Performance Isn't Everything: Personal Characteristics and Career Outcomes of Mutual Fund Managers

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ABSTRACT

We investigate the determinants of mutual fund manager career outcomes. We find that, although career outcomes are largely determined by past performance, measured by returns and fund flows, personal attributes also factor in. All else equal, female managers are less likely to be promoted and have shorter tenures than male fund managers. This finding applies to a greater extent to women who co-manage funds with other managers, which suggests that working in teams negatively affects women's careers when compared to men's. Moreover, we show that, all else equal, younger managers, U.S.-educated managers, and managers who attended elite schools experience better career outcomes than otherwise similar managers.

JEL classification: G11, G14, G23.

Keywords: Women in Finance, Diversity, Career Advancement, Mutual Fund Industry, Mutual Fund Managers, Mutual Fund Manager Performance

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We investigate the determinants of mutual fund manager career outcomes. We find that, although career outcomes are largely determined by past performance, measured by returns and fund flows, personal attributes also factor in. All else equal, female managers are less likely to be promoted and have shorter tenures than male fund managers. This finding applies to a greater extent to women who co-manage funds with other managers, which suggests that working in teams negatively affects women's careers when compared to men's. Moreover, we show that, all else equal, younger managers, U.S.-educated managers, and managers who attended elite schools experience better career outcomes than otherwise similar managers.

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I. Introduction

Hiring and promoting employees solely based on merit should be the goal of any performance-oriented organization. However, an organization's management must exercise some degree of judgement—for example whether good performance should be attributed to skill or luck—and, therefore, various conscious and subconscious biases may affect personnel decisions.[1] If certain employee groups are underrepresented in the workplace, the management may view employees from these groups as inherently less skilled. Good performance of these minority employees would then be more likely to be attributed to good luck, and bad performance to low skill. Moreover, when responsibility is shared, management may disproportionately attribute credit to the employees from the majority group. Indeed, research in economics and organizational behavior documents lower salaries and worse marketplace outcomes for women, minorities, and older people, as well as negative workplace attitudes towards these groups (Bertrand and Mullainathan (2004), Bertrand, Goldin, and Katz (2010), and Azmat and Ferrer (forthcoming), among others).

In this paper, we conduct a large-scale study of promotion and demotion decisions made within competitive organizations. In contrast to Azmat and Ferrer (forthcoming)—a closely related study, our analysis is based on actual rather than self-reported data. Conducting such a study and drawing causal inference is only feasible with an appropriate setting at the researcher's disposal. Being able to observe and measure individual employee performance is a necessary condition. However, due to a lack of available micro data, suitable settings are scarce. In our study, we focus on the mutual fund industry, which offers an ideal setting to analyze the influence of personal attributes on career progression because the performance of individual mutual fund managers is easily measurable. Mutual fund families care about returns and fund flows generated by managers because both increase the value of total net assets (TNA) under management, and fund families collect fees calculated as a percent of TNA.

[1] Psychology research provides ample evidence that people are often unaware of the biased views they hold, which results in subconsciously biased decisions.

In its analysis of the influence of personal attributes on career progression, this paper contributes to the literature on workplace discrimination, which is summarized in more detail in Section II. The empirical documentation of the so-called gender pay gap—the fact that women earn on average about 20% less than men—has garnered considerable attention from researchers and policy makers. The pay gap is largely explained by women's tendency to work in lower-paying fields. Finance is one of the highest paying fields, but women in finance are grossly underrepresented, and the trends are not encouraging. We present statistics showing that, while the fraction of women in the money management industry was rising in the 1990s, the trend changed around the burst of the dot-com bubble, and the percentage of women working as mutual fund managers declined from a peak of 13.83% in August 1999 to 9.78% in December 2016, the end of our sample period.

Our study of fund managers' characteristics and their effects on career progression offers a variety of new insights into the relation between gender and career outcomes. To begin, we address the question of why so few women enter the money management industry. At least part of the answer lies in ingrained cultural attitudes towards women's equality. Ranking the countries of managers' origin by the fraction of female managers from that country, we show that a country's female representation rank is related to its 2016 Global Gender Gap Index produced by the World Economic Forum. This result suggests that there is some degree of self-selection of women into the finance industry. Within the multicultural landscape of the United States, women who hail from more patriarchal cultures are perhaps also less likely to consider entering the industry.

Next, we investigate whether or not female managers are treated fairly once they have become money managers. We present evidence that once a woman becomes a mutual fund manager, she typically has a significantly shorter tenure in the industry than a male manager. That is, she is significantly more likely to permanently leave the industry in any given month, while being under 55 years old or, if age information is missing, having less than 25 years of fund management experience. We find no evidence that the disproportional departures of female fund managers are related to poor performance. In fact, when analyzing in detail the performance of sole managers of active equity funds, we find no significant difference between the performance of male and female

fund managers, in terms of both returns and fund flows. Moreover, female managers' returns are less volatile than the returns of other funds in the same investment category.

Part of the reason for why female managers leave the industry is that they typically have fewer fund management responsibilities than their male counterparts. When a male manager loses one fund, perhaps due to fund closure, he may be managing another fund in parallel, and so he remains in the industry. In contrast, when a female manager loses a fund, she is less likely to be managing another fund at the same time, and she ends up leaving the industry. Yet, controlling for the number of funds and the total net value of the assets that a manager manages does not fully explain why women have shorter tenures in the industry.

A related question is whether female managers face the same career prospects as male managers. We conduct a detailed analysis of fund managers' career outcomes. To that end, we consider a promotion to be a change in fund assignments that results in more fund management responsibilities and a demotion to be a change in fund assignments that results in fewer responsibilities. We find that female managers tend to have worse career trajectories than male managers in similar circumstances, even after controlling for performance and fund management responsibilities.

One may argue that female managers make a deliberate choice not to be promoted or to leave the industry due to family conflicts. This conjecture is not supported by the data. The higher likelihood of prematurely leaving the industry and the lower odds of being promoted compared to men affects women across the age spectrum, and not only women of childbearing age.

We also present a number of noteworthy findings on the relation between managers' characteristics, other than gender, and their career outcomes. In particular, we analyze the influence of attributes that have been associated with workplace discrimination, such as age, foreign origin, terminal degree, and a dummy variable indicating whether a manager attended an elite school. These variables can be identified from the Morningstar dataset of managers' characteristics that provides a managers' names, degrees, schools attended, dates of birth, dates of graduation, and the dates on which each manager started (and finished, if applicable) managing each fund.

One strong and consistent result emerges. Older managers have significantly worse chances of being promoted and significantly higher chances of being demoted than younger managers with similar job responsibilities and similar past performance. While it is possible that older managers voluntarily diminish their job responsibilities, it is clearly not in the interest of mutual fund families to under-employ skilled managers.

Our results also show that managers who attended elite schools are promoted faster than otherwise similar managers from non-elite schools. It also appears that foreign-born managers have lower chances of being promoted. Part of the reason, perhaps, is that foreign managers have smaller professional networks. Consistently, we show that following fund family mergers or closures, foreign managers are significantly less likely to find a new job in the industry.

Of course, the analysis of managers' career outcomes based on the entire sample cannot perfectly control for subtle differences in managers' track records or for minor distinctions between the types of funds that they manage, which could introduce noise in our analysis. Luckily, the mutual fund setting allows us to set up a perfect experiment in which we can compare male and female managers with identical track records and thereby rule out possible estimation biases. We devise a test in which we focus on co-managers of the same fund, who have no prior fund management history and who started to co-manage the fund in the same month. We then track the career progression of these managers. We find that, consistent with our full-sample results, female managers are significantly more likely than male managers to be removed from (or leave) the job of co-managing the fund without any substitute fund management responsibilities. This experiment indeed confirms the insights gained from the complete dataset of mutual fund managers.

Given its focus on mutual funds managers, our study is related to the relatively small number of papers on the determinants of career outcomes of mutual fund managers (e.g., Khorana (1996), Chevalier and Ellison (1999), Hu, Hall, and Harvey (2000), and Evans (2009)). Using a larger dataset, in both the time series and the cross-section, we confirm the earlier findings that managers' career outcomes are strongly related to their past returns. Unlike that literature, we also document a strong relation between career outcomes and fund flows. This result is not surprising given

the finding of Lamont and Frazzini (2008) that fund families create more funds in the investment categories that enjoy high levels of investor sentiment and likely assign the managers who already manage similar funds to manage additional funds in the high-sentiment category.

Finally, we add to the small literature that investigates the relationship between fund manager characteristics and performance. Prior studies show that, for example, managers with undergraduate degrees from colleges with higher average SAT scores generate higher risk-adjusted returns (Chevalier and Ellison (1999)) and managers from wealthy families deliver lower returns (Chuprinin and Sosyura (2016)). Cohen, Frazzini, and Malloy (2008) document that managers perform better on investments in firms to which they have a connection via their education network. Our study shows that gender, foreign origin, or elite-school education are not significant predictors of performance.

The rest of the paper is organized as follows: Section II reviews related literature. Section III describes the data and variable construction. Section IV presents the empirical results. Section V concludes.

II. Related literature

A. Literature on workplace discrimination

Prior literature in economics documents that women and minorities have worse marketplace outcomes than males and whites and analyzes whether the effect can be explained by performance differences or by discrimination. The literature on discrimination distinguishes between statistical and taste-based discrimination. Statistical discrimination arises when an individual is judged based on her group characteristics rather than on her individual characteristics. This mental shortcut is used in decision making when information about an individual or mental resources are scarce. Taste-based discrimination arises when employers, superiors, other employees, or customers have

a "taste" for discrimination; that is, they prefer one group over another based on tastes rather than any economic rationale, perhaps even to a monetary detriment to themselves.

In a prominent study in the literature on workplace discrimination against racial minorities, Bertrand and Mullainathan (2004) set up a field experiment to document a bias held by hiring managers against African Americans in hiring decisions. The authors sent out fictitious resumes in response to job postings in Boston and Chicago area newspapers, randomly using African American-sounding names in a subset of resumes and found that these resumes received 50% fewer call-backs. Beginning with an influential analysis by Scully (1974), a number of papers in economics document racial discrimination in major league baseball against African American and Latino players, which manifests itself in pay differences and in hiring biases (e.g., Christiano (1986) and Palmer and King (2006)). (Baseball is largely an individual sport, and thus offers an opportunity to measure the performance of each individual player and thereby to observe whether discrimination exists.) Racial discrimination also appears to exist at higher educational levels. Ginther, Schaffer, Schnell, Masimore, Liu, Haak, and Kington (2011) analyze the relation between the U.S. National Institutes of Health (NIH) R01 applicants' self-identified race or ethnicity and the probability of receiving an award and find that African Americans and Asians are less likely to receive NIH investigator-initiated research funding than whites.

Several papers document adverse workplace outcomes for female workers. Goldin and Rouse (2000) describe that many prominent symphony orchestra conductors used to be biased against hiring female musicians and, as a result, female musicians used to be severely under-represented in symphony orchestras. The paper shows that the adoption of "blind" auditions, in which the musician auditioning for a spot in an orchestra was obscured from the jury by a screen, increased the odds of female musicians getting to advanced rounds of auditions and eventually being hired by orchestras. Ginther and Kahn (2005) investigate whether gender plays a role in academic careers in science; the science field is subdivided into Science, Life Science, Physical Science, and Engineering. The paper finds that females are less likely than males to get tenure track appointments. Specifically, after controlling for productivity, measured as the combination of the amount of government support received, the total number of papers, and the total number of publications,

female scientists are less likely to get tenure in Life Sciences and less likely to be promoted to full professor in Science and Life Science than their male peers. Ginther and Hayes (2003) focus on academic careers in social sciences and humanities and find that female faculty are less likely to be promoted and have lower salaries than their male peers. The salary gap increases throughout the career progression, and, at the full professor level, an unexplained salary difference between male and female faculty of 12% is observed.

Bertrand, Goldin, and Katz (2010) also observe a salary gap between male and female University of Chicago MBA graduates that increases with the number of years since graduation. They find this salary gap by analyzing salaries, work history and work hours, all of which are self-reported in a web-based survey by the University of Chicago MBA 1990-2006 graduating classes. Some of the salary gap is explained by females working shorter hours and having had gaps in employment, as well as having taken fewer finance classes and having earned somewhat lower GPAs in the MBA program. Still, some of the salary gap remains unexplained.

In a paper closely related to our study, Azmat and Ferrer (forthcoming) use self-reported survey data on young lawyers to study the pay and promotion gap between male and female lawyers.[2] They find substantial differences in performance, both in terms of hours billed to clients and the amount of new client revenue generated, and show that these differences explain almost 50% of the pay and promotion gaps. Moreover, the paper finds that female lawyers have more modest aspirations for becoming an equity partner. The paper also documents a larger performance gap for female lawyers who have young children, while male lawyers with young children do not exhibit worse performance. The paper also provides evidence that childbearing is the cause of lower performance rather than the self-selection into motherhood of lower-skilled females.

Sarsons (2017) documents that, when it comes to tenure decisions, female economics professors get less credit than male peers for published papers that are co-authored with male colleagues. This finding suggests that in a team environment, female employees get less credit for good performance.

[2]The dataset used in the paper is called *After the JD*, which is a survey-based dataset produced by the American Bar Association and other legal associations. Lawyers in the sample are representative of all lawyers first admitted to the bar in 2000.

When it comes to the socioeconomic background, Chuprinin and Sosyura (2016) show that mutual fund managers' family descent matters for career outcomes. Managers born into wealthy families have an easier time being promoted.

Some studies in the literature aim to identify which form of discrimination is at play. For example, List (2004) conducts an experiment in which groups of young white males, young white females, young nonwhite males and white males over age 60 are sent out to buy a particular sportscard at a sportscard show. In this experiment, minority groups (which are all but the first group of negotiators) receive worse initial and final offers. Subsequent analysis reveals that this effect is likely explained by statistical rather than taste-based discrimination of sportscard dealers.

More evidence is accumulating on age discrimination in the workplace. Lahey (2008) conducts a field experiment to show that otherwise similarly qualified older workers have a more difficult time obtaining job interviews. The author sent out fictitious resumes in the greater Boston, Massachusetts and greater St. Petersburg, Florida areas in response to "help-wanted ads" in the Sunday Boston Globe and the Sunday St. Petersburg Times, as well as to randomly chosen firms in each city. High school graduation dates were randomized to create different ages of the job applicants. The older group of fictitious job applicants (those aged 50, 55, and 62) received more than 40 percent fewer callbacks with positive responses from the prospective employers than fictitious applicants aged 35 and 45. The paper finds no support for taste-based discrimination as a reason for this differential, and some suggestive evidence in support of statistical discrimination.

The literature in organizational behavior documents negative workplace attitudes towards certain employee groups (such as women and older workers) predominately based on survey evidence. In particular, a recent study uses survey evidence to document biases held by heterosexual men married to homemakers (a marriage arrangement that the authors refer to as a traditional marriage type) against their female colleagues (Desai, Chugh, and Brief (2014)). The paper presents some evidence that causality may go from the marriage type to the man's attitude towards working women. High-paying fields such as finance have low percentages of women. Since finance salaries are high,

it is likely men in finance are more likely to be in traditional marriages, and the men's attitudes may be detrimental to women's career prospects.

B. Literature on mutual fund managers career outcomes

Given its focus on mutual funds managers, our study is also related to the relatively small number of papers on the determinants of career outcomes of mutual fund managers. Khorana (1996), one of the earliest papers in this literature, studies 339 replacements of mutual fund managers over the 1979-1992 time period. He finds that the probability of a managerial replacement is negatively related to the current and previous years' returns.

Chevalier and Ellison (1999) examine promotion and termination decisions of mutual fund managers over the 1992-1994 period. They only consider sole managers of growth or growth and income funds. The dataset consists of 1,320 manager-fund-year observations and contains only 242 terminations and 38 promotions. The authors find that manager terminations are sensitive to fund alphas and that this sensitivity is higher for younger managers. The authors find no significant relation between past fund returns and manager promotion decisions.

Hu, Hall, and Harvey (2000) study 307 managerial changes over the 1976-1996 time period. They find that promotions are positively and demotions are negatively associated with performance and that fund flows are not a significant predictor of either.

For a sample of U.S. equity funds over the period 1995-2002, Evans (2009) finds that fund return alphas are significant predictors of manager promotions and demotions, but fund flows are not.

Our dataset is larger, in both the time series and the cross-section, than the datasets employed in previous studies. The main dataset covers the period from January 1992—the month when fund returns become available from the monthly CRSP Mutual Fund dataset—to December 2016 and includes 929,946 manager-month observations and 12,669 unique managers. As mentioned earlier, in addition to fund returns and fund flows, as well as other common controls, we include a set of

managers' personal attributes that may factor into their career outcomes. While we confirm the earlier findings that managers' career outcomes are strongly related to their past returns, we also document a strong relation between career outcomes and fund flows.

III. Data and variable construction

A. Datasets

The data on managers' background and career trajectory are obtained from Morningstar. The data for mutual fund monthly returns and TNAs are obtained from the CRSP Mutual Fund dataset. The CRSP data start in January 1992 and end in December 2016, which dictates the start and end dates of our sample for the main tests. For the tests that do not involve the CRSP dataset, we use the entire Morningstar dataset, covering the period from July 1924 to March 2017, although the earlier years have only few managers and funds.

The Morningstar dataset that we obtained consists of three files. The first file provides managers' background information: first and last names, gender, date of birth, names of each school attended for each degree earned (Bachelor, MBA, MA, PhD, and a category called "Other degree" that likely includes J.D. and M.D.), dates of graduation for each degree that is applicable, as well as an indicator of whether or not the manager holds a CFA certificate. We create a dummy for top schools that equals one if a manager earned at least one of his/her degrees from any national university or college ranked in the top 10 by US News and World Report, or any of the top-ten MBA programs ranked as such by the US News and World Report, or any of the Ivy League schools.[3] This file contains 20,840 unique manager observations, though we are not using all of them in the main tests because of the sample period constraints.

[3]We use the 2013 US News and World report rankings, these rankings are very stable over the years, hence, it will not make a big difference if a different ranking year were used instead. It is worthwhile to note that top ten lists typically include more than 10 schools.

Gender information is available for the vast majority of managers. When the gender field is missing, we identify a manager's gender from the first name, and, if it is ambiguous, from the managers' LinkedIn or professional profiles or from fund reports and other material available on the Internet. In the end, we are unable to identify the gender of only one manager.

