Systematic Allocation of Mutual Fund Managers

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This paper investigates whether female portfolio managers are systematically allocated to mutual funds with lower profit-generating value. A unique, hand-collected dataset on the individual characteristics of over 2,100 U.S. equity fund managers shows that, despite similar education and experience profiles across genders, women oversee funds that are older, have lower performance, and collect inferior fee revenues. A comparative matched-pair framework reveals that female fund managers suffer a significant within-firm net-of-style return penalty attributable to allocation practices. Exogenous social and regulatory shocks have divergent impacts on the phenomenon, suggesting that systematic allocation is primarily driven by firm-level strategic placement, with limited indications of managerial self-selection. Furthermore, the paper documents a shielding effect, as female-managed investment vehicles exhibit a lower flow-performance sensitivity, alongside an overrepresentation of female managers leading ESG mutual funds.

JEL-Classification: G11, G23, J16, J24
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1 Introduction

The characteristics of mutual fund managers and the attributes of the investment vehicles they oversee have both been long-standing areas of scrutiny in the pursuit of isolating the drivers of performance. However, the interplay between these two sets of features tends to be overlooked, leaving the question of how they are matched largely unaddressed. Manager gender often becomes a particular point of interest, as this characteristic is readily observable to all parties but highly susceptible to biases, stereotypes, or specialized demand.

Advancing this discourse, Csiky and Pichler (2025) find that, consistent with popular beliefs, female fund managers underperform by 0.73% annually. This univariate result persists after controlling for manager characteristics, but loses its statistical significance after including fund-specific variables in the specification. Such evidence raises the question: What drives this phenomenon? Could the perceived underperformance of female managers be a byproduct of their assignment to mutual funds with specific, plausibly adverse qualities?

Thus, I investigate *systematic allocation* patterns of female portfolio managers to disadvantageous mutual funds. In particular, I distinguish two channels of the phenomenon: *self-selection* and *strategic placement*. Although the analysis provides empirical support for the presence of both mechanisms, the results indicate that the latter is more prevalent. This implies that the allocation outcomes are due more to fund family-level[1] strategic placement decisions than to female managers' voluntary will to be in charge of less promising investment vehicles.[2] The relevance of the phenomenon is compounded by the increasing role of fund families amid the heavy consolidation of the mutual fund industry, granting more leverage to a diminishing number of market participants.[3] Since fund families are profit-maximizing entities, it is reasonable to posit that they follow a strategic approach to managerial assignment, aiming to optimize firm-wide revenues, considering managerial profiles, investor perceptions, and regulatory mandates. In addition, the literature shows that they are no strangers to prioritizing family objectives by engaging in coordinated strategies (see, e.g., Massa, 2003; Nanda et al., 2004; Gaspar et al., 2006; Khorana and Servaes, 2012; Csiky et al., 2024).

[1] Throughout, the terms *family* and *firm* are used interchangeably.

[2] Manager assignments tend to be made by the senior investment leadership of the fund family. Managers, however, can signal preferences, negotiate, or decline a mandate, leaving room for both strategic placement and self-selection.

[3] Whereas in 2005, just 35% (46%) of the assets invested in mutual funds and exchange-traded funds (ETFs) were managed by the five (ten) largest firms in the U.S., this number ascended to 57% (71%) by 2024 (Investment Company Institute, 2025).

Moreover, allocating female managers to funds with adverse features aligns with the "glass cliff" proposed by Ryan and Haslam (2005), suggesting that women are disproportionately appointed to leadership positions that are inherently risky or precarious.

Consequently, I define the value of funds by their profit-generating potential for their family, measured by their performance, age, expense ratio, and fee income. Whereas the first three variables are proposed by Gaspar et al. (2006) as measures of value, I argue similarly to Berk and Van Binsbergen (2015) that dollar revenues are of greater importance in terms of profitability, hence I introduce *fee income* to proxy that. I analyze and identify manager allocation patterns along these axes, using a sample of single-managed U.S. equity open-end funds from Morningstar Direct, covering 2000–2024. I enrich the panel with a unique, manually collected dataset of manager-specific variables, yielding 2,367 funds of 543 families, led by 2,104 managers, of whom 214 are identified as female and 1,890 are male. This asymmetry reflects the puzzling historical underrepresentation of female managers in the mutual fund industry, a phenomenon that could be affected by channeling them into the seats of disadvantageous investment vehicles.

To rule out that allocation effects stem from deviations in credentials and experience, I compare the proportion of managers with MBA, PhD, CFA, and Ivy League degrees by gender. There are no statistically significant differences in their education, and the mean years spent in the finance industry are also comparable. However, the managed investment vehicles diverge substantially; female-led funds tend to be older, underperform, and charge higher percentage fees. Yet, as they are only half the size of male-managed funds, their contribution to family profits is commensurately restrained in magnitude.

Graphical analysis corroborates this systematic allocation of female managers to lower-value funds. In particular, dividing fund-months into family value quartiles reveals a stark inverse relationship between female manager representation and fund desirability. That is, more than one and a half times as many women oversee low-performing investment vehicles as the top ones, and the disparity between old and young funds is even more pronounced. The gap in female manager presence is the widest for the primary value measure, fee income, where they are nearly twice as prevalent among the funds generating the lowest dollar revenues as among those collecting the highest. Only expense ratios point the other way, which I argue does not indicate higher value, as higher fees could erode returns and impede raising capital. In addition, both the percentage of female managers and their systematic allocation to funds of lower value progressively diminish in families with more funds. This pattern is consistent with

smaller firms employing and allocating their female fund managers instrumentally, for instance to signal managerial heterogeneity or ESG commitment. A logit regression framework confirms that women are more likely to lead funds that are older and charge high percentage fees, and less likely to lead those that perform well or collect sizable fee income. In essence, female managers oversee funds that may lack investor visibility due to their age, may struggle to raise capital given their high percentage fees, and exhibit inferior performance, culminating in a modest dollar contribution to family profits.

Performance is a joint function of fund attributes and manager characteristics. Exploiting this dual dependency, I compare the net-of-style returns of female-managed funds to two benchmarks and relate the resulting differences. The first is male-managed funds of the same family. The second is funds that are led by male managers with similar professional qualities but employed by other fund families that do not have female managers, thus unable to engage in gender-based systematic allocation. Comparing the female-male net-of-style return differentials across the two benchmarks isolates the underperformance of female-managed funds that is due to allocation. Specifically, a more negative differential relative to in-family males than to matched out-of-family males indicates systematic allocation effects. A univariate comparison of these measures reveals that 11 basis points (bp) of monthly female underperformance can be attributed to assignment patterns. The phenomenon is present in all five-year subperiods except 2010–2014. Notably, since 2015, female managers have even exceeded the net-of-style returns of their external male peers, most markedly in 2020–2024, by 10 bp monthly on average, notwithstanding their continued deficits relative to their internal male colleagues.

The evidence for systematic allocation is fortified in a panel regression framework, suggesting that the phenomenon is not explained by observable fund and family characteristics. In particular, I document about 1.2% annual female underperformance within family, as an outcome of systematic allocation effects. Given the substantial magnitude of this disparity, I examine whether it arises from the strategic placement of managers by the family, or conversely, from the self-selection of female managers into less promising funds, by investigating the issue through several empirical settings.

First, I test how the #MeToo movement, an exogenous social shock, affected the allocation of female fund managers as reflected by their performance gaps compared to male peers within and outside their families. Following the onset of the movement, female managers' performance lag relative to in-family male peers more than doubled, whereas their gap relative to comparable men outside their family did not change significantly. The sharp internal deterioration is

consistent with a family-level response to investor expectations on institutional diversity amid heightened reputational stakes, indicating that strategic placement by families drives systematic allocation patterns.

To further assess the institutional aspect of the phenomenon, I investigate California's Senate Bill 826 (SB 826, also known as the Women on Boards mandate) as a localized regulatory shock. A triple-difference analysis reveals that while the within-family performance gap of female managers widened in other states, the legal requirement to diversify corporate boards substantially narrowed it at fund firms headquartered in California, although it did not reverse it. The divergent response to the two events studied indicates that whereas social pressure could result in window dressing, regulatory changes may discipline allocation practices of fund families. Since a state-level mandate locally attenuated the return-based indications of allocation patterns, this also points to strategic placement of fund families as the primary source of the phenomenon, rather than managerial self-selection.

To explore whether investor behavior impacts the observed allocation patterns, I investigate the flow-performance relationship across manager gender. Despite the lack of an aggregate gender effect on flows, female-led funds are subject to a 65% smaller flow penalty for poor performance than their male counterparts. In contrast, both genders are similarly rewarded for outstanding net-of-style returns. As this relative flow protection provides an economic rationale for fund families to allocate female managers to funds that are more predisposed to underperform, it can be interpreted as a further indication of strategic placement rather than self-selection.

Seeking to decouple strategic placement from self-selection around manager changes, I construct transition matrices assessing each allocation mechanism and perform hypothesis tests on specific transition probabilities. Whereas nearly all results statistically support strategic placement, corroborating it as the dominant mechanism, I find limited evidence on self-selection.

Finally, I investigate the role of Environmental, Social and Governance (ESG) fund mandates in systematic allocation. Such investment vehicles could be preferentially matched to female managers, owing to women's greater affinity for these matters and the stronger institutional signaling to investors. The results reveal a stark overrepresentation of women leading ESG mutual funds: their presence is more than double that in regular funds, and they are significantly more likely to be appointed to such mandates. In a modest sample, the performance of female managers significantly improves after switching from traditional to ESG funds. The preponderance of female managers in ESG funds could reflect both strategic

placement and self-selection, as their comparative advantage benefits both them and the firms.

This study relates to three strands of the mutual fund literature. First, it contributes to the body of research on gender-based performance, risk, and behavioral deviations in the asset management industry, which has historically reported diverse results. Bliss and Potter (2002) demonstrate that contrary to widespread beliefs, female equity fund managers achieve higher raw returns by managing portfolios with marginally more risk than their male peers. However, controlling for this latter attribute and other potential influences diminishes the difference. Atkinson et al. (2003) report that despite the lack of deviations in investment behavior, performance, and risk attributes of female- and male-managed fixed income funds, the former group of managers receives lower inflows due to the gender effect on investor decision making. Aggarwal and Boyson (2016) find similar patterns for hedge funds, with funds solely led by women facing higher failure rates due to capital-raising difficulties, yet outperforming when conditioning on survival. Niessen-Ruenzi and Ruenzi (2019) also document no gender-based differences in performance but smaller inflows to female-led funds, despite their more stable investment styles. Rau and Wang (2022) report that the flow-performance sensitivity is weaker if the fund is female-led. Together, these studies reveal that, regardless of similar risk, return, and investment styles, female fund managers tend to face investor prejudice, which underscores the importance of unraveling systematic allocations and exploring whether these are driven by shareholder biases. Based on survey responses of fund managers, Beckmann and Menkhoff (2008) conclude that women are more risk averse and less overconfident. Welch and Wang (2013) find a weak but inverse relationship between mutual fund performance and the proportion of women in their management team, alongside a lower female risk appetite. In contrast, Babalos et al. (2015) show higher, but statistically insignificant female-managed fund alphas, accompanied by similar risk metrics to their male peers, corroborated by Clare et al. (2022). Tolikas and Callonnec (2023) also find that despite the marginally higher return and risk of female-managed funds, the effect of gender on performance is insignificant. Showing that female managers are systematically allocated to certain funds could shed new light on the mixed findings of this body of research, suggesting that some results may be driven by assignment patterns rather than skill.

This study also pertains to the literature focusing on fund manager career paths and their labor markets. Khorana (1996), Chevalier and Ellison (1999), Dangl et al. (2008), Porter and Trifts (2014), and Kostovetsky and Warner (2015) find an inverse relation between manager turnover and performance. Khorana (2001) documents that fund performance reverses after manager departures. Assessing recruitment aspects, Guo (2020) reports that performance

and experience affect short-term rehiring and that rehired managers tend to work for smaller, less competitive funds for less compensation, while Dewald et al. (2023) show that large and racially diverse funds are more likely to recruit minority managers. Fang et al. (2014) find that fund families allocate their managers efficiently, accounting for their skill levels. Berk et al. (2017) show that matching managerial skill with capital is a critical source of value, as firms reallocate capital across their managers accordingly. Cici et al. (2025) further document higher risk-adjusted performance when managers' abilities match their jobs. However, to my knowledge, no studies have been conducted on systematic assignment patterns of fund managers based on their gender.

This paper also contributes to the body of research studying fund family level strategies, as one of the allocation mechanisms is strategic placement. Nanda et al. (2004) and Khorana and Servaes (2012) show that fund firms obtain positive spillover generated by star funds in terms of inflows. Fund families tend to launch several funds to capture more market segments, as reported by Massa (2003). Favoritism has also been shown to be a tool in the arsenal of fund firms. Gaspar et al. (2006) report value-based favoritism, which is largely confirmed by Adrianto et al. (2018) within ESG fund firms. Additionally, Csiky et al. (2024) show that families favor their ESG members by advancing their performance. Furthermore, several studies focus on the tools of cross-subsidization. Cici et al. (2010) and Del Guercio et al. (2018) find indications of preferential IPO distribution practices. Chuprinin et al. (2015), Casavecchia and Tiwari (2016), Abdesaken (2019), and Eisele et al. (2020) report that cross-trading is used to reallocate performance among funds. Moreover, Evans et al. (2020) demonstrate that families fostering cooperation between their managers tend to engage in more cross-trading and cross-holding. However, there has been a literature gap on whether families engage in the strategic placement of their managers.

This paper provides a multifaceted contribution to the existing body of research. First, it extends the literature on gender-based performance by showing that the perceived underperformance of female managers could be due to systematic allocation practices instead of inherently different skill levels. I demonstrate that it is primarily an outcome of strategic placement executed by fund families, with limited evidence of self-selection of female managers into certain funds. Second, it contributes to the body of knowledge on managerial careers and the internal labor market by revealing that female fund managers tend to be assigned to funds that have a lower profit-generating potential for their firms, which is consistent with the glass cliff hypothesis of Ryan and Haslam (2005). This structural disadvantage also sheds light on a potential driver of the historical underrepresentation of women in the fund management

industry. Finally, it enriches the literature on fund family practices by revealing strategic placement as a tool of systematic allocation of managers. The implications of these results are substantial for the asset management industry, including investors and regulators. The findings suggest that performance-based evaluations require consideration of the quality of the investment vehicle to which the manager is assigned. The divergent responses in systematic allocation efforts to social diversity pressure versus legal board mandates indicate that window dressing remains a risk, and handling such matters requires profound approaches to prevent adverse effects. Revealing the systematic allocation patterns of female managers highlights the need for greater transparency and efficiency in human capital distribution, ensuring assignment processes that maximize aggregate skill within the fund management industry.

2 Data

The dataset used for this paper consists of mutual fund-, fund family-, and manager-specific variables in a panel of monthly observations, spanning January 2000 through December 2024. The first two, including the value measures, are derived from Morningstar Direct, whereas the third group comes from a unique, hand-collected dataset.

