Race, Gender, and Careers in Asset Management: Evidence from U.S. Administrative Data

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Abstract

Using confidential administrative data from the U.S. Census Bureau, we examine whether race and gender affect compensation and career outcomes in the U.S. asset management industry. We document substantial compensation gaps: female portfolio managers earn 27% less than male peers, and minority managers earn 20% less than White peers. Female and minority managers also face significantly higher rates of forced turnover, and female managers are less likely to be rehired following job separations. These gaps can not be explained by differences in qualifications: minority managers are more likely to attend elite schools and hold advanced degrees. Nor do they reflect differences in performance: we find no systematic disparities in investment performance or in the ability to attract investor flows. Importantly, we show that greater diversity among asset management firm owners helps mitigate these disparities. Together, these findings challenge the notion that meritocratic industries are immune to discrimination and raise concerns about taste-based discrimination and potential talent misallocation in an industry central to capital markets.

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1 Introduction

At the core of the asset management industry are portfolio managers whose decisions shape both the welfare of millions of investors and the allocation of trillions of dollars in the economy. As such, barriers that prevent talented individuals from entering or advancing in the industry can lead to the misallocation of talent, with consequences not only for career trajectories but also for investor outcomes and market efficiency. This paper examines whether race and gender create such barriers in how managerial talent is identified, rewarded, and retained.[1] Using novel confidential individual-level administrative data from the U.S. Census Bureau, we analyze how race and gender affect portfolio manager compensation, hiring, promotion, and retention in the mutual fund industry.

Several institutional features of the mutual fund industry suggest that race- and gender-related bias in career outcomes should be limited. First, fund performance is transparent and readily measurable, as managers' returns are publicly disclosed and evaluated against standardized benchmarks. Second, the industry is highly competitive, resulting in strong performance flow sensitivities (Chevalier and Ellison (1999); Sirri and Tufano (1998); Berk and Green (2004)). Third, compensation is explicitly tied to observable outcomes such as returns and assets under management (Elton et al. (2003); Ma et al. (2019)). Together, these features create a setting where performance-based evaluation should dominate, limiting the scope for discrimination. Despite this transparency, prior work documents evidence of race- and gender-related biases in investor flows. Female and minority fund managers attract significantly lower capital flows than their White male counterparts, despite no significant difference in performance (e.g., Kumar et al. (2015); Barber et al. (2017); Niessen-Ruenzi and Ruenzi (2019); Han et al. (2025)). What remains unclear is whether such investor

[1] Minority representation in the asset management industry has attracted growing attention in the financial press. See, for example, "Where Are the Female Fund Managers?," *Wall Street Journal*, July 6, 2015; "NYC Seeks Diversity Among Its Asset Managers," *Wall Street Journal*, April 30, 2015; "Race and Finance: Asset Managers Fail to Walk the Walk," *Financial Times*, 28 December 2021, and "The Asset Management Industry Continues to Struggle with Diversity," *Institutional Investor*, 10 December 2021.

biases translate into unequal career outcomes for portfolio managers, and more broadly, how race and gender shape labor market decisions such as compensation, hiring, promotion, and retention.

To answer these questions, we conduct a comprehensive analysis of the impact of demographic characteristics on career outcomes in the U.S. mutual fund industry. We construct a unique dataset that links confidential micro-level individual labor market and demographic records from the U.S. Census Bureau with multiple fund- and manager-level datasets covering the asset management sector. This approach enables us to systematically examine the extent to which race and gender shape career trajectories, including compensation growth, hiring, promotions, exits, and re-entries, shedding new light on the labor market dynamics in one of the most transparent and performance-driven segments of the financial sector.

To provide a broader context, we begin by analyzing individual-level administrative data for approximately 170,500 high-skilled investment professionals, including portfolio managers, buy-side analysts, and others who are employed by asset management firms between 1991 and 2020. This sample reveals strong racial and gender homogeneity with women representing about 21% and racial minorities less than 15% (8.9% Asian, 2.1% Black, 2.4% Hispanic, and 1.3% other). While these roles vary in visibility and function, they collectively span the entire landscape of investment-related occupations and capture the industry-wide labor market in which mutual fund managers operate. Analyzing this larger population allows us to establish some baseline patterns of demographic inequality across the industry, thereby informing our subsequent analysis in the more performance-transparent segment of mutual fund managers.

Our results reveal persistent demographic disparities that unfold along multiple dimensions of career outcomes. We first document significant pay disparities: on average, female asset managers earn 25% less than male managers, and Black, Asian, and Hispanic managers earn 22%, 21%, and 14% less than White managers, respectively. In addition, female

and minority asset managers are significantly less likely to receive promotions, defined as a substantial salary increase (e.g., at least 20% or 50%) within the same firm or following a job change. These disadvantages accumulate over time and are reflected in attrition patterns: survival analyses reveal that female and minority professionals face significantly higher annual exit hazards. Taken together, these patterns point to widespread disparities in both career advancement and industry retention. However, because most roles lack standardized and observable performance metrics, we cannot directly attribute these gaps to discrimination. To address this limitation, we focus on the subsample of mutual fund portfolio managers, where individual productivity is both observable and objectively measurable, allowing us to test whether these disparities persist after accounting for skill and other characteristics.

Within this portfolio manager subsample, the demographic homogeneity is even more pronounced: only 10% are female and 8.6% are racial minorities (5.2% Asian, 1.5% Black, 1.2% Hispanic, and 0.7% other). Consistent with earlier evidence from the broader asset management industry, these underrepresented groups also earn substantially less than their White male counterparts. Between 1991 and 2020, female and minority managers earn 27% and 20% less than male and White managers, respectively, after controlling for investment performance, return volatility, assets under management (AUM), and year and firm fixed effects. In particular, Asian managers are paid 32% less than their White peers. Strikingly, minority female managers appear to be underpaid by as much as 44% relative to White male managers. These estimates closely mirror the pay gaps we document in the broader asset management sample, suggesting that the disparities observed there likely reflect real compensation differences rather than unobserved variation in performance.

Having documented evidence on pay gaps, we next examine the likelihood of involuntary job separation (i.e., forced turnover). We define forced turnover as cases in which a manager below retirement age leaves an asset management firm and either joins a new one with

reduced assets under management or does not rejoin another firm within a year. Since managerial compensation is closely related to the amount of assets they manage (e.g., Bai et al. (2024), Cen et al. (2023)), exits accompanied by declines in AUM are unlikely to be voluntary. We find that female and minority managers are 0.5 and 0.9 percentage points more likely to be forcefully turned over than male and White peers, respectively. In particular, Asian managers are 1.2 percentage points more likely to be involuntarily turned over. These estimates are economically significant as the unconditional likelihood of forced turnover in our sample is only 2.7%. Overall, the results point to systematic disparities in turnover risk that disproportionately affect minority managers in the mutual fund industry.

We next analyze re-entry outcomes for managers who were involuntarily turned over to determine whether exits are more permanent for female and minority managers. Conditional on an involuntary job separation, female managers are approximately 14 percentage points less likely to ever be rehired into a portfolio manager role, indicating a meaningful long-term career penalty. In contrast, we find no statistically significant differences in rehiring probabilities for Black, Asian, or Hispanic managers relative to White managers. These results suggest that female managers face persistent barriers to re-entry, while the disadvantages for other minority groups may manifest earlier in the career cycle through lower promotion rates and greater exposure to forced turnover rather than through reduced access to re-employment opportunities.

Our final set of analysis investigates several potential explanations for the disparate career outcomes across demographic groups. First, one may argue that differences in qualifications and educational backgrounds could account for these patterns. We find no evidence that minority and female managers possess inferior credentials. In fact, minority managers are significantly more likely than White males to have attended elite institutions and hold an advanced degree (i.e., master's degree or higher). However, they are less likely to hold finance or economics undergraduate degrees. Holding advanced degrees in non-finance fields from

elite schools may reflect a differential route to portfolio management - one that is rooted in domain-specific expertise rather than the traditional finance training path - and thus serves as a strategy for minority managers to navigate and overcome systemic career barriers. Taken together, these findings challenge the view that minority managers lack qualifications and instead suggest that they often advance through alternative career trajectories, relying on distinct forms of expertise and credentials to surmount the structural barriers they face.

Second, we investigate whether minority managers exhibit differences in their ability to deliver investment performance or attract investor flows, both of which are crucial to asset management firms. We find no empirical support for this hypothesis. We find no systematic differences in risk-adjusted performance, measured by Carhart (1997) four-factor alpha or value-added measure of Berk and van Binsbergen (2015), between minority and non-minority managers. Moreover, minority managers do not underperform in attracting investor flows after controlling for fund performance and observable characteristics. These results suggest that neither investment performance nor fundraising ability could explain the observed disparities in compensation, promotion, or risk of turnover.

Having ruled out explanations based on qualifications and performance, we turn to classic models of discrimination to interpret these disparities. In Becker (1971)'s taste-based model, employers hold a distaste for minority workers and may avoid hiring them or offer lower pay, even when productivity is equal. By contrast, statistical discrimination models (e.g., Phelps (1972); Arrow (1973); Aigner and Cain (1977)) attribute disparities to imperfect information: employers use group traits as proxies when individual signals of ability are noisy. In this view, unequal treatment may reflect perceived differences in expected productivity, rather than bias. Our findings are more consistent with the taste-based framework than with statistical discrimination models, as we document substantial compensation gaps, differential turnover rates, and rehiring penalties that persist despite equivalent or better qualifications, similar risk-adjusted performance, and comparable fundraising ability. The persistence of these

disparities even after controlling for comprehensive measures of productivity and performance suggests that factors beyond information constraints may be influencing career outcomes.

Finally, to further shed light on the potential sources for race- and gender-related bias, we examine whether increased diversity in the owners of asset management firms can mitigate some of these disparities. Using information on direct owners of asset management firms from regulatory filings (i.e., Schedule A of Form ADV), we find that greater female and minority representation in firm ownership provides protection against discriminatory treatment. Increased female and minority ownership reduced forced turnover risk by 1.7 and 2.3 percentage points, respectively, relative to male and White managers. Furthermore, increased female ownership reduces gender pay disparities, especially for minority females. This set of evidence further corroborates the explanation of taste-based discrimination. It also highlights the importance of ownership diversity of asset management firms in shaping internal labor market dynamics and fostering more equitable career outcomes.