To calculate a manager's age, we use the date of birth. When it is not available, we assume that managers are 22 when they are awarded their undergraduate degrees (as in Chevalier and Ellison (1999)). If the year of the undergraduate degree is missing, we use the years when other degrees were awarded, assuming that managers are 26 when awarded an MBA, MA or Other degree, and 29 when awarded a Ph.D. Because the graduation year information is often missing, just as the birth year information, we are able to identify age for only 33.29% of managers. For this reason, we present results based on the length of time that a manager first started managing a fund, which is available for all managers and should be highly correlated with age.

We identify managers' country of origin based on the location of the school from which they received their undergraduate degree and create a dummy variable indicating whether a manager is of foreign origin. (Managers who attended a Canadian school are not considered to be of foreign origin.) However, the dummy *Foreign* is only defined for managers with non-missing school information. In the original sample of 20,840 managers, 67.76% of managers have school information available. In some tests, in order to increase the sample size, we use the dummy variable *Foreign+Guess* that equals one if a manager is of foreign origin based on school data or, in case the school information is missing, if both first and last names are of non-Anglo-Saxon origin, and zero otherwise.

The second Morningstar file provides for each manager, identified with a unique manager code, all his or her present or historical manager-fund assignments and the exact dates when the manager started and finished (if applicable) managing a fund. Each fund is identified with a unique identifier, FUNDID. A missing end date of a fund assignment means that the manager is still employed in the fund as of March 2017, the end of our sample period. We use this file to match a manager to the funds s/he manages at each point in time. This file is also used to identify the number of

co-managers that a fund has on any particular date by checking how many managers are listed as managing the fund in a given month.[4]

The third Morningstar file provides mutual-fund-specific information, including FUNDID; fund name; fund family; investment objective category; fund ticker; fund CUSIP; inception date; the end date of fund operation, if applicable; fund status (active, closed, merged); and the reason for obsolescence, if applicable.

In some tests, we use our own fund categorization, rather than the categorization provided by Morningstar. To that end, we perform keyword searches of fund names and investment categories in the third Morningstar file to identify index funds, socially responsible and tax-managed funds, real estate funds, metals and commodities funds, utilities funds, international funds, corporate bond funds, and government and municipal bond funds.[5]

According to the business press, managers of index funds are paid substantially less than managers of actively-managed funds. Moreover, index funds represent an entirely different employment category than actively-managed funds, as managers typically do not move from actively-managed funds to index funds, and vice versa. We, therefore, exclude index fund managers from our analysis.

While Morningstar uses FUNDID as a unique fund identifier, the CRSP Mutual Fund dataset uses a different unique fund identifier called FUNDNO. The CRSP Mutual Fund dataset and Morningstar are merged on fund ticker or, if ticker is missing, on fund CUSIP.[6]

[4]The information on the number and identities of managers for each co-managed fund is more precise than the information available in the CRSP mutual fund dataset, which does not identify manager changes precisely and frequently codes co-managed funds as "team-managed" without providing details on the identities of the managers.

[5]For example, we identify index funds by searching fund names for the keywords "index," "ishares," "S&P," "100," "500," "1500," "3000," with variations in the spelling (we additionally use a CRSP flag for index funds to supplement our identification of index funds), and socially responsible and tax-managed funds with variations of the keywords "social," "soc aware", "responsible," "clean env," "catholic," and "tax."

[6]In case that the fund identifiers are reused, we make sure that the FUNDID-FUNDNO match that we construct is valid in a given month.

B. Variable construction

B.1. Manager-level performance measures

For each mutual fund manager, we construct monthly performance measures based on the fund return and the fund flow calculated over a rolling 12-month window.

We calculate monthly fund flows as the change in a fund's TNA, relative to that in the prior month, that is unexplained by the fund's return (ret):

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

For each fund-month observation, we further compute CAPM alphas, fund flows, and return standard deviations realized over a rolling 12-month period.

Since fund returns and fund flows are expected to differ across fund categories, we rank each fund's CAPM alpha and fund flow, estimated as described above, from 1 to 10 within each investment objective code. We only consider sufficiently populous investment objective codes that have at least ten funds in a given month. If the number of funds within an investment objective code in a particular month is less than ten, we set the return and fund flow ranks as missing.

If a manager manages more than one fund in parallel, we aggregate the manager's performance measures across the funds that s/he manages. If all funds that a manager manages are sole-managed funds, we simply average the return and fund flow ranks across the funds to calculate a manager-specific performance rank. For the co-managed funds in a manager's fund portfolio, the funds' return and fund flow ranks are weighted by $\frac{1}{number\ of\ co\text{-}managers}$. For example, if a manager is a sole manager of fund A and is one of two co-managers of fund B, fund A will be weighted by $\frac{1}{1+1/2}$ and fund B by $\frac{1/2}{1+1/2}$. We have also tried equal-weighting the performance ranks across all managed funds. Although thus-weighted measures are very similar to the ones described above, they work slightly worse in explaining managers' career outcomes.

B.2. Identifying firings, promotions, and demotions

Money managers are among the highest paid professionals, and, as per our conversations with money managers, many choose to retire before they reach the Social Security's full-benefit retirement age of 65. To account for this fact, we assume that if a manager permanently leaves the fund management industry and is over 55 (rather than 65) years old or, if age information is missing, has over 25 years of fund management experience, the departure is voluntary.[7] An earlier permanent departure from the industry is assumed to be a firing.[8]

Each month we check for promotions and demotions as follows. We being by calculating the total number of funds managed by a manager in each month. If a manager co-manages a fund, we calculate the fraction of the fund managed as $\frac{1}{number\ of\ co\text{-}managers}$. Thus, if a given manager sole-manages fund A and co-manages fund B with one other manager, we calculate the number of funds managed by that manager as 1.5. When a manager leaves a fund in a particular month, we check whether the manager was assigned one or more additional funds to sole-manage or co-manage in that month, or one month before or one month after the departure. Likewise, when a managers starts to manage a new fund, we check whether a manager has departed a previously managed fund one month before or one month after the event. In months in which no changes in fund management assignments occur, we set the change in fund management assignments to zero.

Next, whenever a manager has left a fund or started managing a new fund, we compute the change in the fund management responsibilities as the change in the number of funds managed by the manager scaled by the number of funds s/he managed in the previous month, which can be interpreted as the growth in the number of funds managed by the manager. A positive (negative) growth indicates a promotion (demotion). In the example above, if the manager leaves the sole-managed fund and gains no additional funds to manage, the growth in the number of managed

[7] As we will discuss later in the paper (Table II, Panel C), managers get their first fund management job at 32 years of age, on average, and the 25 years of fund management experience would correspond to a retirement age of 57.

[8] In unreported robustness checks, we consider alternative thresholds for retirement: (1) being 65 years of age or having over 35 years of fund management experience; (2) being 60 years of age or having over 30 years of fund management experience; and (3) being 50 years of age or having over 20 years of fund management experience. These robustness checks produce very similar results.

funds is $\frac{-1}{1.5} = -0.67$, which is considered a demotion (as with firings, when a manager is past the retirement threshold, we assume that no demotion has occurred). Alternatively, if a manager gains a fund co-managed with two other managers and loses none of the previously managed funds, the growth in the number of managed funds is $\frac{+1/3}{1.5} = 0.22$, which is considered a promotion. When a manager is fired, s/he loses all managed funds and the growth in the number of funds managed takes on the lowest possible value of -1.[9]

C. Sample description

Table I reports, for the sample of all managers that have school information available in the dataset, the fraction of female managers for each country of origin as well as the total number of managers from that country. As shown in the table, a large number of countries have zero female managers in the Morningstar dataset. The table ranks countries from 1 to 10 based on female representation in the money management industry, with rank 1 (10) assigned to countries with the largest (smallest) fraction of female managers. The table additionally reports country gender gap ranks obtained from the 2016 Global Gender Gap Index compiled by the World Economic Forum.[10] For all countries present in the Morningstar dataset, the table reprints the comprehensive country index and four subindices based on (1) economic participation and opportunity; (2) educational attainment; (3) health and survival; and (4) political empowerment. Rank 1 is assigned to the country with the lowest gender gap (highest level of equality), while the highest rank is assigned to the country with the highest gender gap (highest level of inequality).

[9] According to our calculation, when a manager simply swaps one fund for another fund with the same number of co-managers, we consider such a career change to be neither a promotion nor a demotion, irrespective of the funds' relative TNAs. One reason is that a move to a smaller fund may not constitute a demotion if the fund has a higher management fee or higher growth prospects. Moreover, even if a manager's move to a smaller fund is in fact a demotion, intuitively, such an event is not as significant as losing a fund altogether, and our goal is to construct a continuous variable capturing deliberate promotion and demotion decisions.

[10] http://reports.weforum.org/global-gender-gap-report-2016/rankings/.

The table presents suggestive evidence that countries with more gender inequality have a lower fraction of women in the mutual fund industry. To show this, we run a regression of a country's female representation rank on the country's gender gap index:

$$\textit{Country Female Representation Rank}_i = \alpha + \beta \times \textit{Gender Gap Rank}_i + \varepsilon_i. \tag{2}$$

The regression coefficients corresponding to each gender gap rank and their t-statistics are presented in the last row of Table I. According to these results, female representation among mutual fund managers is significantly positively related to the overall gender gap rank (with a regression coefficient on the gender gap rank of 0.021 and a t-statistic of 1.98). That is, countries with higher levels of gender equality have a larger fraction of female mutual fund managers. Looking at the coefficients on the subindices, we also find a significantly positive relation between female representation in the mutual fund management field and the level of female equality in (1) economic participation and opportunity, (2) educational attainment, and (3) health and survival outcomes. The ranks based on economic opportunity and education appear to be particularly important, with regression coefficients being statistically significant at the 1% level and exceeding 0.03 in magnitude. These results suggest that the internalized cultural attitudes toward gender equality affect the self-selection of women into the money management industry and appear to, at least partially, explain the underrepresentation of women in the industry.

Figures 1, 2, 3, and 4 plot, both for the entire set of managers in the Morningstar dataset and the subset of managers of mainstream active domestic equity funds, the evolution of certain manager characteristics over time. Interestingly, Figure 1 shows that the fraction of female managers increased in the 1990s, reached its peak in 2001, and has declined ever since.[11]

Further descriptive statistics for the entire dataset are presented in Table II. Panel A of the table shows manager characteristics by aggregated fund investment objective categories (IOC) that we constructed ourselves for the purpose of summarizing the data; Appendix Table AI shows the

[11] In unreported tests, we find that there is a structural break in the time series of the growth rate of the fraction of female managers in the year 2001.

same statistics by Morningstar investment objective categories (in that table, we only present the summary statistics for categories that have at least ten unique funds). It can be seen that the fraction of female managers differs across fund categories, with a relatively higher fraction of female managers in municipal bond funds and a relatively lower fraction in real estate and commodity funds.

Panel B of Table II presents statistics on the set of career events that constitute promotions and demotions. Monthly promotion and demotion probabilities are just under 3%. Moreover, managers have a significantly higher chance of gaining or losing a co-managed fund than a sole-managed fund. As shown in Panel A of Appendix Table AII, promotion and demotion probabilities are very similar for the sample limited to managers of mainstream active domestic equity funds.

Panel C of Table II and Panel B of Appendix Table AII present summary statistics on differences between male and female managers. On average, male managers have significantly more years of industry experience and are older than female managers. There are substantially more male managers over 55 years of age than female managers in this age group. These results dovetail with our findings that female managers are more likely to permanently leave the industry in any given month before retirement age. Moreover, there are more foreign-born managers among female managers. When it comes to education, women are less likely to hold MBA or Other degrees and slightly less likely to have a CFA certificate. In addition, female managers tend to work for larger mutual fund families, which employ more managers.

Comparing management responsibilities, the table shows that female managers sole-manage and co-manage significantly fewer funds (in contrast, in the set of managers of mainstream active domestic equity funds, women co-manage significantly more funds, as shown in Table AII in the Appendix). Total net assets attributable to a manager are significantly higher for male managers, which is consistent with our finding presented later in the paper that, all else equal, women are less likely to be promoted than men.

In terms of performance metrics, Table II shows that, without controlling for fund size, expense ratio, etc., women underperform men. Table AII shows no significant differences in fund alphas but a slight underperformance by female managers in terms of fund flows.

Turning to various career events, the tables show that women are just as likely as men to have a gap of 6 months or longer in fund management assignments; the average length of the employment gap is just over two years for both genders. Women are significantly more likely to permanently leave the industry in any given month before retirement age. Finally, the unconditional probability of female managers getting promoted is lower than that for male managers, while the unconditional probability of being demoted is the same for male and female managers. For the subset of managers of mainstream active domestic equity funds, female managers are more likely than male managers to get both promoted and demoted (Panel B of Table AII).

IV. Empirical results

A. Manager characteristics and performance

In this section, we empirically investigate to what extent managers' gender and other manager characteristics influence their performance, which is measured by returns and fund flows. The univariate performance statistics in Table II suggest a slight underperformance by female managers compared to male managers. However, to draw meaningful inference on the effect of gender on performance, we need to control for fund-level factors that affect returns and fund flows, such as the expense ratio, turnover, 12B-1 fees, fund TNA, fund age, and an institutional fund dummy, as well as manager-level characteristics, such as experience and education. All these controls are included in regressions explaining fund flows and returns at the individual fund level.

We limit the regression sample to sole-managed funds in order to more precisely determine the possible effects of manager characteristics. Moreover, for a fund to be included in the regressions, we require that the fund's manager has managed the fund for at least the prior 12 months because

fund flows may be sensitive to lagged manager characteristics as well as lagged fund flows and returns.[12]

To control for differences in fund flows and returns across different investment objective codes, we analyze style-adjusted fund flows and style-adjusted CAPM alphas by subtracting out the average fund flow and CAPM alpha among the funds in the same investment objective category in a given month. We consider only funds in investment objective categories that contain at least three other funds.

Because fund flows and returns are likely to be serially correlated and susceptible to the same market-wide shocks, we include year dummies and double cluster standard errors by fund and month. Finally, because fund flows exhibit well known seasonal patterns, such as patterns linked to tax and bonus seasons, we include month dummies in all but one regression specifications.

Panel A of Table III presents the regression results for monthly style-adjusted fund flows. As shown in the table, all else equal, being female is associated with lower monthly fund flows. Depending on the specification, the difference in monthly fund flows between female and male managers is between 0.07% and 0.10%. (This result is consistent with the findings of Niessen-Ruenzi and Ruenzi (2017) who show that female fund managers get lower fund flows than otherwise similar male fund managers.) Managers holding a Ph.D. get significantly higher fund flows than managers with lesser degrees. The length of time a manager managed the fund is a significant negative predictor of fund flows; the length of industry experience is also negatively related to future fund flows, but the effect is nonlinear—this variable squared is a positive predictor of fund flows. All other manager characteristics that we consider do not appear to influence fund flows. A follow-up question is why female managers earn lower fund flows: Investors may have a preference for male managers or fund families may disproportionately direct marketing dollars to funds with male managers.

[12] As is customary in studies analyzing fund flows, we exclude monthly observations with absolute values of fund flows in excess of 1; such observations are considered to be the result of data errors. We also only consider funds with TNA over $5 million.

Turning to fund returns, Panel B of Table III presents the results for monthly style-adjusted CAPM alphas. The results for raw style-adjusted returns are shown in Table AIII in the Appendix. Both tables show that managers' gender does not predict returns, nor do other manager characteristics (with the exception of Other degree, which is a positive predictor of returns in our sample). As is the case with fund flows, the results show that the longer a manager has worked at a fund, the lower the predicted fund returns are.

As a robustness check, we focus on a more uniform set of funds. Specifically, we limit the sample to actively-managed mainstream domestic equity funds and thereby exclude from the sample bond funds, international funds, funds that specialize in real estate, utilities, and commodities, and tax-managed and socially responsible funds. The results, presented in Table AIV in the Appendix, are very similar to those obtained for the larger sample of funds, with the exception that being female is no longer associated with lower fund flows.[13] In unreported results, we also find that female managers tend to have lower return volatilities than other managers in the same investment objective categories.

To sum up, with the exception of female sole managers getting slightly lower fund flows than male sole managers with similar fund characteristics and performance, we do not observe reliable performance differences that can be attributed to manager gender or other manager characteristics. Nevertheless, we will control for past performance in the regressions explaining manager career outcomes.

B. Explaining industry departures and career outcomes

In this section, we estimate monthly regressions to explain industry departures and managers' comprehensive career outcomes, which include all promotions and demotions. In all regressions, we include either fund family dummies or fund family characteristics. Fund family characteristics in-

[13]The difference between this result and the results of Niessen-Ruenzi and Ruenzi (2017), who also focus on active equity funds, is likely attributable to a somewhat different sample and different regression specifications; their sample covers the period 1992-2009, regressions are run at an annual frequency, and standard errors are single-clustered at the fund level.

clude the combined TNA of all funds that a fund family manages, the number of funds in the fund family, and the number of managers working at the fund family as of the end of the prior month.

Managers' careers may be affected by investor sentiment towards the fund categories that they manage. For example, commodity funds may be shut down after investor sentiment toward commodities turns negative. To control for investor sentiment toward particular investment objective categories, we include the variable *IOC Trend*, which is calculated over a rolling 12-month window as the average fund flow into that investment objective category. As mutual fund families may also take into account the volatility of managers' returns when making promotion and demotion decision, we include, as an additional control, the standard deviation of the monthly alpha ranks attributed to a manager, calculated over the trailing window over which performance is measured. In addition, the set of controls includes the log of the combined TNA that a manager manages and the number of funds s/he manages.

We include the following performance measures for each manager: the within-IOC rank of managers' CAPM alphas and fund flows (1 to 10). These ranks are calculated over the trailing windows $[-12,-1]$, $[-24,-13]$, and $[-36,-25]$ months, corresponding to subscripts $t-1$, $t-2$, and $t-3$ in the tables, by averaging managers' monthly ranks over these windows. If a manager manages more than one fund in a particular month, the funds' ranks are weighted by the fraction of the fund attributable to the manager, as described earlier. When computing performance ranks, we require that a manager had at least 12, 24, or 36 months of continuous fund management experience. The reason for including performance measures lagged by up to three years is that career decisions may be based on performance information from prior years.