2.1 Fund Sample and Manager Data

I obtain a sample of open-end U.S.-domiciled equity funds with USD base currency from Morningstar Direct. This selection sets the focus on the most prominent subset of the largest mutual fund market globally.[4] In addition, it provides a relatively homogeneous sample in terms of investment universe and foreign exchange risk, enabling the assessment of manager allocation patterns. To prevent performance distortion in the analysis, index funds are excluded from the dataset as their returns are predetermined mechanically instead of signaling managerial skill. Prior studies document that funds with subpar returns are more predisposed to liquidation, hence eliminating them could artificially inflate performance measures[5] and may mask manager allocation patterns. Thus, to circumvent survivorship bias, I include all funds in the sample

[4] As reported by the Investment Company Institute (2025), the U.S. mutual fund industry maintains its position as the largest in the world with USD 28.5 trillion in total net assets. Equity mutual funds encompass 53% of it, making them its principal constituent.

[5] See, e.g., Brown et al. (1992), Brown and Goetzmann (1995), Elton et al. (1996) and Carhart et al. (2002).

that meet the selection criteria, irrespective of whether they remained in operation or became defunct.

I retrieve the history of managers for the qualifying mutual funds from Morningstar Direct. The lack of information available regarding the contribution of management team members would make the identification of manager allocation patterns ambiguous; therefore, I constrain the sample to single-manager fund-months.[6] To identify the gender of these managers, I download and consolidate the most popular female and male baby names by decade files from the United States Social Security Administration's (SSA) website.[7] In instances where gender cannot be determined from the first name, I ascertain it based on their second name. Due to the prevalence of non-Anglo-Saxon given names, I extend the gender-matching pool with lists of diverse baby names available at Pampers' website,[8] making it possible to identify the gender of nearly all managers. Then, I collect information on them manually. First, I verify and supplement the gender variable to ensure accuracy. In addition, I gather several manager features: their undergraduate and graduate institutions, whether they have an MBA, PhD or a CFA or similar designation,[9] as well as the year they started working in the finance industry and in a strategic position[10]. Morningstar provides brief biographical summaries of some fund managers on its website, which serve as the first point of reference. However, it is frequently sparse, fragmentary, or unavailable. Thus, I also draw on SEC filings, fund prospectuses and websites, university journals, yearbooks and reunion documents, obituaries, judicial records, Bloomberg biographies, as well as LinkedIn and Facebook profiles to create a comprehensive and unique dataset of mutual fund managers.[11]

Using these records, I construct manager-specific variables that capture the education and experience, hence enable comparability and accurate matching of individuals with similar attributes in the analysis. Specifically, I create an Ivy League degree dummy, that is 1 if the

[6] I exclude all fund-month observations for which more than one manager is listed. Furthermore, I omit time periods for each investment vehicle, where there is a reference for team management or where information on who is overseeing the fund is unavailable.

[7] https://www.ssa.gov

[8] https://www.pampers.com

[9] I classify CFA, CPA, CFP, CMT, CAIA, CIC, CTFA, CPFA, ChFC, CPCU, FRM, and AIF as "CFA or similar".

[10] A position is considered strategic if it involves decision-making authority or seniority, imposing greater responsibility on the jobholder. These primarily include supervisory, executive, and portfolio management roles.

[11] The fund manager data used in this study is an updated version of the dataset introduced by Csiky and Pichler (2025), covering a more recent period that offers richer coverage of manager-specific variables and a larger number of observable female managers, both supporting better matching quality.

manager obtained either an undergraduate or graduate degree (or both) from an Ivy League university, 0 otherwise. This variable is a proxy that could suggest superior performance due to higher quality of studies, robust social connections, hence privileged access to certain fund firms, or simply a preferable signal of augmented human capital to the employers. I also construct an MBA, as well as a PhD dummy, that equals 1 if the manager obtained the corresponding level of education, 0 otherwise. Similarly, I assign a CFA or similar dummy variable, that is 1 if the manager has such designation, 0 in other cases. The latter three variables are the measures of academic profile and specialized certificate of the managers. In particular, for all education-related variables, 0 represents both those who do not hold the specific qualification and those for which the information is missing. The reason for this approach is that during the hand-collection of data, the extent to which mutual fund managers (and their employers) preferred to demonstrate their credentials and achievements was remarkable, plausibly to signal their expertise to their current and future investors. Thus, I argue that this approach captures managers' academic achievements with considerable accuracy.[12] Industry and strategic experience of managers are computed as the years elapsed since they first obtained respective positions. Finally, tenure is calculated as the years since the manager began their mandate at the given fund, capturing specialized expertise.

2.2 Fund and Family Variables

To create a comprehensive panel, I retrieve share-class-specific static and monthly time series variables from Morningstar Direct for the 25-year sample period. The latter comprise return, net assets, and the annual net expense ratio. Flows are calculated following Sirri and Tufano (1998), and consolidated along with net assets to the fund level. To ensure uniqueness, I collapse the data to the oldest share class.

I construct variables that capture the *value* a fund offers to its family, drawing upon Gaspar et al. (2006). However, I extend their three metrics with an additional, core measure designed to proxy profitability. First, I compute net-of-style return, the main performance measure, as the difference between a fund's return and the value-weighted mean return of funds sharing the same style. Style is identified as the descriptive Morningstar Category, which assigns funds to

[12] As documented by Csiky and Pichler (2025), in terms of performance it matters more whether managers disclose their education than the reputation and type of degrees or certificates.

nine investment style groups, according to their portfolio holdings.[13] Fund age is the difference between a given date and the inception date of the fund's oldest share class. Fees are proxied by the net expense ratio, which Gaspar et al. (2006) associate with higher value, although high percentage fees may also erode returns. However, to capture the absolute *value added* by a fund to its firm – an attribute posited to be of superior importance by Berk and Van Binsbergen (2015) for instance – I introduce *fee income*, which is the product of net assets and the net expense ratio. That is, it measures the implied annual dollar revenue contribution of a fund to its family, given its contemporaneous monthly size, making it the principal value measure. Fundamentally, I posit that funds characterized by superior performance, younger age, or, most importantly, robust fee income, represent paramount value to their families.

According to Morningstar, Inc. (2026), branding name is a global umbrella of asset management companies with shared management philosophy, marketing, and distribution channels. Therefore, this is the primary definition of mutual fund family, also referred to as fund firm. However, in case the branding name is unobservable, I use the firm name[14] variable from Morningstar to identify the family. This hierarchical approach ensures broader coverage and hence a more comprehensive dataset to assess family-level strategies.

Family age is estimated as the years since the inception of the family's oldest fund in the sample. I proxy family size by summing up the net assets of funds belonging to the family in a given month, in the sample, yielding the variable family total net assets.

To identify ESG funds, I follow a two-step procedure, similar to Csiky et al. (2024). The first point of reference is the sustainable investment overall variable provided by Morningstar, which captures if the fund is considered to be a sustainable product according to its prospectus or different regulatory filings. I extend this list of investment vehicles by searching for strings in the fund names that refer to an ESG focus.[15]

[13] The Morningstar Categories are Large Value, Large Blend, Large Growth, Mid-Cap Value, Mid-Cap Blend, Mid-Cap Growth, Small Value, Small Blend, and Small Growth.

[14] Morningstar, Inc. (2026) defines firm name as a company which offers mutual funds, and is usually included in the fund name.

[15] The strings used to identify ESG funds are: Catholic, Church, Clean, Climate, ESG, Faith, Green, Impact, KLD, Social, SRI, CSR, Environ, Sustain, Responsib, Women, Woman, Female, Equality.

2.3 Sample and Descriptive Statistics

To ensure a representative, yet comprehensive sample, I apply a number of filters to the dataset. I exclude observations lacking return, manager, or fund family information, as these are required for meaningful empirical analysis. Similarly to Gaspar et al. (2006), I omit the first six months of a fund's lifetime. Moreover, I require a minimum of six return observations per year for each fund. In order to mitigate the influence of extreme outliers, I apply conservative winsorization on several of the time series variables at tailored thresholds.[16]

Ultimately, the sample (also referred to as *full sample*) includes 2,367 funds belonging to 543 families, overseen by 2,104 managers. However, there is a pronounced gender imbalance, with 214 female and 1,890 male managers. Considering that some of the analyses implicitly focus on fund families where allocation of (female) managers is possible, I also create a *female-represented family subsample*. This only features observations belonging to those firms that have at least two members, of which minimum one, but not all, are managed by a woman in a given month. Restricting the scope to these families enables carving out within-firm allocation patterns in the environments where a real "playing field" exists, making them more empirically distinct. The female-represented family subsample encompasses 1,189 funds of 100 firms employing 1,017 managers. By construction, the disparity in gender representation is attenuated, with 190 female and 827 male managers.

As depicted by Figure 1, despite the initial growth in the total number of mutual fund families in the early 2000s, there has been a continuous decline ever since. In particular, the number of fund firms nearly halved in the 25 years of the sample period, reflecting a strong pattern of consolidation in the institutional landscape. Although in a more monotonic way, the trend observable in female-represented families is similar, even in magnitude.[17] This tendency in both samples highlights the steady concentration of the mutual fund market in the hands of fewer, hence more influential families. Furthermore, the phenomenon underscores the importance of understanding fund firms' operation, particularly scrutinizing whether they engage in any systematic allocation of their managers.

Assessing the trajectory of female representation in mutual fund management in Figure 2, the

[16] To address the right-skewness of net assets and net expense ratio, I apply a moderate 0.1% upper-tail adjustment. For more volatile metrics, such as family total net assets and fund flows, I winsorize at the 1% and 99% levels, whereas for returns at the 0.1% and 99.9% thresholds to account for atypical observations or potential reporting errors.

[17] As the two lines in Figure 1 gradually converge, one may infer that surviving families could be predominantly the larger complexes with broader managerial pool, including females.

Figure 1: The Number of Mutual Fund Families over Time
This figure demonstrates the monthly number of mutual fund families with single-managed equity mutual funds for both the full sample and female-represented family subsample, from January 2000 to December 2024.

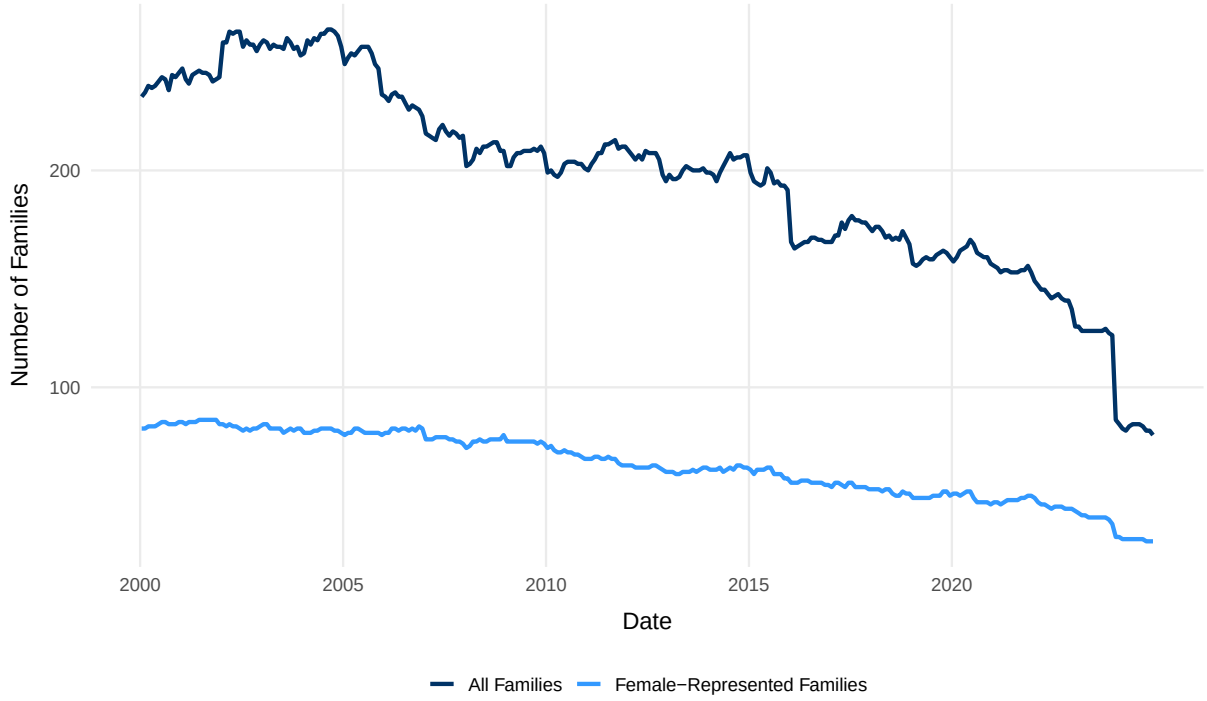
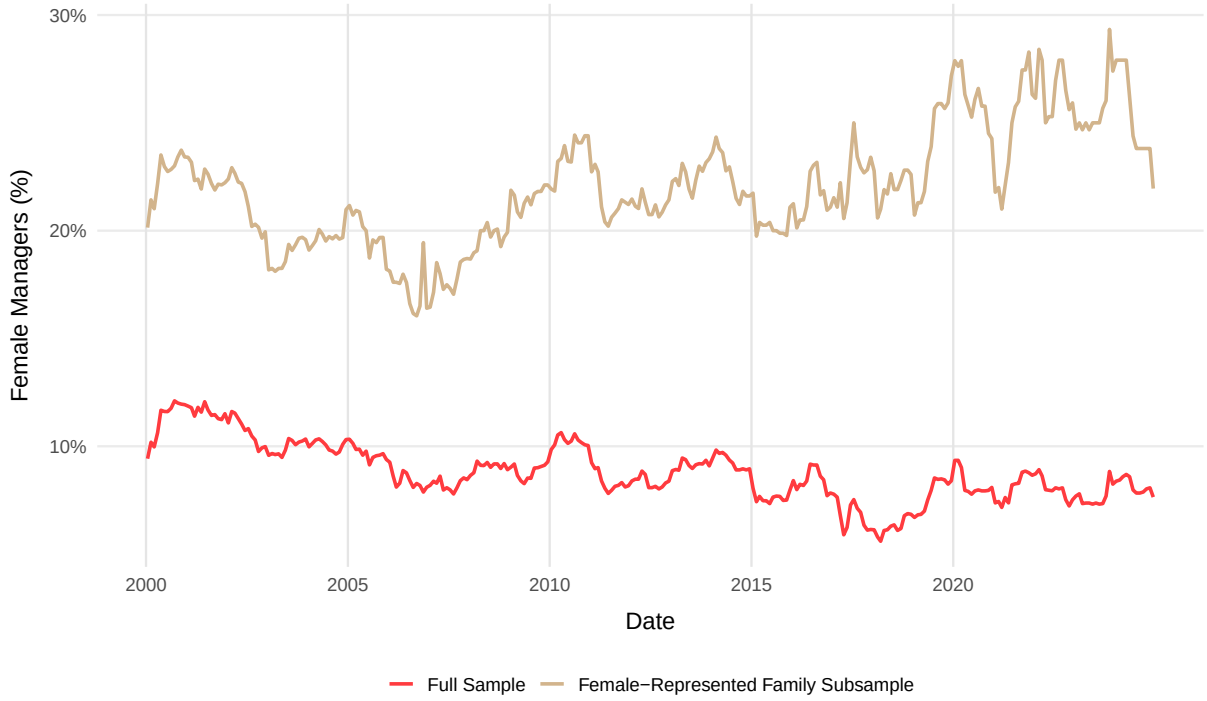


Figure 2: The Evolution of Female Representation in Equity Mutual Fund Management
This figure illustrates the trajectory of the monthly percentage of female equity mutual fund managers for both the full sample and female-represented family subsample, covering the period from January 2000 to December 2024.



persistently descending share of women in the full sample is salient. Despite a few increases, their percentage hardly surpassed 12% at its highest point. This trend, coupled with their modest 10.17% sample representation, is in stark contrast to the substantial and growing presence of women in other highly skilled and competitive professions (U.S. Bureau of Labor Statistics, 2025).[18] On the other hand, the case of female-represented families paints a vastly different picture, showcasing a more volatile but upward development in the representation of female managers, especially after 2007. Particularly, they exceeded 25% on several occasions following 2020 and account for 18.68% of managers in this subsample. The divergent paths of the full sample and the female-represented family subsample imply that manager gender diversity is increasing, yet concentrated in a specific subset of firms, whereas the rest remains entrenched in its historical imbalances. This contrast suggests that female-represented families could have some special features and motives to increase the employment of female managers.