Our paper contributes to the asset management literature by providing the first comprehensive evidence on demographic disparities in compensation and career outcomes in this important sector. While prior studies have examined demographic biases in this industry (e.g., Kumar et al. (2015); Barber et al. (2017); Niessen-Ruenzi and Ruenzi (2019); Lu et al. (2024); Han et al. (2025)), their analysis primarily relies on investor flows and AUM differentials as proxies for career success. Such flow-based measures reflect investor responses and offer limited insight into internal firm decisions and labor market dynamics for investment professionals. We complement and advance this literature by analyzing career outcomes within organizations, tracing compensation growth, promotion, and involuntary exits, and by testing the mechanisms through which discrimination may operate in shaping these outcomes. In this regard, our paper also adds to the literature on the determinants of career outcomes and compensation of mutual fund managers (e.g., Khorana (1996); Chevalier and Ellison (1999); Chuprinin and Sosyura (2018); Ma et al. (2019); Bai et al. (2024)).

Leveraging confidential administrative data, we uncover the first systematic evidence that race and gender significantly shape career trajectories and compensation in ways not explained by performance or other observable characteristics. Such barriers to entry are particularly striking given prior work suggesting that asset management firms are highly effective in matching talent with capital (e.g., Berk and van Binsbergen (2015) and Berk et al. (2017)). Our findings challenge the view that asset management is a meritocratic profession and raise concerns about taste-based discrimination and potential talent misallocation in a sector central to capital markets. An important implication of our study is that greater diversity among asset management firm owners could help alleviate these barriers.

Our paper also adds to the broader literature on labor market discrimination, which has documented disparities across a wide range of industries, occupations, and demographic groups (see Altonji and Blank (1999) and Bertrand and Duflo (2017) for reviews). A central challenge in this literature, however, is disentangling whether observed disparities arise from biased evaluation or unobserved productivity differences. The mutual fund industry provides a unique laboratory to test this: performance is transparent, compensation is closely tied to observable outcomes, and the industry is competitive. These features imply that persistent demographic disparities are less likely to stem from unobserved ability and more likely to reflect differential treatment. Our findings suggest that discrimination persists even where incentives and information should, in theory, constrain it most. Importantly, while much of the discrimination literature has focused on Blacks and Hispanics, our study uncovers novel evidence on discrimination against Asians, complementing recent studies on Asians in asset management by Agarwal et al. (2024) and Lu et al. (2024).

The rest of the paper proceeds as follows. Section 2 describes the data and methodology. Section 3 documents career disparities across the asset management industry. Section 4 examines mutual fund portfolio managers, where transparent performance metrics enable rigorous tests of discrimination. Section 5 concludes.

2 Data

Our analysis of demographic disparities in the asset management industry requires comprehensive data on employment, compensation, and performance outcomes. We construct two unique individual-level panels that contain micro-level information on compensation, various demographic characteristics, and educational and professional qualifications. We utilize multiple data sources, including the U.S. Census Bureau Longitudinal Employer-Household Dynamics (LEHD) data files, the Individual Characteristics File (ICF), the Longitudinal Business Database (LBD), Morningstar Direct, LexisNexis Public Records, Intelius, LinkedIn, and ADV data from the Securities and Exchange Commission (SEC). Below we outline each of the data sets we use in greater detail.

2.1 U.S. Census Bureau Data

We utilize the U.S. Census Bureau's LEHD dataset, which contains records of all individuals who appear in the U.S. unemployment insurance filings. The earnings are comprised of an individual's total compensation that is covered by unemployment insurance, which includes regular hourly earnings, bonuses, overtime, and sick pay. However, these figures exclude investment income such as dividend income and stock option-based compensation. Around 95% of all U.S. private sector jobs are contained in this comprehensive dataset. We further supplement the LEHD data with the Individual Characteristics File (ICF), which provides person-level demographic information including sex, age, date of birth, place of birth, race, ethnicity, and educational attainment.

Both the LEHD and ICF datasets are confidential and accessible only through Census Research Data Centers under strict disclosure restrictions. Our research proposal was approved by 22 states plus Washington D.C.[2] We link individuals across datasets using Personal

[2]The states that approved our study are Arizona, Arkansas, California, Colorado, Delaware, the District of Columbia, Hawaii, Illinois, Indiana, Iowa, Kansas, Maine, Maryland, Montana, Nebraska, Nevada, New

Identification Keys (PIKs) obtained through the Census Bureau's Person Identification Validation System, which requires providing Personally Identifiable Information (PII) including names, birth dates, SSNs, and addresses to help locate the PIKs of our portfolio managers. We collect this information from a number of sources, including LexisNexis, LinkedIn, and Intellius.[3]

We aggregate quarterly LEHD earnings data to calculate annual compensation and use state employer identification numbers (SEINs) to link employers to the Census Bureau's Longitudinal Business Database (LBD). The LBD provides establishment-level information including location, industry codes, employment, revenue, and payroll since 1976. We use SIC and NAICS codes to identify and filter for asset management industry workers while excluding non-financial firms.

2.2 Morningstar Direct Mutual Fund Database

We obtain data on fund names, manager names, returns, total net assets, expense ratios, turnover ratios, investment styles, and other fund characteristics from the survivorship-bias free Morningstar Direct Mutual Fund (MDMF) database. This database is widely recognized in the literature as having the most accurate information on fund portfolio managers' identities (Massa et al. (2010), Pastor et al. (2015), Patel and Sarkissian (2017),and Chuprinin and Sosyura (2018)). For mutual funds with multiple share classes, we aggregate all observations at the fund level using the unique fund identifier provided by the MDMF database. Consistent with the mutual fund literature, we retain only U.S. based, actively managed, diversified equity funds from the year 1991 through 2020. Importantly, we also include the assets and returns of any separately managed accounts (SMAs) to ensure that we properly measure the total amount of assets under management for which each portfolio manager is responsible. Failing to do so may induce measurement error in the measure of scale and

Mexico, Ohio, Oklahoma, Pennsylvania, Tennessee, Virginia, and Washington.

[3]For more detailed information on this process, see Bai et al. (2024).

could thus create a bias in the impact scale has on investment performance (Huang et al. (2023)). Data on SMAs are also obtained from the Morningstar Direct database.

2.3 ADV Form Schedule A

Finally, to understand and identify who owns and runs the firms that employ our portfolio managers, we utilize the SEC's form ADV, which is a mandatory annual filing for every registered investment advisor. In particular, we focus on Schedule A of the form, which provides detailed information on the direct owners of the firm. For each of these individuals, an ownership code is also provided. Ownership code A represents at least 5% but less than 10% ownership, B represents at least 10% but less than 25%, C represents at least 25% but less than 50%, D represents at least 50% but less than 75%, and E represents 75% or more.

We utilize these two sources to get a complete list of the largest owners of the firm. For each advisor-year, we determine the highest ownership code that appears and classify those individuals as the firms largest owners. Using these names, we then employ two different classification algorithms to identify the race and sex of these individuals.[4] When the two algorithms disagree on the classifications, we manually verify each case and identify the race and sex by the individual's name, biographical information, and photograph. This process allows us calculate, for every advisor-year, the share of female and minority executives among all Schedule A individuals.

[4]We use the Namsor and NamePrism Classification APIs.

3 Sample Construction

3.1 Sample Overview

We construct two unique samples that allow us to examine demographic disparities from different angles within the asset management industry. Naturally, our paper can be split into two main parts: i) the industry-level workforce analysis and ii) the portfolio manager analysis. The industry-level workforce sample is constructed using purely data from the LEHD and ICF. We begin by selecting individuals who work within an asset management firm and who make $100K (in 2020 dollars) in their first year of being employed in the industry.[5] This threshold ensures that the sample captures individuals in economically significant roles within the asset management industry. We track these individuals over time, resulting in a sample of 170,500 unique workers and 1,318,000 worker-years spanning 22 states from 1991 to 2020. This dataset allows us to study demographic differences in employment dynamics and career outcomes, including compensation, promotion, and attrition within the broader asset management workforce.

The second sample, hereafter the portfolio manager sample, is constructed using a combination of LEHD, ICF, Morningstar Direct, and LinkedIn data. After applying the filters outlined in Section 2.2 to the Morningstar data, we identify 7,500 unique managers across 3,483 funds. We then merge these managers with LEHD and ICF to obtain compensation and demographic information. Since we only have employment records for 22 states, we are able to obtain compensation data for about 35% of our sample. Accordingly, we analyze two related datasets. The first consists of 7,500 portfolio managers and 61,500 manager-year observations spanning 1991–2020. The second is a subset of the first, covering 2,625 managers and 20,500 manager-years for whom LEHD compensation is available. We use the portfolio manager sample to examine whether gender and race affect compensation, promotion, forced

[5] We select 2017 NAICS code of 523920 or 523930, or a SIC code of 6282 or 6211

turnover, and rehiring outcomesconduct while controlling for other measures such as risk-adjusted performance and managerial workload (e.g., number of funds managed and total assets under management).

3.2 Variable Construction

We calculate a set of fund- and manager-level variables that follow conventional definitions in the mutual fund literature. We first construct fund-level variables and then aggregate them to the manager level, following Berk et al. (2017). Throughout, we use the following indices: t for calendar months, k for funds, i for individual portfolio managers, and $h \in \{1, 2, 3, 5\}$ for the trailing horizon in years.