The monthly fund return and TNA sample is available from January 1992 to December 2016. Because we forecast career changes one month ahead, our main sample period January 1992 to January 2017.[14] In model specifications that include performance measures computed over a trailing 36-month window, the sample period is reduced by the initial 36 months. The sample is further

[14] In a robustness check, we end the sample one year earlier, in January 2016, in order to allow for the possibility that managers may have a one-year career gap due to parental leave, which we do not want to identify as firings. This modification does not affect the results.

reduced in models that use school information to identify whether a manager is of foreign origin, whether s/he has an advanced degree, and whether s/he went to a top school. In all regression specifications, we only consider investment categories with at least ten funds and fund families with at least five funds or five managers. Since time series and cross-sectional correlations in the error terms are likely, we double cluster standard errors by year and manager. Finally, because managers' career outcomes are affected by the state of the stock market (for example, we observe large manager exoduses after the dot-com and real estate collapses), we include year dummies in all regressions.

The linear probability regressions explaining manager firings—defined, as described above, as instances in which managers permanently leave the fund management industry while being under the retirement threshold—are presented in Table IV. The table is structured as follows. Panel A presents the results for subsamples organized by the minimum required years of managers' uninterrupted fund management experience. Panel B presents the results for the subset of managers with at least three years of prior uninterrupted fund management experience and includes a richer set of controls, such as managers' education information. In the regressions in Panel A, we use the variable *Foreign+Guess* in order to retain observations with missing school information. Subpanels A1-A3 and B1-B3 report the results for the samples comprised of all managers, only sole managers, and only co-managers, respectively.

Turning to the results in Subpanel A1, it is noteworthy, though not surprising, that the probability of a premature departure from the industry is highly negatively related to past performance, measured by both alphas and fund flows. Strikingly, the regression coefficients on the dummy *Female* are positive and highly significant in all specifications, ranging between 0.0024 and 0.0033. Given that, according to Panel D of Table II, male managers have an unconditional probability of being fired in a given month of 0.0064%, these estimates imply that female managers face a 38% to 52% higher likelihood of being fired in a given month than male managers. Among the other control variables, the combined TNA and the number of funds managed are significant predictors of departures. Overall, however, the inclusion of other control variables has very limited effect on

the coefficient estimate on the dummy *Female*. Finally, regardless of the regression specification, managers of foreign origin do not face a higher probability of being fired than U.S.-born managers.

Comparing the results for the subsamples of sole managers and co-managers in Subpanels A2 and A3, respectively, reveals that, as managers gain years of industry experience, the difference in firing probabilities between men and women disappears for sole managers but increases for co-managers. That is, female co-managers' position in the industry gets progressively more precarious compared to male co-managers as years of fund management experience accumulate. This result echoes the result of Sarsons (2017) that women get less credit for work completed in teams.

The regressions with additional controls, reported in Panel B, reveal additional noteworthy results. First, we check whether female managers tend to leave the industry early in their career, which could be explained by conflicting family responsibilities. However, we find that female managers are *not* disproportionately more likely to exit the industry early in their career. Second, while all managers are more likely to exit the industry following poor performance, female managers, on average, do not appear to be singled out by fund families for firing due to bad performance. In fact, in the samples considering all managers or only co-managers (Subpanels B1 and B3), female managers are slightly less likely to be fired after low returns in the prior year, as indicated by a positive coefficient on the term interacting the dummies *Female* and *Low Alpha*. However, in the sample of sole managers, a positive and significant coefficient on the term interacting the dummies *Female* and *Low FFlow* indicates that female sole managers are more likely to leave the industry following a year of low fund flows.

Specifications (7) through (13) rely on managers' school information and therefore contain roughly 15% fewer manager-month observations. In these specifications, we define foreign origin purely based on whether or not a manager attended a foreign college or university. We find that a manager's foreign origin does not affect his likelihood of being fired. Moreover, we find that none of the education variables factor into firing probabilities either.

Next, we investigate the determinants of managers' promotions and demotions that do not result in firings (e.g., demotions after which a manager does not permanently disappear from the industry).

According to Panels B and C of Table II, promotions and demotions are significantly more prevalent than firings. As described earlier, promotions and demotions are measured as the growth in the number of funds managed, with a co-managed fund being counted as the fraction of the fund that the manager manages, that is, $\frac{1}{number\ of\ co\text{-}managers}$.

The regression results for promotions and demotions are presented in Table V. Subpanel A1 shows that, as expected, managers' career advancement strongly depends on past returns and fund flows. However, female managers have worse career outcomes than male managers with the same performance and similar fund management responsibilities. The regression coefficient on the dummy *Female* becomes less negative as women gain industry experience. As implied by coefficient estimates between -0.0047 and -0.0011, the expected growth in the number of funds managed is 0.11% to 0.47% below that for otherwise similar male managers.

A comparison of the results for the subsamples comprising only sole managers (Subpanel A2) and only co-managers (Subpanel A3) reveals that female sole managers become more similar to male managers in terms of expected career advancements as their tenure in the industry increases, while the difference in career prospects between female and male co-managers does not vanish as a manager's experience increases. That is, female co-managers appear to have worse career outcomes than male co-managers throughout their tenure in the industry, after controlling for performance and fund management responsibilities. Consistent with the findings in Table IV, these results indicate that working in teams negatively affects women's career opportunities.

The coefficients on the dummy variable *Foreign+Guess* are negative but insignificant. Therefore, as with firings, managers of foreign origin do not appear to suffer worse career outcomes than U.S.-born managers.

Panel B reports the results of detailed regressions for the subsample of managers with at least three years of continuous fund management experience. These results generally confirm the finding that, all else equal, female managers face worse career outcomes than male managers. The results also show that female managers' promotions are *not* more sensitive to past performance than male managers' promotions. In both samples comprising all managers and only co-managers, younger

managers are more likely to be promoted than older managers; however, women's promotions are *not* more sensitive to the stage of their career than men's promotions, which suggests that women do *not* deliberately avoid getting promoted due to potential family conflicts early in their careers.

The results for regression specifications (7) through (13) that rely on managers' school information show that, all else equal, managers who attended top schools have better career trajectories, while foreign-born managers have worse career trajectories. When it comes to sole managers, as reported in Subpanel B2, career progressions of foreign managers, managers who attended top schools, and managers with advanced degrees are more sensitive to past returns than career progressions of otherwise similar managers.

We perform two robustness tests for our results. In the first robustness check, we change the sample start date to January 2006. Rerunning the regressions based on a sample starting in 2006 helps alleviate any concerns about possible survivorship bias in the Morningstar data and its possible effect on the results. Survivorship bias in the 2006–2017 sample should be negligible because we combined the Morningstar files that we received in 2005, 2009, 2011, 2013, and 2017 to construct our dataset. Panels A and B of Table AV in the Appendix show the regression results for firings and career advancements, respectively. Overall, the results for the 2006–2017 sample are very similar to the results for the entire sample presented in Subpanels A1 in Tables IV and V. Hence, our results are not affected by possible survivorship bias in the data.

In the second robustness check, we analyze the sample comprising only managers of mainstream active domestic equity funds. Panel A of Appendix Table AVI presents the regression results explaining firings. In general, firing patterns for equity managers are very similar to those found in the comprehensive dataset, as reported in Subpanel A1 of Table IV. Panel B presents the regression results for career advancements. Although the coefficient on the dummy *Female* is negative in all regression specifications, it is not as significant as in the comprehensive sample (Subpanel A1 of Table V).

C. Career outcomes of co-managers with identical track records

In this section, we provide additional results that should mitigate any biases that may occur if we omitted control variables that may affect our outcome variables and are correlated with our covariates of interest. One may, for example, be concerned that we do not perfectly control for the types of funds that managers manage, and the results may be biased if the types of funds managed by women are more likely to become obsolete and female managers disproportionately leave the industry for that reason.

In this section, we investigate career outcomes of co-managers who are indistinguishable from each other in terms of both their employment history and past performance. To that end, we form cohorts that consist of co-managers who started managing the same mutual fund in the same month and had no prior recorded mutual fund management history or other concurrent mutual fund management responsibilities. Figure 5 provides a graphical illustration of how cohorts are formed. Since, in this setting, the observable performance of co-managers in the same cohort is identical, there should not be any systematic differences in future promotions or demotions related to fund manager characteristics. In the tests that follow, because we do not need to link the Morningstar data to the return and TNA data in the CRSP Mutual Fund dataset, we employ a sample comprising all managers in the Morningstar dataset.

We begin by investigating whether female co-managers have the same career outcomes as their male cohort peers. For this test, we require that at least one member in a cohort be female. Sample statistics are provided in Panel A of Table VI. The sample contains 139 cohorts and 375 unique managers, and the average number of co-managers in a cohort is 3.33. Male managers outnumber female managers by 7%.

Demotions and promotions are defined as follows: If a manager's tenure with a fund ends and the manager gets no other mutual fund management responsibilities, we consider the manager to be fired and code this observation as a demotion with the career outcome variable set to -1. If a manager stays in the same position until the end of our sample period, we code this observation

as neither a promotion nor a demotion and set the value of the career outcome variable to 0. If a manager leaves the fund and gets a new co-management responsibility at another fund, we also code this observation as neither a promotion nor a demotion and set the career outcome variable to 0. Finally, if a manager subsequently gets a sole-management responsibility or becomes a co-manager of an additional fund, we code this observation as a promotion and set the career outcome variable to $+1$.

To test whether career outcomes systematically differ across managers, we run the following regression:

$$CareerOutcome_{ij} = \alpha X_i + \sum_{j=1}^{N} \beta_j Cohort_j + \varepsilon_{ij}, \tag{3}$$

where i denotes a manager, j denotes a cohort, X_i is a vector of manager characteristics, and $Cohort_j$ is a cohort indicator variable intended to capture cohort fixed effects. We run linear probability regressions separately for promotions and demotions. Additionally, we run OLS regressions for comprehensive career outcomes, with the career outcome variable taking on values -1, 0, or $+1$, as described above.

Panel B of Table VI reports the regression results. As indicated by the first set of columns, female co-managers' probability of losing a co-management job is between 9.2% and 10.5% higher than that for male co-managers in the same cohort. The likelihood of a promotion for women is somewhat lower than that for male cohort members, but the difference is insignificant. When explaining comprehensive career outcomes, overall, female co-managers tend to have significantly worse career outcomes than otherwise identical male co-managers.

Panel C of Table VI considers the identical co-managers from the mixed male-female teams who have permanently disappeared from the mutual fund dataset immediately following the first portfolio assignment (we exclude subadvisors from this search). Out of the total of 95 managers, we are able to find online information for 50 managers (from websites such as LinkedIn, as well as various industry announcements and press releases). The table shows that roughly 72% of these managers end up in clearly lower positions, and the demotion likelihood is slightly higher for women (at 76%) than for men (at 69%), but the difference between the male and female managers is

not statistically significant. Managers who are demoted may be demoted to non-manager positions in their own institutions or in other financial institutions (for example, they end up with jobs in client relations or in positions such as portfolio specialist or a buy-side analyst). They may also become fund managers at various endowments and employee- and state-owned funds that are likely to pay a lower salary. Some managers go into wealth management or financial advice (we have observed several instances of managers advising funds on socially responsible investing). A subset of managers moved to a different industry altogether (for example, data- or IT-related), while some appear to be unemployed. Still, a smaller subset of managers appears to have made a lateral move to another fund type (e.g., to managing a foreign fund not sold in the U.S. or a private equity fund). None of the managers that we could look up moved to a hedge fund. Thus, the table shows that the managers that have left the mutual fund universe predominately ended up in lower-paying positions, and there is no significant difference in the attractiveness of the next position between male and female managers.

Next, we investigate to what extent manager characteristics, including gender, affect the time it takes a manager to get promoted. Specifically, we investigate the probability of a promotion in each subsequent month, conditional on the manager remaining in the fund until then, using a Cox proportional hazard rate model of the following form:

$$ln[h(t)/h_0(t)]_{ij} = \alpha X_i + \sum_{j=1}^{N} \beta_j Cohort_j. \tag{4}$$

The inclusion of the indicator variable $Cohort_j$ forces the baseline probability of a promotion to be the same for all co-managers in the same cohort. When estimating the model, we take into account that our sample is censored at the end of our sample period, that is, promotions that may occur beyond the end of the sample are not observed. We use all fund-co-manager cohorts in this analysis, requiring only that each cohort has some variation in at least one manager characteristic of interest. In this analysis, we code the co-managers that were fired as not being promoted.

As shown in Panel A of Table VII, the sample for this analysis comprises 439 cohorts and is somewhat larger than that in Table VI. The sample contains 1,083 unique managers, and the fraction of female managers is lower than in the previous analysis, in which we required at least one member of a cohort to be female, reflecting the generally low percentage of female managers in the industry.

Panel B presents the results of the hazard regressions, including the standard errors of the estimated coefficients and the hazard ratios for the explanatory variables. Conditional on having stayed in the fund until month t, managers who hold MBA degrees have a significantly higher probability of being promoted in month $t+1$ than other managers in their cohort. We do not find significant effects of other manager characteristics, likely due to the small sample size.

D. Professional networks: suggestive evidence

In this section, we investigate the role of professional networks in finding a new job. Having a strong professional network is arguably one of the crucial prerequisites for a successful career because it helps generate outside offers. A strong professional network is especially important when looking for a new job. Assessing the career outcomes of mutual fund managers who must find new jobs subsequent to their fund families merging or closing allows us to document some suggestive evidence on the importance of a professional network for a manager's career.

As in the main results for the overall sample, we consider the sample of fund families with at least five funds and five managers employed.[15] As before, the sample period is from January 1992 to December 2016. In this sample, we find eleven observations of fund family closings, involving 114 mutual fund managers.[16] Among these managers, 13 are female and ten are of foreign origin (here we use the dummy *Foreign+Guess* to increase the sample size).[17]

[15] The results are similar when we broaden our sample to include fund families that consist of at least two funds and two managers.

[16] We obtain the dates of fund family closings from the CRSP Mutual Fund dataset.

[17] As before, Canadian managers are not considered to be foreign.

The unconditional probability of a manager permanently disappearing from the mutual fund industry in the month in which his fund family closes, while being under 55 years old or, if age information is missing, having less than 25 years of fund management experience, is 51%. We run a linear probability regression explaining permanent departures from the industry following fund family closures and mergers on manager characteristics. To account for the possibility that each fund family closure may have a different effect on the reputation of the managers involved, we include fund family fixed effects. The coefficient estimates on the dummies *Female* and *Foreign+Guess* are 0.02 (t-statistic=0.13) and 0.30 (t-statistic=1.71), respectively. That is, foreign managers are 30% less likely to find another job in the mutual fund industry after their fund family disappears, which is a statistically and economically significant result.

While it is difficult to draw strong conclusions from the results based on such a small sample, the results are suggestive of foreign-educated managers having worse career outcomes in terms of promotions and permanent departures following fund family closures due to smaller professional networks.

V. Conclusion

In this paper, we investigate whether being in the minority adversely affects an employee's career prospects. We conduct this investigation in the mutual fund industry which offers a nice setting for several reasons: First, mutual fund manager identities are readily available. Second, the industry is highly transparent because of the required disclosures of mutual fund returns and total net asset values, which makes it easy to measure managers' performance. Finally, we are able to observe career outcomes as changes in managers' fund management responsibilities.

We find that past performance is a very important determinant of managers' promotions, demotions, and firings. This finding suggests that the money management industry is a largely meritocratic profession that rewards performance. However, we document that managers' personal attributes also influence their career outcomes. For example, a female manager with the same fund

management duties and past performance as a male manager is significantly less likely to be promoted and significantly more likely to leave the industry before retirement age. This observation is stronger still for female co-managers, who likely get less credit for good fund performance than their male co-managers.

Additionally, we find a strong positive effect of young age and some impact of elite school education on career advancement, even after controlling for performance. Foreign-educated managers appear to have worse career outcomes, in part because of smaller social networks.

Overall, the results in this paper suggest that, despite the fact that the mutual fund industry is transparent and performance-oriented, traces of bias against some employee groups still exist. Therefore, it is plausible that biases against underrepresented employees are even worse in less transparent and less performance-oriented organizations.

The paper also highlights an empirical fact that merits further analysis: Women are severely underrepresented in the population of mutual fund managers, with the trend not improving. Our paper offers two explanations for the dearth of female fund managers. First, there appears to be some culturally explained aversion of women to entering the money management industry and, second, once female managers enter the industry, they have shorter tenures than male managers despite having similar performance.

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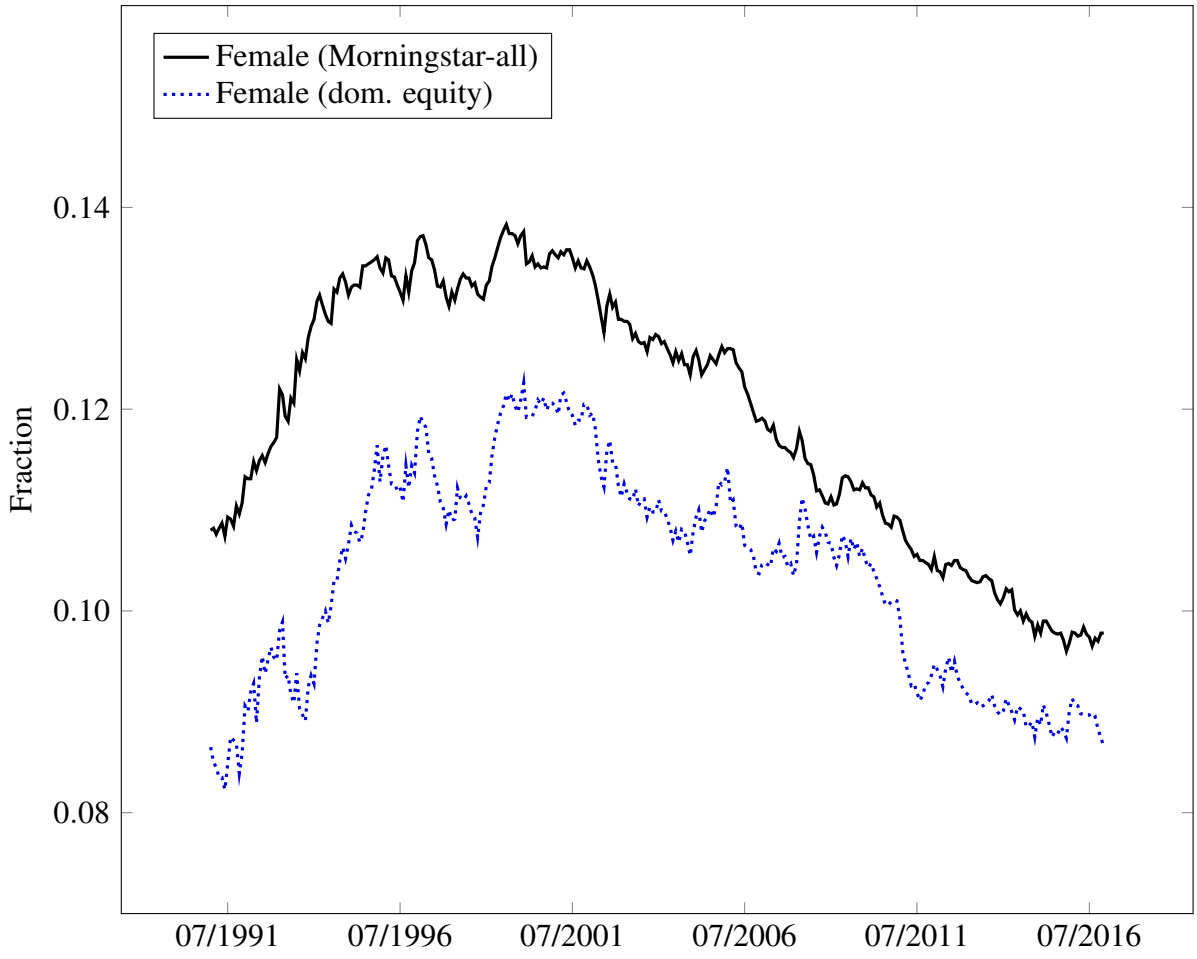

Figure 1. Fraction of female managers. The figure plots the fraction of female fund managers by month. The solid line plots the fraction for all managers in the Morningstar dataset and the dotted line plots the fraction for managers of mainstream active domestic equity funds.