To investigate whether there are systematic deviations in the characteristics of female and male managers or the funds they are in charge of, I compare these features in Table 1 by gender. After calculating the means of these variables for females and males, I take their difference and test whether they significantly differ from zero with p-values from t-tests, and to account for potential non-normal distributions, from Wilcoxon Rank-Sum tests. As reported in Panel A of Table 1, there are no significant differences in the proportion of female and male managers who obtained a degree in an Ivy League university, have an MBA, PhD, or CFA or similar, that is, their level and type of education are similar, on average. Although female fund managers have spent marginally fewer years (0.17) in the finance industry, they have slightly longer experience in strategic positions, implying they are at least as qualified as their male colleagues, on average. However, they tend to have 1.6 years shorter tenure at the given fund, suggesting higher turnover. Overall, education and experience are comparable across genders, so a lack of competence or credentials is unlikely to explain any adverse allocation of female managers. In spite of this, female-led funds' monthly mean returns, as well as net-of-style returns, significantly lag behind by 14 bp and 5 bp, respectively. Nonetheless, this could be affected by the higher percentage fees charged, which may erode performance. Although higher fees would suggest that female-managed funds are of higher value in the framework of Gaspar et al. (2006), as their investment vehicles are less than half the size of those managed by men, their mean fee income does not even reach 60% of the male contribution to family revenues. Together with their weaker performance, the significantly older age of women-led

[18] For perspective, in 2024, 57.2% of accountants and auditors, 42.7% of financial and investment analysts, 42% of lawyers, 38.8% of dentists, as well as 33% of chief executives were women, and their representation has been steadily climbing in the United States (U.S. Bureau of Labor Statistics, 2025).

Table 1: Univariate Comparison of Manager and Fund Characteristics by Gender
This table summarizes the mean manager characteristics (panel A) and mean fund attributes (panel B), both by manager gender in the sample. It also reports the p-values from t-tests and Wilcoxon Rank-Sum tests of the null hypothesis that the reported variables do not significantly differ across manager gender. Ivy League degree is a dummy variable that is 1 if the manager completed undergraduate and/or graduate studies at an Ivy League university, 0 otherwise. MBA is a dummy variable equal to 1 if the manager has an MBA, 0 otherwise. PhD is a dummy variable that takes the value 1 if the manager has a PhD, 0 otherwise. CFA or similar is a dummy variable that is 1 if the manager obtained the CFA or similar designation, 0 otherwise. Industry experience is measured as the years since the manager began their career in the finance industry. Strategy experience denotes the years since the manager first acquired a strategic position in the finance industry, such as a management or portfolio manager role. Manager tenure measures the number of years since the manager began managing a given fund. The return, net expense ratio, and net assets are acquired from Morningstar Direct. Net-of-style return is the difference between the return and the value-weighted mean return of the funds belonging to the same Morningstar Category. Fund age is measured as the years since the inception of the fund's oldest share class. Fee income is the product of the net expense ratio and net assets.

	Female	Male	Difference	p-value$_t$	p-value$_{WRS}$	N_{Female}	N_{Male}
Panel A: Manager Characteristics							
Ivy League degree (%)	24.30	22.22	2.08	0.50	0.49	214	1890
CFA or similar (%)	57.01	52.28	4.73	0.19	0.19	214	1890
MBA (%)	46.73	51.59	-4.86	0.18	0.18	214	1890
PhD (%)	4.21	3.49	0.71	0.62	0.59	214	1890
Industry experience (years)	23.46	23.63	-0.17	0.03	0.20	13684	135379
Strategy experience (years)	17.25	16.63	0.63	0.00	0.00	13332	133688
Manager tenure (years)	5.13	6.73	-1.60	0.00	0.00	14947	149360
Panel B: Fund Characteristics							
Return (%)	0.45	0.59	-0.14	0.00	0.01	14947	149360
Net-of-style return (%)	-0.06	-0.01	-0.05	0.00	0.00	14947	149360
Net expense ratio (%)	1.22	1.18	0.04	0.00	0.00	14947	149360
Net assets ($M)	822.54	1658.08	-835.54	0.00	0.81	14947	149360
Fund age (years)	15.43	14.26	1.17	0.00	0.00	14947	149360
Fee income ($M)	7.96	13.36	-5.40	0.00	0.00	14947	149360

funds also implies lower value in the Gaspar et al. (2006) sense. These patterns, particularly the substantial disparity in the value contribution to their firms, support the hypothesis of systematic allocation of female managers to lower-value funds.

Table 2: Univariate Comparison of Manager and Fund Characteristics by Gender in the Female-Represented Family Subsample

This table summarizes the mean manager characteristics (panel A) and mean fund attributes (panel B), both by manager gender in the female-represented family subsample. It also reports the p-values from t-tests and Wilcoxon Rank-Sum tests of the null hypothesis that the reported variables do not significantly differ across manager gender. Ivy League degree is a dummy variable that is 1 if the manager completed undergraduate and/or graduate studies at an Ivy League university, 0 otherwise. MBA is a dummy variable equal to 1 if the manager has an MBA, 0 otherwise. PhD is a dummy variable that takes the value 1 if the manager has a PhD, 0 otherwise. CFA or similar is a dummy variable that is 1 if the manager obtained the CFA or similar designation, 0 otherwise. Industry experience is measured as the years since the manager began their career in the finance industry. Strategy experience denotes the years since the manager first acquired a strategic position in the finance industry, such as a management or portfolio manager role. Manager tenure measures the number of years since the manager began managing a given fund. The return, net expense ratio, and net assets are acquired from Morningstar Direct. Net-of-style return is the difference between the return and the value-weighted mean return of the funds belonging to the same Morningstar Category. Fund age is measured as the years since the inception of the fund's oldest share class. Fee income is the product of the net expense ratio and net assets.

	Female	Male	Difference	p-value$_t$	p-value$_{WRS}$	N_{Female}	N_{Male}
Panel A: Manager Characteristics							
Ivy League degree (%)	25.79	27.69	-1.90	0.59	0.60	190	827
CFA or similar (%)	58.42	52.36	6.06	0.13	0.13	190	827
MBA (%)	45.79	58.28	-12.49	0.00	0.00	190	827
PhD (%)	3.68	3.39	0.30	0.84	0.84	190	827
Industry experience (years)	23.07	21.58	1.49	0.00	0.00	12524	46163
Strategy experience (years)	17.15	14.24	2.91	0.00	0.00	12247	44719
Manager tenure (years)	5.05	5.58	-0.53	0.00	0.00	13385	49936
Panel B: Fund Characteristics							
Return (%)	0.45	0.56	-0.11	0.03	0.03	13385	49936
Net-of-style return (%)	-0.04	0.04	-0.08	0.00	0.00	13385	49936
Net expense ratio (%)	1.16	1.01	0.15	0.00	0.00	13385	49936
Net assets ($M)	900.78	3028.85	-2128.08	0.00	0.00	13385	49936
Fund age (years)	15.38	15.15	0.23	0.10	0.00	13385	49936
Fee income ($M)	8.68	24.21	-15.53	0.00	0.00	13385	49936

The same univariate comparisons executed in the female-represented family subsample presented in Table 2 reveal more pronounced disparities. There are no significant differences in the percentage of female and male managers' educational attainments, except for the MBA, which nearly 13 percentage points more male managers hold. Female managers statistically significantly exceed their male counterparts in the mean years spent in the finance industry and in strategic positions; however, their slightly lower tenure persists in this subsample.

Pivoting to fund features, the gender gaps are even higher than in the full sample, with the exception of returns and fund age. In particular, the disparity in net expense ratios is more magnified. As men are responsible for funds with more than triple the net assets of their colleagues, the fee income provided by female-led investment vehicles hardly exceeds a third of that achieved by males. That is, despite similar credentials, the profit-generating capacity of female-led funds is markedly inferior compared to males in the female-represented firm subsample, reinforcing the possibility that female managers might be strategically allocated to funds of lower family value.

3 Results

This section outlines the empirical approaches used to assess indications of systematic allocation, its two channels, patterns of the phenomenon, and demonstrates the obtained results. First, it presents evidence of the assignment patterns of female managers to funds with lower profit-generating value for their families. Subsequently, it reports indications of gender-based systematic allocation in a matched-sample comparison of net-of-style returns and extends this framework with two exogenous shocks. Then, it turns to investor perception by examining the flow-performance relationship of female- and male-managed funds. Leveraging manager changes, it tests hypotheses of strategic placement and self-selection by comparing probabilities obtained from transition matrices. Finally, it explores the ESG aspect of the observed systematic allocation patterns.

3.1 Systematic Allocation of Female Managers to Low-Value Funds

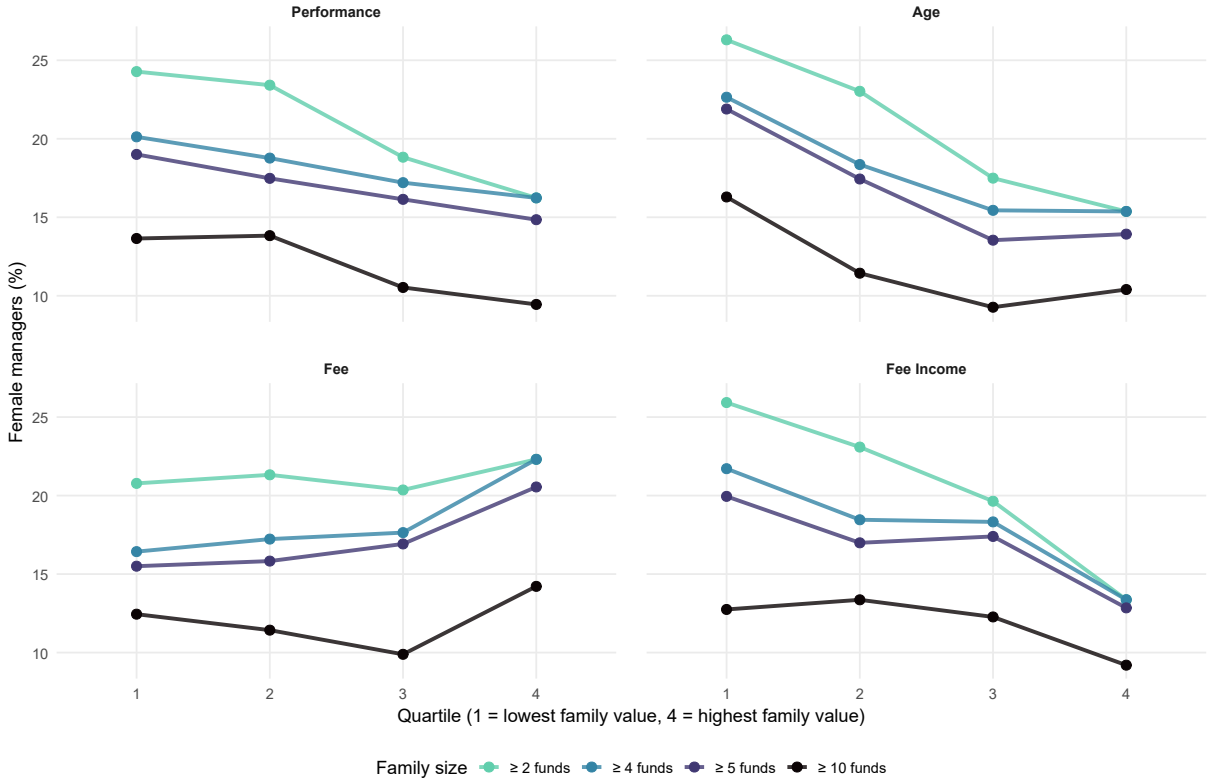
To investigate systematic allocation of female managers, I first assess whether they oversee low value mutual funds. Given the lack of considerable gender-based differences in education and experience among managers in the sample, consistent patterns of such assignment confirm the phenomenon and lay the foundation for further analysis. I define low value by the profit-generating power a fund has for its family, thus its significance to the firm. In this framework, value also reflects how advantageous the fund is for its manager. That is, a higher-value fund provides them with a better positioning for success, ensuring a possibility to earn more and improve their reputation, culminating in superior career advancement options.

I assess fund value along four dimensions. Following Gaspar et al. (2006), the first three variables are performance measured by year-to-date (YTD) return, fund age expressed in years, and percentage fees, gauged by the net expense ratio. However, since the definition of fund value is different in this paper and is primarily determined by the profit-generating potential of the investment vehicle, I introduce fee income as the main variable of interest. Calculated as the product of the monthly net assets and the annual net expense ratio, it proxies the implied proceeds of the fund for its family. The more fee income a fund generates, the higher value it has in this framework. As defined by Gaspar et al. (2006), higher performance, lower fund age, and higher percentage fees imply superior value, which I mainly follow. Nevertheless, the case of the latter is not as clear-cut in the analysis here.

Figure 3 depicts female portfolio manager representation patterns by fund value quartiles in families. To obtain a visual overview, I calculate the mean monthly percentage of female managers in each value-based quartile within their respective firms. These numbers are obtained in four subsamples based on family features. Naturally, a common restriction is that there has to be a minimum of one female fund manager in a given month. The most comprehensive sample includes families with at least two funds in each month, which is denoted with the lightest shade of blue. To capture the allocation of female managers in families with more funds – proxying bigger firms – I create subsamples including fund-month observations from families with a minimum 4, 5, and 10 funds, respectively.

For each value measure, the lowest quartile coincides with the lowest firm value, i.e., with the lowest performance, highest age, lowest fee and lowest fee income. Therefore, a steep downward slope indicates the systematic allocation of female managers to lower-value funds. Zooming in on the broadest subsample denoted with the lightest blue, I find such a pattern in the case of performance, age, and fee income. In particular, there are one and a half times more women managing funds with the lowest YTD return than in the top-performing ones, and their presence is showing a diminishing pattern in the second and third quartiles. The disparity is even more evident in the case of fund age, with 1.7 times more females leading the oldest funds than the ones belonging to the youngest quartile. Nevertheless, percentage fees exhibit a flat but slightly upward trend with 1.5 percentage points more female managers overseeing the most expensive funds than the ones in the cheapest quartile. This, in the framework of Gaspar et al. (2006), would mean that women are allocated to higher-value funds. However, I argue that higher percentage fees could have an adverse effect on fund value by eroding returns, as well as potentially impeding raising capital by deterring investors who may prefer cheaper options. The systematic allocation pattern is the most pronounced in the case of fee income, confirming

Figure 3: Female Representation Patterns by Value Quartiles in Fund Families
This figure demonstrates the mean monthly percentage of solo female managers across value-based quartiles within their respective fund families. The value variables are performance (YTD Return), fund age, fee (net expense ratio), and fee income (the product of net expense ratio and net assets). The first quartiles offer the lowest firm value, which in case of performance, fee, and fee income coincide with the lowest numerical values, whereas for fund age, it contains the oldest funds. Increasingly darker shades of blue represent more restrictive subsamples with a minimum of 2, 4, 5, and 10 single-managed equity funds per family, respectively.



that despite the trend indicated by the expense ratios, female-led funds generate substantially lower dollar revenues for their families. In particular, female managers are nearly twice as prevalent among funds in the lowest fee income quartile as among those in the highest. This stark contrast supports the hypothesis that they are systematically allocated to funds with inferior revenue-generating potential, a disparity that could be exacerbated by older age and higher percentage fees that dampen investor attention and inherently deter capital inflows.

