46)
$MRET_{t-1}$	0.1665***	0.1421***	0.1859***
	(5.66)	(3.95)	(6.59)
$Flow_{t-1}$	0.2208***	0.1131***	0.2792***
	(8.86)	(4.97)	(10.79)
$Expense_{t-1}$	−0.2965***	−0.1025	−0.1738
	(−2.99)	(−0.82)	(−1.23)
Age_{t-1}	−0.0943***	0.0162	−0.1405***
	(−3.85)	(0.47)	(−5.37)
$FamilySize_{t-1}$	0.0153	0.0327	0.0176
	(0.83)	(0.86)	(1.22)
$Tenure_{t-1}$	0.1245*	−0.1010	0.1796**
	(1.96)	(−1.26)	(2.26)
Constant	−0.2259	−1.2191***	0.0772
	(−1.29)	(−4.57)	(0.41)
Observations	83,691	33,869	49,822
R-squared	0.097	0.067	0.136
Category FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Clustered STD	Yes	Yes	Yes

Internet Appendix to

"Gender Disparities in Mutual Fund Industry: Investor Flows, Selection Bias, and Managerial Skill"

(not for publication)

Abstract

We present supplementary results not included in the main body of the paper.

Figure A.1. Flow-performance relation by gender

This figure shows the unconditional performance between funds with and without female manager(s). The dark (light) gray bars present the alphas of funds with (without) female manager(s). The alphas are obtained from Fama-French 3-factor and Carhart 4-factor models in the left and right groups, respectively.

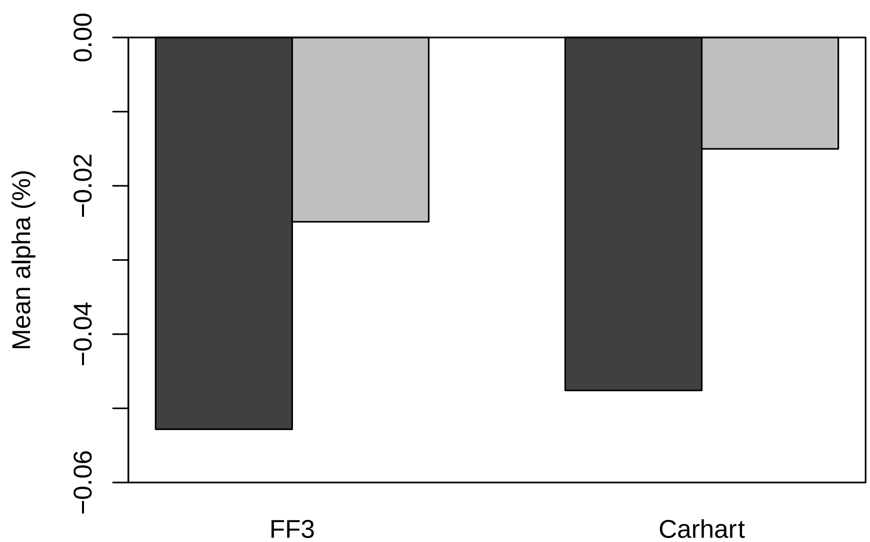

Table A.1. Summary statistics by style

This table presents the demography of female manager(s) by investment style according to Lipper objective codes, during the period from January 1992 to December 2022. The column 'Female' shows the female percentage based on which this table is sorted. 'Team' indicates the fraction of team-managed funds. 'Size' is the average of the funds' total net asset in trillion dollars.

Code	Objective class name	Female	Team	Size	# of funds
NR	Natural Resources	0.01	0.49	0.90	3159
TK	Science & Technology	0.07	0.49	1.13	6612
TL	Telecommunication	0.07	0.46	0.24	913
MLVE	Multi-Cap Value	0.08	0.69	2.71	20512
MLCE	Multi-Cap Core	0.08	0.70	2.20	17744
LCGE	Large-Cap Growth	0.08	0.62	2.15	19033
SCVE	Small-Cap Value	0.09	0.68	1.18	15785
MCCE	Mid-Cap Core	0.09	0.62	1.59	8900
LCVE	Large-Cap Value	0.09	0.67	4.32	13901
SCGE	Small-Cap Growth	0.10	0.76	0.79	15706
MLGE	Multi-Cap Growth	0.10	0.61	1.97	14413
MCVE	Mid-Cap Value	0.10	0.66	1.03	8649
SCCE	Small-Cap Core	0.10	0.74	0.69	15088
EIEI	Equity Income	0.11	0.70	2.41	12802
LCCE	Large-Cap Core	0.11	0.59	3.31	15876
MCGE	Mid-Cap Growth	0.13	0.71	0.83	10971
FS	Financial Services	0.15	0.33	0.34	3561
H	Health/Biotechnology	0.16	0.41	2.01	4447
S	Specialty/Miscellaneous	0.19	0.18	0.59	3052
UT	Utility	0.22	0.51	0.46	3090
ID	Industrials	0.35	0.68	0.08	231