For every fund k at time t, we estimate the Carhart (1997) four-factor model to obtain the annualized alpha ($\alpha_{k,t}^{(h)}$), annualized gross alpha ($\alpha_{k,t}^{\text{gross},(h)}$), and the annualized return volatility ($\sigma_{k,t}^{(h)}$) over the trailing horizons. Additional fund-level inputs are the total expense ratio ($\text{TER}_{k,t}$), net asset flows ($\text{Flow}_{k,t}^{(h)}$), and assets under management ($\text{AUM}_{k,t}$), calculated using standard conventions. $R_{k,t}^{(h)}$ is the fund's compounded net return over the h year period. Additionally, we define fund-level value-added ($\text{VA}_{k,t}^{(h)}$) following Berk and van Binsbergen (2015).

$$\text{Flow}_{k,t}^{(h)} = \frac{\text{AUM}_{k,t} - \text{AUM}_{k,t-12h}\left(1 + R_{k,t}^{(h)}\right)}{h \cdot \text{AUM}_{k,t-12h}} \tag{1}$$

$$\text{VA}_{k,t}^{(h)} = \alpha_{k,t}^{\text{gross},(h)} \text{AUM}_{k,t-1} \tag{2}$$

To construct manager-level variables, we first establish each manager's total assets under management (AUM). If a fund is co-managed, its assets are divided equally among all its managers. An individual manager's total AUM is the sum of their shares from all the funds they oversee ($\Omega_{i,t}$):

$$\text{AUM}_{i,t} = \sum_{k \in \Omega_{i,t}} \frac{\text{AUM}_{k,t}}{N_{k,t}} \tag{3}$$

Using these AUM allocations as weights, we define manager-level performance, flows, expense ratios, and return volatility. For a manager overseeing multiple funds, these variables are the weighted average of the corresponding fund-level metrics:

$$\alpha_{i,t}^{(h)} = \frac{1}{\text{AUM}_{i,t-12h}} \sum_{k \in \Omega_{i,t}} \frac{\text{AUM}_{k,t-12h}}{N_{k,t-12h}} \alpha_{k,t}^{(h)} \tag{4}$$

$$\text{Flow}_{i,t}^{(h)} = \frac{1}{\text{AUM}_{i,t-12h}} \sum_{k \in \Omega_{i,t}} \frac{\text{AUM}_{k,t-12h}}{N_{k,t-12h}} \text{Flow}_{k,t}^{(h)} \tag{5}$$

$$\sigma_{i,t}^{(h)} = \frac{1}{\text{AUM}_{i,t-12h}} \sum_{k \in \Omega_{i,t}} \frac{\text{AUM}_{k,t-12h}}{N_{k,t-12h}} \sigma_{k,t}^{(h)} \tag{6}$$

$$\text{TER}_{i,t} = \frac{1}{\text{AUM}_{i,t-12h}} \sum_{k \in \Omega_{i,t}} \frac{\text{AUM}_{k,t-12h}}{N_{k,t-12h}} \text{TER}_{k,t} \tag{7}$$

$$\text{VA}_{i,t}^{(h)} = \sum_{k \in \Omega_{i,t}} \frac{\text{VA}_{k,t}^{(h)}}{N_{k,t-1}} \tag{8}$$

3.3 Summary Statistics

Table 1 contains the summary statistics for the key variables that are used in our analysis. We are only able to present the means, standard deviations, pseudo medians, and counts for all variables in our samples due to the Census Bureau's disclosure restrictions.[6] Summary statistics are presented for both the industry-level workforce and the portfolio manager samples.[7] The industry-level workforce sample reveals strong racial and gender homogeneity. The workforce is heavily male dominated, with women comprising only 21% of the sample. White workers represent the largest racial group at 85%. Minority repre-

[6] Pseudo-percentiles are calculated by taking the mean value from a subset of observations around the percentile. These observations are the 5 observations before and 5 observations after the true quantile, for a total of 11 observations. Pseudo-percentiles are naturally very close to their true quantile values but have induced noise to ensure that they do not pose any disclosure risk.

[7] Due to Census disclosure restrictions, we only disclose summary statistics for the panel dataset

sentation is limited, with Black workers accounting for 2.1%, Asians 8.9%, Hispanics 2.4% and other groups—including American Indian, Hawaiian, and multiracial individuals—1.3%. The workforce is highly educated, with approximately 80% holding at least a bachelor's degree. Compensation is also high, with average annual earnings of $375,080 (in 2020 dollars), excluding stock-based pay. Finally, the average worker in this industry is about 47 years old.

[Insert Table 1 Here]

Table 2 provides the summary statistics for our portfolio manager sample. The demographic homogeneity is even more profound in this group: only 10% of managers are female, 5.2% Asian, 1.5% black, 1.2% Hispanic, and 0.7% other minority.[8] Thus, around 90% of our sample is comprised of White portfolio managers. These numbers are consistent with those of Han et al. (2025), who use the same racial classification system as the Census Bureau, but manually verify the races of portfolio managers. As expected, portfolio managers are highly educated, with around 40% of them attending an elite school, 56% having an MBA, 21% having a CFA, and 50% having an advanced degree. They are also well compensated, with the average annual salary of approximately $1,600,000, not including stock compensation. The average age is 47, mirroring the broader asset management workforce. Taken together, the statistics underscore the overwhelming dominance of White males in the industry and highlight the significant under-representation of women and minorities among portfolio managers.

[Insert Table 2 Here]

[8] Our percentage of female portfolio managers is consistent with industry reports: https://www.morningstar.com/sustainable-investing/women-account-smaller-percentage-managers-today-compared-with-2002

4 Industry-wide Labor-Market Outcomes

We begin by examining career outcomes across the broader asset management industry. This analysis provides important context and baseline results for industry-wide employment patterns and how they vary across demographic groups. We focus on investment professionals in core decision-making roles (e.g., analysts, portfolio managers) to ensure that our analysis captures those individuals most directly responsible for investment outcomes. We track these individuals over time and examine how race and gender correlate with career outcomes such as compensation, internal and external promotion, and turnover throughout a manager's career.

4.1 Compensation and Wage Growth

We begin our analysis of the broader asset management industry by examining compensation differences across demographic groups: a central outcome in labor economics. For every worker-year, we regress log earnings on the demographic variables described above. We conduct the analysis using the full sample over 1991 – 2020 as well as two subperiods (1991 – 2005 and 2006 – 2020) and present specifications with and without firm fixed effects:

$$\log\big(\text{Compensation}_{i,t}\big) = c + \beta' X_{i,t} + \lambda_j + \delta_t + \varepsilon_{i,t} \tag{9}$$

where λ_j are firm fixed effects, δ_t are year fixed effects, and $X_{i,t}$ is the vector of dummies for demographic controls, education controls, age, and tenure at firm j.

Table 3 reports the results, which show that the earnings differentials across demographic groups are sizable, significant, and stable across sample periods. Female workers earn an average of 25% less than male workers in the full sample, with the differential narrowing

only slightly to 24% in the 2006 to 2020 period.[9] Black workers' earnings are 22% lower, Asian workers' 21% lower, Hispanic workers' 14% lower, and other minorities' 12% lower than White workers in the full sample, after controlling for year and firm fixed effects. These estimates suggest that compensation differences in the asset management industry are economically meaningful and display remarkable persistence over nearly three decades.

[Insert Table 3 Here]

Given the significant compensation gaps observed, we next look at the wage growth dynamics across demographic groups. We define cumulative wage growth as $\frac{Compensation_t}{Compensation0}$, the ratio of compensation in year t to compensation in the entry year (year zero). Figure 1 shows that male wage growth consistently exceeds female wage growth each year up to fifteen years post-entry, with all differences being both economically large and statistically significant. Males consistently earn more than females, with wage growth differences ranging from 6.4 percentage points in year one to 34.8 percentage points in year fifteen, relative to year zero. Notably, the wage difference not only persists over time, but also grows. We observe a similar patten for White males and non White-males, but it is less pronounced. Initially, there is a wage gap between these two groups, starting at 4.7 percentage points in year one and peaking at around 13.7 percentage points in year nine. However, after that, the difference in wage growth falls and remains statistically insignificant for the majority of the rest of the period. This is likely due to survivorship bias, as the subset of workers remaining in the sample by the end of the period represents a highly selected group with comparable traits across demographic categories.

[Insert Figure 1 Here]

Finally, we examine the post-industry-exit earning differentials among demographic groups. For each worker who has exited the asset management industry, we compute the ratio of

[9] We exponentiate the coefficients using the following: $\left(e^{\hat{\beta}} - 1\right) \times 100$.

first-year salary after exit to last-year salary before exit, and test for demographic differences. All groups experience lower pay upon leaving asset management, with a 1% decrease for males and a 0.9% decrease for White males, but females and non White-males experience an even larger drop. Females make around 4.6 percentage points less than males, and non White-males make about 3.3 percentage points less than White males, and both differences are statistically significant. Combined, the results in this section indicate that female and minority managers: i) experience slower wage growth during their tenures in, ii) are more likely to exit, and iii) experience sharper pay cuts upon their exit from the asset management industry.

4.2 Promotion Analysis

Next, we examine whether the wage growth differentials we document in Figure 1 also extend to promotion outcomes. We define promotions based on observed salary increases. Specifically, we define an internal promotion as an instance when a worker receives a salary increase of at least 20% within the same firm, an external promotion occurs when they receive a salary increase of at least 20% upon moving to a new firm, and an overall promotion when either an internal or external promotion occurs.[10] For each outcome $Y_{i,t} \in \{\text{Promotion}, \text{Internal Promotion}, \text{External Promotion}\}$ we estimate the following linear probability model:

$$Y_{i,t} = c + \beta' X_{i,t} + \lambda_j + \delta_t + \varepsilon_{i,t} \tag{10}$$

where λ_j are firm fixed effects, δ_t are year fixed effects, and $X_{i,t}$ is the vector of variables for demographic controls, education controls, starting age, and tenure at firm j. Standard errors are clustered at the worker level. Additionally, as workers can experience multiple

[10] Our results are robust to define promotions based on 50% salary increases.

promotions over time, we do not censor the individual after the first promotion.