After establishing visual evidence of systematic assignment of female managers in the broadest subsample, I investigate the pattern by fund family size. Figure 3 depicts the results obtained in samples restricted to fund families with a minimum of 4, 5, and 10 funds, denoted by gradually darker shades of blue. The more restrictive the subsample, the more muted the systematic allocation patterns become in the case of performance, age, and fee income, as indicated by the flatter slopes. That is, firms with more single-managed equity funds allocate women less actively to lower-value investment vehicles of this type. Although this does not rule out that these firms simply tend to assign their female managers to teams or to funds incorporating other asset classes, it is also consistent with the premise that larger families likely have more diverse stakeholder bases, exposing them to heightened institutional scrutiny, motivating them to prioritize and formalize their diversity and inclusion practices. It would also be in line with strategic placement as a mechanism, seemingly more prevalent in smaller families. That is, to match industry standards, they would hire and assign female managers to funds with lower profit-generating value, hence lower stakes. Such practice would coincide with the window dressing of diversity, as well as with the glass cliff hypothesis proposed by Ryan and Haslam (2005). The latter refers to the practice of women achieving leadership positions in precarious situations, which the authors documented for board appointments at FTSE 100 companies.[19] This paper's findings on systematic allocation are similar in the sense that older funds with weaker performance and less profit-generating power are less desirable and exhibit limited upside potential. Consequently, this mechanism could contribute to the 1.6-year gap in mean tenure between female and male managers in the dataset.

Although Figure 3 provides compelling visual support of the adverse systematic allocation of female fund managers, it does not account for the joint variation of the value measures or for the time-invariant differences across families. Thus, to evaluate how the value-generating

[19]The glass cliff has been documented across organizational, political, and legal settings following its introduction. For a review of the evidence and explanations, see Ryan et al. (2016).

metrics relate to manager gender, I estimate the following baseline logit model:

$$\begin{aligned} &Logit(P(\text{Gender}_{i,f,t} = 1)) = \\ &\quad \alpha + \beta_1 \text{Return}_{i,f,t} + \beta_2 \text{Age}_{i,f,t} + \beta_3 \text{NER}_{i,f,t} + \beta_4 \text{Fee income}_{i,f,t} \end{aligned} \tag{1}$$

where the $Logit(P)$ function denotes the natural logarithm of the odds ($\ln(\frac{P}{1-P})$). Hence, in this specification, $P(\text{Gender}_{i,f,t} = 1)$ denotes the probability that the manager of fund i, belonging to family f at time t is female. $\text{Return}_{i,f,t}$ is measured in percentage points. The fund's $\text{Age}_{i,f,t}$ is in years, whereas the net expense ratio, denoted by $\text{NER}_{i,f,t}$ is in percentage points. Fee $\text{income}_{i,f,t}$ is the product of the net expense ratio and net assets, and is measured in USD millions. The model also incorporates month fixed effects to absorb aggregate market trends, as well as family fixed effects to account for time-invariant firm-level characteristics, such as corporate culture. Importantly, due to the family fixed effects, the coefficients are identified from variation across funds within the same family, that is, they compare the funds led by women with those led by men in the same family. Families without female managers therefore do not contribute to the estimation. To mitigate potential serial correlation and heteroskedasticity, standard errors are double-clustered at the month and fund family level and are transformed via the delta-method. Finally, although the model is expressed in terms of log-odds, I report the exponentiated coefficients (e^{β}), i.e., the odds ratios in Table 3.

In Table 3, Model (1) includes all independent variables, whereas Model (2) omits the net expense ratio to account for its potential multicollinearity with the fee income. Nevertheless, it barely affects the results exhibited by the main variables of interest. The odds ratios confirm that female fund managers are more likely to lead funds that are older, have subpar performance, and despite charging higher expense ratios, collect inferior fee income. That is, women manage lower-value funds within their families. This confirms both the visual results demonstrated in Figure 3 and the existence of systematic allocation of female managers to less advantageous investment vehicles. Whether this allocation translates into performance differences, and whether it stems from strategic placement by families or self-selection by managers, is examined in the following sections.

Table 3: Fund Family Value Perspectives of Female Manager Allocation
This table reports odds ratios (e^{β}) from logit regressions of gender on variables measuring value-generating capacity of funds to their families. The regression equation used to obtain the estimated coefficients of Model (1) is:

$$Logit(P(\text{Gender}_{i,f,t} = 1)) = \alpha + \beta_1 \text{Return}_{i,f,t} + \beta_2 \text{Age}_{i,f,t} + \beta_3 \text{NER}_{i,f,t} + \beta_4 \text{Fee income}_{i,f,t} + \epsilon_{i,f,t},$$

where Gender is a binary indicator variable that equals 1 if a fund is managed by a female, 0 otherwise. Return and net expense ratio are measured in percentage points, age (denoting fund age) in years. Fee income is the product of the net expense ratio and the monthly net assets, and is measured in USD millions. Model (2) omits the net expense ratio as an independent variable. Observations are fund-months. In each estimation, month and family fixed effects are included. Standard errors, reported in parentheses, are double-clustered at the month and fund family level and are transformed by the delta method. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Gender	
	(1)	(2)
Return	0.989*	0.989*
	(0.006)	(0.006)
Age	1.015**	1.015**
	(0.006)	(0.006)
Net expense ratio	1.547*	
	(0.394)	
Fee income	0.989**	0.988**
	(0.005)	(0.005)
Month FE	Yes	Yes
Family FE	Yes	Yes
Observations	98,989	98,989
Within R^2	0.158	0.155

3.2 Matched Sample Analysis of Performance

One might argue that returns are a function of both managerial skill and fund attributes, hence they may not be the strongest indicator of disadvantageous systematic allocation. However, a framework comparing gender-based performance differentials facilitates isolating family-level assignment effects from the confounding skill aspect. In particular, I compare female-managed mutual fund returns to male-managed ones, distinguishing between same-family peers and out-of-family matched counterparts. This approach treats male-managed fund performance as benchmarks and enables me to determine the positioning of women within families by investigating their relative net-of-style returns.

The approach is inspired by Gaspar et al. (2006); however, it is tailored to the research question of this paper. First, I pair each female manager with all male managers within her family, regardless of their credentials. These within-family pairs capture the relative positioning of women within their family, compared to any male colleague. Second, for each female manager and month, I find a matching male manager from another family with very similar credentials and experience. Specifically, I identify out-of-family male matches by requiring exact correspondence across MBA, PhD, CFA, and Ivy League degree reports, ultimately selecting the manager with the smallest difference in years spent in the finance industry.[20] Importantly, I require the out-of-family male match to come from a fund family that has no female managers at the given time, preventing the possibility of systematic allocation strategies in their family.[21] Thus, the out-of-family males represent professional credential-matched performance benchmarks in the absence of allocation strategies. That is, the funds they oversee, hence the performance they achieve, indicate what a comparable female manager could achieve under such conditions.

Then, I calculate female-male net-of-style return differentials for both the case when the male is in the same fund family as the female, and when he comes from a different one. As the matched male managers have similar credentials and experience, based on their skills

[20] I use a two-stage approach that is both theory-driven and data-validated to select the matching variables. First, I consider human resources aspects, suggesting that managerial assignment is affected by their educational levels, prestige, and experience. Second, I apply a LASSO regression on relative ranks of the candidate variables to obtain the ones with the most effect on fund net-of-style returns, while accounting for the panel data structure.

[21] Due to the sample selection, technically what I restrict is that there are no other female single-managers. It is indeed possible that the families employ women in management teams or as solo managers of funds with other asset class in focus. However, in the single-managed equity fund territory these fund firms are unable to engage in gender-based systematic allocation.

and knowledge, they should be overseeing likewise favorable funds and achieve comparable performance. Therefore, in the absence of gender-based systematic allocation, the female-male return differentials when the male is from the same family and when he is not, should be the same. However, if women are systematically assigned inferior funds relative to any male within the same family, female-managed funds will perform worse relative to their in-family peers than relative to their out-of-family matches. That is, female-male return gaps calculated with in-family peers falling below (i.e. less favorable than) those calculated with out-of-family matched males indicate adverse gender-based systematic allocation. If, instead, female managers underperformed both benchmarks to a similar extent, the gap would rather reflect differences in managerial skill, and assigning them to lower-value funds would be consistent with skill-based allocation (Fang et al., 2014).

3.2.1 Univariate Matched Sample Analysis

Table 4 presents the univariate comparison of mean female-male net-of-style return spreads, relative to same-family male peers and out-of-family matched managers. In the full sample, female-led funds underperform male-overseen ones by 10 bp monthly within their families, whereas their net-of-style return, on average, exceeds that of the out-of-family males by 1 bp, and the deviation between the two gaps is statistically significant. That is, 1.31% annual underperformance of female managers could be attributed to their systematic allocation to unfavorable mutual funds. Meanwhile, relative to comparable men outside their family, female managers do not underperform, suggesting that their lag reflects their position within the family rather than inferior skill.

To investigate the temporal dynamics of the phenomenon, I partition the sample into five-year subperiods. The 2000-2004 period is characterized by a stark, 13 bp relative underperformance of females within their families. During the 2005-2009 period, which encompasses the global financial crisis, female managers exhibited superior performance compared to both male cohorts. However, their advantage was less pronounced against in-family peers, resulting in a -17 bp monthly allocation-attributable gap. It is followed by the only five-year period without significant deviation in the net-of-style gaps calculated with different male-managed funds. Nevertheless, the most notable are the 2015-2019 and 2020-2024 periods. During these times, while female managers lagged behind their male peers by 5 bp monthly within their own families, on average, they simultaneously outperformed male managers by 5 bp and 10 bp, respectively. That is, the systematic allocation indicated by the intra-family performance

penalty persists in nearly all five-year subsamples, remaining sizeable in the most recent period. This consistency over time indicates that the phenomenon is not an artifact of market shocks such as the global financial crisis or the COVID-19 pandemic but a structural feature of the industry.

Table 4: Univariate Matched Sample Performance Gap
This table reports mean net-of-style return differentials in percentage points, between female and male mutual fund managers for the full sample and five-year sub-periods. These spreads are constructed using two comparison groups: male managers within the same fund family as the female *(Same Family Male)* and male managers from other fund families, which do not have female solo equity fund managers *(Out-of-Family Male)*. The table also reports p-values from t-tests with the null hypothesis of no difference in means between the return gaps calculated with same-family and out-of-family male managers.

Period	Mean *(Same Family Male)*	Mean *(Out-of-Family Male)*	p-value
2000–2024	-0.10	0.01	0.00
2000–2004	-0.24	-0.11	0.04
2005–2009	0.02	0.19	0.00
2010–2014	-0.09	-0.05	0.28
2015–2019	-0.05	0.05	0.06
2020–2024	-0.05	0.10	0.07

3.2.2 Matched Sample Regression Framework

To confirm the univariate results, I also employ a multivariate regression framework with fund and year fixed effects, controlling for observable structural characteristics and unobserved heterogeneity across both funds and time. I estimate the following specification:

$$\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta \text{Same family}_{i,j} + \zeta \text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t}, \quad (2)$$

where $\text{Net return}^{F}_{i,t}$ is the net-of-style return of a female-managed fund i in month t, and $\text{Net return}^{M}_{j,t}$ is the corresponding net-of-style return of its paired male-managed fund j in month t. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. Controls include the net expense ratio, size, and age of both the female- and paired male-managed funds, as well as the size and age of their respective fund families.

Table 5 summarizes the estimates of Equation (2). As reported in Model (1), without controls I document a 9.4 bp monthly within-family female underperformance attributable to systematic

allocation effects to unfavorable funds. Crucially, incorporating fund- and family-specific controls in Model (2) leaves this penalty virtually unchanged at 9.9 bp per month.[22] Hence, the within-family penalty is not explained by observable fund and family characteristics, and is consistent with the allocation of female managers to less favorable funds. The observed 1.2% annual within-family underperformance due to allocation effects is not only substantial, but also unaffected by whether females manage the same style as the paired male peer.

Table 5: Matched Sample Regression Tests of Systematic Allocation
This table reports the estimates of net-of-style return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables. The coefficients are obtained from the following specification:

$$\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta \text{Same family}_{i,j} + \zeta \text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},$$

where $\text{Net return}^{F}_{i,t}$ is the net-of-style return of a female-managed fund i in month t, and $\text{Net return}^{M}_{j,t}$ is the corresponding net-of-style return of its matched male-managed fund j in month t. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. Model (1) is estimated with year and fund fixed effects. Model (2) extends the specification with controls for the fees, size and age of both the female and male-managed funds, as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month. Heteroskedasticity-robust standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Net-of-Style Return Differential	
	(1)	(2)
Same family	-0.094^{***}	-0.099^{***}
	(0.028)	(0.032)
Same style	-0.019	-0.014
	(0.020)	(0.020)
Controls	No	Yes
Year FE	Yes	Yes
Fund FE	Yes	Yes
Observations	128,310	128,310
R^2	0.028	0.029

3.2.3 The Impact of the #MeToo Movement on Systematic Allocation

#MeToo is a global social movement to raise awareness about sexual harassment and abuse. It went viral following the tweet of actress Alyssa Milano on October 15, 2017, after The New York Times and The New Yorker published articles earlier the same month about severe misconduct

[22]The detailed effect of the controls is reported in Table A-2 of the Appendix.

allegations against Harvey Weinstein. The originally online movement had a profound societal impact, pressuring corporate cultures to promote gender equality within firms, also in the finance industry.

Therefore, the #MeToo movement is an exogenous shock that enhances reputational risk if firms do not respond to the new societal norms by shifting their incentives. Its timing was determined by events outside the asset management industry and is thus unrelated to the prior performance of individual funds or the past allocation decisions of fund families. Particularly, it creates a diversity pressure that firms need to respond to in order to avoid biased or homogeneous demographic representation. In the case of fund families, this may result in a strategic imperative to hire female managers to increase their representation and hence boost overall diversity, or at least to promote them to positions with higher responsibility, such as solo-manager of an equity mutual fund. Although this incentive alone should enhance the status of female managers, what might remain hidden from the public and investors at a first glance is which funds they are assigned to. That is, these could be funds that are low value, hence at lower stakes with less visibility.