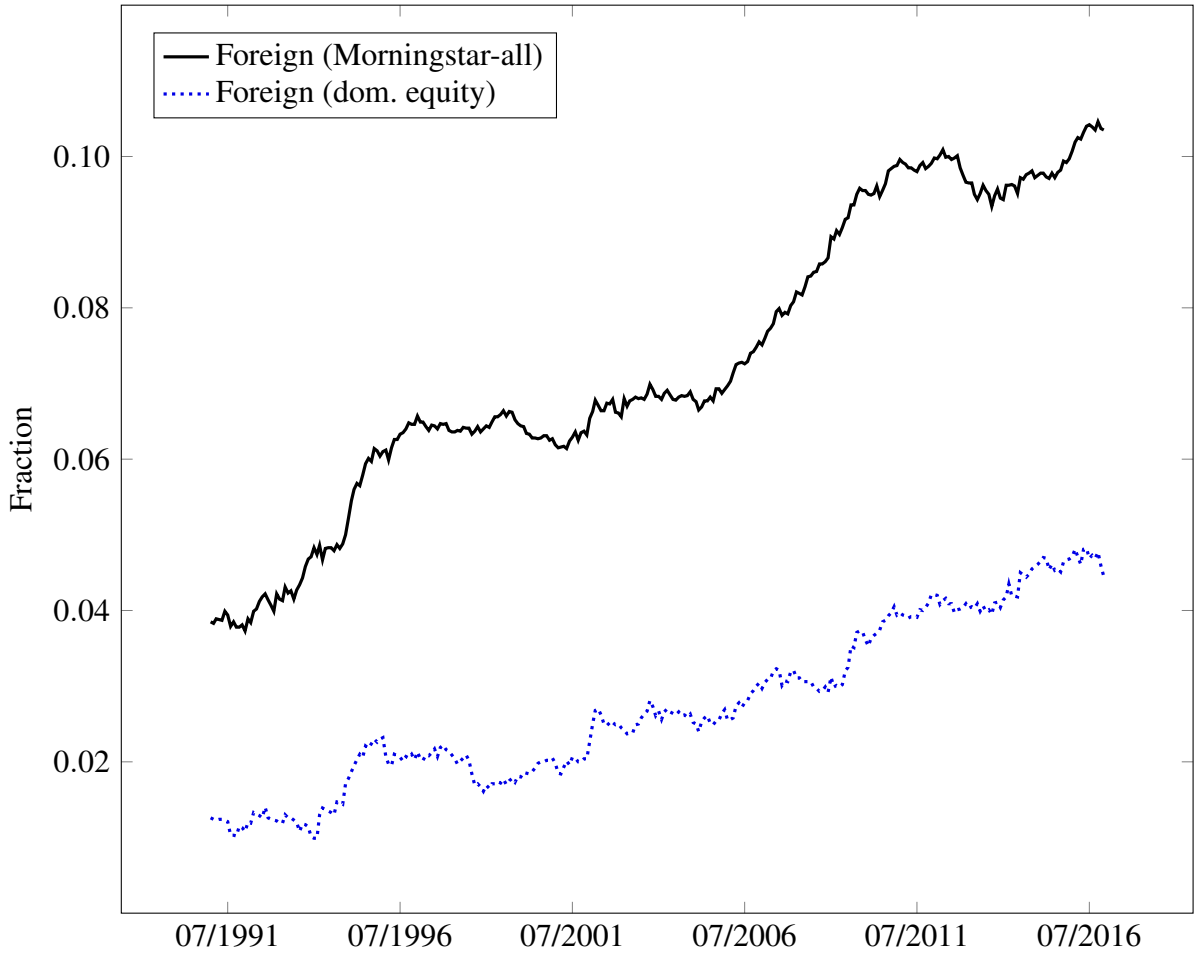

Figure 2. Fraction of foreign managers. The figure plots the fraction of foreign fund managers by month. The solid line plots the fraction for all managers in the Morningstar dataset and the dotted line plots the fraction for managers of mainstream active domestic equity funds. Canadian managers are not considered to be foreign.

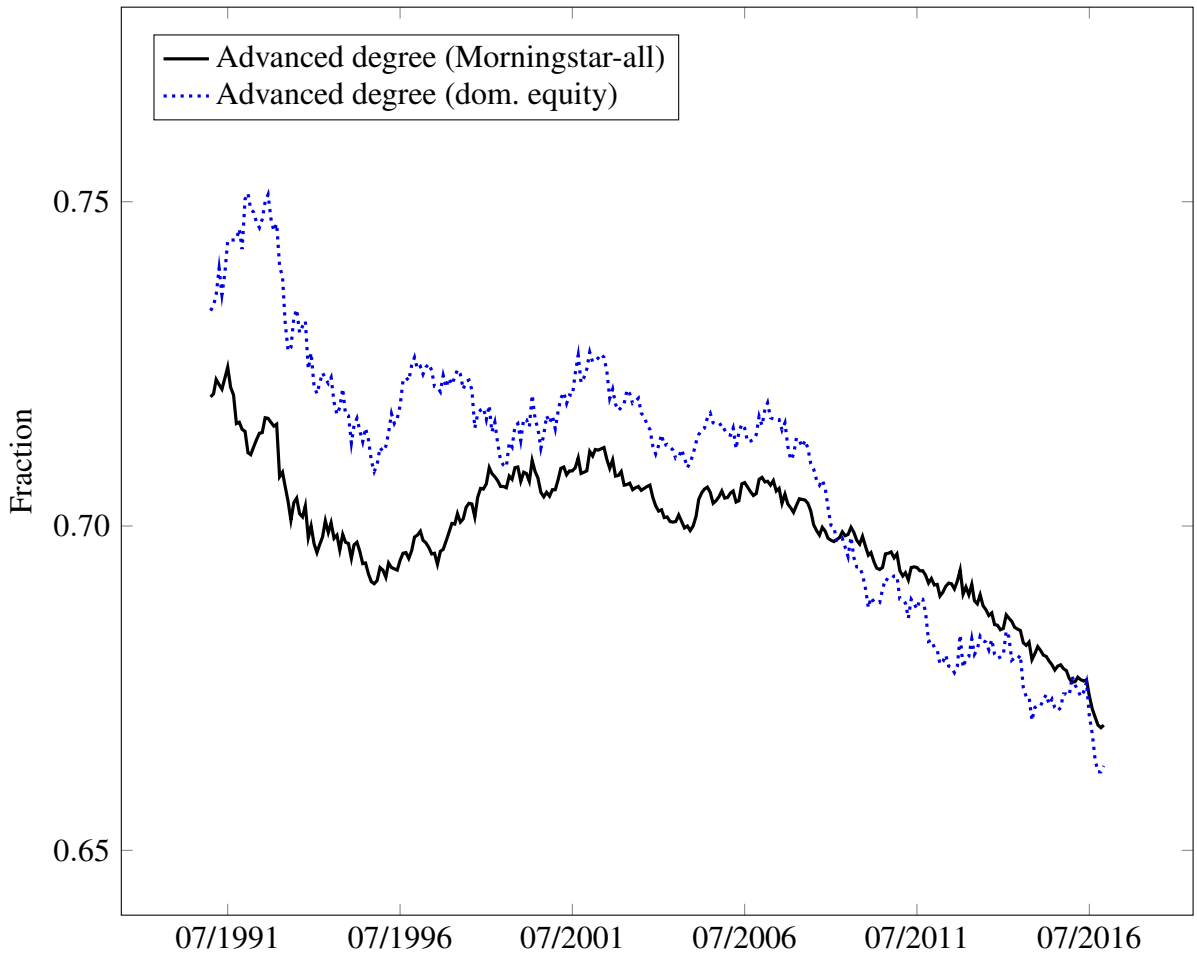

Figure 3. Fraction of managers holding an advanced degree. The figure plots the fraction of fund managers who hold an advanced degree. An advanced degree is any degree earned after a Bachelor's degree. The solid line plots the fraction for all managers in the Morningstar dataset and the dotted line plots the fraction for managers of mainstream active domestic equity funds.

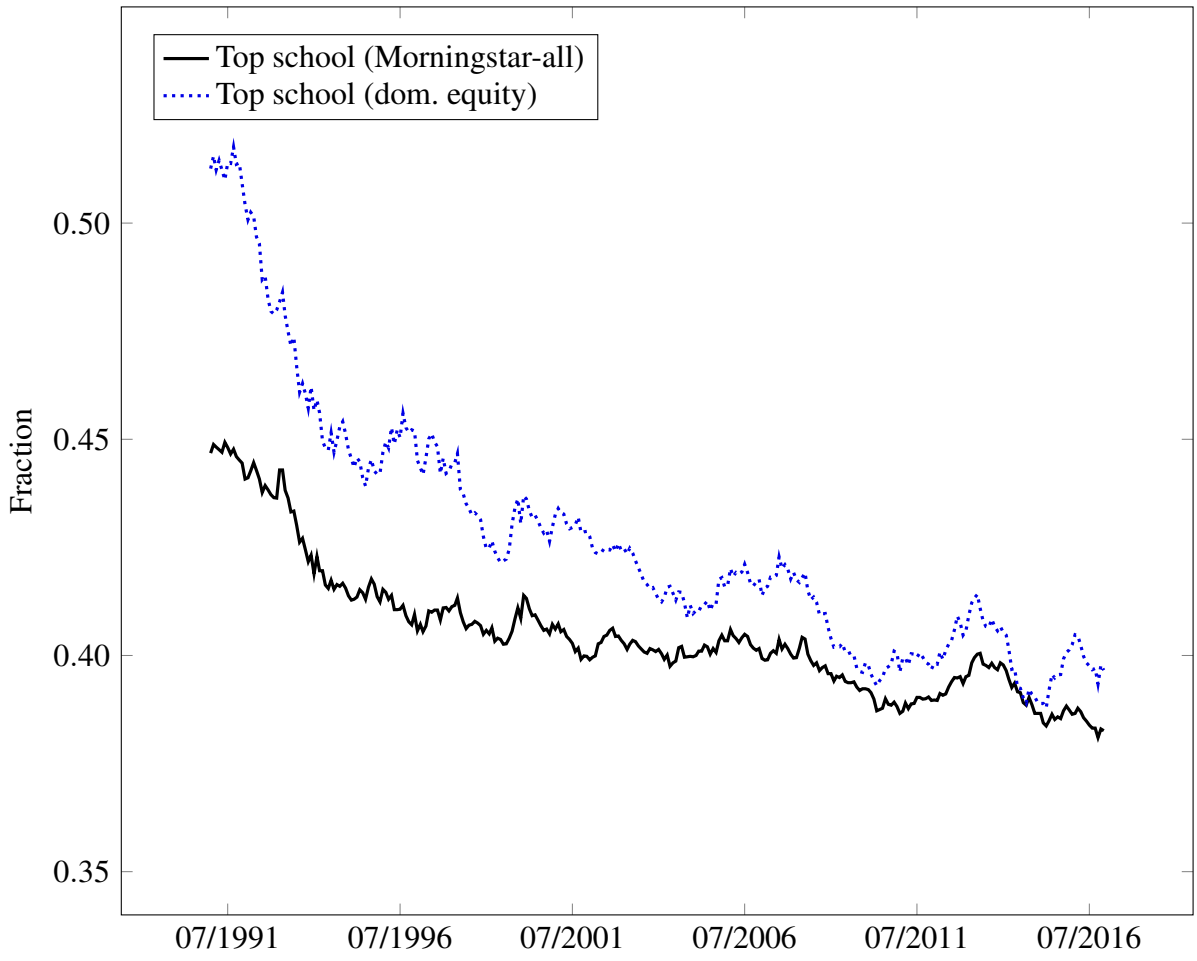

Figure 4. Fraction of managers who attended top schools. The figure plots the fraction of fund managers who obtained at least one of their degrees from a top-ten college, a top-ten university, a top-ten MBA program, or any Ivy League school. The solid line plots the fraction for all managers in the Morningstar dataset and the dotted line plots the fraction for managers of mainstream active domestic equity funds.

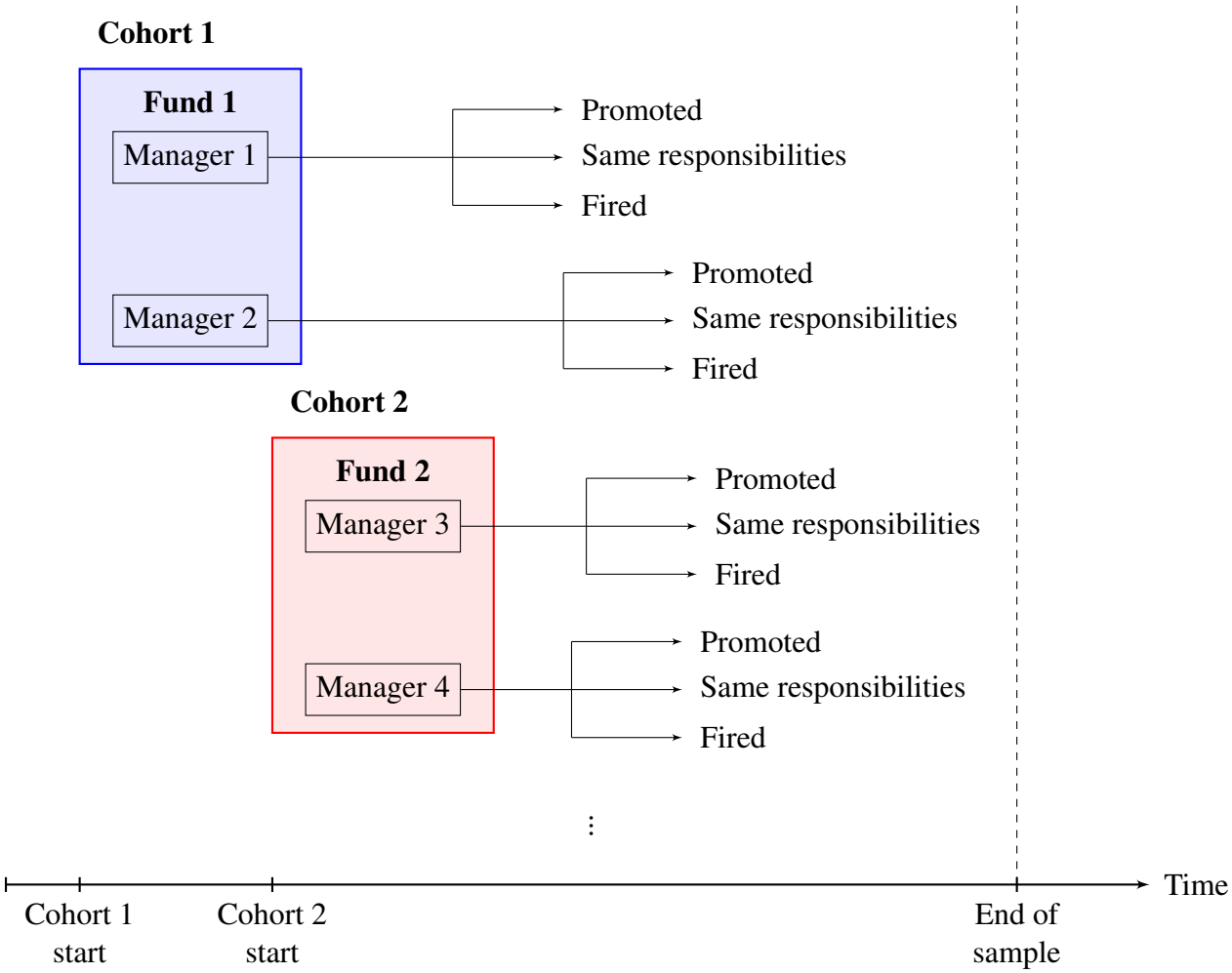

Figure 5. Graphical illustration of fund-co-manager cohorts. The figure provides a graphical illustration of how fund-co-manager cohorts are constructed. A cohort comprises all co-managers who started managing a fund in the same month and have no other fund management responsibilities and no prior fund management history.

Table I
Manager statistics by country of origin

This table presents information on managers' countries of origin. The country of origin is inferred by the location of the school(s) that a manager attended. If at least one of the schools is located in a foreign country, the manager is considered to be of foreign origin. Observations with missing school information are excluded. The second column presents the fraction of female managers for each country in the sample, and the third column shows countries' ranks from 1 (lowest) to 10 (highest) based on the female representation rank. Columns on the right-hand side show the countries' ranks from the 2016 Global Gender Gap Index produced by World Economic Forum, which include ranks from the comprehensive index as well as the four subindices based on (1) economic participation and opportunity; (2) educational attainment; (3) health and survival; and (4) political empowerment. The bottom rows of the table present results from regression of the female representation rank on the gender gap indices. ^{a}, ^{b}, and ^{c} indicate significance at the 1%, 5% and 10% levels, respectively.