[Insert Table 4 Here]

Table 4 summarizes the results. All demographic groups have a lower likelihood of receiving a promotion as compared to their male and White counterparts. Female workers are 1.7 percentage points less likely to be promoted than male workers, which corresponds to an 8% lower probability relative to the mean promotion rate of 20.6%. Black, Asian, Hispanic, and other-minority workers are 2.2, 2.4, 0.8, and 0.8 percentage points less likely to be promoted than White workers, respectively. This is around 11%, 12%, and 4% lower relative to the mean promotion rate. Results are similar in magnitude for internal promotions. These findings align with the wage growth differentials observed in Figure 1, revealing a consistent pattern where female and minority workers face systematic disadvantages not only in compensation growth but also in career advancement opportunities in the asset management industry.

4.3 Survival Analysis

The patterns documented above point to the existence of systematic differences in career trajectories across demographic groups. This raises the question of whether similar differentials exist in industry retention rates. To formally test this hypothesis, we estimate Cox proportional hazard models, which model the relationship between survival time (time spent in the asset management industry) and certain predictor variables (investment professionals' characteristics). Specifically, we estimate the following hazard function:

$$h_{i,j}(t) \;=\; h_{0,j}(t)\,\exp\!\big(\beta' X_{i,j}\big) \tag{11}$$

where $h_{0,j}(t)$ is the baseline hazard for firm j, t is the time in years, $X_{i,j}$ is the vector of

individual covariates (gender, race, education, and starting age in the industry) that are time-invariant, and β is the corresponding coefficient vector. We assume proportional hazards so that relative risks remain constant over time.

We consider an individual to have left the asset management industry if he or she no longer works for a firm with the NAICS and SIC codes listed in Section 3.1. The exit event is flagged in the last year in which a worker appears in the industry. The time scale is measured in years from first employment in asset management to the year of a given observation. There are a few caveats to this analysis. First, because we only have access to employment records for 22 states, we can not observe cases in which a worker moves to a state for which we do not have data. Second, because our sample ends in 2020, we cannot observe any employment outcomes beyond 2020 for the employees who remain in the sample as of 2020. In both cases, we right censor the employee after the final year for which we can observe their employment.[11]

Our baseline specification includes time-invariant demographics (gender, race, starting age, and education) and is estimated in two ways: a pooled model with a single baseline hazard across firms, and a set of baseline hazard models estimated separately for each firm. The results are shown in Table 5. In all specifications, the coefficients for the demographic covariates are positive and statistically significant. Female workers have an 18% higher probability of exiting the industry, as compared to males in the same firms. Black, Asian, Hispanic, and other minority workers have 22%, 24%, 11%, and 18% higher probabilities of exiting the industry relative to White workers within the same firm.[12] When we estimate the models without firm stratification, we find that the coefficients increase in magnitude, indicating that part of the differential estimated is attributable to firm-level heterogeneity. In sum, we find strong evidence that female and minority investment professionals are significantly

[11]There is one exception to this rule. We also have access to a dataset (called the Earnings Indicator File) which allows us to see if a worker is employed in any US state. If the individual is not employed at all, we consider them to have exited the industry in the prior year.

[12]We convert the coefficients to percentages using $\left(e^{\hat{\beta}} - 1\right) \times 100$.

more likely to exit asset management than their male and White counterparts.

[Insert Table 5 Here]

Our findings so far suggest that female and minority investment professionals experience systematically less favorable career outcomes in the asset management industry. Controlling for firm and year fixed effects, we document that female and minority workers earn lower compensation, are promoted less frequently, face higher attrition rates, and suffer larger financial penalties upon exiting the industry. These patterns raise important questions about the sources of such disparities. Potential explanations include differences in performance and productivity, as well as race- and gender-based biases such as taste-based discrimination. We examine these possible mechanisms in the next section.

5 Labor Market Outcomes of Portfolio Managers

Due to the lack of data on observable performance metrics for all employees in the industry-wide sample, we cannot fully disentangle the channels through which these career differentials arise. To address this limitation, we turn to the subsample of mutual fund portfolio managers, for whom we have observable measures of performance and productivity. The sample provides a unique setting in this regard, as it offers transparent and standardized performance metrics such as risk-adjusted returns, fund flows, and value-added measures that directly shape compensation and career outcomes. If the disparities documented in the previous section are the result of differences in performance, then controlling for these measures should significantly reduce or eliminate these gaps. However, if we continue to find evidence of large wage gaps and increased exit likelihoods after controlling for measures of performance and productivity, our findings would challenge the prevailing view that the industry allocates rewards purely based on merit.

5.1 Compensation Determinants and Demographics

We begin by examining whether managers' race and gender can explain their level of compensation after controlling for various performance and workload measures. To do so, we estimate the following panel regressions:

$$\log\big(\text{Compensation}_{i,t}\big) = c + \beta' D_i + \gamma' P_{i,t-1}^{(h)} + \kappa' F_{i,t-1} + \lambda_j + \delta_t + \varepsilon_{i,t} \qquad h \in \{1,2,3\} \quad (12)$$

where $\text{Compensation}_{i,t}$ is the total annual salary of manager i at the end of year t, D_i is the vector of demographic dummies, $P_{i,t-1}^{(h)}$ contains the performance covariates such as four-factor α, flows, and return volatility over the h-year window and ending in year t-1, $F_{i,t-1}$ contains manager-level fund characteristics, specifically the number of funds they manage, $\log(\text{ Funds}_{i,t-1})$ and their assets under management, $\log(\text{AUM}_{i,t-1})$. λ_j denotes firm fixed effects and δ_t captures year fixed effects. Standard errors are double clustered at the manager and year levels.

[Insert Table 6 Here]

Table 6 presents the results. Columns 1 – 3 in Panel A examine the effect of gender on compensation. The coefficients on the female variable range from -0.233 to -0.254 and all are statistically significant. These coefficients indicate that female managers earn 21% to 22% less than male managers. We augment these regressions with firm fixed effects in Columns 1 – 3 of panel B. The results slightly increase though remain largely unchanged; female managers earn 24 – 27% lower compensation than their male colleagues within the same firm. We observe similar patterns for minority managers. For example, we find that Asian managers earn 31% to 32% less than White managers.

The most pronounced results involve minority female managers, which include Black, Asian, Hispanic, American Indian, Hawaiian, and Multiracial mangers. We find that mi-

nority female managers earn roughly 44% lower compensation than their counterparts, indicating that the intersection of gender and minority status is associated with the largest compensation penalty.

Taken together, the results in this section indicate that the observed wage gaps cannot be fully explained by differences in performance or productivity. Instead, they persist even after accounting for these factors, suggesting that other forces—such as discrimination—may play an important role. Importantly, the magnitudes of the disparities documented in the portfolio manager sample are closely aligned with those found in the broader asset management sample. For instance, we find a 25% gender wage gap across the broader industry and a 24%–27% gap among portfolio managers. This consistency across samples highlights the robustness of our findings and suggests that systematic inequities permeate the industry rather than being confined to a particular group.

5.2 Forced Turnover and Rehire Probability

Next, we examine whether race and gender affect forced turnover and rehire probability among portfolio managers. We define *Forced Turnover* equal to 1 for a manager if he: i) leaves the firm in that year, ii) either joins a new one with reduced assets under management (AUM) or does not rejoin another firm within a year, and iii) is below the retirement age of 65. We set these conditions to ensure that the manager did not leave due to retirement or voluntary transition to a better position. We define *Rehire* equal to 1 for a manager if i) *Forced Turnover* equals 1 for the manager's prior role, ii) he departs his prior firm at an age less than 65 years old, and iii) he finds another portfolio manager job. Next, we run panel regressions of these variables on our demographic and performance control variables. We estimate linear probability models using the following specification:

$$\text{Forced Turn}_{i,t} \;=\; c + \beta' D_i + \gamma' P^{(h)}_{i,t-1} + \kappa' F_{i,t-1} + \lambda_j + \delta_t + \varepsilon_{i,t} \qquad h \in \{1,2,3,5\} \tag{13}$$

where D_i is the vector of demographic dummies, $P_{i,t-1}^{(h)}$ contains the performance covariates such as four-factor manager α, flows, and return volatility over the h-year window and ending in year t-1, $F_{i,t-1}$ contains manager-level fund characteristics, specifically the number of funds they manage, log($\text{Funds}_{i,t-1}$) and their assets under management, log($\text{AUM}_{i,t-1}$). λ_j denotes firm fixed effects, while δ_t captures year fixed effects. Standard errors are double clustered at the manager and year levels.

[Insert Table 7 Here]

Table 7 presents the results from this analysis. We note, prior to discussing the results, that managers are fired at an average rate of 2.7% per year. Regressions (1) – (3) compare the forced turnover rates of men and women after controlling for 1-, 2- and 3-year performance measures and year fixed effects. The coefficients on the female variable are about 0.5 percentage points, which indicates that females have about an 18.5% higher likelihood of being terminated from their firms. This effect is even more pronounced for minority and Asian managers, who face a roughly 30-33% and 41-44% higher relative likelihood of forced turnover, relative to white male managers, respectively.

Next, we test whether there are differences in rehire rates for female and minority portfolio managers after controlling for these managers' past performance. We estimate the same specification as in the forced turnover analysis, but with *Rehire* as the dependent variable. Our sample contains all managerial turnover events. *Rehire* is equal to one if a manager is rehired by another firm as a portfolio manager and zero otherwise. We estimate these models with year fixed effects, and standard errors are double clustered at the manager and year levels:

$$\text{Rehire}_{i,t} = c + \beta' D_i + \gamma' P_{i,t-1}^{(h)} + \kappa' F_{i,t-1} + \delta_t + \varepsilon_{i,t} \qquad h \in \{1, 2, 3\} \tag{14}$$

Table 8 presents the results of this analysis. Columns (1) – (3) compare the rehire rates

of female and male managers after controlling for 1-, 2-, and 3 years of past performance.[13] The average rehire rate in our sample is approximately 32%. Our results show that female managers are 13-14 percentage points less likely to be rehired, which translates to a re-entry rate that is over 40% lower than that of male managers. Columns (4) – (6) compare the rehire rates for minority and non-minority manager. Perhaps surprisingly, we do not find a statistically significant difference in the rate at which minority portfolio managers are rehired relative to their non-minority peers. These results are interesting, because they suggest that females are significantly less likely to re-enter the industry after leaving the industry. Conversely, minorities have a higher likelihood of being turned over but do not face significant rehiring disadvantages.