This setting allows me to distinguish the two channels of systematic allocation, as they yield opposing predictions. If it stems from strategic placement, families facing pressure to visibly increase female representation at low cost would place women on less promising funds, widening the within-family gap after October 2017. If instead it arises from self-selection, the movement should not worsen the gap, as it is highly unlikely that in an environment that appears favorable and supportive for their career advancement, female managers willingly start to choose more disadvantageous positions. Moreover, the matched design separates a family-level response from other changes. If the movement affected the skill, effort, or investor perception of female managers in general, for instance through the productivity increase documented by Cici et al. (2021), it would also shift their performance relative to comparable men outside their family, whose families employ no solo female managers and thus have no allocation to adjust. Hence, a widening of the within-family gap without a corresponding change in the out-of-family gap points to strategic placement by fund families.

$$\begin{aligned}\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta\text{Same family}_{i,j} + \gamma(\text{Same family}_{i,j} \times MT_t) \\ + \delta MT_t + \zeta\text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},\end{aligned} \tag{3}$$

where MT_t is a dummy variable that is 1 for the post-October 2017 period, i.e., following

the onset of the #MeToo movement, 0 otherwise. The coefficient of main interest is γ, which captures the estimate of how the intra-family systematic allocation penalty changes following the #MeToo movement. All other variables and controls remain as defined in Equation (2).

Table 6 presents the estimates of Equation (3), where Model (1) excludes controls and Model (2) includes them, both supporting the previous results on systematic allocation effects. The interaction term (Same family$_{i,j} \times MT_t$) is negative and statistically significant, indicating that the within-family underperformance of female managers worsened by over 14 bp monthly after October 2017. With controls, the within-family penalty before the movement is negative but not statistically significant, suggesting that the deterioration is concentrated in the post-movement period. As the Post-#MeToo coefficient, capturing the change in the gap relative to out-of-family matches, is insignificant, the observed internal penalty appears to be an outcome of assignment patterns rather than a general change in female managers' relative performance.[23] These results support that strategic placement is the primary mechanism behind the phenomenon. Furthermore, the findings indicate that intense diversity pressures, such as the #MeToo movement, could ultimately have an adverse effect on female managers within their firms. That is, diversity actions of fund families could amount to window dressing to meet societal expectations. These results might appear to contradict Cici et al. (2021), reporting that the productivity of female mutual fund managers increased after the onset of the #MeToo movement. However, these dynamics are not mutually exclusive. It is indeed possible that while the absolute performance of female managers improved during this period, their relative achievements within their families significantly deteriorated.

3.2.4 The Impact of the California Women on Boards Mandate on Systematic Allocation

California was the first state in the U.S. that not only supported more balanced gender representation in corporate boards, but also signed it into law. SB 826 (also known as Women on Boards) required all publicly held corporations whose principal executive offices are located in the state to have at least one female director on their boards by December 31, 2019. This had to be executed either by filling an open seat or adding one. Furthermore, by the end of 2021, these firms had to have a minimum number of female directors determined by the size of their

[23] Figure A-1 in the Appendix shows no differential trend in the within-family penalty prior to the movement.

Table 6: Systematic Allocation amid the #MeToo Movement

This table reports the estimates of net-of-style return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables, including an indicator capturing the months after the beginning of the #MeToo movement. The coefficients are obtained from the following specification:

$$\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta \text{Same family}_{i,j} + \gamma \text{Same family}_{i,j} \times MT_t + \delta MT_t + \zeta \text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},$$

where Net return$^{F}_{i,t}$ is the net-of-style return of a female-managed fund i in month t, and Net return$^{M}_{j,t}$ is the corresponding net-of-style return of its matched male-managed fund j in month t. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. MT_t is a dummy variable that is 1 for the post-October 2017 period, i.e., following the onset of the #MeToo movement. Model (1) is estimated with year and fund fixed effects. Model (2) extends the specification with controls for the fees, size and age of both the female and male-managed funds, as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month. Fund family clustered standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Net-of-Style Return Differential	
	(1)	(2)
Same family	-0.075^{**}	-0.076
	(0.037)	(0.050)
Same family × Post-MeToo	-0.142^{**}	-0.162^{***}
	(0.057)	(0.061)
Post-MeToo	0.279	0.259
	(0.241)	(0.234)
Same style	-0.018	-0.013
	(0.020)	(0.021)
Controls	No	Yes
Year FE	Yes	Yes
Fund FE	Yes	Yes
Observations	128,310	128,310
R^2	0.028	0.029

board.[24] Fund families organized as, or owned by, publicly held corporations headquartered in California were thus directly subject to the mandate, while privately held fund firms in the state faced heightened regional scrutiny regarding gender diversity.

Thus, the Women on Boards mandate is an exogenous policy shock to the governance of fund firms, which allows a test of how it affected the systematic allocation of female managers and its main channel. Its timing was set by the state legislature and is unrelated to the prior performance or allocation decisions of fund families. Although boards do not directly assign managers, their oversight of senior management and firm-level policies could induce a spillover effect that indirectly shapes the position of women in fund firms. The two channels of systematic allocation yield different predictions. If it stems from strategic placement, a governance change that increases female representation and accountability at the top of the firm should constrain such practices and narrow the within-family gap at California fund firms. If instead it arises from self-selection, a mandate targeting corporate boards should leave the preferences of female managers largely unaffected, and the gap should not change. Nevertheless, the possibility cannot be excluded that female directors also act as role models, encouraging female managers not to self-select into less promising funds. To assess these effects, I extend Equation (2) with triple and double interaction terms, accounting for the firms headquartered in California and the time period after SB 826 came into force. That is, I estimate the following specification:

$$\begin{aligned}\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta\text{Same family}_{i,j} + \gamma(\text{Same family}_{i,j} \times CA_i \times P_t) \\ + \text{Interactions} + \zeta\text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},\end{aligned} \tag{4}$$

where CA_i is a dummy variable equal to 1 if the fund firm of the female manager is headquartered in California, 0 otherwise, and P_t is a dummy variable that is 1 in the months after and including January 2019, 0 before. Interactions comprise all lower-order terms of the triple interaction. All other variables and controls remain as defined in Equation (2). Since the mandate coincides with the aftermath of the #MeToo movement, comparing California-headquartered firms with those in other states, which were equally exposed to the movement, nets out its effect, as well as any other nationwide trends. As presented in Table 7, SB 826 significantly mitigated systematic allocation effects in California. That is, in this state, the within-family performance gap of female managers narrowed by a significant 48.7

[24] In May 2022, the Los Angeles Superior Court ruled SB 826 unconstitutional (*Crest v. Padilla*). As board compositions adopted before the ruling are unlikely to have reversed immediately, the post-period extends through the end of the sample.

bp monthly relative to the counterfactual, leaving a post-mandate within-family disadvantage of 28.2 bp per month.[25] At the same time, the relative performance of female managers at California firms compared to their out-of-family matches weakened by an even more considerable extent. Thus, the narrowing stems from the diminishing advantage of their in-family male peers rather than an improvement in the performance of female managers, consistent with a more balanced allocation of favorable funds within these families after the mandate. This supports that the main mechanism of the systematic allocation effect is strategic placement, although self-selection cannot be completely ruled out either.

While the baseline allocation penalty is observable nationwide, the within-family gap was larger in California before the mandate. The post-mandate improvement may therefore partially reflect convergence. Nevertheless, its timing points to the regulatory shock as a driver of this adjustment. In contrast, the within-family gap widened in other states over the same period, suggesting that the narrowing in California reflects the mandate rather than a nationwide trend.

[25] As a caveat, the magnitude of this coefficient is likely influenced by the limited number of California-headquartered firms with female managers in the sample.

Table 7: Systematic Allocation and Women on Boards Mandate of California
This table reports the estimates of monthly net-of-style return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables, using a triple-difference (DDD) specification. In the DDD model, treated funds are the ones belonging to a California-headquartered firm and the post-treatment period begins in 2019 to capture the effect of the Women on Boards (SB 826) gender mandate. The coefficients are obtained from the following specification:

$$\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta \text{Same family}_{i,j} + \gamma(\text{Same family}_{i,j} \times CA_i \times P_t) + \text{Interactions} + \zeta \text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},$$

where $\text{Net return}^{F}_{i,t}$ is the net-of-style return of a female-managed fund i in month t, and $\text{Net return}^{M}_{j,t}$ is the corresponding net-of-style return of its matched male-managed fund j in month t. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. CA_i is a dummy variable equal to 1 if the fund belongs to a California-headquartered firm, 0 otherwise. P_t is a dummy equal to 1 for the period starting in 2019. "Interactions" includes the baseline double-interaction terms ($\text{Same family}_{i,j} \times CA_i$, $\text{Same family}_{i,j} \times P_t$, and $CA_i \times P_t$), Model (1) includes fund and year fixed effects. Model (2) extends the specification with controls for the fees, size and age of both the female- and male-managed funds, as well as the size and age of their respective fund families. The baseline CA and Post-SB826 effects are absorbed by the fund and year fixed effects, respectively. The unit of observation is female-male managed fund-pair month. Fund family clustered standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Net-of-Style Return Differential	
	(1)	(2)
Same family	−0.127*	−0.157**
	(0.074)	(0.077)
Same family × CA × Post-SB826	0.668***	0.487**
	(0.207)	(0.206)
Same family × CA	−0.367*	−0.352*
	(0.203)	(0.196)
Same family × Post-SB826	−0.223*	−0.260**
	(0.120)	(0.121)
CA × Post-SB826	−0.935***	−0.877***
	(0.238)	(0.268)
Same style	−0.001	−0.008
	(0.011)	(0.011)
Controls	No	Yes
Year FE	Yes	Yes
Fund FE	Yes	Yes
Observations	128,310	128,310
R^2	0.044	0.046

3.3 Flow-Performance Relationship

To investigate the perspective and role of investors in systematic allocation, I examine the flow-performance relationship of mutual funds by manager gender. To provide a visual overview, I sort mutual funds into quartiles according to their net-of-style return in the month $t-1$. Then, for each gender and performance quartile, Figure 4 illustrates their subsequent mean percentage flows in month t. Regardless of manager gender, the plots support the convex relationship of fund returns and flows, documented in numerous studies (see, for instance, Spitz, 1970; Smith, 1978; Goetzmann and Peles, 1997; Sirri and Tufano, 1998; Fant and O'Neal, 2000; Huang et al., 2007; Niessen-Ruenzi and Ruenzi, 2019). That is, whereas investors seem to highly reward outstanding performance, they do not punish poor net-of-style returns to the same extent. In particular, there is a striking asymmetry in how investors respond to the performance of female- and male-managed funds, especially in the "penalty" aspect. Whereas male-led investment vehicles experience outflows, female-overseen funds still attract mild inflows according to Figure 4. Nevertheless, while being in the second performance quartile leads to similar inflows across genders, belonging to the third quartile is visibly more rewarded for male-led funds. Both this and the asymmetry in investor response for lowest-quartile performance are consistent with less investor attention and reaction toward female managers (see, e.g., Rau and Wang, 2022). However, in the case of outstanding net-of-style returns, women appear to be rewarded with slightly higher percentage inflows.

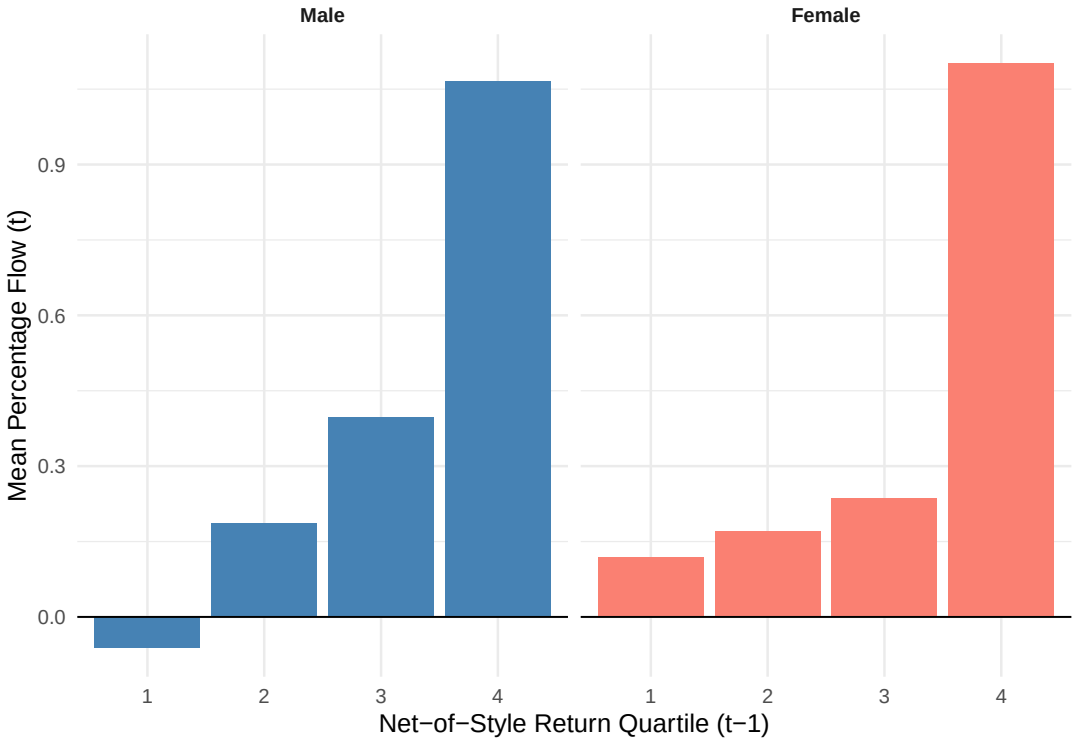
To formalize the visual intuition and test whether investors evaluate female and male mutual fund managers differently, I estimate the following specification:

$$\begin{aligned}\text{Flow}_{i,t} = \alpha &+\beta_G \text{Gender}_{i,t} + \beta_L \text{Low}_{i,t-1} + \beta_H \text{High}_{i,t-1} \\ &+\delta_L(\text{Low}_{i,t-1} \times \text{Gender}_{i,t}) + \delta_H(\text{High}_{i,t-1} \times \text{Gender}_{i,t}) \\ &+\gamma_1 \text{Log}(\text{Net assets})_{i,t-1} + \gamma_2 \text{NER}_{i,t} + \gamma_3 \text{Age}_{i,t} + \epsilon_{i,t},\end{aligned} \tag{5}$$

where $\text{Flow}_{i,t}$ is the percentage flow of fund i in month t. $\text{Gender}_{i,t}$ is a dummy variable equal to 1 if in month t fund i is managed by a female, 0 otherwise. $\text{Low}_{i,t-1}$ ($\text{High}_{i,t-1}$) is a dummy variable equal to 1 if fund i in month $t-1$ falls into the lowest (highest) net-of-style return quartile, 0 otherwise. By interacting the manager's gender with the indicator variables for outstanding and poor performance, the model isolates whether female managers are associated with different investor treatment, reflected by the flows.