Country	Fraction female	Female repr. rank	Total number of managers	Global Gender Gap Index				
				Overall	Economic	Educational	Health	Political
Mexico	0.000	10	11	66	122	51	1	34
Denmark	0.000	10	7	19	34	1	106	29
Chile	0.000	10	4	70	119	38	39	39
Pakistan	0.000	10	3	143	143	135	124	90
Poland	0.000	10	3	38	58	31	40	44
Bolivia	0.000	10	2	23	98	98	1	11
Georgia	0.000	10	2	90	61	78	119	114
Hungary	0.000	10	2	101	67	67	40	138
Lebanon	0.000	10	2	135	133	108	102	143
Portugal	0.000	10	2	31	46	63	76	36
Dominican Republic	0.000	10	1	97	78	77	97	118
Egypt	0.000	10	1	132	132	112	95	115
Finland	0.000	10	1	2	16	1	1	2
Guatemala	0.000	10	1	105	102	107	1	96
Kenya	0.000	10	1	63	48	116	83	64
Morocco	0.000	10	1	137	139	122	93	98
Nigeria	0.000	10	1	118	52	134	135	109
Norway	0.000	10	1	3	7	28	68	3
Peru	0.000	10	1	80	111	80	100	60
Italy	0.045	8	22	50	117	56	72	25
Netherlands	0.048	7	42	16	76	60	103	14
New Zealand	0.056	7	18	9	24	40	104	16
Australia	0.068	7	88	46	42	1	72	61
South Africa	0.071	7	28	15	63	55	1	13
Argentina	0.077	7	13	33	101	54	1	22
Germany	0.098	7	61	13	57	100	54	10
Israel	0.100	6	10	49	62	1	67	48
Sweden	0.100	6	10	4	11	36	69	6
United States	0.117	6	12,452	45	26	1	62	73
India	0.123	6	171	87	136	113	142	9
Japan	0.125	6	48	111	118	76	40	103
Canada	0.129	5	233	35	36	1	108	49
Switzerland	0.133	5	30	11	30	61	72	15
Belgium	0.154	5	13	24	37	1	64	35
Brazil	0.167	5	18	79	91	42	1	86
Iceland	0.182	5	33	1	9	1	104	1
Ireland	0.182	5	33	6	49	1	54	5
France	0.227	5	75	17	64	1	1	19
Venezuela	0.250	4	4	74	71	33	1	89
Greece	0.286	4	7	92	85	85	54	101
Spain	0.286	4	7	29	72	43	91	26
China	0.327	4	104	99	81	99	144	74
Bulgaria	0.333	3	3	41	43	65	40	51
Austria	0.375	3	8	52	84	86	1	41
Philippines	0.500	2	6	7	21	1	1	17
Jamaica	0.500	2	4	42	35	1	1	63
Ukraine	0.500	2	4	69	40	26	40	107
Belarus	0.500	2	2	30	5	29	40	80
Romania	0.500	2	2	76	54	68	40	112
Singapore	0.545	2	22	55	17	95	121	97
Colombia	0.667	2	3	39	28	37	40	66
Czech Republic	1.000	1	2	77	89	1	40	85
Latvia	1.000	1	1	18	18	1	1	38
Lithuania	1.000	1	1	25	25	1	40	43
Paraguay	1.000	1	1	96	82	59	1	122
Coefficient estimate on gender gap index				0.021^{c}	0.033^{a}	0.032^{a}	0.022^{b}	0.011
(t-statistic)				(1.98)	(3.16)	(3.32)	(2.23)	(0.02)

Table II
Descriptive statistics on mutual fund managers

This table presents descriptive statistics on mutual fund managers. Firings, promotions, and demotions are defined in the main text. The sample period is January 1992 – December 2016.

Panel A: Manager characteristics by fund category

Fund category	Female	Top school	Foreign	MBA	MA	PhD	Other degree	CFA	Age	Avg. no. of funds	No. obs.
Domestic equity	0.10	0.30	0.05	0.47	0.14	0.04	0.03	0.50	47.3	612	1,935,414
Soc. resp. & tax-managed	0.21	0.33	0.01	0.48	0.04	0.01	0.03	0.51	47.9	876	6,350
Industry-focused equity	0.18	0.30	0.04	0.51	0.10	0.05	0.01	0.53	47.4	30	9,030
Real estate	0.06	0.41	0.02	0.50	0.14	0.02	0.01	0.41	46.3	124	30,758
Corporate bonds	0.11	0.23	0.03	0.45	0.11	0.02	0.02	0.43	45.7	340	803,498
Government bonds	0.14	0.28	0.04	0.36	0.15	0.03	0.03	0.42	45.3	104	334,561
Commodity	0.05	0.33	0.13	0.33	0.14	0.03	0.04	0.34	46.9	55	17,966
International	0.13	0.39	0.24	0.38	0.21	0.06	0.04	0.39	46.3	358	745,896

Panel B: Statistics on promotions and demotions (monthly probabilities)

Promotion - gain additional sole-managed fund(s)	0.00576
Promotion - gain additional co-managed fund(s)	0.02124
Total probability of promotion	0.02700
Demotion - lose sole-managed fund(s)	0.00708
Demotion - lose co-managed fund(s)	0.02267
Total probability of demotion	0.02975

Panel C: Statistics on employment gaps and firings (monthly probabilities)

Gap in employment over 6 months	0.00137
Fired (leave the industry $<$55 y.o. or $<$25 yrs experience)	0.00640

Panel D: Male vs. female managers

			Difference	
	Male	Female	Female - male	*t*-statistic
Fraction of manager-months	0.877	0.123		
Number of unique managers	11,119	1,550		
Years in industry	10.015	8.986	-1.029	(-62.63)
Age	48.159	45.913	-2.246	(-58.46)
Age first started	32.455	31.653	-0.802	(-2.49)
Under 35 y. o.	0.054	0.055	0.001	(0.87)
Over 55 y. o.	0.218	0.119	-0.099	(-63.13)
Foreign	0.123	0.146	0.022	(2.13)
MBA	0.405	0.343	-0.062	(-5.02)
MA	0.128	0.132	0.003	(0.40)
PhD	0.032	0.027	-0.004	(-1.03)
Other degree	0.031	0.016	-0.015	(-4.46)
Top school	0.387	0.395	0.008	(0.52)
CFA	0.417	0.378	-0.039	(-3.08)
No. of sole-managed funds	0.557	0.478	-0.079	(-14.54)
No. of co-managed funds	2.820	2.730	-0.089	(-7.28)
Managed TNA (millions of $)	1,438.00	1,116.64	-321.36	(-28.97)
No. of managers in fund family	43.884	48.616	4.733	(34.80)
Alpha rank	4.558	4.517	-0.041	(-3.81)
Fund flow rank	4.450	4.361	-0.089	(-4.85)
Prob. employment gap over 6 months	0.001	0.001	-0.000	(-0.60)
Length of empl. gap (yrs)	2.147	2.236	0.089	(0.68)
Prob. fired	0.006	0.008	0.003	(8.97)
Prob. demoted (but not fired)	0.026	0.026	-0.000	(-0.06)
Prob. promoted	0.024	0.023	-0.001	(-2.21)

Table III
Explaining style-adjusted fund flows and CAPM alphas

This table presents the results of OLS regressions explaining monthly style-adjusted fund flows (Panel A) and style-adjusted CAPM alphas (Panel B), which are computed by subtracting out the average fund flows and CAPM alphas earned by the funds in the same investment objective category in a given month. The set of funds only includes sole-managed funds, and we require that a fund manager has been with a fund for at least 13 months. Return controls include style-adjusted CAPM alphas lagged by one, two, and three months, and the average alpha earned by a fund over months $t-12$ to $t-4$, with CAPM betas estimated over the rolling 12-month window, as well as the standard deviation of the CAPM residuals over the period $t-12$ to $t-1$. Fund flow controls include style-adjusted fund flows lagged by one, two, and three months, and the average fund flow earned over months $t-12$ to $t-4$. Fund controls include 12b-1 fees, the expense ratio, an indicator for institutional funds, total net assets under management, and the turnover ratio. Fund family controls include the total number of managers employed in the fund family as well as the total number of funds and the total TNA of all funds in the fund family. Managers' time in the industry and fund age are expressed in days. Managers are identified as foreign if they have attended a foreign college or university for at least one of their degrees, with universities and colleges located in Canada not being considered foreign schools. All variables are known at the end of month $t-1$. The sample period is 1993-2016. Standard errors, clustered by fund and month, are reported in parentheses.

Panel A: Style-adjusted fund flows

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.0010	-0.0014	-0.0012	-0.0009	-0.0010	-0.0010	-0.0007	-0.0007	-0.0008	-0.0007
	(-2.62)	(-3.69)	(-3.17)	(-2.73)	(-2.89)	(-2.62)	(-1.70)	(-1.78)	(-1.85)	(-1.71)
Time in industry	.	.	.	.	.	.	.	.	.	-0.0000
	.	.	.	.	.	.	.	.	.	(-4.06)
Time in industry^2	.	.	.	.	.	.	.	.	.	0.0000
	.	.	.	.	.	.	.	.	.	(3.39)
Foreign	.	.	.	.	.	.	0.0003	0.0002	0.0003	0.0000
	.	.	.	.	.	.	(0.50)	(0.33)	(0.49)	(0.03)
Foreign$\times$female	.	.	.	.	.	.	.	0.0010	.	.
	.	.	.	.	.	.	.	(0.58)	.	.
MBA	.	.	.	.	.	.	0.0004	0.0004	0.0004	0.0004
	.	.	.	.	.	.	(1.43)	(1.42)	(1.45)	(1.58)
MA	.	.	.	.	.	.	0.0005	0.0005	0.0005	0.0006
	.	.	.	.	.	.	(1.48)	(1.49)	(1.53)	(1.68)
PhD	.	.	.	.	.	.	0.0015	0.0015	0.0015	0.0015
	.	.	.	.	.	.	(2.37)	(2.36)	(2.27)	(2.30)
Other degree	.	.	.	.	.	.	.	.	.	0.0009
	.	.	.	.	.	.	.	.	.	(1.11)
CFA	.	.	.	.	.	.	.	.	.	-0.0001
	.	.	.	.	.	.	.	.	.	(-0.54)
Top school	.	.	.	.	.	.	.	.	.	-0.0001
	.	.	.	.	.	.	.	.	.	(-0.19)
Time at the fund	.	.	.	.	.	.	.	.	-0.0000	.
	.	.	.	.	.	.	.	.	(-3.43)	.
Fund flow controls	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Fund return controls	Y	Y	N	Y	Y	Y	Y	Y	Y	Y
Fund controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month dummy	Y	Y	Y	Y	Y	N	Y	Y	Y	Y
IOC dummy	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
Fund family dummy	Y	Y	Y	N	N	Y	Y	Y	Y	Y
Fund family controls	N	N	N	Y	Y	N	N	N	N	N
Obs.	257,174	262,061	258,749	257,247	257,247	257,174	220,285	220,285	220,285	220,285
Adj. RSq.	0.1159	0.0597	0.1023	0.1106	0.1080	0.1158	0.1177	0.1177	0.1178	0.1178

Panel B: Style-adjusted CAPM alphas

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.0001	-0.0001	-0.0001	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(-1.06)	(-1.03)	(-1.18)	(-0.43)	(-0.69)	(-1.06)	(-1.07)	(-0.73)	(-1.15)	(-1.04)
Time in industry	.	.	.	.	.	.	.	.	.	-0.0000
	.	.	.	.	.	.	.	.	.	(-1.11)
Time in industry^2	.	.	.	.	.	.	.	.	.	0.0000
	.	.	.	.	.	.	.	.	.	(0.29)
Foreign	.	.	.	.	.	.	0.0001	0.0001	0.0000	-0.0001
	.	.	.	.	.	.	(0.31)	(0.69)	(0.31)	(-0.32)
Foreign×female	.	.	.	.	.	.	.	-0.0008	.	.
	.	.	.	.	.	.	.	(-1.51)	.	.
MBA	.	.	.	.	.	.	0.0001	0.0001	0.0001	0.0001
	.	.	.	.	.	.	(0.84)	(0.87)	(0.85)	(0.94)
MA	.	.	.	.	.	.	0.0000	0.0000	0.0000	0.0000
	.	.	.	.	.	.	(0.11)	(0.07)	(0.14)	(0.20)
PhD	.	.	.	.	.	.	-0.0001	-0.0001	-0.0001	-0.0001
	.	.	.	.	.	.	(-0.54)	(-0.52)	(-0.59)	(-0.57)
Other degree	.	.	.	.	.	.	.	.	.	0.0007
	.	.	.	.	.	.	.	.	.	(2.86)
CFA	.	.	.	.	.	.	.	.	.	0.0000
	.	.	.	.	.	.	.	.	.	(0.58)
Top school	.	.	.	.	.	.	.	.	.	0.0000
	.	.	.	.	.	.	.	.	.	(0.01)
Time at the fund	.	.	.	.	.	.	.	.	-0.0000	.
	.	.	.	.	.	.	.	.	(-1.93)	.
Fund flow controls	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Fund return controls	Y	Y	N	Y	Y	Y	Y	Y	Y	Y
Fund controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month dummy	Y	Y	Y	Y	Y	N	Y	Y	Y	Y
Fund family dummy	Y	Y	Y	N	N	Y	Y	Y	Y	Y
Fund family controls	N	N	N	Y	Y	N	N	N	N	N
Obs.	257,319	262,669	258,901	257,392	257,392	257,319	220,412	220,412	220,412	220,412
Adj. RSq.	0.0189	0.0187	0.0112	0.0123	0.0120	0.0189	0.0206	0.0206	0.0206	0.0206

Table IV
Explaining manager premature departures (firings)

This table presents the results of linear probability regressions explaining manager firings. We assume that a manager is fired when s/he permanently disappears from the mutual fund industry and is under 55 years old or, if age information is missing, has less than 25 years of fund management experience. Panel A presents the regression results organized by the years of managers' fund management experience. In Panel B presents the results of regressions that include a richer set of controls and the sample includes only managers with at least 36 months of uninterrupted fund management history. Subpanels A1-A3 and B1-B3 contain the results for samples comprised of all managers, only sole managers, and only co-managers. Standard errors, clustered by manager and year. t-statistics are reported in parentheses. All controls variables are described in the main text and in the Appendix. The sample period January 1992 – January 2017.

Panel A: Conditioning on years of experience

A1: All managers (premature departures (firings))

	Years of fund management experience									
	All observations				$\geq$ 1 year		$\geq$ 5 years		$\geq$ 10 years	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	0.0028	0.0029	0.0024	0.0024	0.0027	0.0023	0.0033	0.0025	0.0029	0.0024
	(11.60)	(12.05)	(9.95)	(9.95)	(11.33)	(9.42)	(10.98)	(8.03)	(6.90)	(5.52)
Foreign+Guess	.	.	.	-0.0001	.	-0.0001	.	0.0002	.	0.0003
	.	.	.	(-0.23)	.	(-0.45)	.	(0.57)	.	(0.59)
Alpha_{t-1}	.	.	.	.	.	-0.0010	.	-0.0009	.	-0.0007
	.	.	.	.	.	(-10.75)	.	(-7.39)	.	(-4.50)
Alpha_{t-2}	.	.	.	.	.	.	.	-0.0005	.	-0.0006
	.	.	.	.	.	.	.	(-3.81)	.	(-3.65)
Alpha_{t-3}	.	.	.	.	.	.	.	-0.0003	.	-0.0001
	.	.	.	.	.	.	.	(-2.60)	.	(-0.79)
FFlow_{t-1}	.	.	.	.	.	-0.0010	.	-0.0008	.	-0.0007
	.	.	.	.	.	(-18.44)	.	(-8.82)	.	(-6.09)
FFlow_{t-2}	.	.	.	.	.	.	.	-0.0000	.	0.0001
	.	.	.	.	.	.	.	(-0.23)	.	(0.68)
FFlow_{t-3}	.	.	.	.	.	.	.	-0.0001	.	-0.0001
	.	.	.	.	.	.	.	(-0.63)	.	(-1.28)
Stdev	.	.	.	.	.	-0.0215	.	-0.0249	.	0.0053
	.	.	.	.	.	(-1.75)	.	(-1.32)	.	(0.21)
Manager TNA	.	.	-0.0021	-0.0021	.	-0.0020	.	-0.0022	.	-0.0022
	.	.	(-39.20)	(-39.13)	.	(-37.71)	.	(-29.80)	.	(-21.35)
Num. funds managed	.	.	-0.0002	-0.0002	.	-0.0002	.	-0.0002	.	-0.0001
	.	.	(-8.54)	(-8.54)	.	(-8.53)	.	(-6.60)	.	(-4.06)
IOC trend	.	.	0.0001	0.0001	.	0.0022	.	0.0024	.	0.0004
	.	.	(0.19)	(0.20)	.	(3.11)	.	(2.33)	.	(0.32)
Exp. ratio	.	.	-0.0001	-0.0001	.	-0.0001	.	-0.0002	.	-0.0002
	.	.	(-1.53)	(-1.53)	.	(-2.45)	.	(-3.65)	.	(-2.16)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	929,946	929,946	921,168	921,168	923,266	914,011	579,427	509,266	295,196	262,692
Adj. RSq.	0.0016	0.0003	0.0042	0.0040	0.0016	0.0046	0.0020	0.0055	0.0039	0.0063

A2: Only sole managers (premature departures (firings))