[Insert Table 8 Here]

Combined, these results challenge the view that the portfolio management industry is purely meritocratic. Our results provide strong evidence that race and gender play significant and, in many cases, detrimental roles in determining career outcomes. In the next section, we investigate the potential reasons that could explain these differences.

5.3 Qualifications and Performance

One potential explanation for the differences in career outcomes is that female and minority managers systematically differ from White male managers in qualifications, performance, or the age at which they enter the profession. To test this possibility, we estimate a series of regressions where the dependent variables are i) the managers' educational and professional qualifications (e.g., advanced degrees, elite college degrees, CFA certifications), ii) various performance measures, and iii) the age at which the portfolio managers first start running

[13] We were not able to disclose the coefficients on these control variables because of concerns regarding confidentiality.

a mutual fund. The key independent variables are demographic group indicators, with year fixed effects included.

We first examine whether portfolio manager qualifications differ across demographic groups and estimate the following regression specification where $Y_i \in \{\text{EliteSchool}_i,\ \text{MBA}_i,\ \text{CFA}_i,\ \text{AdvDeg}_i\}$:

$$Y_i = c + \beta' D_i + \delta_t + \varepsilon_i \tag{15}$$

where D_i is one of the demographic dummies, and δ_t are year fixed effects.

Table 9 contains the results. We find that minority managers exhibit significantly stronger educational qualifications relative to White managers. Specifically, minority managers are 13% more likely to have attended an elite school, 4.7% more likely to hold an advanced degree and 4.8% more likely to have an MBA. This pattern is even more pronounced among Asian (minority female) managers, as they are 15.2% (17%) more likely to possess a degree from an elite school, and 7.4% (9.6%) more likely to hold an advanced degree relative to their peers. Combined, these results suggest that minority managers have a higher qualification threshold for entry into portfolio management. In untabulated results, we also find that minority managers are less likely to hold finance or economics undergraduate degrees. Holding advanced degrees in non-finance fields from elite schools may reflect a differential route to portfolio management, likely a strategy for minority managers to navigate and overcome systemic career barriers.

[Insert Table 9 Here]

Next, we examine whether there are differences in performance across demographic groups. To do so, we estimate the following regression specification:

$$\text{Y}_i = c + \beta' D_i + \delta_t + \varepsilon_i \tag{16}$$

where Y_i is a performance outcome such as $\alpha_{i,t}^{(hYear)}$, $VA_{i,t}^{(hYear)}$, $Flow_{i,t}^{(hYear)}$ or, $\log(AUM_{i,t})$, D_i is one of the demographic dummies, and δ_t are year fixed effects.

Table 10 presents the results, with those on investment performance in Panel A and fund flows in Panel B. We find that all coefficients on risk-adjusted returns and value-added are statistically insignificant in Panel A across all minority groups. This suggests that females and minorities exhibit comparable performance and similar investment skills. In terms of fund flows, we do not find any results that female or minority managers attract less investor flow compared to their peers. There is some evidence of higher 1-year fund flows for minority (Asian) managers, though this result is not robust across specifications. Furthermore, we test whether there is a statistically significant difference in assets under management across demographic groups. We do not find robust evidence that female and minority groups show no statistically significant difference in assets under management compared to White and male managers. Overall, these results suggest that neither investment performance nor the ability to attract flows could explain the disparities we observe in compensation, promotion, and turnover risk.

[Insert Table 10 Here]

Lastly, we examine whether certain demographic groups start working as portfolio managers earlier or later than others. We estimate the following regression specification:

$$\text{AgeStart}_i = c + \beta' D_i + \delta_t + \varepsilon_i \tag{17}$$

where D_i is one of the demographic dummies, and δ_t are year fixed effects. *AgeStart* is defined as the age in which a portfolio manager is first observed in Morningstar having responsibility for running a mutual fund. As shown in Table 11, we find that female and male managers start as portfolio managers in the industry around the same age. However, minorities enter the industry as portfolio managers about 2.0 years younger than White managers. Similar

results hold for Asians and minority females. These results suggest that minority managers likely specialize in portfolio management earlier after their unique educational paths than White managers.

[Insert Table 11 Here]

Overall, these results suggest that the standards required for female and minority managers may be more demanding than they are for male and non-minority managers. Additionally, it appears that the pathways into portfolio management are different for various demographic groups. However, we do not find that manager qualifications and performance support the notion that minority and female managers have worse outcomes due to inferior skills or credentials.

5.4 Female and Minority Owners in Asset Management Firms

The results in the prior sections suggest that the less favorable career outcomes we document for female and minority mutual fund managers can not be explained by lesser qualifications or worse performance. One potential explanation is that these managers are adversely affected by taste-based discrimination. In Becker (1971)'s taste-based discrimination model, employers have a distaste for minority workers and may avoid hiring them or offer lower pay, even when productivity is equal. In contrast, statistical discrimination models of Phelps (1972), Arrow (1973), and Aigner and Cain (1977) attribute disparities to imperfect information: employers use group traits as proxies when individual signals of ability are noisy. In their view, unequal treatment may reflect perceived differences in expected productivity, rather than bias. Our results to this point are more aligned with the taste-based models than with statistical discrimination models.

Although taste-based discrimination is inherently difficult to test empirically, our setting provides a unique opportunity to examine it. Specifically, because we can observe the iden-

tities of each firm's executives and owners, we can compare the career outcomes of women and minorities who work for firms with or without diverse ownership and leadership. If the effects we document are concentrated in White- or male-owned firms, it would suggest that taste-based discrimination can at least partially explain our results.

We obtain firm ownership information from Schedule A of Form ADV filings, which provides detailed information on every control person in advisory firms and their level of ownership. For every advisor-year, we determine the highest ownership tier that appears, and classify all individuals at that tier as the firm's largest owners. We then collect race and gender information on these individuals. Then, for every firm where a large owner is a female or a minority, we calculate the share of the firm's large owners who belong to each demographic group. We then merge those advisor-level ownership shares onto our manager-year panel, so every portfolio manager is linked to the same "percentage female large owner" and "percentage minority large owner" for the advisory firm that employs them.

We test whether greater ownership presence of one's demographic group reduces the gender and racial gaps in forced turnover risk and compensation using the following regression specifications where $Y_{i,t} \in \{\log(\text{Compensation}_{i,t}),\ \text{ForcedTurn}_{i,t}\}$:

$$\text{Y}_{i,t} = c + \beta_1 D_i + \beta_2 S_{i,t} + \beta_3 \big(D_i \times S_{i,t}\big) + \gamma' P^{(h)}_{i,t-1} + \kappa' F_{i,t-1} + \delta_t + \varepsilon_{i,t}, \qquad h \in \{1, 2\} \quad (18)$$

D_i is the manager-level demographic dummy, $S_{i,t}$ is the fraction of top-owner shares held by either i) females or ii) minorities in manager i's firm in year t, $P^{(h)}_{i,t-1}$ contains the performance covariates such as four-factor manager α, flows, and return volatility over the h-year window and ending in year t-1, $F_{i,t-1}$ contains manager-level fund characteristics, specifically the number of funds they manage, $\log(\text{ Funds}_{i,t-1})$ and their assets under management, $\log(\text{AUM}_{i,t-1})$, and δ_t are year fixed effects. Standard errors are double clustered at the

manager and year level.

[Insert Table 12 Here]

Table 12 presents the results from this analysis. Regressions (1) and (2) show that female or minority forced-turnover risk is mitigated when there is a higher share of female and minority owners. Consistent with our earlier forced turnover analysis, we find that being a female manager raises the forced turnover probability by about 0.5 percentage points, representing an 18.5% increased probability relative to the 2.7% mean forced turnover rate. However, we find that this penalty is reduced by increased female representation. An increase in female ownership from 0% to 100% is associated with a 1.7 percentage point decrease in turnover probability for female managers relative to male managers. Restated, in firms that are fully female-owned, female portfolio managers would then be *less* likely to be terminated than male managers. Relative to the baseline forced turnover rate, this would translate to a 63% decrease in forced turnover probability. A similar dynamic holds for minority managers, for whom a corresponding increase in minority ownership is associated with a 2.3 percentage point decrease in turnover risk, relative to White managers. Relative to the baseline forced turnover rate, this would be an 85% decrease in the probability of forced turnover for minority managers. This indicates that ownership representation does in fact provide meaningful protection to these demographic groups.

Regressions (3) and (4) examine the same dynamics, but with compensation. We see that female and minority-female managers earn approximately 23% and 57% less, respectively, than their White male counterparts. The ownership effects on compensation vary by demographic group. For females, it appears that increased female ownership has no differential effect on compensation dynamics. However, for minority females, the pay disparity shrinks dramatically as the share of female leadership at a firm increases. A one percentage point increase in female ownership is associated with a roughly 1.9% increase in pay for minority-female managers, relative to White male managers.

Taken together, these results suggest that minority and female ownership mitigate the discrimination that women and minority managers face in the asset management industry. Greater representation in firm ownership reduces the likelihood of forced turnover for females and minorities. Female ownership appears to mitigate the pay gap for minority females. Our results suggest that increasing diversity in firm ownership could be a potential mechanism for reducing the demographic disparities in the asset management industry.

6 Conclusion

In this paper, we conduct a comprehensive analysis of the role of race and gender on career outcomes and trajectories in the U.S. asset management industry. Using administrative earnings and demographic data from the U.S. Census Bureau, we examine employment patterns across the broader asset management industry and find systematic disadvantages for female and minority managers: they exit the industry earlier, experience slower wage growth, receive fewer promotions, and receive substantially less compensation than their White male counterparts.