As confirmed by the estimates presented in Table 8, investors indeed chase past performance,

Figure 4: Flow-Performance Relationship by Manager Gender
This figure illustrates the relationship between lagged fund performance and subsequent flows, partitioned by manager gender. Funds are sorted into quartiles according to their monthly net-of-style return in month $t-1$. For each gender and performance quartile, the mean percentage flow in month t is calculated and depicted by the bars. The left panel (blue) and right panel (salmon) represent male-managed and female-managed fund-months, respectively.



yet punish poor net-of-style returns significantly less. The reward of belonging to the top performance quartile is 0.705 percentage points additional flow monthly, about two-thirds larger in absolute terms than the penalty for being in the bottom quartile. That is, the results suggest a convex flow-performance relationship. The interaction term estimates reveal that investor flow response is strikingly asymmetric to extreme performance by manager gender. Whereas female-led funds receive similar flows following top-tier performance, in the case of belonging to the bottom tier their flows are 0.273 percentage points higher than those of males, offsetting about two-thirds of the bottom-tier penalty of -0.421 percentage points. These findings suggest that female-managed funds have a shielding or safety net effect, experiencing a substantially weaker investor punishment for poor performance, on average. This could be either due to attenuated investor focus on female managers (see, e.g., Rau and Wang, 2022), or due to the attributes of the investment vehicle. A particular case of the latter is if a higher proportion of the female-managed funds are ESG-focused, as their investors have stronger loyalty (Bollen, 2007) and less sensitivity to returns (Benson and Humphrey, 2008; Albuquerque et al., 2023). One may also argue that the asymmetric performance-flow relationship between genders stems from the characteristics of the funds they are allocated to. Although this possibility cannot be excluded, to alleviate such effects, I control for the size, fees, and age of the funds and find an inverse relationship with flows for each of the variables.

Nevertheless, female managers do not collect significantly lower flows on average, and their funds are also more protected from investment withdrawals in the case of poor performance. As profit-maximizing entities, fund families earn fees on their assets under management; hence, smaller outflows after poor performance preserve the revenues of funds predisposed to underperform. These correlational observations suggest that female managers are suitable candidates to lead the investment vehicles that provide lower value to their fund families. Consequently, this analysis supports that the observed systematic allocation patterns are primarily driven by strategic placement strategies of fund firms. However, since the observed flow-performance relationship secures some convenience and a safety net of minimal punishment of investment withdrawal in response to lagging returns, it could also encourage female managers to self-select themselves into the less promising funds. Such mechanism is consistent with Ludwig et al. (2017), reporting that women shy away from competition and demanding jobs, as these require demonstrating confidence in one's ability, and they avoid the shame arising from potentially overestimating themselves.

Table 8: Analysis of the Flow-Performance Relationship by Manager Gender
This table reports the estimates of fund flows regressed on manager gender, previous month's low and high performance quartiles, their interactions, as well as fund characteristics. The coefficients are obtained from the following specification:

$$\begin{aligned}\text{Flow}_{i,t} = \alpha &+\beta_G \text{Gender}_{i,t} + \beta_L \text{Low}_{i,t-1} + \beta_H \text{High}_{i,t-1} \\ &+\delta_L(\text{Low}_{i,t-1} \times \text{Gender}_{i,t}) + \delta_H(\text{High}_{i,t-1} \times \text{Gender}_{i,t}) \\ &+\gamma_1 \text{Log(Net assets)}_{i,t-1} + \gamma_2 \text{NER}_{i,t} + \gamma_3 \text{Age}_{i,t} + \epsilon_{i,t},\end{aligned}$$

where $\text{Flow}_{i,t}$ is the percentage flow of fund i in month t. $\text{Gender}_{i,t}$ is a dummy variable equal to 1 if in month t fund i is managed by a woman, 0 otherwise. $\text{Low}_{i,t-1}$ ($\text{High}_{i,t-1}$) is a dummy variable equal to 1 if fund i in month $t-1$ falls into the lowest (highest) net-of-style return quartile, 0 otherwise. Lagged Net assets are in dollar terms, NER denotes the percentage net expense ratio, and the Age of funds is measured in years. The estimates are obtained with month fixed effects. The unit of observation is fund-month. Fund-clustered standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Fund Flow
Gender	−0.095
	(0.113)
Low performance × Gender	0.273**
	(0.116)
High performance × Gender	0.134
	(0.186)
Low performance	−0.421***
	(0.039)
High performance	0.705***
	(0.048)
Log(Net assets)	−0.189***
	(0.017)
Net expense ratio	−0.452***
	(0.059)
Fund age	−0.035***
	(0.004)
Month FE	Yes
Observations	160,508
R^2	0.045

3.4 Manager Changes and the Mechanisms of Systematic Allocation

I construct transition matrices around manager changes to test hypotheses of strategic placement and self-selection by comparing corresponding transition probabilities. I define the mutually exclusive states as the combination of performance tier and manager gender for each mechanism of systematic allocation and calculate conditional probabilities. I conduct the analysis in a sample restricted to families with at least two funds in a given month, to ensure that allocation practices are feasible. Then, I identify manager replacements in the sample when I observe that the name of the single fund manager changed, and a maximum of two months passed between the alterations.[26]

To obtain the transition matrix assessing strategic placement, I define the *from state* as a conjunction of the past performance tercile of the fund, determined by its preceding 12 months of cumulative net-of-style returns (good, average, or bad), and the gender of the outgoing manager (female or male). I specify the *to state* as a combination of the past 12-month cumulative net-of-style return tercile and the gender of the incoming manager.[27] This approach is motivated by the viewpoint of fund families. That is, at the time of the manager replacement, what they can observe about the fund in focus is its past return, and their assumption of the destination state, i.e., the qualities of the managers can only be based on their performance achieved at other investment vehicles. Then, transition probabilities are calculated in the standard way, by dividing the number of transitions into each to state by the total number of transitions originating from that initial from state. To account for the baseline gender imbalance in the sample, I use a stratified bootstrap approach with 5,000 resamples to estimate standard errors, ensuring that even rare initial states are consistently represented in every iteration. Moreover, I apply a Lidstone smoothing parameter of 0.3 to address the empirically rare or zero-frequency transitions. Table 9 reports the transition matrix assessing strategic placement. Strikingly, most statistically significant transition probabilities are observable towards male management, also reflecting their predominance among incoming managers. The only significant transition probabilities from any quality of male manager to a female happen from Average Male or Bad Male to Bad Female managers, and from Bad

[26] I allow a maximum gap of two months between a departing and an incoming manager, as it likely represents a transitionary period with team management. The analysis covers 170 manager changes in which the incoming manager has a 12-month track record in the sample, 19 of which involve an incoming and 28 an outgoing female manager. To conserve space, I report the number of observed transitions in Table A-8 and Table A-9 in the Appendix.

[27] If the incoming manager led more than one fund, I cumulate the net asset-weighted average net-of-style returns they achieved in the 12 months leading up to their transition to the fund in focus.

Male to Good Female managers, the latter two being consistent with the glass cliff hypothesis formalized by Ryan and Haslam (2005). That is, female managers succeed male managers almost exclusively at funds outside the top performance tercile, and well-performing women do so only at the worst-performing investment vehicles. The highest transition probabilities are from Good or Average Female to Good Male (54.55% and 55.56%, respectively), indicating success bias.

Table 9: Transition Matrix Assessing Strategic Placement

This table reports the percentage transition probabilities around manager replacements across states of performance and manager gender. The *From State* (rows) is a combination of the fund's performance tercile determined by the preceding 12 months of cumulative net-of-style return (Good, Average or Bad) and the gender of the outgoing manager (Male or Female). The *To State* (columns) is a combination of the incoming manager's net-asset-weighted performance tercile determined by their prior 12-month cumulative net-of-style return (Good, Average or Bad) and their gender (Male or Female). Standard errors reported in parentheses are obtained by a stratified bootstrap with 5,000 resamples and a Lidstone smoothing parameter of 0.3. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	To State					
From State	Good/Male	Average/Male	Bad/Male	Good/Female	Average/Female	Bad/Female
Good/Male	42.42***	30.30***	21.21***	0.00	6.06	0.00
	(8.10)	(7.61)	(6.70)	(0.00)	(3.97)	(0.00)
Average/Male	48.57***	20.00***	20.00***	0.00	2.86	8.57*
	(7.79)	(6.49)	(6.43)	(0.00)	(2.65)	(4.49)
Bad/Male	24.32***	35.14***	27.03***	5.41**	1.35	6.76**
	(4.84)	(5.45)	(5.06)	(2.61)	(1.28)	(2.85)
Good/Female	54.55***	9.09	9.09	9.09	18.18*	0.00
	(12.93)	(7.54)	(7.50)	(7.45)	(9.97)	(0.00)
Average/Female	55.56***	22.22*	22.22*	0.00	0.00	0.00
	(14.03)	(11.61)	(11.80)	(0.00)	(0.00)	(0.00)
Bad/Female	37.50***	37.50***	25.00**	0.00	0.00	0.00
	(13.78)	(13.90)	(12.42)	(0.00)	(0.00)	(0.00)

I also estimate a transition matrix assessing self-selection with a similar approach, however, modeling it from the viewpoint of the manager. That is, I define the *from state* based on the incoming manager's gender and track record at previous funds according to their 12-month cumulative net-of-style return tercile. Conversely, I specify the *to state* as the fund's performance tercile in the 12 months leading up to the manager change and the gender of the predecessor. The motivation of this approach is that at the time of the change, the manager can observe their achievements over the previous twelve months, allowing them to position themselves and potentially have certain bargaining power accordingly for their next fund(s) to manage. What managers can learn about the fund they are about to start to manage is the investment vehicle's past performance as an *ex ante* estimate of the to state. The

transition matrix assessing self-selection is reported in Table 10. Incoming managers most frequently take over poorly performing funds previously led by men, reflecting that manager changes concentrate on underperforming investment vehicles. Notably, well-performing female managers predominantly take over such funds, whereas well-performing male managers are distributed almost evenly across the performance terciles. This mirrors the pattern observed from the perspective of fund families in Table 9.

Table 10: Transition Matrix Assessing Self-Selection

This table reports the percentage transition probabilities around manager replacements across states of performance and manager gender. The *From State* (rows) is a combination of the incoming manager's net-asset-weighted performance tercile determined by their prior 12-month cumulative net-of-style return (Good, Average or Bad) and their gender (Male or Female). The *To State* (columns) is a combination of the fund's performance tercile determined by the preceding 12 months of cumulative net-of-style return (Good, Average or Bad) and the gender of the outgoing manager (Male or Female). Standard errors reported in parentheses are obtained by a stratified bootstrap with 5,000 resamples and a Lidstone smoothing parameter of 0.3. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	To State					
From State	Good/Male	Average/Male	Bad/Male	Good/Female	Average/Female	Bad/Female
Good/Male	22.22***	26.98***	28.57***	9.52***	7.94**	4.76*
	(5.04)	(5.35)	(5.48)	(3.64)	(3.35)	(2.58)
Average/Male	20.41***	14.29***	53.06***	2.04	4.08	6.12*
	(5.51)	(4.76)	(6.82)	(1.95)	(2.75)	(3.27)
Bad/Male	17.95***	17.95***	51.28***	2.56	5.13	5.13
	(5.94)	(5.87)	(7.67)	(2.44)	(3.38)	(3.38)
Good/Female	0.00	0.00	80.00***	20.00	0.00	0.00
	(0.00)	(0.00)	(13.09)	(13.09)	(0.00)	(0.00)
Average/Female	33.33**	16.67	16.67	33.33**	0.00	0.00
	(14.56)	(11.91)	(11.60)	(14.71)	(0.00)	(0.00)
Bad/Female	0.00	37.50***	62.50***	0.00	0.00	0.00
	(0.00)	(14.13)	(14.13)	(0.00)	(0.00)	(0.00)

To formalize these observations and identify the channels of systematic allocation, I perform pairwise bootstrap hypothesis tests with 5,000 resamples, evaluating strategic placement and self-selection by comparing transition probabilities. I create an exhaustive set of hypotheses belonging to four categories, listed with their output in Table A-7 of the Appendix. Under the *crisis* hypotheses, which compare the transition probabilities of funds moving from a bad initial state to a different one by manager, I test strategic placement. As reported in Table 11, based on a selection of the hypothesis tests, it is more likely that a fund in a bad state will be assigned a Good or Average Male than a Good or Average Female, indicating strategic placement. That is, families might trust male managers more to turn around the bad funds, or at least to convince their investors about this. Then, I test hypotheses of *success bias*,

assessing the probabilities of managers remaining at or being allocated to better quality funds than they manage, by gender. Males are more likely both to keep good funds, as well as to improve the quality of a fund they transfer to than females, providing further support for strategic placement. To investigate self-selection, I also test the *retention gap*, which, similarly to the success bias, studies the possibility of keeping or improving the fund quality with the transfer, however from the manager's perspective. Moreover, I test hypotheses of *decline*, i.e., whether there is a deviation between the probabilities of downgrading to a bad fund from an average or good one by gender. None of these hypotheses yields statistically significant differences.[28] In summary, by exploiting changes in fund managers, I find suggestive evidence of strategic placement as the primary channel of systematic allocation, while empirical support for self-selection remains limited.

Table 11: Main Hypotheses of Self-Selection and Strategic Placement
This table reports selected hypotheses of strategic placement (SP) and self-selection (SS), based on the entries of transition matrices reported in Table 9 and Table 10, respectively. It depicts the outcomes of pairwise bootstrap tests of the differences between transition probabilities involved in each hypothesis. For each comparison of probabilities, I calculate the difference between them within each of the 5,000 resamples. The Estimate is the mean difference across all resamples. SE denotes standard error and is the standard deviation of these differences. The p-value is the empirical probability that the observed difference is zero or opposite to the hypothesized Direction. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Hypothesis	Category	Description	Estimate	SE	p-value	Direction
SP-H1a	Crisis	$P(\text{BM} \to \text{GM}) > P(\text{BF} \to \text{GF})$	21.05***	4.84	0.00	$>$
SP-H1b	Crisis	$P(\text{BM} \to \text{AM}) > P(\text{BF} \to \text{AF})$	31.72***	5.45	0.00	$>$
SP-H2b	Success Bias	$P(\text{AM} \to \text{GM}) > P(\text{AF} \to \text{GF})$	44.17***	7.79	0.00	$>$
SS-H1a	Retention Gap	$P(\text{GF} \to \text{GF}) < P(\text{GM} \to \text{GM})$	-2.91	13.96	0.39	$<$
SS-H1b	Retention Gap	$P(\text{GF} \to \text{GF}) < P(\text{BM} \to \text{GM})$	1.13	14.38	0.50	$<$

3.5 The Role of ESG in Systematic Allocation

Women tend to be associated with greater affinity towards ESG matters, potentially making them suitable candidates for funds with such focus. The corporate governance literature reports a positive relationship between female board representation and corporate social responsibility (CSR) considerations and performance of firms (see, e.g., Byron and Post, 2016; Liu et al., 2020; Bosone et al., 2022). This dynamic is documented to extend to mutual funds. Gangi et al. (2021) report that a higher female proportion in European equity mutual fund management

[28]The complete set of hypotheses is reported in Table A-7 of the Appendix.

teams has a positive impact on the ESG rating of their portfolios. Similarly, studying European mutual funds, Lobán et al. (2025) and Dimic et al. (2026) demonstrate that female managers have a significant role in promoting sustainable investment practices.

Therefore, I investigate whether the ESG space serves as a channel of systematic allocation, by examining the baseline proportion of female managers overseeing these investment vehicles, as well as their odds of being assigned to an ESG mutual fund. If female fund managers are systematically allocated to such mandates, it could partially explain the phenomenon, as ESG funds tend to be smaller and charge higher percentage fees, which aligns with the observations about the female-managed funds, on average. However, ESG funds also tend to be younger, which is in stark contrast to the findings about the female-led investment vehicles.