Table A.2. Liquidity Risk

This table reports the regressions of liquidity risk measures following fund's appointments of female managers. Appointed Female is an indicator of positive change of female percentage in a fund. MTNA is monthly total net asset under management. Monthly Flow is calculated as $[MTNA_t - MTNA_{t-1} \times (1+Rret_t)]/MTNA_{t-1}$. MRET is monthly gross return. Age is the number of months since find initiation. Tenure is the industry experience in number of years of the fund's managers. Expense is the fund's annual expense ratio. FamilySize is the natural log of total asset under management for the fund family to which the equity fund belongs.CFA, MBA, Ivy is the number of female managers who hold a CFA certificate, an MBA degree, and had education from an Ivy league institution. All regressions incorporate year-month and category fixed effects, and standard errors are clustered at both the category and year-month level. t-statistics are reported in parentheses. ***, **, and * indicate p-values less than 1%, 5%, and 10%, respectively.

	Dependent variable: Liquidity risk measures					
	Equity	AR1	Turnover	Equity	AR1	Turnover
	(1)	(2)	(3)	(4)	(5)	(6)
AppointFemale	0.0283	−1.5581	−0.6188	0.0465	−1.6832	−0.0683
	(0.20)	(−1.02)	(−0.40)	(0.39)	(−1.02)	(−0.04)
$MTNA_{t-1}$	−6.5909**	−7.0101*	−28.2469	−5.1578	−8.8344**	−37.8305
	(−2.35)	(−2.07)	(−1.06)	(−1.70)	(−2.37)	(−1.48)
$MRET_{t-1}$	0.0273***	−0.0714	−0.2149	0.0236**	−0.0926*	−0.1375
	(3.04)	(−1.68)	(−1.53)	(2.57)	(−1.99)	(−1.03)
$Flow_{t-1}$	0.0285***	−0.0193	−0.0555	0.0286***	−0.0125	−0.0517
	(5.80)	(−1.25)	(−0.52)	(5.15)	(−0.90)	(−0.38)
$Expense_{t-1}$	0.1357	−0.6597*	−1.4636	0.0132	−0.7579*	−2.5309***
	(1.18)	(−2.06)	(−1.54)	(0.11)	(−2.07)	(−3.03)
Age_{t-1}	0.0204	0.0277	0.4837***	0.0141	0.0296	0.4275**
	(0.88)	(1.38)	(3.33)	(0.59)	(1.23)	(2.39)
$FamilySize_{t-1}$	−0.0274	0.0136	−0.0298	−0.0420	0.0167	−0.0441
	(−1.13)	(0.31)	(−0.25)	(−1.60)	(0.33)	(−0.30)
$Tenure_{t-1}$	−0.0906	−0.2448	1.3540**	−0.0631	−0.2743	1.5645**
	(−1.68)	(−1.24)	(2.19)	(−0.85)	(−1.22)	(2.51)
CFA_{t-1}				−0.0001	−0.0100	−0.8899*
				(−0.01)	(−0.26)	(−2.03)
MBA_{t-1}				−0.0176	0.0316	0.7763**
				(−0.66)	(0.77)	(2.22)
Ivy_{t-1}				−0.0094	0.0043	−0.3442
				(−0.28)	(0.11)	(−1.23)
Constant	−0.2572	0.8205	−1.6680	−0.0908	0.9352	−1.2609
	(−1.45)	(1.61)	(−1.28)	(−0.42)	(1.67)	(−1.11)
Observations	416,825	332,472	119,506	358,682	297,858	97,842
R-squared	0.111	0.005	0.010	0.108	0.005	0.012
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered STD	Yes	Yes	Yes	Yes	Yes	Yes