We then focus specifically on the mutual fund portfolio manager subsample, where performance is transparent, measurable, and objective. This transparency, combined with the industry's highly competitive nature and performance-based compensation structures, creates conditions where merit-based evaluation should be the key determinant of career outcomes. We leverage this unique setting by creating a matched panel that links individual-level employment data to fund-level performance records, enabling us to test whether demographic disparities persist even after controlling for objective measures of productivity. Consistent with our broader asset management findings, we document significant career outcome differentials that cannot be explained by performance differences or manager qualifications.

After controlling for performance and fund-level variables such as four-factor alpha, assets

under management, and number of funds managed, female managers earn 27% less than male peers, while minority managers earn 20% less than White peers. Minority female managers face the most significant compensation penalty, with up to 44% lower compensation, despite possessing equal or superior qualifications and similar risk-adjusted returns and flows. Beyond compensation, we find that minority and female managers experience higher forced turnover rates, while female managers are less likely to be rehired after job separations. These disparities can not be explained by differences in qualifications: minority managers are more likely to attend elite schools and hold advanced degrees. Nor do they reflect differences in performance: we find no systematic difference in investment performance or in the ability to attract investor flows. Importantly, we document that these disparities can be meaningfully mitigated through increased diversity in firm leadership: greater female and minority representation in asset management firm owners helps reduce forced turnover risk for minority managers and gender compensation gaps. These findings suggest that the mutual fund industry does not operate as a pure meritocracy, and that gender- and race-driven biases play significant roles in determining the career outcomes in asset management.

Our results are most consistent with taste-based models of discrimination, where employers hold biases against certain demographic groups, leading to differential treatment even when productivity is identical. The persistence of substantial compensation gaps alongside turnover and rehiring differentials, after controlling for performance measures, suggests that these disparities reflect biased evaluation rather than unobserved differences in performance or productivity. These findings have troubling implications for the efficiency of capital allocation and talent retention, raising questions about the asset management industry's ability to allocate capital to its most efficient uses.

Finally, our paper challenges the view that competitive, performance-driven industries are immune to discrimination and biases. We show that even when objective measures of performance are available and economic incentives should reward merit, discrimination per-

sists and continues to influence critical career decisions, including compensation, promotion, and retention. These findings have important implications for understanding labor market discrimination more broadly, particularly in high-skilled environments where transparent performance measurement is expected to most effectively constrain biased treatment.

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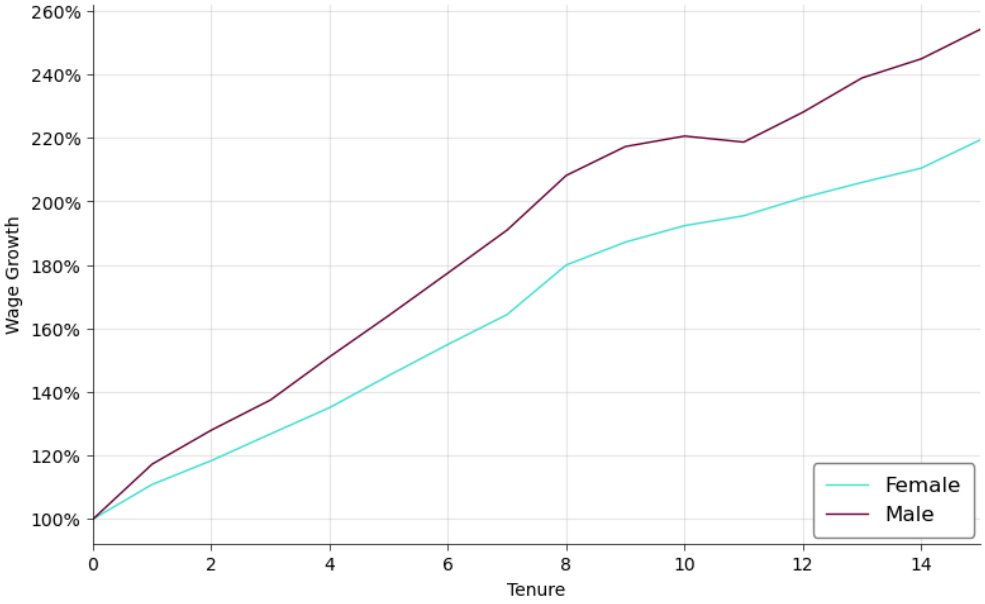
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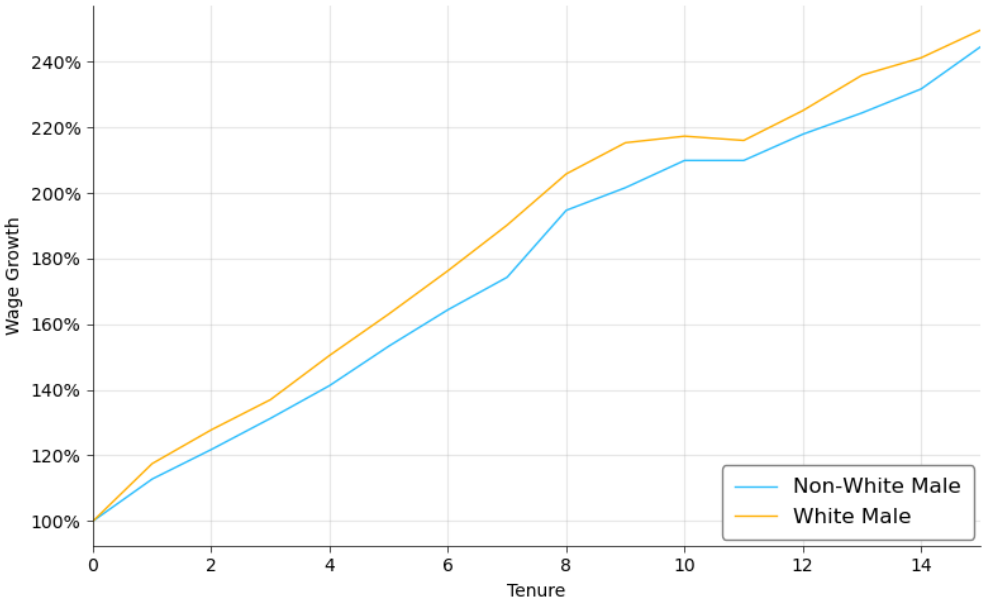
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Figure 1: Wage Growth Over Tenure in Asset Management

These figures plot the cumulative wage-growth rate for our initial sample of 170,500 asset management workers over a fifteen-year period. Cumulative wage growth is defined as the ratio between average compensation in year t and average compensation in year 0, for each demographic group. Panel (a) plots wage growth differences between Male and Female workers; panel (b) plots differences between White Male and non White-Male workers. Non White-Male workers are defined as any worker that is not a White Male.



(a) Wage Growth by Gender



(b) Wage Growth by Race

Table 1: Summary Statistics for Asset-Management

This table presents summary statistics for the industry-wide analysis, drawing data from both the LEHD and ICF files. Summary statistics are presented for the panel sample of initial 170,500 investment professionals for the years 1991 to 2020. Internal promotions are defined as salary increases of at least 20% between year t and t+1 within the same firm. External promotions are defined as salary increases of at least 20% between year t and t+1 accompanied by a change in employer. Quarterly salary represents annual salary divided by the total number of non-missing or non-zero quarters. "Pseudo 50%" refers to the pseudo-median, calculated by averaging the five observations on either side of the true median to comply with Census disclosure requirements.

Panel A: Demographics and Education

Variable	Mean	Pseudo 50%	SD	N
Female	0.213	0	0.410	1,318,000
Black	0.021	0	0.145	1,318,000
Asian	0.089	0	0.285	1,318,000
Hispanic	0.024	0	0.153	1,318,000
Other Minority	0.013	0	0.113	1,318,000
Bachelor's or More	0.803	1	0.398	1,318,000
Age	46.61	46	11.30	1,318,000

Panel B: Promotions and Tenure

Variable	Mean	Pseudo 50%	SD	N
Promotion	0.206	0	0.405	1,318,000
Internal Promotion	0.180	0	0.384	1,318,000
External Promotion	0.026	0	0.159	1,318,000
Quarterly Salary ($)	93,770	54,360	126,000	1,318,000
Time in Firm (Years)	7.924	6	6.65	1,318,000

Table 2: Summary Statistics for Portfolio Management

This table presents summary statistics for the mutual-fund sample. Manager compensation and employment data come from the U.S. Census Bureau's LEHD. Demographics and gender variables come from the ICF. Fund characteristics come from Morningstar. Education variables come from LinkedIn and other data sources. Minorities are defined as Asian, Black, Hispanic, or Other Minority. Other Minority is defined as American Indian, Hawaiian, or multi-racial. "Pseudo 50%" is the pseudo-median, computed by averaging the five observations on either side of the true median to satisfy Census disclosure rules. Due to disclosure restrictions, true counts are masked - we assigned missing values to zero and applied a small weight (0.0001) in summary calculations.