First, I assess the static representation of female fund managers in ESG funds relative to traditional ones. Table 12 reports the results of binomial tests comparing these proportions. In the full sample, female managers oversee 20.69% of the ESG funds, which is more than double their benchmark representation in traditional funds. This significant overrepresentation is inherently even more pronounced within the female-represented family subsample, where females manage 45% of the ESG funds compared to an expected benchmark of 18.60%.

Table 12: Relative Representation of Female Managers in ESG Funds
This table reports the results of binomial tests comparing the proportion of female managers leading ESG funds against the proportion of female managers overseeing traditional (non-ESG) funds. The female-represented family subsample is restricted to families managing minimum two funds and employing at least one female manager. The number of female-managed ESG funds is denoted with k, n is the total number of ESG funds. Benchmark represents the expected female manager proportion in traditional funds, and Success Probability is their observed proportion in ESG funds, both expressed in percentages. The p-value indicates the statistical significance of one-sided exact binomial tests, assessing whether the female manager proportion in ESG funds is significantly greater than their proportion in traditional funds.

Sample	k	n	Benchmark	Success Probability	p-value
Full Sample	18	87	10.21	20.69	0.0028
Female-Represented Family Subsample	18	40	18.60	45.00	0.0001

To corroborate that this concentration is affected by allocation practices, I estimate logit regressions predicting the likelihood that the newly assigned fund has an ESG focus. That is, I estimate:

$$Logit(P(\text{ESG}_{i,f} = 1)) = \alpha + \beta \text{Gender}_{i,f,t} + \Gamma' \mathbf{X}_{f,t}, \tag{6}$$

where the $Logit(P)$ function denotes the natural logarithm of the odds. $\text{ESG}_{i,f}$ is a dummy variable that equals 1 if fund i of family f is an ESG fund, 0 otherwise. $\text{Gender}_{i,f,t}$ is a dummy

variable that equals 1 if a fund i, belonging to family f is allocated to a female manager in time t, 0 otherwise. $\mathbf{X}_{f,t}$ denotes the vector of family-specific controls, calculated in the complete sample. However, the estimates are obtained in the election sample, i.e., the fund-months where a new manager is appointed to a fund.

As summarized in Table 13, the odds ratios for the gender dummy remain statistically significant (at the 10% level in Model (4)) and economically meaningful across all specifications. That is, even after absorbing temporal trends and controlling for family characteristics such as size, age, and the number of female-managed funds in Model (4), the odds of being appointed to an ESG fund are 2.22 times higher for female than for male managers. Consequently, these findings support the notion that female managers are more likely to be appointed to ESG mutual funds. Thus, the observed systematic allocation could be affected by this pattern.

To further explore the performance implications of transitioning to ESG mandates by gender, I estimate an event study. Due to the limited sample size of such switches, the output is reported in Table A-10 of the Appendix. While male managers do not experience a statistically significant change in their performance after transitioning to ESG funds, female managers achieve markedly superior returns. This post-switch premium persists even after incorporating manager and family fixed effects. This indicates that their comparative advantage is likely driven by a combination of factors: unique affinity and skill set for leading ESG funds, coupled with a more loyal investor base (Bollen, 2007). Therefore, systematic allocation to the ESG space could be driven both by strategic placement and self-selection, as the limited-sample evidence suggests that it is mutually beneficial for fund families and managers.

Table 13: ESG Funds and Female Manager Allocation
This table reports odds ratios (e^{β}) from logit regressions of ESG on manager gender and fund family attributes.

$$Logit(P(\text{ESG}_{i,f} = 1)) = \alpha + \beta \text{Gender}_{i,f,t} + \Gamma' \mathbf{X}_{f,t} + \epsilon_{i,f,t},$$

where $\text{ESG}_{i,f}$ is a dummy variable that equals 1 if fund i of family f is an ESG fund, 0 otherwise. $\text{Gender}_{i,f,t}$ is a dummy variable that equals 1 if a fund i, belonging to family f, is allocated to a female manager in time t, 0 otherwise. $\mathbf{X}_{f,t}$ denotes the vector of family-specific controls. Log(Total net assets) measures the size of the family. Family age is measured in years. Number of female-managed funds and number of funds refer to firm-level counts. All family-specific variables are obtained in the complete sample, however, the estimates are obtained in the election sample, i.e. including those fund-months where a new manager is appointed to a fund. Standard errors, reported in parentheses, are clustered at the fund level and are transformed with the delta method. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	ESG			
	(1)	(2)	(3)	(4)
Gender	2.806***	3.421**	2.771**	2.224*
	(1.097)	(2.002)	(1.121)	(0.921)
Log(Total net assets)			0.982	1.131
			(0.079)	(0.113)
Family age			0.988	0.993
			(0.010)	(0.009)
Number of female-managed funds			0.996	1.146**
			(0.037)	(0.063)
Number of funds				0.934***
				(0.023)
Year FE	Yes	Yes	Yes	Yes
Family FE	No	Yes	No	No
Observations	1,982	405	1,982	1,982
Pseudo R^2	0.064	0.303	0.077	0.101

3.6 Robustness

To ensure the validity and stability of the main findings of this paper, I conduct a series of robustness tests with alternative performance measures, econometric specifications, and matching criteria. To conserve space, the corresponding tables are reported in the Appendix.

Fund Family Value Perspectives of Female Manager Allocation Models: To confirm that the value-based allocation pattern results reported in Table 3 are not exclusive to the chosen performance measure and logit model, I estimate several alternative specifications and report them in Table A-1. The results not only persist when replacing returns with net-of-style and lagged net-of-style returns, but the systematic allocation pattern of female managers to underperforming funds becomes more prevalent. Substituting month fixed effects with year fixed effects yields consistent estimates, suggesting that the findings are not driven by high-frequency temporal unobservables. Moreover, estimating the specification with a linear probability model (LPM) on the complete sample ensures that the results are not solely driven by the originally used logit model mechanically dropping all-male fund family observations. Although their inclusion dilutes the aggregate marginal effects, causing the noisier raw return variable to lose its statistical significance, the net-of-style return and the other value measures remain robust with the LPM.

Matched Sample Regression Specification: I assess whether the matched sample within-family performance penalty of female managers is sensitive to standard error assumptions or benchmark choices. As the matching structure pairs a female manager with multiple male peers simultaneously, I re-estimate Equation (2) with standard errors clustered by the female-managed fund to account for potential mechanical cross-sectional correlation. The output in Table A-3 confirms that the results remain virtually unaffected. I verify that net-of-style return is a robust performance measure by replacing it in Equation (2) with Morningstar Analyst Assigned Benchmark[29] excess return. As shown in Table A-4, the magnitude and significance of the results are retained after this adjustment in the specification.

Alternative Matching Approaches: To show that the matched sample regression results are not driven by the reported matching specification, I introduce several alterations to it and report the output in Table A-5. In the main results, male matches are found for the female managers by having exact educational qualities and most alike experience measured by years

[29]Morningstar Analyst Assigned Benchmarks are Russell Indices mapped to each fund's Morningstar category. I retrieve their return indices from LSEG Workspace Datastream.

spent in industry. In the case of ties, I select deterministically the first male match for reproducibility.[30] To test the sensitivity of this design, I choose a random match in the case of ties, and estimate Equation (2) with the adjusted matched sample. As shown in Models (1) and (2), the within-family gap remains negative and statistically significant, although the point estimates are moderately attenuated. A natural limitation of the matching procedure is that while there is one out-of-family male match for each female manager, there might be several within-family matches for her. To alleviate plausible concerns that this asymmetry, or deviations in the proportion of female and male representation in families might bias the results, I create synthetic within-family male matches for the female managers. That is, I aggregate the attributes of all within-family male manager peers and their funds using equal weighting (value-weighting by net assets), and estimate Equation (2) using this sample in Models (3) and (4) (Models (5) and (6)). The within-family allocation penalty remains robust to these alterations too, demonstrating that the findings are not driven by the specific mechanics of the matching procedure.

Alternative Matching Design: Instead of linking the out-of-family benchmark to the female manager's own credentials, I match a separate out-of-family male manager to each within-family male peer based on the peer's educational profile and industry experience, estimate Equation (2), and report the results in Table A-6. This relaxed "benchmark" selection is less a direct test of gender-based allocation and more a robustness check on whether the within-family return gap survives without imposing credential similarity between the female manager and her out-of-family counterpart. The same-family coefficient remains negative and statistically significant across all four specifications, confirming that the within-family performance penalty is not an artifact of the matching benchmark construction. However, it shrinks to around half in magnitude, reflecting a muted, aggregate family-level allocation effect rather than the sharper credential-adjusted performance penalty identified in the main specification.

Dynamic Effects of the #MeToo Movement: To verify that the within-family female underperformance is a response to the #MeToo event and not a pre-existing trend, Figure A-1 plots the annual interaction estimates of the same-family indicator and calendar years, relative to the 2016 baseline. In the periods prior to the baseline, the interaction coefficients are statistically indistinguishable from zero. That is, the within-family penalty was stable leading

[30] Specifically, in case of ties in the matching, I order the oldest share class's security identifiers alphabetically and select the first one with the corresponding male manager. Such instances often involve the same individual leading multiple funds at the same time.

up to the beginning of #MeToo. However, after the start of the movement, the post-baseline estimates are all negative, several of them significantly, consistent with the widening of the within-family return gap coinciding with the onset of #MeToo.

4 Conclusion

This paper empirically analyzes whether female managers are systematically allocated to mutual funds with lower profit-generating value. The analysis is executed on a U.S. equity mutual fund sample covering the period from 2000 to 2024, enriched with manually collected data, yielding comprehensive insights into the phenomenon. Despite similar educational credentials and experience, female managers tend to lead significantly smaller, older, and underperforming mutual funds that charge higher percentage fees yet generate lower dollar revenue. That is, they manage investment vehicles that have lower value to their families. The effect is substantial, as reflected by the diminishing representation of female managers from lowest to highest value quartiles of performance, fund age, and fee income. Moreover, the effect is more pronounced in families with fewer mutual funds, suggesting the "window dressing" of diversity practices to meet industry standards or investor expectations.

To isolate the performance implications of systematic allocation, I employ a matched-sample framework. Comparing female–male performance gaps among cases when the male peer is from the same or from a different fund family without female managers reveals a substantial within-family allocation penalty of about 1.2% annually. This poses the question whether gender-based skill gaps documented in the literature are due to the lower underlying quality of the investment vehicles assigned to female managers.

To identify whether systematic allocation is primarily driven by strategic placement of fund families or the self-selection of managers, I leverage exogenous societal and regulatory shocks. The #MeToo movement exacerbated the within-family underperformance of female managers, suggesting firms adjusted female representation to meet public expectations, yet appointed them to investment vehicles at lower stakes. Conversely, SB 826 narrowed the within-family performance gap attributable to systematic allocation at fund firms headquartered in California. Both findings, especially the former, support that strategic placement is the main mechanism of the systematic allocation practices. Hypothesis tests on transition probabilities assessing both channels are consistent with strategic placement as the primary factor, while

providing no significant evidence of self-selection.

Analyzing the flow-performance relationship by gender elucidates an incentive for systematic allocation practices, as female-managed funds are less punished by investors for poor performance, yielding a shielding effect. This downside protection might incentivize families to strategically assign female managers to investment vehicles that are more predisposed to underperform, reinforcing strategic placement as the main mechanism. Furthermore, female fund managers face significantly higher odds of being appointed to ESG funds, and consequently are overrepresented in such mandates. There are also indications that they exhibit a comparative performance advantage after transitioning to ESG funds. This suggests that systematic allocation of female managers in the ESG niche is mutually beneficial for all parties, supporting both self-selection and strategic placement as feasible mechanisms.

These findings demonstrate that evaluating manager performance without accounting for the attributes of the underlying investment vehicle could lead to biased estimates. Moreover, the systematic allocation of female managers to funds with lower family value and less favorable prospects is not only consistent with the glass cliff hypothesis of Ryan and Haslam (2005) but could also provide insight into their historically low representation in the mutual fund industry. As even the pursuit of diversity can have adverse effects, revealing the systematic allocation patterns emphasizes the need for transparency to ensure an efficient allocation of managerial talent in the mutual fund industry.

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5 Appendix

In the Appendix, I report extended results and robustness tests supporting the findings in the main body. Specifically, Table A-1 documents the output of the value-based allocation models with alternative performance measures, fixed effects, and a linear probability model. Table A-2 presents the matched sample regression tests of systematic allocation with the full set of control estimates. Table A-3 and Table A-4 confirm that these results are robust to clustering standard errors by female-managed funds and to an alternative performance benchmark, respectively. Table A-5 summarizes the analysis with alterations to the matching procedure, whereas Table A-6 presents a different matching design with variations.

Table A-7 lists the exhaustive set of transition-probability hypothesis tests assessing strategic placement and self-selection. Table A-8 and Table A-9 summarize the number of observed manager changes that are used in the calculations of the respective transition matrices. Table A-10 reports event study estimates of manager performance by gender around switching from regular to ESG funds. Finally, Figure A-1 depicts the annual interaction estimates of the same-family indicator with calendar years on the female-male return gap around the #MeToo movement.