	Years of fund management experience									
	All observations				≥ 1 year		≥ 5 years		≥ 10 years	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	0.0021	0.0020	0.0016	0.0016	0.0021	0.0014	0.0013	-0.0001	0.0004	-0.0006
	(3.77)	(3.74)	(2.91)	(2.91)	(3.81)	(2.59)	(1.78)	(-0.17)	(0.37)	(-0.51)
Foreign+Guess	.	.	.	-0.0002	.	-0.0000	.	-0.0007	.	0.0012
	.	.	.	(-0.23)	.	(-0.05)	.	(-0.70)	.	(0.83)
$Alpha_{t-1}$	.	.	.	.	.	-0.0010	.	-0.0012	.	-0.0019
	.	.	.	.	.	(-5.24)	.	(-4.38)	.	(-4.95)
$Alpha_{t-2}$	.	.	.	.	.	.	.	-0.0006	.	-0.0011
	.	.	.	.	.	.	.	(-2.20)	.	(-2.74)
$Alpha_{t-3}$	.	.	.	.	.	.	.	-0.0003	.	-0.0003
	.	.	.	.	.	.	.	(-1.16)	.	(-0.64)
$FFlow_{t-1}$	.	.	.	.	.	-0.0009	.	-0.0007	.	-0.0006
	.	.	.	.	.	(-7.55)	.	(-3.47)	.	(-1.97)
$FFlow_{t-2}$	.	.	.	.	.	.	.	-0.0001	.	-0.0000
	.	.	.	.	.	.	.	(-0.25)	.	(-0.08)
$FFlow_{t-3}$	.	.	.	.	.	.	.	-0.0004	.	-0.0005
	.	.	.	.	.	.	.	(-2.09)	.	(-1.86)
Stdev	.	.	.	.	.	-0.0316	.	-0.0513	.	-0.0891
	.	.	.	.	.	(-1.12)	.	(-1.07)	.	(-1.31)
Manager TNA	.	.	-0.0009	-0.0009	.	-0.0009	.	-0.0011	.	-0.0019
	.	.	(-7.07)	(-7.07)	.	(-7.01)	.	(-5.91)	.	(-6.38)
Num. funds managed	.	.	-0.0005	-0.0005	.	-0.0006	.	-0.0006	.	-0.0006
	.	.	(-4.00)	(-4.01)	.	(-4.27)	.	(-3.82)	.	(-2.55)
IOC trend	.	.	-0.0023	-0.0023	.	-0.0008	.	0.0034	.	0.0001
	.	.	(-1.66)	(-1.65)	.	(-0.56)	.	(1.53)	.	(0.04)
Exp. ratio	.	.	0.0000	0.0000	.	-0.0000	.	-0.0001	.	-0.0001
	.	.	(0.04)	(0.03)	.	(-0.10)	.	(-1.13)	.	(-0.26)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	130,670	130,670	129,359	129,359	129,852	128,430	81,388	69,468	38,479	34,119
Adj. RSq.	0.0041	0.0009	0.0050	0.0046	0.0041	0.0054	0.0058	0.0092	0.0102	0.0141

A3: Only co-managers (premature departures (firings))

	Years of fund management experience									
	All observations				≥ 1 year		≥ 5 years		≥ 10 years	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	0.0019	0.0019	0.0018	0.0018	0.0020	0.0018	0.0024	0.0022	0.0027	0.0025
	(7.27)	(7.35)	(6.69)	(6.71)	(7.35)	(6.75)	(7.60)	(6.77)	(5.93)	(5.55)
Foreign+Guess	.	.	.	-0.0004	.	-0.0004	.	-0.0002	.	-0.0004
	.	.	.	(-1.32)	.	(-1.41)	.	(-0.47)	.	(-0.71)
$Alpha_{t-1}$	.	.	.	.	.	-0.0008	.	-0.0008	.	-0.0007
	.	.	.	.	.	(-7.02)	.	(-5.67)	.	(-3.90)
$Alpha_{t-2}$	.	.	.	.	.	.	.	-0.0001	.	-0.0001
	.	.	.	.	.	.	.	(-1.03)	.	(-0.58)
$Alpha_{t-3}$	.	.	.	.	.	.	.	0.0000	.	0.0002
	.	.	.	.	.	.	.	(0.30)	.	(0.96)
$FFlow_{t-1}$	.	.	.	.	.	-0.0005	.	-0.0003	.	-0.0005
	.	.	.	.	.	(-8.17)	.	(-3.03)	.	(-3.67)
$FFlow_{t-2}$	.	.	.	.	.	.	.	-0.0001	.	0.0001
	.	.	.	.	.	.	.	(-0.75)	.	(0.90)
$FFlow_{t-3}$	.	.	.	.	.	.	.	-0.0002	.	-0.0002
	.	.	.	.	.	.	.	(-1.72)	.	(-1.73)
Stdev	.	.	.	.	.	-0.0471	.	-0.0433	.	0.0170
	.	.	.	.	.	(-3.32)	.	(-2.10)	.	(0.62)
Manager TNA	.	.	-0.0011	-0.0011	.	-0.0010	.	-0.0008	.	-0.0008
	.	.	(-15.15)	(-15.19)	.	(-14.35)	.	(-9.06)	.	(-6.32)
Num. funds managed	.	.	-0.0000	-0.0000	.	-0.0000	.	-0.0001	.	-0.0000
	.	.	(-1.67)	(-1.71)	.	(-2.63)	.	(-2.82)	.	(-1.49)
IOC trend	.	.	0.0016	0.0016	.	0.0034	.	0.0025	.	0.0020
	.	.	(1.74)	(1.79)	.	(3.72)	.	(2.10)	.	(1.19)
Exp. ratio	.	.	-0.0001	-0.0001	.	-0.0001	.	0.0000	.	0.0000
	.	.	(-1.51)	(-1.52)	.	(-1.83)	.	(0.11)	.	(0.22)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	432,733	432,733	430,385	430,385	430,450	427,981	292,104	264,479	156,559	142,719
Adj. RSq.	0.0036	0.0002	0.0043	0.0043	0.0036	0.0047	0.0037	0.0049	0.0053	0.0061

Panel B: Detailed analysis of managers with at least 3 years of fund management experience

B1: All managers (premature departures (firings), managers with $\geq$ 3 yrs of experience)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	0.0025	0.0018	0.0019	0.0018	0.0018	0.0017	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015
	(8.72)	(5.69)	(6.11)	(3.32)	(5.73)	(5.59)	(4.76)	(4.75)	(4.76)	(4.76)	(4.73)	(4.72)	(4.72)
Early career	.	.	-0.0016	-0.0016	.	.	.	.	.	.	.	.	.
	.	.	(-7.16)	(-6.76)	.	.	.	.	.	.	.	.	.
Late career	.	.	0.0023	0.0022	.	.	.	.	.	.	.	.	.
	.	.	(5.69)	(5.11)	.	.	.	.	.	.	.	.	.
Female×Early career	.	.	.	-0.0000	.	.	.	.	.	.	.	.	.
	.	.	.	(-0.05)	.	.	.	.	.	.	.	.	.
Female×Late career	.	.	.	0.0021	.	.	.	.	.	.	.	.	.
	.	.	.	(1.39)	.	.	.	.	.	.	.	.	.
Female× Low Alpha dummy$_{t-1}$	.	.	.	.	-0.0469	.	.	.	.	.	.	.	.
	.	.	.	.	(-1.83)	.	.	.	.	.	.	.	.
Female×Low FFlow dummy$_{t-1}$	.	.	.	.	.	0.0012	.	.	.	.	.	.	.
	.	.	.	.	.	(0.44)	.	.	.	.	.	.	.
Foreign	.	.	.	.	.	.	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	.	.	.	.	.	.	(-0.63)	(-0.61)	(-0.63)	(-0.64)	(-0.54)	(-0.60)	(-0.60)
Top school	.	.	.	.	.	.	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
	.	.	.	.	.	.	(1.39)	(1.39)	(1.40)	(1.40)	(1.36)	(1.36)	(1.36)
Adv. degree	.	.	.	.	.	.	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	.	.	.	.	.	.	(-0.89)	(-0.89)	(-0.88)	(-0.87)	(-0.85)	(-0.85)	(-0.94)
Foreign × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	-0.0184	.	.	.	.	.
	.	.	.	.	.	.	.	(-0.85)	.	.	.	.	.
Top school × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	.	-0.0149	.	.	.	.
	.	.	.	.	.	.	.	.	(-0.90)	.	.	.	.
Adv. degree × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	-0.0259	.	.	.
	.	.	.	.	.	.	.	.	.	(-1.56)	.	.	.
Foreign × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	-0.0021	.	.
	.	.	.	.	.	.	.	.	.	.	(-0.60)	.	.
Top school × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	-0.0001	.
	.	.	.	.	.	.	.	.	.	.	.	(-0.03)	.
Adv. degree × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	.	0.0017
	.	.	.	.	.	.	.	.	.	.	.	.	(0.86)
Low Alpha dummy$_{t-1}$	.	.	.	.	0.0363	.	.	0.0037	0.0069	0.0158	.	.	.
	.	.	.	.	(5.05)	.	.	(0.41)	(0.64)	(1.24)	.	.	.
Low FFlow dummy$_{t-1}$	.	.	.	.	.	0.0054	.	.	.	.	0.0042	0.0041	0.0029
	.	.	.	.	.	(5.32)	.	.	.	.	(4.13)	(3.15)	(1.71)
Alpha$_{t-1}$	.	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010
	.	(-8.77)	(-8.65)	(-8.66)	(-8.48)	(-8.70)	(-8.12)	(-8.10)	(-8.10)	(-8.10)	(-8.08)	(-8.08)	(-8.08)
Alpha$_{t-2}$	.	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005
	.	(-3.87)	(-3.72)	(-3.73)	(-3.84)	(-3.80)	(-4.07)	(-4.06)	(-4.08)	(-4.08)	(-4.02)	(-4.02)	(-4.02)
Alpha$_{t-3}$	.	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003
	.	(-3.60)	(-3.45)	(-3.46)	(-3.64)	(-3.57)	(-2.81)	(-2.81)	(-2.80)	(-2.80)	(-2.80)	(-2.80)	(-2.80)
FFlow$_{t-1}$	.	-0.0010	-0.0010	-0.0010	-0.0010	-0.0009	-0.0010	-0.0010	-0.0010	-0.0010	-0.0009	-0.0009	-0.0009
	.	(-11.43)	(-11.36)	(-11.36)	(-11.48)	(-10.08)	(-10.65)	(-10.66)	(-10.64)	(-10.64)	(-9.66)	(-9.66)	(-9.67)
FFlow$_{t-2}$	.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	.	(-0.71)	(-0.60)	(-0.60)	(-0.68)	(-0.69)	(-0.47)	(-0.47)	(-0.48)	(-0.49)	(-0.46)	(-0.46)	(-0.46)
FFlow$_{t-3}$	.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	.	(-1.27)	(-0.86)	(-0.86)	(-1.27)	(-1.42)	(-0.89)	(-0.89)	(-0.89)	(-0.90)	(-1.02)	(-1.02)	(-1.02)
Controls	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	741,607	631,907	631,907	631,907	631,907	631,907	538,453	538,453	538,453	538,453	538,453	538,453	538,453
Adj. RSq.	0.0016	0.0055	0.0057	0.0057	0.0056	0.0056	0.0053	0.0053	0.0053	0.0053	0.0053	0.0053	0.0053

B2: Only sole managers (premature departures (firings), managers with $\geq$ 3 yrs of experience)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	0.0020	0.0004	0.0004	-0.0003	0.0004	0.0002	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(2.80)	(0.48)	(0.46)	(-0.22)	(0.47)	(0.27)	(-0.49)	(-0.50)	(-0.50)	(-0.50)	(-0.49)	(-0.50)	(-0.54)
Early career	.	.	-0.0010	-0.0011	.	.	.	.	.	.	.	.	.
	.	.	(-1.71)	(-1.83)	.	.	.	.	.	.	.	.	.
Late career	.	.	0.0014	0.0015	.	.	.	.	.	.	.	.	.
	.	.	(1.18)	(1.16)	.	.	.	.	.	.	.	.	.
Female×Early career	.	.	.	0.0011	.	.	.	.	.	.	.	.	.
	.	.	.	(0.64)	.	.	.	.	.	.	.	.	.
Female×Late career	.	.	.	-0.0004	.	.	.	.	.	.	.	.	.
	.	.	.	(-0.12)	.	.	.	.	.	.	.	.	.
Female×Low Alpha dummy$_{t-1}$	.	.	.	.	0.0025	.	.	.	.	.	.	.	.
	.	.	.	.	(0.06)	.	.	.	.	.	.	.	.
Female×Low FFlow dummy$_{t-1}$	.	.	.	.	.	0.0104	.	.	.	.	.	.	.
	.	.	.	.	.	(1.83)	.	.	.	.	.	.	.
Foreign	.	.	.	.	.	.	0.0007	0.0007	0.0007	0.0007	0.0007	0.0008	0.0007
	.	.	.	.	.	.	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)	(0.73)	(0.72)
Top school	.	.	.	.	.	.	0.0006	0.0006	0.0006	0.0006	0.0006	0.0005	0.0006
	.	.	.	.	.	.	(1.02)	(1.03)	(1.03)	(1.03)	(1.05)	(0.90)	(1.05)
Adv. degree	.	.	.	.	.	.	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0000
	.	.	.	.	.	.	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)	(0.35)	(0.03)
Foreign × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	0.0000	.	.	.	.	.
	.	.	.	.	.	.	.	(0.00)	.	.	.	.	.
Top school × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	.	0.0024	.	.	.	.
	.	.	.	.	.	.	.	.	(0.09)	.	.	.	.
Adv. degree ×Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	0.0024	.	.	.
	.	.	.	.	.	.	.	.	.	(0.09)	.	.	.
Foreign × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	0.0071	.	.
	.	.	.	.	.	.	.	.	.	.	(0.74)	.	.
Top school × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	0.0057	.
	.	.	.	.	.	.	.	.	.	.	.	(1.39)	.
Adv. degree ×Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	.	0.0137
	.	.	.	.	.	.	.	.	.	.	.	.	(3.17)
Low Alpha dummy$_{t-1}$	.	.	.	.	-0.0096	.	.	-0.0096	-0.0113	-0.0113	.	.	.
	.	.	.	.	(-0.84)	.	.	(-0.80)	(-0.50)	(-0.50)	.	.	.
Low FFlow dummy$_{t-1}$	.	.	.	.	.	0.0035	.	.	.	.	0.0056	0.0036	-0.0033
	.	.	.	.	.	(1.64)	.	.	.	.	(2.60)	(1.32)	(-0.91)
Alpha$_{t-1}$	.	-0.0014	-0.0014	-0.0014	-0.0014	-0.0014	-0.0013	-0.0013	-0.0013	-0.0013	-0.0012	-0.0012	-0.0012
	.	(-5.12)	(-5.07)	(-5.05)	(-5.17)	(-5.11)	(-4.55)	(-4.60)	(-4.60)	(-4.60)	(-4.50)	(-4.47)	(-4.47)
Alpha$_{t-2}$	.	-0.0009	-0.0008	-0.0008	-0.0009	-0.0009	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008
	.	(-3.01)	(-2.94)	(-2.93)	(-3.02)	(-3.03)	(-2.88)	(-2.89)	(-2.89)	(-2.89)	(-2.89)	(-2.88)	(-2.87)
Alpha$_{t-3}$	.	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003
	.	(-1.06)	(-1.02)	(-0.99)	(-1.05)	(-1.05)	(-0.96)	(-0.94)	(-0.95)	(-0.95)	(-0.98)	(-0.99)	(-0.97)
FFlow$_{t-1}$	.	-0.0008	-0.0008	-0.0008	-0.0008	-0.0007	-0.0008	-0.0008	-0.0008	-0.0008	-0.0007	-0.0007	-0.0007
	.	(-4.27)	(-4.23)	(-4.23)	(-4.25)	(-3.60)	(-4.03)	(-4.01)	(-4.01)	(-4.01)	(-3.33)	(-3.34)	(-3.35)
FFlow$_{t-2}$	.	-0.0001	-0.0000	-0.0000	-0.0001	-0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	.	(-0.27)	(-0.20)	(-0.19)	(-0.28)	(-0.26)	(0.41)	(0.41)	(0.41)	(0.41)	(0.46)	(0.47)	(0.43)
FFlow$_{t-3}$	.	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0006	-0.0006	-0.0006	-0.0006	-0.0007	-0.0007	-0.0006
	.	(-2.77)	(-2.64)	(-2.63)	(-2.77)	(-2.87)	(-3.28)	(-3.28)	(-3.28)	(-3.28)	(-3.42)	(-3.42)	(-3.36)
Controls	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	102,646	83,573	83,573	83,573	83,573	83,573	73,038	73,038	73,038	73,038	73,038	73038	73,038
Adj. RSq.	0.0042	0.0087	0.0088	0.0088	0.0088	0.0087	0.0077	0.0077	0.0077	0.0077	0.0077	0.0077	0.0077