Panel A: Demographics	Mean	Pseudo 50%	SD	N
Female	0.103	0.000	0.305	61,500
Minorities	0.086	0.000	0.280	61,500
Asian	0.052	0.000	0.221	61,500
Black	0.015	0.000	0.122	61,500
Hispanic	0.012	0.000	0.108	61,500
Other Minority	0.007	0.000	0.085	61,500
Minority Female	0.014	0.000	0.119	61,500
Panel B: Education and Age				
Elite School	0.394	0.000	0.489	61,500
MBA	0.556	1.000	0.497	61,500
CFA	0.207	0.000	0.405	61,500
Finance/Economics Degree	0.479	0.000	0.500	61,500
Advanced Degree	0.503	1.000	0.500	61,500
Manager Age	46.80	46.00	10.20	61,500
log(Manager Age)	3.820	3.830	0.215	61,500
Panel C: Manager-Level Flows				
Avg flow (1y)	0.003	-0.001	0.153	61,500
Avg flow (2y)	0.003	0.000	0.117	61,500
Avg flow (3y)	0.003	0.000	0.085	61,500
Avg flow (5y)	0.003	0.001	0.061	61,500
Panel D: Manager-Level Fund Characteristics				
Expense ratio (%)	1.120	1.090	0.420	61,500
Turnover ratio (%)	74.00	55.00	69.30	61,500
Return Volatility (1yr %)	14.30	12.80	17.00	61,500
log(#Funds Overseen)	1.220	1.100	0.588	61,500
log(AUM)	19.20	19.20	2.200	61,500
Panel E: Manager Outcomes				
Forced Turnover	0.027	0.000	0.162	61,500
Rehire	0.320	0.000	0.467	61,500
Manager Compensation (2020 $)	1,600,000	445,000	3,520,000	61,500
log(Manager Compensation)	13.20	13.00	1.450	61,500

Table 3: Compensation and Demographics in Asset Management

This table presents results from a compensation analysis examining race and gender pay differentials among asset managers. We regress log earnings on demographic controls for every worker-year observation.The analysis is conducted across three time periods: 1991-2020 (full sample), 1991-2005 (early period), and 2006-2020 (recent period). Each period includes specifications both with and without firm fixed effects to examine whether pay gaps persist within firms or are driven by sorting across firms. Coefficients are interpreted as percentage changes in compensation relative to the baseline group, calculated as $\left(e^{\hat{\beta}} - 1\right) \times 100$ for log-level interpretation. Standard errors are clustered at the worker level. t-statistics are reported in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	log(compensation$_{i,t}$)					
	1991–2020	1991–2005	2006–2020	1991–2020	1991–2005	2006–2020
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.287***	-0.306***	-0.277***	-0.285***	-0.306***	-0.274***
	(–21.55)	(–18.12)	(–18.54)	(–12.96)	(–10.98)	(–12.66)
Black	-0.267***	-0.280***	-0.261***	-0.252***	-0.254***	-0.247***
	(–13.92)	(–12.07)	(–11.31)	(–12.53)	(–10.11)	(–10.29)
Asian	-0.182***	-0.217***	-0.179***	-0.234***	-0.246***	-0.233***
	(–9.20)	(–10.24)	(–8.26)	(–12.63)	(–9.38)	(–12.05)
Hispanic	-0.140***	-0.176***	-0.125***	-0.146***	-0.175***	-0.133***
	(–8.43)	(–8.32)	(–7.00)	(–11.77)	(–9.85)	(–10.16)
Other Minority	-0.108***	-0.151***	-0.093***	-0.131***	-0.157***	-0.120***
	(–5.19)	(–4.89)	(–3.97)	(–6.07)	(–5.51)	(–5.01)
Bachelor's Degree or Higher	0.293***	0.289***	0.315***	0.307***	0.253***	0.328***
	(11.39)	(5.58)	(11.97)	(13.28)	(5.33)	(14.23)
Age	-0.003***	-0.001	-0.004***	0.001	0.002	-0.001
	(–2.83)	(–0.28)	(–3.98)	(0.56)	(1.51)	(–0.14)
Observations	1,318,000	488,000	830,000	1,318,000	488,000	830,000
Adj. R^2	0.030	0.033	0.030	0.135	0.129	0.145
Firm FE	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Promotion Analysis

This table presents results from a linear probability model analyzing promotion likelihood across demographic groups in the asset management industry. We define three promotion outcomes: (i) internal promotion as a salary increase of at least 20% within the same firm, (ii) external promotion as a salary increase of at least 20% at a new firm, and (iii) overall promotion as receiving either an internal or external promotion. These results are robust to a 50% salary increase definition. The analysis employs a multiple-failure framework where each promotion terminates the current "spell" and the individual immediately re-enters the risk set in the following period. This approach ensures that workers remain "at risk" for further promotions throughout their careers without biasing coefficient estimates on gender and race. Standard errors are clustered at the worker level. t-statistics are reported in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	Promotion	Internal Promo	External Promo
	(1)	(2)	(3)
Female	-0.017***	-0.015***	-0.004***
	(-5.01)	(-4.35)	(-6.01)
Black	-0.022***	-0.022***	-0.001
	(-5.49)	(-5.99)	(-0.72)
Asian	-0.024***	-0.023***	-0.003***
	(-6.69)	(-6.35)	(-3.64)
Hispanic	-0.008***	-0.008***	-0.001
	(-3.03)	(-2.86)	(-1.31)
Other Minority	-0.008*	-0.009**	0.001
	(-1.97)	(-2.36)	(0.87)
Bachelor's Degree or Higher	0.010	0.012*	-0.002
	(1.56)	(1.87)	(-0.87)
Starting Age	-0.003***	-0.003***	-0.001***
	(-16.02)	(-14.88)	(-8.86)
Tenure	0.005***	0.004***	0.001***
	(5.74)	(5.35)	(5.01)
Observations	1,318,000	1,283,000	1,080,000
Adj. R-squared	0.044	0.038	0.083
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Mean (Dependent Variable)	0.206	0.180	0.026

Table 5: Exit Hazard for Workers in Asset Management

This table presents results from a Cox proportional hazards regression analyzing the probability of exiting the asset management industry. Exit is defined as leaving the industry in year t. Right censoring in year t occurs if i) the last worker observation is in 2020 or ii) the worker stops appearing in our sample. Employment and demographic data come from the LEHD and ICF files, respectively. The Cox model examines how demographic characteristics affect the likelihood of industry exit at any given point in time. The model assumes proportional hazards so that relative risks remain constant over time. Columns (1) and (2) differ by the pooled vs firm specific baseline hazard model. Control variables include demographic characteristics (gender, race), education, and age at entry variables. Other Minority is defined as American Indian, Hawaiian, or multi-racial. t-statistics are in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Probability of Exiting Industry	
VARIABLES	(1)	(2)
Female	0.238***	0.166***
	(30.42)	(22.32)
Black	0.284***	0.197***
	(13.94)	(10.25)
Asian	0.271***	0.220***
	(24.27)	(20.62)
Hispanic	0.185***	0.104***
	(8.88)	(5.45)
Other Minority	0.216***	0.168***
	(7.75)	(6.51)
Bachelor's Degree or Higher	-0.248***	-0.196***
	(-8.90)	(-7.66)
Starting Age	0.001***	0.010***
	(3.41)	(30.57)
Observations	1,318,000	1,318,000
Baseline Model	Pooled	Firm Specific

Table 6: Portfolio Manager Compensation and Demographics

This table presents OLS regression results examining the relationship between demographic characteristics and log compensation among portfolio managers, controlling for performance measures. Performance controls include one-,two-, and three-year alpha, flow, return volatility, log(Funds$_{i,t-1}$), and log(AUM$_{i,t-1}$). Panel A reports results with year fixed effects, and panel B reports results with both year and firm fixed effects. Minorities are defined as Asian, Black, Hispanic, American Indian, Hawaiian, or multi-racial. Coefficients on control variables and intercept not reported. Standard errors are clustered by manager and year, and t-statistics are in parentheses.*, **, *** denote significance at the 10%,5%, and 1% levels, respectively.

	Panel A: log(compensation$_{i,t}$)											
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	-0.233***	-0.245**	-0.254**									
	(-2.81)	(-2.74)	(-2.59)									
Minorities				-0.039	0.005	0.054						
				(-0.41)	(0.05)	(0.47)						
Asian							-0.185*	-0.180	-0.158			
							(-1.77)	(-1.56)	(-1.26)			
Minority Female										-0.724***	-0.772***	-0.806***
										(-3.55)	(-3.41)	(-3.15)
Perf Controls	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Observations	20,000	17,000	14,500	20,000	17,000	14,500	20,000	17,000	14,500	20,000	17,000	14,500
Adj. R^2	0.187	0.196	0.206	0.185	0.194	0.204	0.186	0.194	0.204	0.188	0.197	0.206
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	No	No	No	No	No

	Panel B: log(compensation$_{i,t}$)											
VARIABLES	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Female	-0.278***	-0.297***	-0.316***									
	(-3.80)	(-3.74)	(-3.69)									
Minorities				-0.271**	-0.264**	-0.227*						
				(-2.69)	(-2.35)	(-1.83)						
Asian							-0.365***	-0.397***	-0.389**			
							(-3.01)	(-3.00)	(-2.61)			
Minority Female										-0.542**	-0.578***	-0.569***
										(-2.68)	(-2.79)	(-3.19)
Perf Controls	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Observations	20,000	17,000	14,500	20,000	17,000	14,500	20,000	17,000	14,500	20,000	17,000	14,500
Adj. R^2	0.697	0.714	0.731	0.697	0.713	0.729	0.697	0.714	0.730	0.697	0.713	0.730
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Probability of Forced Turnover

This table shows results of linear probability models examining forced turnover probability among portfolio managers across demographic groups. Performance controls include one-,two-, and three-year alpha, flow, return volatility, log(Funds$_{i,t-1}$), and log(AUM$_{i,t-1}$).The regressions include year fixed effects. The unconditional probability is reported at the bottom. Standard errors are double clustered at the manager and year levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	Forced Turnover$_{i,t}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	0.003	0.005**	0.005*						
	(1.47)	(2.10)	(1.89)						
Minorities				0.008***	0.009***	0.008**			
				(3.20)	(3.17)	(2.77)			
Asian							0.011***	0.012***	0.011**
							(3.52)	(3.33)	(2.59)
$\alpha_{i,t-1}^{(1Year)}$	-0.063*			-0.063*			-0.063*		
	(-2.02)			(-2.01)			(-2.00)		
Flow$_{i,t-1}^{(1Year)}$	-0.296***			-0.297***			-0.297***		
	(-6.33)			(-6.35)			(-6.34)		
$\sigma_{i,t-1}^{(1Year)}$	-0.003			-0.003			-0.003		
	(-0.41)			(-0.42)			(-0.44)		
$\alpha_{i,t-1}^{(2Year)}$		-0.116***			-0.116***			-0.116***	
		(-3.65)			(-3.64)			(-3.61)	
Flow$_{i,t-1}^{(2Year)}$		-0.371***			-0.373***			-0.372***	
		(-7.28)			(-7.29)			(-7.30)	
$\sigma_{i,t-1}^{(2Year)}$		-0.004			-0.004			-0.004	
		(-1.10)			(-1.11)			(-1.15)	
$\alpha_{i,t-1}^{(3Year)}$			-0.163***			-0.162***			-0.162***
			(-9.11)			(-9.14)			(-9.09)
Flow$_{i,t-1}^{(3Year)}$			-0.376***			-0.378***			-0.377***
			(-6.68)			(-6.70)			(-6.68)
$\sigma_{i,t-1}^{(3Year)}$			-0.004			-0.005			-0.005
			(-1.25)			(-1.28)			(-1.33)
log(# Funds$_{i,t-1}$)	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.008***	-0.007***
	(-3.82)	(-3.79)	(-3.60)	(-3.89)	(-3.84)	(-3.64)	(-3.92)	(-3.87)	(-3.65)
log(AUM$_{i,t-1}$)	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.52)	(-0.70)	(-0.68)	(-0.50)	(-0.69)	(-0.68)	(-0.51)	(-0.70)	(-0.70)
Observations	53500	45500	38500	53500	45500	38500	53500	45500	38500
Adj. R^2	0.004	0.006	0.006	0.004	0.006	0.006	0.005	0.006	0.006
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean (Dependent Variable)	0.027								