Table A-1: Fund Family Value Perspectives of Female Manager Allocation Robustness

This table reports estimates from logit and linear probability model (LPM) regressions of gender on variables measuring the value-generating capacity of funds to their families. All columns use the following baseline specification:

$$Logit\big(P(\text{Gender}_{i,f,t}=1)\big) = \alpha + \beta_1 \text{Performance}_{i,f,t} + \beta_2 \text{Age}_{i,f,t} + \beta_3 \text{NER}_{i,f,t} + \beta_4 \text{Fee income}_{i,f,t} + \epsilon_{i,f,t},$$

where Gender equals 1 if a fund is managed by a female and 0 otherwise, and Performance denotes the performance measure, which varies by column. In Models (1) and (5), it is the monthly raw return; in Models (2) and (6), it is the net-of-style return; in Model (3), it is the one-month lagged net-of-style return. In Model (4), year fixed effects replace the month fixed effects of the baseline. Models (1)–(4) report logit log-odds coefficients; odds ratios for column (1) are reported in Table 3. Models (5)–(6) report OLS coefficients from the linear probability model estimated on the full sample. Return, net-of-style return, and net expense ratio are measured in percentage points, age in years. Fee income is the product of the net expense ratio and the monthly net assets, measured in USD millions. The unit of observation is fund-month. In each estimation time and family fixed effects are included. Standard errors, reported in parentheses, are double-clustered at the month and fund family level (at the year and fund family level for column (4)). The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Gender					
	(1)	(2)	(3)	(4)	(5)	(6)
Return	−0.011*			−0.003*	−0.001*	
	(0.006)			(0.002)	(0.0005)	
Net-of-style return		−0.018**				−0.001*
		(0.008)				(0.001)
Lagged net-of-style return			−0.016**			
			(0.008)			
Fund age	0.015**	0.015**	0.015**	0.015**	0.001*	0.001*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)
Net expense ratio	0.436*	0.436*	0.439*	0.436*	0.034	0.034
	(0.254)	(0.255)	(0.255)	(0.255)	(0.021)	(0.021)
Fee income ($M)	−0.012**	−0.012**	−0.012**	−0.011**	−0.0004***	−0.0004***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.0001)	(0.0001)
Model	Logit	Logit	Logit	Logit	LPM	LPM
Month FE	Yes	Yes	Yes	No	Yes	Yes
Year FE	No	No	No	Yes	No	No
Family FE	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster	M+F	M+F	M+F	Y+F	M+F	M+F
Observations	98,989	98,989	98,563	98,989	132,574	132,574
Within R^2 / R^2	0.014	0.014	0.014	0.014	0.170	0.170

Table A-2: Matched Sample Regression Tests of Systematic Allocation with Detailed Controls

This table reports the estimates of net-of-style return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables. The coefficients are obtained from the following specification:

$$\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta \text{Same family}_{i,j} + \zeta \text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},$$

where Net return$^{F}_{i,t}$ is the net-of-style return of a female-managed fund i in month t, and Net return$^{M}_{j,t}$ is the corresponding net-of-style return of its matched male-managed fund j in month t. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. Model (1) is estimated with year and fund fixed effects. Model (2) extends the specification with controls for the fees, size and age of both the female and matched male-managed funds (denoted with subscript M), as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month. Heteroskedasticity-robust standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Net-of-Style Return Differential	
	(1)	(2)
Same family	-0.094^{***}	-0.099^{***}
	(0.028)	(0.032)
Same style	-0.019	-0.014
	(0.020)	(0.020)
Net expense ratio		-0.343^{***}
		(0.086)
Net expense ratio$_M$		0.110^{***}
		(0.028)
Log(Net assets)		-0.129^{***}
		(0.015)
Log(Net assets$_M$)		-0.0003
		(0.004)
Fund age		0.070^{***}
		(0.024)
Fund age$_M$		0.0001
		(0.0005)
Log(Total net assets)		-0.002
		(0.052)
Log(Total net assets$_M$)		0.005
		(0.013)
Family age		0.016^{***}
		(0.005)
Family age$_M$		0.001
		(0.001)
Year FE	Yes	Yes
Fund FE	Yes	Yes
Observations	128,310	128,310
R^2	0.028	0.029

Table A-3: Matched Sample Regression with Alternative Standard Error Clustering
This table reports the estimates of net-of-style return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables. The coefficients are obtained from the following specification:

$$\text{Net return}^{F}_{i,t} - \text{Net return}^{M}_{j,t} = \alpha + \beta \text{Same family}_{i,j} + \zeta \text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},$$

where Net return$^{F}_{i,t}$ is the net-of-style return of a female-managed fund i in month t, and Net return$^{M}_{j,t}$ is the corresponding net-of-style return of its matched male-managed fund j in month t. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. Model (1) is estimated with year and fund fixed effects. Model (2) extends the specification with controls for the fees, size and age of both the matched female and male-managed funds, as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month. Standard errors clustered by the female-managed funds are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Net-of-Style Return Differential	
	(1)	(2)
Same family	-0.094^{***}	-0.099^{***}
	(0.024)	(0.029)
Same style	-0.019	-0.014
	(0.020)	(0.020)
Controls	No	Yes
Year FE	Yes	Yes
Fund FE	Yes	Yes
Observations	128,310	128,310
R^2	0.028	0.029

Table A-4: Matched Sample Regression with an Alternative Performance Measure
This table reports the estimates of Morningstar Analyst Assigned Benchmark excess return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables. The coefficients are obtained from the following specification:

$$\text{Exc return}^{F}_{i,t} - \text{Exc return}^{M}_{j,t} = \alpha + \beta \text{Same family}_{i,j} + \zeta \text{Same style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},$$

where $\text{Exc return}^{F}_{i,t}$ is the return of a female-managed fund i in month t in excess of the Morningstar analyst assigned benchmark, and $\text{Exc return}^{M}_{j,t}$ is the corresponding return of its matched male-managed fund j in month t in excess of its Morningstar analyst assigned benchmark. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. Model (1) is estimated with year and fund fixed effects. Model (2) extends the specification with controls for the fees, size and age of both the female and male-managed funds, as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month. Heteroskedasticity-robust standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Benchmark Excess Return Differential	
	(1)	(2)
Same family	-0.085^{***}	-0.105^{***}
	(0.030)	(0.035)
Same style	-0.030	-0.024
	(0.021)	(0.021)
Controls	No	Yes
Year FE	Yes	Yes
Fund FE	Yes	Yes
Observations	128,310	128,310
R^2	0.025	0.026

Table A-5: Alternative Matching Approaches

This table reports the estimates of net-of-style return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables. All specifications are equivalent to Model (1) and Model (2) in Table 5. In Models (1) and (2), I pair female managers with all male managers within their families, and I find for them the closest outside-family male match that shares the same features in their education (measured by having an MBA, CFA, PhD, and Ivy League degree) and has the lowest Euclidean distance based on their years spent in the finance industry; in case of ties, I select a random one of those matches. In Models (3) and (4), I follow the same in-family pairing as in Table 5, but create a synthetic within-family male match by equally weighting the attributes of the within-family male peers of each female manager. In Models (5) and (6), I proceed as in Models (3) and (4), but value-weight the within-family manager attributes by net assets. Same family is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family, and 0 otherwise. In Models (3)–(6), Same style is the proportion of within-family male peers constructing the synthetic match that share the same style as the female manager. In Models (1) and (2), it remains the standard indicator equal to 1 if the female- and matched male-managed fund share the same investment style. Models (1), (3), and (5) are estimated with year and fund fixed effects. Models (2), (4), and (6) extend the specification with controls for the fees, size and age of both the female and matched male-managed funds, as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month for Models (1)–(2), and female-synthetic-male-pair month for Models (3)–(6). Female-managed fund clustered standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Net-of-Style Return Differential					
	(1)	(2)	(3)	(4)	(5)	(6)
Same family	-0.071^{***}	-0.069^{*}	-0.081^{**}	-0.097^{**}	-0.071^{**}	-0.099^{**}
	(0.027)	(0.039)	(0.032)	(0.043)	(0.033)	(0.043)
Same style	-0.009	-0.006	-0.186^{**}	-0.154^{*}	-0.175^{**}	-0.152^{*}
	(0.029)	(0.029)	(0.087)	(0.091)	(0.081)	(0.085)
Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128,310	128,310	23,179	23,179	23,179	23,179
R^2	0.028	0.029	0.040	0.042	0.039	0.041

Table A-6: Alternative Matching Design

This table reports the estimates of net-of-style return differentials between female and male mutual fund managers (in percentage points) regressed on fund and family specific variables. All specifications are equivalent to Model (1) and Model (2) in Table 5. In this design, female managers are paired with all male managers within their family, as in the main specification. However, rather than matching an out-of-family male to the female manager based on her own credentials, I instead match a separate out-of-family male to each individual in-family male peer, based on his education profile (MBA, CFA, PhD, and Ivy League degree) and the lowest Euclidean distance based on his years spent in the finance industry. In Models (1) and (2), ties between equally close out-of-family candidates are broken by selecting the first match; in Models (3) and (4), ties are broken by selecting a random match. Same-family pairings for which no out-of-family male shares the in-family peer's exact credentials on a given date are dropped from both sides of the comparison. Same family (Same style) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. Models (1) and (3) are estimated with year and fund fixed effects. Models (2) and (4) extend the specification with controls for the fees, size and age of both the female and male-managed funds, as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month. Female-managed fund clustered standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Net-of-Style Return Differential			
	(1)	(2)	(3)	(4)
Same family	-0.050^{***}	-0.045^{***}	-0.045^{***}	-0.056^{***}
	(0.011)	(0.016)	(0.011)	(0.015)
Same style	0.046^{**}	0.050^{**}	0.021	0.020
	(0.021)	(0.021)	(0.022)	(0.022)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	232,290	232,290	232,290	232,290
R^2	0.024	0.025	0.022	0.023

Table A-7: Hypotheses of Self-Selection and Strategic Placement

This table reports hypotheses of strategic placement (SP) and self-selection (SS), based on the entries of transition matrices reported in Table 9 and Table 10, respectively. It depicts the outcomes of pairwise bootstrap tests of the differences between transition probabilities involved in each hypothesis. For each comparison of probabilities, I calculate the difference between them within each of the 5,000 resamples. The Estimate is the mean difference across all resamples. SE denotes standard error and is the standard deviation of these differences. The p-value is the empirical probability that the observed difference is zero or opposite to the hypothesized Direction. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Hypothesis	Category	Description	Estimate	SE	p-value	Direction
SP-H1a	Crisis	$P(\text{BM} \to \text{GM}) > P(\text{BF} \to \text{GF})$	21.05***	4.84	0.00	$>$
SP-H1b	Crisis	$P(\text{BM} \to \text{AM}) > P(\text{BF} \to \text{AF})$	31.72***	5.45	0.00	$>$
SP-H1c	Crisis	$P(\text{BF} \to \text{BF}) > P(\text{BM} \to \text{BM})$	-23.68	5.06	1.00	$>$
SP-H2a	Success Bias	$P(\text{GM} \to \text{GM}) > P(\text{GF} \to \text{GF})$	30.92***	10.87	0.00	$>$
SP-H2b	Success Bias	$P(\text{AM} \to \text{GM}) > P(\text{AF} \to \text{GF})$	44.17***	7.79	0.00	$>$
SP-H2c	Success Bias	$P(\text{GF} \to \text{AF}) > P(\text{GM} \to \text{AM})$	-11.81	12.58	0.83	$>$
SP-H2d	S*u*ccess Bias	$P(\text{GF} \to \text{GM}) > P(\text{GF} \to \text{GF})$	39.28**	16.96	0.02	$>$
SP-H2e	S*u*ccess Bias	$P(\text{GF} \to \text{GM}) > P(\text{GM} \to \text{GF})$	48.50***	12.93	0.00	$>$
SS-H1a	Retention Gap	$P(\text{GF} \to \text{GF}) < P(\text{GM} \to \text{GM})$	-2.91	13.96	0.39	$<$
SS-H1b	Retention Gap	$P(\text{GF} \to \text{GF}) < P(\text{BM} \to \text{GM})$	1.13	14.38	0.50	$<$
SS-H1c	Retention Gap	$P(\text{AF} \to \text{GF}) < P(\text{AM} \to \text{GM})$	9.36	15.80	0.72	$<$
SS-H2a	Decline	$P(\text{AF} \to \text{BF}) > P(\text{AM} \to \text{BM})$	-47.89	6.82	1.00	$>$
SS-H2b	Decline	$P(\text{GF} \to \text{BF}) > P(\text{GM} \to \text{BM})$	-23.82	5.48	1.00	$>$

Table A-8: Transition Counts Assessing Strategic Placement

This table reports the number of manager replacements across states of performance and manager gender. The *From State* (rows) is a combination of the fund's performance tercile determined by the preceding 12 months of cumulative net-of-style return (Good, Average or Bad) and the gender of the outgoing manager (Male or Female). The *To State* (columns) is a combination of the incoming manager's net-asset-weighted performance tercile determined by their prior 12-month cumulative net-of-style return (Good, Average or Bad) and their gender (Male or Female).

	To State					
From State	Good/Male	Average/Male	Bad/Male	Good/Female	Average/Female	Bad/Female
Good/Male	14	10	7	0	2	0
Average/Male	17	7	7	0	1	3
Bad/Male	18	26	20	4	1	5
Good/Female	6	1	1	1	2	0
Average/Female	5	2	2	0	0	0
Bad/Female	3	3	2	0	0	0

Table A-9: Transition Counts Assessing Self-Selection

This table reports the number of manager replacements across states of performance and manager gender. The *From State* (rows) is a combination of the incoming manager's net-asset-weighted performance tercile determined by their prior 12 month cumulative net-of-style return (Good, Average or Bad) and their gender (Male or Female). The *To State* (columns) is a combination of the fund's performance tercile determined by the preceding 12 months of cumulative net-of-style return (Good, Average or Bad) and the gender of the outgoing manager (Male or Female).

	To State					
From State	Good/Male	Average/Male	Bad/Male	Good/Female	Average/Female	Bad/Female
Good/Male	14	17	18	6	5	3
Average/Male	10	7	26	1	2	3
Bad/Male	7	7	20	1	2	2
Good/Female	0	0	4	1	0	0
Average/Female	2	1	1	2	0	0
Bad/Female	0	3	5	0	0	0

Table A-10: Manager Switches from Traditional to ESG Funds

This table reports event study difference-in-difference estimates of performance around the transition of a manager from a traditional to an ESG fund. The coefficients are obtained from the following specification:

$$\text{Return}_{m,t} = \alpha + \beta \text{Gender}_{m,t} \times \text{P}_{m,t} + \delta \text{Gender}_{m,t} + \gamma \text{P}_{m,t} + \epsilon_{m,t},$$

where $\text{Return}_{m,t}$ is the asset-weighted return of manager m at time t. $\text{Gender}_{m,t}$ is the gender of the manager at time t. $\text{P}_{m,t}$ denotes the post-switch period, i.e. the 12 months following a manager's switch from a traditional to an ESG fund. The estimation window is restricted to 12 months before and after the switch. The unit of observation is manager-month. Standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Return		
	(1)	(2)	(3)
Gender × Post-switch	3.447***	3.608***	2.234*
	(1.114)	(1.186)	(1.253)
Gender	−2.680***		
	(0.885)		
Post-switch	−0.688	−0.711	−0.250
	(0.664)	(0.675)	(0.744)
Constant	1.025**		
	(0.491)		
Manager FE	No	Yes	Yes
Family FE	No	No	Yes
Observations	387	387	387
R^2	0.029	0.087	0.118

Figure A-1: Dynamic Event Study on Relative Within-Family Return Differentials
This figure reports the annual dynamic interaction estimates of net-of-style return differentials between female and male mutual fund managers around the #MeToo movement. The plotted coefficients (γ_k) and the corresponding 95% confidence intervals are estimated with the following specification:

$$\begin{aligned}\text{Net_return}^F_{i,t} - \text{Net_return}^M_{j,t} = \alpha_i + \lambda_t + \beta\text{Same_family}_{i,j} \\ + \sum_{k\in\{-5,\ldots,5\}\setminus\{-1\}} \gamma_k(\text{Same_family}_{i,j} \times \mathbb{I}[\text{BinnedYear}_t = k]) \\ + \zeta\text{Same_style}_{i,j} + \text{Controls} + \epsilon_{i,j,t},\end{aligned}$$

where $\text{Net_return}^F_{i,t}$ is the net-of-style return of a female-managed fund i in month t, and $\text{Net_return}^M_{j,t}$ is the corresponding net-of-style return of a matched male-managed fund j in month t. $\text{Same_family}_{i,j}$ ($\text{Same_style}_{i,j}$) is a dummy variable equal to 1 if the female- and male-managed funds belong to the same family (share the same investment style), and 0 otherwise. $\mathbb{I}[\text{BinnedYear}_t = k]$ represents dynamic calendar year indicators relative to the October 2017 #MeToo movement. Calendar year 2016 ($k = -1$) serves as the baseline reference period. To stabilize distant panel horizons, endpoint years are binned at $k \leq -5$ (≤ 2012) and $k \geq 5$ (≥ 2022). The specification is estimated with time (λ_t) and fund (α_i) fixed effects. Controls include the net expense ratio, size, and age of both the female and matched male-managed funds, as well as the size and age of their respective fund families. The unit of observation is female-male managed fund-pair month. Vertical error bars represent 95% confidence intervals based on fund family clustered standard errors.