B3: Only co-managers (premature departures (firings), managers with $\geq$ 3 yrs of experience)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	0.0027	0.0022	0.0024	0.0029	0.0022	0.0021	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022
	(7.57)	(5.62)	(6.13)	(4.16)	(5.66)	(5.56)	(5.31)	(5.32)	(5.32)	(5.32)	(5.29)	(5.29)	(5.29)
Early career	.	.	-0.0019	-0.0017	.	.	.	.	.	.	.	.	.
	.	.	(-6.70)	(-5.97)	.	.	.	.	.	.	.	.	.
Late career	.	.	0.0029	0.0028	.	.	.	.	.	.	.	.	.
	.	.	(5.76)	(5.26)	.	.	.	.	.	.	.	.	.
Female×Early career	.	.	.	-0.0010	.	.	.	.	.	.	.	.	.
	.	.	.	(-1.15)	.	.	.	.	.	.	.	.	.
Female×Late career	.	.	.	0.0027	.	.	.	.	.	.	.	.	.
	.	.	.	(1.41)	.	.	.	.	.	.	.	.	.
Female×Low Alpha dummy$_{t-1}$	.	.	.	.	-0.0758	.	.	.	.	.	.	.	.
	.	.	.	.	(-2.14)	.	.	.	.	.	.	.	.
Female×Low FFlow dummy$_{t-1}$	.	.	.	.	.	0.0004	.	.	.	.	.	.	.
	.	.	.	.	.	(0.11)	.	.	.	.	.	.	.
Foreign	.	.	.	.	.	.	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005
	.	.	.	.	.	.	(-1.18)	(-1.16)	(-1.18)	(-1.19)	(-1.10)	(-1.16)	(-1.17)
Top school	.	.	.	.	.	.	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
	.	.	.	.	.	.	(1.45)	(1.45)	(1.46)	(1.45)	(1.42)	(1.49)	(1.42)
Adv. degree	.	.	.	.	.	.	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0003
	.	.	.	.	.	.	(-1.23)	(-1.23)	(-1.22)	(-1.20)	(-1.20)	(-1.20)	(-1.14)
Foreign × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	-0.0331	.	.	.	.	.
	.	.	.	.	.	.	.	(-1.29)	.	.	.	.	.
Top school × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	.	-0.0256	.	.	.	.
	.	.	.	.	.	.	.	.	(-0.78)	.	.	.	.
Adv. degree × Low Alpha dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	-0.0435	.	.	.
	.	.	.	.	.	.	.	.	.	(-1.80)	.	.	.
Foreign × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	-0.0028	.	.
	.	.	.	.	.	.	.	.	.	.	(-0.68)	.	.
Top school × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	-0.0018	.
	.	.	.	.	.	.	.	.	.	.	.	(-0.77)	.
Adv. degree × Low FFlow dummy$_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	.	-0.0014
	.	.	.	.	.	.	.	.	.	.	.	.	(-0.56)
Low Alpha dummy$_{t-1}$	.	.	.	.	0.0635	.	.	0.0179	0.0113	0.0264	.	.	.
	.	.	.	.	(6.37)	.	.	(1.22)	(0.86)	(1.64)	.	.	.
Low FFlow dummy$_{t-1}$	.	.	.	.	.	0.0054	.	.	.	.	0.0036	0.0041	0.0043
	.	.	.	.	.	(4.34)	.	.	.	.	(2.81)	(2.58)	(2.04)
Alpha$_{t-1}$	.	-0.0011	-0.0011	-0.0011	-0.0010	-0.0011	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010
	.	(-7.19)	(-7.09)	(-7.08)	(-6.88)	(-7.13)	(-6.51)	(-6.48)	(-6.48)	(-6.48)	(-6.49)	(-6.49)	(-6.49)
Alpha$_{t-2}$	.	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005
	.	(-3.17)	(-3.04)	(-3.04)	(-3.17)	(-3.10)	(-3.22)	(-3.22)	(-3.23)	(-3.23)	(-3.18)	(-3.18)	(-3.18)
Alpha$_{t-3}$	.	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	.	(-3.50)	(-3.35)	(-3.35)	(-3.54)	(-3.47)	(-2.70)	(-2.70)	(-2.70)	(-2.70)	(-2.68)	(-2.68)	(-2.68)
FFlow$_{t-1}$	.	-0.0011	-0.0011	-0.0011	-0.0011	-0.0010	-0.0011	-0.0011	-0.0011	-0.0011	-0.0010	-0.0010	-0.0010
	.	(-9.78)	(-9.77)	(-9.76)	(-9.82)	(-8.70)	(-9.25)	(-9.26)	(-9.26)	(-9.25)	(-8.56)	(-8.55)	(-8.55)
FFlow$_{t-2}$	.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	.	(-0.47)	(-0.42)	(-0.41)	(-0.43)	(-0.46)	(-0.41)	(-0.41)	(-0.42)	(-0.42)	(-0.41)	(-0.43)	(-0.42)
FFlow$_{t-3}$	.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	.	(-1.14)	(-0.78)	(-0.78)	(-1.16)	(-1.25)	(-0.51)	(-0.51)	(-0.51)	(-0.51)	(-0.59)	(-0.59)	(-0.59)
Controls	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	552,092	470,755	470,755	470,755	470,755	470,755	395,570	395,570	395,570	395,570	395,570	395,570	395,570
Adj. RSq.	0.0028	0.0071	0.0074	0.0074	0.0072	0.0072	0.0067	0.0067	0.0067	0.0068	0.0068	0.0068	0.0068

Table V
Explaining career changes

This table presents the results of regressions explaining managers' career changes. Career changes are computed as month-to-month growth in the number of managed funds, as described in the text. We assume that a manager is retired after the age 55 or, if age information is missing, has less than 25 years of fund management experience. Panel A presents the regression results organized by the years of managers' fund management experience. In Panel B presents the results of regressions that include a richer set of controls and the sample includes only managers with at least 36 months of uninterrupted fund management history. Subpanels A1-A3 and B1-B3 contain the results for samples comprised of all managers, only sole managers, and only co-managers. Standard errors are clustered by manager and year. and t-statistics are reported in parentheses. All controls variables are described in the main text and in the Appendix. The sample period January 1992 – January 2017.

Panel A: Conditioning on years of experience

A1: All managers (career changes)

	Years of fund management experience									
	All observations				≥ 1 year		≥ 5 years		≥ 10 years	
Female	-0.0041	-0.0042	-0.0047	-0.0047	-0.0040	-0.0044	-0.0034	-0.0029	-0.0014	-0.0011
	(-3.44)	(-3.54)	(-3.92)	(-3.92)	(-3.28)	(-3.61)	(-3.03)	(-2.57)	(-0.88)	(-0.75)
Foreign+Guess	.	.	.	-0.0006	.	-0.0005	.	-0.0017	.	-0.0023
	.	.	.	(-0.49)	.	(-0.37)	.	(-1.40)	.	(-1.37)
$Alpha_{t-1}$	.	.	.	.	.	0.0017	.	0.0021	.	0.0030
	.	.	.	.	.	(3.79)	.	(4.82)	.	(5.53)
$Alpha_{t-2}$	.	.	.	.	.	.	.	0.0023	.	0.0016
	.	.	.	.	.	.	.	(5.17)	.	(2.77)
$Alpha_{t-3}$	.	.	.	.	.	.	.	0.0006	.	0.0001
	.	.	.	.	.	.	.	(1.46)	.	(0.13)
$FFlow_{t-1}$	.	.	.	.	.	0.0026	.	0.0021	.	0.0023
	.	.	.	.	.	(9.84)	.	(6.68)	.	(5.58)
$FFlow_{t-2}$	.	.	.	.	.	.	.	0.0009	.	0.0011
	.	.	.	.	.	.	.	(2.52)	.	(2.37)
$FFlow_{t-3}$	.	.	.	.	.	.	.	-0.0004	.	-0.0002
	.	.	.	.	.	.	.	(-1.23)	.	(-0.60)
Stdev	.	.	.	.	.	0.1068	.	0.3029	.	0.3286
	.	.	.	.	.	(1.73)	.	(4.53)	.	(3.85)
Manager TNA	.	.	-0.0013	-0.0013	.	-0.0013	.	-0.0006	.	-0.0000
	.	.	(-4.73)	(-4.76)	.	(-4.87)	.	(-2.44)	.	(-0.10)
Num. funds managed	.	.	-0.0009	-0.0009	.	-0.0008	.	-0.0005	.	-0.0005
	.	.	(-8.70)	(-8.71)	.	(-7.88)	.	(-5.27)	.	(-4.73)
IOC trend	.	.	0.0119	0.0119	.	0.0064	.	0.0033	.	0.0059
	.	.	(3.30)	(3.32)	.	(1.76)	.	(0.92)	.	(1.23)
Exp. ratio	.	.	-0.0013	-0.0013	.	-0.0012	.	-0.0007	.	-0.0008
	.	.	(-6.08)	(-6.09)	.	(-5.74)	.	(-3.67)	.	(-2.94)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	929,946	929,946	921,168	921,168	923,266	914,011	579,427	509,266	295,196	262,692
Adj. RSq.	0.0011	0.0024	0.0032	0.0013	0.0011	0.0014	0.0020	0.0029	0.0029	0.0043

A2: Only sole managers (career changes)

	Years of fund management experience									
	All observations				≥ 1 year		≥ 5 years		≥ 10 years	
Female	-0.0035	-0.0028	-0.0031	-0.0031	-0.0035	-0.0024	-0.0019	-0.0007	-0.0017	-0.0009
	(-2.97)	(-2.55)	(-2.62)	(-2.63)	(-2.96)	(-2.07)	(-1.33)	(-0.44)	(-0.77)	(-0.40)
Foreign+Guess	.	.	.	-0.0008	.	-0.0011	.	-0.0006	.	-0.0027
	.	.	.	(-0.58)	.	(-0.79)	.	(-0.30)	.	(-0.95)
$Alpha_{t-1}$	.	.	.	.	.	0.0023	.	0.0022	.	0.0035
	.	.	.	.	.	(5.60)	.	(4.13)	.	(4.59)
$Alpha_{t-2}$	.	.	.	.	.	.	.	0.0011	.	0.0016
	.	.	.	.	.	.	.	(1.88)	.	(2.05)
$Alpha_{t-3}$	.	.	.	.	.	.	.	0.0021	.	0.0021
	.	.	.	.	.	.	.	(3.89)	.	(2.76)
$FFlow_{t-1}$	.	.	.	.	.	0.0020	.	0.0018	.	0.0016
	.	.	.	.	.	(7.97)	.	(4.60)	.	(2.92)
$FFlow_{t-2}$	.	.	.	.	.	.	.	-0.0004	.	-0.0002
	.	.	.	.	.	.	.	(-0.81)	.	(-0.35)
$FFlow_{t-3}$	.	.	.	.	.	.	.	0.0003	.	0.0006
	.	.	.	.	.	.	.	(0.88)	.	(1.15)
Stdev	.	.	.	.	.	0.2566	.	0.2260	.	0.2700
	.	.	.	.	.	(4.24)	.	(2.34)	.	(2.03)
Manager TNA	.	.	0.0015	0.0015	.	0.0016	.	0.0021	.	0.0026
	.	.	(5.56)	(5.51)	.	(5.74)	.	(5.38)	.	(4.43)
Num. funds managed	.	.	-0.0016	-0.0016	.	-0.0013	.	-0.0013	.	-0.0014
	.	.	(-5.92)	(-5.94)	.	(-4.54)	.	(-3.95)	.	(-2.94)
IOC trend	.	.	0.0044	0.0045	.	0.0012	.	-0.0016	.	0.0036
	.	.	(1.49)	(1.51)	.	(0.38)	.	(-0.35)	.	(0.53)
Exp. ratio	.	.	-0.0001	-0.0001	.	-0.0002	.	-0.0000	.	-0.0002
	.	.	(-0.47)	(-0.48)	.	(-0.78)	.	(-0.16)	.	(-0.42)
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	130,670	130,670	129,359	129,359	129,852	128,430	81,388	69,468	38,479	34,119
Adj. RSq.	0.0055	0.0088	0.0119	0.0058	0.0055	0.0069	0.0073	0.0099	0.0102	0.0137
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

A3: Only co-managers (career changes)

	Years of fund management experience									
	All observations				$\geq$ 1 year		$\geq$ 5 years		$\geq$ 10 years	
Female	-0.0031	-0.0031	-0.0030	-0.0030	-0.0030	-0.0028	-0.0028	-0.0015	-0.0034	-0.0017
	(-3.35)	(-3.42)	(-3.23)	(-3.23)	(-3.19)	(-2.98)	(-2.34)	(-1.23)	(-2.03)	(-1.04)
Foreign+Guess	.	.	.	0.0003	.	0.0004	.	0.0001	.	-0.0010
	.	.	.	(0.30)	.	(0.45)	.	(0.09)	.	(-0.54)
$Alpha_{t-1}$	.	.	.	.	.	0.0015	.	0.0018	.	0.0021
	.	.	.	.	.	(4.05)	.	(3.64)	.	(3.27)
$Alpha_{t-2}$	.	.	.	.	.	.	.	0.0025	.	0.0017
	.	.	.	.	.	.	.	(5.01)	.	(2.66)
$Alpha_{t-3}$	.	.	.	.	.	.	.	-0.0004	.	-0.0004
	.	.	.	.	.	.	.	(-0.74)	.	(-0.65)
$FFlow_{t-1}$	.	.	.	.	.	0.0035	.	0.0032	.	0.0033
	.	.	.	.	.	(15.72)	.	(8.29)	.	(6.86)
$FFlow_{t-2}$	.	.	.	.	.	.	.	0.0004	.	0.0004
	.	.	.	.	.	.	.	(1.05)	.	(0.64)
$FFlow_{t-3}$	.	.	.	.	.	.	.	0.0000	.	-0.0003
	.	.	.	.	.	.	.	(0.05)	.	(-0.71)
Stdev	.	.	.	.	.	0.1472	.	0.2376	.	0.1421
	.	.	.	.	.	(2.95)	.	(3.14)	.	(1.48)
Manager TNA	.	.	0.0010	0.0010	.	0.0008	.	0.0009	.	0.0019
	.	.	(4.03)	(4.04)	.	(3.11)	.	(2.71)	.	(4.32)
Num. funds managed	.	.	-0.0004	-0.0004	.	-0.0004	.	-0.0003	.	-0.0005
	.	.	(-6.45)	(-6.44)	.	(-5.48)	.	(-3.20)	.	(-4.51)
IOC trend	.	.	0.0120	0.0119	.	0.0029	.	0.0023	.	0.0036
	.	.	(3.77)	(3.75)	.	(0.90)	.	(0.53)	.	(0.61)
Exp. ratio	.	.	-0.0003	-0.0003	.	-0.0001	.	-0.0002	.	-0.0003
	.	.	(-1.51)	(-1.51)	.	(-0.67)	.	(-0.74)	.	(-0.93)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	432,733	432,733	430,385	430,385	430,450	427,981	292,104	264,479	156,559	142,719
Adj. RSq.	0.0037	0.0106	0.0123	0.0042	0.0036	0.0046	0.0039	0.0057	0.0060	0.0091

Panel B: Detailed analysis of managers with at least 3 years of fund management experience

B1: All managers (career changes, managers with $\geq$ 3 yrs of experience)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	-0.0035	-0.0029	-0.0031	-0.0023	-0.0060	-0.0013	-0.0027	-0.0027	-0.0027	-0.0027	-0.0027	-0.0027	-0.0027
	(-3.56)	(-2.97)	(-3.10)	(-1.32)	(-1.17)	(-0.43)	(-2.47)	(-2.46)	(-2.47)	(-2.47)	(-2.47)	(-2.46)	(-2.47)
Early career	.	.	0.0028	0.0029	.	.	.	.	.	.	.	.	.
	.	.	(3.91)	(3.91)	.	.	.	.	.	.	.	.	.
Late career	.	.	-0.0001	-0.0003	.	.	.	.	.	.	.	.	.
	.	.	(-0.11)	(-0.23)	.	.	.	.	.	.	.	.	.
Female×Early career	.	.	.	-0.0014	.	.	.	.	.	.	.	.	.
	.	.	.	(-0.66)	.	.	.	.	.	.	.	.	.
Female×Late career	.	.	.	0.0028	.	.	.	.	.	.	.	.	.
	.	.	.	(0.59)	.	.	.	.	.	.	.	.	.
Female× $Alpha_{t-1}$	.	.	.	.	0.0007	.	.	.	.	.	.	.	.
	.	.	.	.	(0.61)	.	.	.	.	.	.	.	.
Female×$FFlow_{t-1}$	.	.	.	.	.	-0.0004	.	.	.	.	.	.	.
	.	.	.	.	.	(-0.62)	.	.	.	.	.	.	.
Foreign	.	.	.	.	.	.	-0.0026	-0.0075	-0.0026	-0.0026	-0.0057	-0.0026	-0.0026
	.	.	.	.	.	.	(-2.12)	(-1.22)	(-2.12)	(-2.14)	(-1.61)	(-2.11)	(-2.12)
Top school	.	.	.	.	.	.	0.0013	0.0013	0.0003	0.0013	0.0013	0.0027	0.0013
	.	.	.	.	.	.	(1.73)	(1.72)	(0.09)	(1.73)	(1.71)	(1.29)	(1.74)
Adv. degree	.	.	.	.	.	.	0.0001	0.0001	0.0001	-0.0055	0.0001	0.0001	0.0007
	.	.	.	.	.	.	(0.14)	(0.13)	(0.14)	(-1.38)	(0.13)	(0.15)	(0.29)
Foreign × $Alpha_{t-1}$	.	.	.	.	.	.	.	0.0011	.	.	.	.	.
	.	.	.	.	.	.	.	(0.81)	.	.	.	.	.
Top school × $Alpha_{t-1}$	.	.	.	.	.	.	.	.	0.0002	.	.	.	.
	.	.	.	.	.	.	.	.	(0.28)	.	.	.	.
Adv. degree × $Alpha_{t-1}$	.	.	.	.	.	.	.	.	.	0.0012	.	.	.
	.	.	.	.	.	.	.	.	.	(1.44)	.	.	.
Foreign × $FFlow_{t-1}$	.	.	.	.	.	.	.	.	.	.	0.0007	.	.
	.	.	.	.	.	.	.	.	.	.	(0.94)	.	.
Top school × $FFlow_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	-0.0003	.
	.	.	.	.	.	.	.	.	.	.	.	(-0.70)	.
Adv. degree × $FFlow_{t-1}$	.	.	.	.	.	.	.	.	.	.	.	.	-0.0001
	.	.	.	.	.	.	.	.	.	.	.	.	(-0.26)
$Alpha_{t-1}$	.	0.0020	0.0019	0.0019	0.0019	0.0020	0.0021	0.0020	0.0020	0.0013	0.0021	0.0021	0.0021
	.	(5.15)	(5.09)	(5.09)	(4.68)	(5.14)	(5.17)	(4.72)	(3.89)	(1.73)	(5.17)	(5.18)	(5.17)
$Alpha_{t-2}$	.	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019	0.0019
	.	(4.92)	(4.85)	(4.85)	(4.91)	(4.91)	(4.58)	(4.58)	(4.58)	(4.59)	(4.59)	(4.58)	(4.58)
$Alpha_{t-3}$	.	0.0006	0.0006	0.0006	0.0006	0.0007	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006
	.	(1.74)	(1.69)	(1.68)	(1.74)	(1.75)	(1.48)	(1.48)	(1.48)	(1.49)	(1.48)	(1.48)	(1.48)
$FFlow_{t-1}$	.	0.0022	0.0022	0.0022	0.0022	0.0022	0.0019	0.0019	0.0019	0.0019	0.0018	0.0020	0.0020
	.	(7.73)	(7.71)	(7.71)	(7.74)	(7.63)	(6.28)	(6.28)	(6.27)	(6.26)	(5.88)	(5.71)	(4.34)
$FFlow_{t-2}$	.	0.0009	0.0009	0.0009	0.0009	0.0009	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
	.	(2.77)	(2.72)	(2.73)	(2.77)	(2.77)	(3.00)	(2.99)	(3.00)	(3.00)	(3.00)	(3.01)	(3.00)
$FFlow_{t-3}$	.	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003
	.	(-1.15)	(-1.32)	(-1.32)	(-1.15)	(-1.15)	(-0.90)	(-0.90)	(-0.90)	(-0.89)	(-0.90)	(-0.90)	(-0.90)
Controls	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	741,607	631,907	631,907	631,907	631,907	631,907	538,453	538,453	538,453	538,453	538,453	538,453	538,453
Adj. RSq.	0.0017	0.0027	0.0028	0.0028	0.0027	0.0027	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029