Table 8: Probability of Rehire After Forceful Termination

This table shows results of linear probability models analyzing rehiring probability across demographic groups among portfolio managers who were previously forced out of the industry. Rehiring is defined as occurring when a manager was forcefully turned over from their firm, was younger than retirement age when they left, and found another portfolio manager position. We control for performance measures including one-, two-, and three-year performance metrics and fund characteristics. The regressions include year fixed effects and standard errors are double clustered at the manager and year levels. The unconditional probability is reported at the bottom. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	$\text{Rehire}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.138***	-0.128***	-0.140***			
	(4.90)	(4.10)	(3.61)			
Minorities				0.019	0.009	0.016
				(0.62)	(0.25)	(0.43)
Performance Controls	1 Year	2 Year	3 Year	1 Year	2 Year	3 Year
Observations	1,400	1,200	950	1,400	1,200	950
Adj. R-squared	0.22	0.209	0.228	0.211	0.201	0.218
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean (Dependent Variable)	0.320					

Table 9: Portfolio Manager Educational Outcomes

This table reports the results of linear probability models examining the relationship between education and qualifications, and demographic variables. Minorities are defined as Asian, Black, Hispanic, American Indian, Hawaiian, or multi-racial. Year fixed effects are included and standard errors are double clustered by manager and year. t-statistics are reported in parentheses and *, **, *** denote significance at the 10%, 5%, and 1% levels.

Panel A

VARIABLES	Elite School	MBA	CFA	Advanced Deg	Elite School	MBA	CFA	Advanced Deg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.024	-0.040**	0.014	0.008				
	(1.38)	(-2.21)	(0.76)	(0.37)				
Minorities					0.130***	0.048**	-0.014	0.047**
					(6.83)	(2.53)	(-0.76)	(2.24)
Observations	7,500	7,500	5,600	5,600	7,500	7,500	5,600	5,600
Adj. R^2	0.001	0.001	0.001	0.001	0.006	0.001	0.001	0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

VARIABLES	Elite School	MBA	CFA	Advanced Deg	Elite School	MBA	CFA	Advanced Deg
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Asian	0.152***	0.038	-0.006	0.074***				
	(6.39)	(1.60)	(-0.27)	(2.87)				
Minority Female					0.169***	0.064	-0.042	0.096**
					(4.00)	(1.54)	(-1.13)	(2.09)
Observations	7,500	7,500	5,600	5,600	7,500	7,500	5,600	5,600
Adj. R^2	0.006	0.001	0.001	0.001	0.002	0.001	0.001	0.001
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Demographic Effects on Performance Measures

This table reports OLS estimates linking manager outcomes to demographic indicators. For horizon $h \in \{1, 3, 5\}$, $\alpha_{i,t}^{(hYr)}$, $\text{VA}_{i,t}^{(hYr)}$, and $\text{Flow}_{i,t}^{(hYr)}$ are computed over trailing $12h$-month windows. $\log(\text{AUM}_{i,t})$ is the natural log of assets under management at the start of period t. Panel A focuses on performance-related outcomes, while Panel B examines flow and asset dynamics. Minorities are defined as Asian, Black, Hispanic, American Indian, Hawaiian, or multi-racial. Year and firm fixed effects are included and standard errors are double clustered by manager and year. t-statistics are reported in parentheses and *, **, *** denote significance at the 10%, 5%, and 1% levels.

Panel A

VARIABLES	$\alpha_{i,t}^{(1Yr)}$ (1)	$\alpha_{i,t}^{(5Yr)}$ (2)	$\text{VA}_{i,t}^{(1Yr)}$ (3)	$\text{VA}_{i,t}^{(5Yr)}$ (4)	$\alpha_{i,t}^{(1Yr)}$ (5)	$\alpha_{i,t}^{(5Yr)}$ (6)	$\text{VA}_{i,t}^{(1Yr)}$ (7)	$\text{VA}_{i,t}^{(5Yr)}$ (8)	$\alpha_{i,t}^{(1Yr)}$ (9)	$\alpha_{i,t}^{(5Yr)}$ (10)	$\text{VA}_{i,t}^{(1Yr)}$ (11)	$\text{VA}_{i,t}^{(5Yr)}$ (12)
Female	-0.074	-0.157	-3.75	-6.36								
	(-0.86)	(-1.27)	(-1.66)	(-1.30)								
Minorities					-0.002	-0.034	0.626	4.40				
					(-0.01)	(-0.24)	(0.20)	(0.62)				
Asian									-0.073	-0.076	-3.07	3.54
									(-0.39)	(-0.39)	(-0.85)	(0.39)
Observations	52000	27000	52000	27000	52000	27000	52000	27000	52000	27000	52000	27000
Adj. R^2	0.152	0.398	0.008	0.139	0.152	0.398	0.008	0.139	0.152	0.398	0.008	0.139
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

VARIABLES	$\text{Flow}_{i,t}^{(1Yr)}$ (13)	$\text{Flow}_{i,t}^{(3Yr)}$ (14)	$\text{Flow}_{i,t}^{(5Yr)}$ (15)	$\log(\text{AUM}_{i,t})$ (16)	$\text{Flow}_{i,t}^{(1Yr)}$ (17)	$\text{Flow}_{i,t}^{(3Yr)}$ (18)	$\text{Flow}_{i,t}^{(5Yr)}$ (19)	$\log(\text{AUM}_{i,t})$ (20)	$\text{Flow}_{i,t}^{(1Yr)}$ (21)	$\text{Flow}_{i,t}^{(3Yr)}$ (22)	$\text{Flow}_{i,t}^{(5Yr)}$ (23)	$\log(\text{AUM}_{i,t})$ (24)
Female	0.002	0.03	0.056	-0.077								
	(0.04)	(0.53)	(0.91)	(-1.52)								
Minorities					0.143***	0.107*	0.011	-0.044				
					(2.94)	(1.93)	(0.18)	(-0.78)				
Asian									0.178**	0.109	-0.022	-0.134*
									(2.31)	(1.42)	(-0.25)	(-1.98)
Observations	52000	37500	27000	52000	52000	37500	27000	52000	52000	37500	27000	52000
Adj. R^2	0.198	0.346	0.438	0.757	0.198	0.346	0.438	0.757	0.198	0.346	0.438	0.757
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Portfolio Manager Starting Age by Demographic Group

This table presents results of OLS regressions of starting age on various demographic variables. Minorities are defined as Asian, Black, Hispanic, American Indian, Hawaiian, or multi-racial. All specifications include year fixed effects and standard errors are double clustered by manager and year. t-statistics are in parentheses and *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	AgeStart_i			
	(1)	(2)	(3)	(4)
Female	-0.557^{*}			
	(-1.76)			
Minorities		-2.030^{***}		
		(-6.39)		
Asian			-2.130^{***}	
			(-5.73)	
Minority Female				-1.900^{***}
				(-2.85)
Observations	7,500	7,500	7,500	7,500
Adj. R^2	0.001	0.004	0.003	0.001
Year FE	Yes	Yes	Yes	Yes

Table 12: Firm Ownership and Demographics

This table presents regression results examining whether female or minority ownership in advisory firms mitigates the career disadvantages experienced by these demographic groups. The analysis uses firm ownership data from Schedule A of Form ADV filings, which identify control persons and their ownership classifications.The regressions test whether greater ownership representation of one's demographic group reduces compensation gaps and forced turnover gaps using interaction terms between manager demographics and ownership shares. Columns (1) and (2) examine log compensation, while columns (3) and (4) analyze forced turnover probability. Control variables include 1-year performance measures and fund characteristics. The specification includes year fixed effects. Minorities are defined as Asian, Black, Hispanic, American Indian, Hawaiian, or multi-racial. Standard errors are double clustered at the manager and year levels, and t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	$\log(\text{Compensation}_{i,t})$		Forced $\text{Turnover}_{i,t}$	
	(1)	(2)	(3)	(4)
Female	-0.257***		0.005*	
	(-3.32)		(2.02)	
% Female Large Owner	0.278*	0.248	-0.007	
	(1.78)	(1.62)	(-1.60)	
Female × % Female Large Owner	0.189		-0.017**	
	(0.43)		(-2.30)	
Minorities				0.011***
				(3.60)
% Minorities Large Owner				-0.004
				(-0.39)
Minorities × % Minorities Large Owner				-0.023**
				(-2.14)
Minority Female		-0.835***		
		(-4.78)		
Minority Female × % Female Large Owner		1.860***		
		(7.68)		
Performance Controls	1 Year	1 Year	1 Year	1 Year
Observations	20,000	20,000	54,500	54,500
Adj. R-squared	0.189	0.190	0.006	0.006
Year FE	Yes	Yes	Yes	Yes