B2: Only sole managers (career changes, managers with $\geq$ 3 yrs of experience)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	-0.0032	-0.0015	-0.0016	-0.0014	-0.0033	-0.0023	-0.0010	-0.0011	-0.0010	-0.0010	-0.0010	-0.0010	-0.0010
	(-2.47)	(-1.05)	(-1.08)	(-0.55)	(-0.49)	(-0.60)	(-0.67)	(-0.69)	(-0.64)	(-0.66)	(-0.66)	(-0.67)	(-0.67)
Early career	.	.	0.0007	0.0008	.	.	.	.	.	.	.	.	.
	.	.	(0.67)	(0.69)	.	.	.	.	.	.	.	.	.
Late career	.	.	0.0020	0.0016	.	.	.	.	.	.	.	.	.
	.	.	(0.92)	(0.69)	.	.	.	.	.	.	.	.	.
Female×Early career	.	.	.	-0.0004	.	.	.	.	.	.	.	.	.
	.	.	.	(-0.14)	.	.	.	.	.	.	.	.	.
Female×Late career	.	.	.	0.0025	.	.	.	.	.	.	.	.	.
	.	.	.	(0.40)	.	.	.	.	.	.	.	.	.
Female× Alpha_{t-1}	.	.	.	.	0.0004	.	.	.	.	.	.	.	.
	.	.	.	.	(0.27)	.	.	.	.	.	.	.	.
Female×FFlow_{t-1}	.	.	.	.	.	0.0002	.	.	.	.	.	.	.
	.	.	.	.	.	(0.22)	.	.	.	.	.	.	.
Foreign	.	.	.	.	.	.	-0.0018	-0.0173	-0.0019	-0.0018	-0.0030	-0.0019	-0.0020
	.	.	.	.	.	.	(-0.93)	(-2.02)	(-0.97)	(-0.95)	(-0.58)	(-0.97)	(-1.02)
Top school	.	.	.	.	.	.	-0.0001	-0.0001	-0.0127	-0.0001	-0.0001	-0.0026	-0.0001
	.	.	.	.	.	.	(-0.10)	(-0.12)	(-2.74)	(-0.08)	(-0.11)	(-0.96)	(-0.13)
Adv. degree	.	.	.	.	.	.	-0.0006	-0.0006	-0.0005	-0.0087	-0.0006	-0.0006	-0.0048
	.	.	.	.	.	.	(-0.50)	(-0.51)	(-0.43)	(-1.72)	(-0.51)	(-0.48)	(-1.62)
Foreign × Alpha_{t-1}	.	.	.	.	.	.	.	0.0034	.	.	.	.	.
	.	.	.	.	.	.	.	(1.86)	.	.	.	.	.
Top school × Alpha_{t-1}	.	.	.	.	.	.	.	.	0.0027	.	.	.	.
	.	.	.	.	.	.	.	.	(2.80)	.	.	.	.
Adv. degree × Alpha_{t-1}	.	.	.	.	.	.	.	.	.	0.0018	.	.	.
	.	.	.	.	.	.	.	.	.	(1.65)	.	.	.
Foreign × FFlow_{t-1}	.	.	.	.	.	.	.	.	.	.	0.0003	.	.
	.	.	.	.	.	.	.	.	.	.	(0.26)	.	.
Top school × FFlow_{t-1}	.	.	.	.	.	.	.	.	.	.	.	0.0006	.
	.	.	.	.	.	.	.	.	.	.	.	(1.01)	.
Adv. degree × FFlow_{t-1}	.	.	.	.	.	.	.	.	.	.	.	.	0.0010
	.	.	.	.	.	.	.	.	.	.	.	.	(1.55)
Alpha_{t-1}	.	0.0023	0.0023	0.0023	0.0023	0.0023	0.0021	0.0019	0.0010	0.0008	0.0021	0.0021	0.0021
	.	(4.54)	(4.52)	(4.51)	(4.18)	(4.54)	(4.10)	(3.49)	(1.49)	(0.90)	(4.09)	(4.07)	(4.09)
Alpha_{t-2}	.	0.0003	0.0003	0.0003	0.0003	0.0003	0.0001	0.0002	0.0002	0.0002	0.0001	0.0001	0.0001
	.	(0.56)	(0.54)	(0.53)	(0.55)	(0.56)	(0.28)	(0.30)	(0.30)	(0.32)	(0.28)	(0.27)	(0.22)
Alpha_{t-3}	.	0.0017	0.0017	0.0017	0.0017	0.0017	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016
	.	(3.44)	(3.43)	(3.41)	(3.43)	(3.44)	(3.03)	(3.04)	(3.16)	(3.12)	(3.03)	(3.05)	(3.02)
FFlow_{t-1}	.	0.0018	0.0018	0.0018	0.0018	0.0018	0.0019	0.0019	0.0019	0.0019	0.0019	0.0016	0.0012
	.	(4.81)	(4.81)	(4.81)	(4.82)	(4.55)	(4.99)	(4.99)	(4.92)	(4.99)	(4.83)	(3.67)	(2.02)
FFlow_{t-2}	.	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	.	(-0.00)	(-0.01)	(-0.01)	(-0.00)	(-0.00)	(-0.50)	(-0.52)	(-0.51)	(-0.51)	(-0.49)	(-0.52)	(-0.49)
FFlow_{t-3}	.	0.0002	0.0002	0.0002	0.0002	0.0002	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
	.	(0.48)	(0.47)	(0.47)	(0.48)	(0.48)	(1.23)	(1.22)	(1.23)	(1.22)	(1.23)	(1.23)	(1.20)
Controls	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	102,646	83,573	83,573	83,573	83,573	83,573	73,038	73,038	73,038	73,038	73,038	73,038	73,038
Adj. RSq.	0.0061	0.0083	0.0083	0.0083	0.0083	0.0083	0.0089	0.0089	0.0090	0.0089	0.0089	0.0089	0.0089

B3: Only co-managers (career changes, managers with $\geq$ 3 yrs of experience)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	-0.0038	-0.0033	-0.0035	-0.0015	-0.0087	-0.0017	-0.0029	-0.0028	-0.0029	-0.0029	-0.0029	-0.0028	-0.0029
	(-3.00)	(-2.54)	(-2.69)	(-0.66)	(-1.30)	(-0.45)	(-1.97)	(-1.97)	(-1.97)	(-1.97)	(-1.98)	(-1.96)	(-1.98)
Early career	.	.	0.0033	0.0037	.	.	.	.	.	.	.	.	.
	.	.	(3.59)	(3.76)	.	.	.	.	.	.	.	.	.
Late career	.	.	-0.0003	-0.0004	.	.	.	.	.	.	.	.	.
	.	.	(-0.15)	(-0.20)	.	.	.	.	.	.	.	.	.
Female×Early career	.	.	.	-0.0032	.	.	.	.	.	.	.	.	.
	.	.	.	(-1.14)	.	.	.	.	.	.	.	.	.
Female×Late career	.	.	.	0.0027	.	.	.	.	.	.	.	.	.
	.	.	.	(0.42)	.	.	.	.	.	.	.	.	.
Female× Alpha_{t-1}	.	.	.	.	0.0012	.	.	.	.	.	.	.	.
	.	.	.	.	(0.82)	.	.	.	.	.	.	.	.
Female×FFlow_{t-1}	.	.	.	.	.	-0.0004	.	.	.	.	.	.	.
	.	.	.	.	.	(-0.43)	.	.	.	.	.	.	.
Foreign	.	.	.	.	.	.	-0.0032	-0.0063	-0.0032	-0.0033	-0.0063	-0.0032	-0.0032
	.	.	.	.	.	.	(-2.05)	(-0.80)	(-2.05)	(-2.07)	(-1.41)	(-2.02)	(-2.04)
Top school	.	.	.	.	.	.	0.0018	0.0018	0.0035	0.0018	0.0018	0.0054	0.0019
	.	.	.	.	.	.	(1.83)	(1.82)	(0.71)	(1.82)	(1.81)	(1.92)	(1.84)
Adv. degree	.	.	.	.	.	.	0.0002	0.0002	0.0002	-0.0044	0.0002	0.0002	0.0029
	.	.	.	.	.	.	(0.21)	(0.20)	(0.21)	(-0.83)	(0.20)	(0.22)	(0.97)
Foreign × Alpha_{t-1}	.	.	.	.	.	.	.	0.0007	.	.	.	.	.
	.	.	.	.	.	.	.	(0.40)	.	.	.	.	.
Top school × Alpha_{t-1}	.	.	.	.	.	.	.	.	-0.0004	.	.	.	.
	.	.	.	.	.	.	.	.	(-0.34)	.	.	.	.
Adv. degree × Alpha_{t-1}	.	.	.	.	.	.	.	.	.	0.0010	.	.	.
	.	.	.	.	.	.	.	.	.	(0.89)	.	.	.
Foreign × FFlow_{t-1}	.	.	.	.	.	.	.	.	.	.	0.0007	.	.
	.	.	.	.	.	.	.	.	.	.	(0.73)	.	.
Top school × FFlow_{t-1}	.	.	.	.	.	.	.	.	.	.	.	-0.0008	.
	.	.	.	.	.	.	.	.	.	.	.	(-1.35)	.
Adv. degree × FFlow_{t-1}	.	.	.	.	.	.	.	.	.	.	.	.	-0.0006
	.	.	.	.	.	.	.	.	.	.	.	.	(-0.96)
Alpha_{t-1}	.	0.0018	0.0017	0.0017	0.0016	0.0018	0.0019	0.0019	0.0021	0.0012	0.0019	0.0019	0.0019
	.	(3.52)	(3.47)	(3.48)	(3.06)	(3.51)	(3.50)	(3.22)	(2.97)	(1.27)	(3.50)	(3.51)	(3.51)
Alpha_{t-2}	.	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023	0.0023
	.	(4.50)	(4.45)	(4.45)	(4.49)	(4.50)	(4.15)	(4.15)	(4.15)	(4.15)	(4.16)	(4.14)	(4.15)
Alpha_{t-3}	.	0.0004	0.0004	0.0004	0.0004	0.0004	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
	.	(0.78)	(0.72)	(0.72)	(0.77)	(0.78)	(0.51)	(0.51)	(0.51)	(0.51)	(0.51)	(0.50)	(0.51)
FFlow_{t-1}	.	0.0022	0.0022	0.0022	0.0022	0.0022	0.0018	0.0018	0.0018	0.0018	0.0018	0.0022	0.0023
	.	(5.89)	(5.89)	(5.89)	(5.90)	(5.81)	(4.51)	(4.52)	(4.52)	(4.50)	(4.20)	(4.56)	(3.72)
FFlow_{t-2}	.	0.0012	0.0012	0.0012	0.0012	0.0012	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015
	.	(2.97)	(2.94)	(2.94)	(2.97)	(2.97)	(3.23)	(3.22)	(3.23)	(3.23)	(3.22)	(3.24)	(3.23)
FFlow_{t-3}	.	-0.0004	-0.0005	-0.0005	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0004
	.	(-1.32)	(-1.48)	(-1.47)	(-1.32)	(-1.32)	(-1.21)	(-1.21)	(-1.21)	(-1.21)	(-1.21)	(-1.21)	(-1.20)
Controls	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	552,092	470,755	470,755	470,755	470,755	470,755	395,570	395,570	395,570	395,570	395,570	395,570	395,570
Adj. RSq.	0.0019	0.0029	0.0030	0.0030	0.0030	0.0030	0.0032	0.0032	0.0032	0.0032	0.0032	0.0032	0.0032

Table VI
Career outcomes of co-managers with identical track record

This table presents summary statistics and regression results for career outcomes of co-managers who started co-managing the same fund in the same month and had no other mutual fund management responsibilities and no prior fund management history. The regression results are presented separately for promotions, demotions, and both career outcome combined. The outcome variables are demeaned by the mean across all co-managers in the corresponding cohort. A manager is considered to be promoted if s/he gets a sole-management responsibility or becomes co-manager of an additional fund. A manager is considered to be demoted if s/he loses the fund co-management assignment and gains no other fund management responsibilities. The career outcome variable is set to $+1$ for a promotion, -1 for a demotion, and 0 for no change in the fund management responsibilities by the end of the sample period. Panel A presents the summary statistics. Panel B presents the regression results. Panel C presents statistics on the next employment outcomes of the identical in-house co-managers that we could look up who permanently disappeared from the mutual fund dataset, as well as the difference in the demotion probability between male and female managers. The sample period is July 1924 – March 2017. ^{a}, ^{b}, and ^{c} indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Sample characteristics

No. of cohorts	Avg. no. of co-managers	No. of unique managers	Fraction female
139	3.33	375	0.43

	Foreign	MBA	MA	PhD	Other deg.	CFA	Top School
Male	0.25	0.31	0.15	0.06	0.04	0.35	0.45
Female	0.19	0.22	0.11	0.01	0.03	0.29	0.36

Panel B: Explaining career outcomes

	Demotions				Promotions				Comprehensive career outcomes			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Female	0.092	0.105	0.097	0.101	-0.037	-0.056	-0.051	-0.056	-0.129	-0.162	-0.148	-0.157
	(3.30)	(3.25)	(3.00)	(3.07)	(-1.31)	(-1.62)	(-1.45)	(-1.57)	(-2.65)	(-2.80)	(-2.56)	(-2.67)
Foreign	.	0.025	0.036	0.029	.	-0.024	-0.016	-0.013	.	-0.048	-0.053	-0.042
	.	(0.66)	(0.92)	(0.71)	.	(-0.58)	(-0.39)	(-0.30)	.	(-0.72)	(-0.75)	(-0.58)
MBA	.	.	-0.040	-0.037	.	.	0.039	0.040	.	.	0.079	0.077
	.	.	(-1.16)	(-1.01)	.	.	(1.05)	(1.02)	.	.	(1.29)	(1.18)
MA	.	.	-0.111	-0.107	.	.	0.025	0.026	.	.	0.136	0.134
	.	.	(-2.70)	(-2.57)	.	.	(0.56)	(0.58)	.	.	(1.85)	(1.79)
PhD	.	.	.	0.041	.	.	.	-0.043	.	.	.	-0.084
	.	.	.	(0.60)	.	.	.	(-0.58)	.	.	.	(-0.69)
Other degree	.	.	.	0.085	.	.	.	-0.050	.	.	.	-0.135
	.	.	.	(1.17)	.	.	.	(-0.64)	.	.	.	(-1.04)
Top school	.	.	.	0.002	.	.	.	-0.042	.	.	.	-0.044
	.	.	.	(0.07)	.	.	.	(-1.16)	.	.	.	(-0.74)
CFA	.	.	.	-0.003	.	.	.	0.038	.	.	.	0.042
	.	.	.	(-0.10)	.	.	.	(1.10)	.	.	.	(0.72)
Obs.	375	250	250	250	375	250	250	250	375	250	250	250
Adj. RSq.	0.028	0.042	0.070	0.077	0.005	0.011	0.016	0.029	0.018	0.032	0.048	0.058

Panel C: Next employment outcomes of the identical co-managers who have disappeared from the mutual fund manager dataset

New position	All managers	Male	Female
Non-manager position at the same institution	4%	3%	5%
Non-manager position at a different financial inst.	38%	38%	38%
Manager at state, endowment, employee-owned fund, etc.	2%	0%	5%
Investment advice/wealth management	14%	10%	19%
Nonfinancial firm or unemployed	14%	17%	10%
Total demotions	72%	69%	76%
		Difference (Female-Male)	
		7.2% (t-statistic=0.56)	
Money manager at another fund type (e.g., foreign, PE)	28%	31%	24%
Hedge fund manager	0%	0%	0%
Total managers	50	29	21

Table VII
Promotion hazard rates for co-managers with identical track record

This table presents the results of Cox proportional hazard rates regressions explaining co-managers' promotions. All regression specifications include cohort fixed effects for cohorts of co-managers who started co-managing the same fund in the same month and had no other mutual fund management responsibilities and no prior fund management history. A manager is considered to be promoted if s/he gets a sole-management responsibility or becomes co-manager of an additional fund. Panel A presents the sample characteristics and Panel B presents the regression results. Standard errors are shown in parentheses and hazard ratios in italics. The sample period is July 1924 – March 2017. ^{a}, ^{b}, and ^{c} indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Sample characteristics

No. of cohorts	No. of mgrs	Avg. no. of co-mgrs	Fraction of Female	Foreign	MBA	MA	PhD	Other deg.	CFA	Top Sch.
439	1,083	2.87	0.17	0.17	0.39	0.12	0.04	0.04	0.39	0.43

Panel B: Hazard rates of promotion

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.010	.		.	0.063	-0.265	-0.264	-0.266	-0.289
	(0.123)	.	.	.	(0.142)	(0.240)	(0.240)	(0.244)	(0.245)
	0.990	.	.	.	*1.066*	*0.767*	*0.768*	*0.767*	*0.749*
Foreign	.	-0.001	.	.	0.021	0.258	0.311	0.229	0.198
	.	(0.122)	.	.	(0.123)	(0.273)	(0.266)	(0.272)	(0.279)
	.	*0.999*	.	.	*1.021*	*1.295*	*1.365*	*1.258*	*1.220*
Adv. deg.	.	.	0.148	.	0.118	0.449^{b}	.		.
	.	.	(0.106)	.	(0.109)	(0.180)	.	.	.
	.	.	*1.160*	.	*1.126*	*1.566*	.	.	.
MBA	.		.		.	.	0.580^{a}	0.605^{a}	0.648^{a}
	.	.	.	.	.	.	(0.166)	(0.167)	(0.176)
	.	.	.	.	.	.	*1.786*	*1.831*	*1.912*
MA	.		.		.	.	0.090	0.114	0.112
	.	.	.	.	.	.	(0.228)	(0.230)	(0.234)
	.	.	.	.	.	.	*1.094*	*1.121*	*1.118*
PhD	.		.		.		.	0.276	0.306
	.	.	.	.	.	.	.	(0.348)	(0.350)
	.	.	.	.	.	.	.	*1.317*	*1.359*
Other deg.	.		.		.		.	0.405	0.448
	.	.	.	.	.	.	.	(0.385)	(0.388)
	.	.	.	.	.	.	.	*1.499*	*1.566*
Top sch.	.		.	0.183^{c}	0.162	-0.124	.	.	-0.236
	.	.	.	(0.098)	(0.101)	(0.182)	.	.	(0.185)
	.	.	.	*1.201*	*1.176*	*0.883*	.	.	*0.790*
CFA	.		.		.	0.145	.	.	0.137
	.	.	.	.	.	(0.182)	.	.	(0.185)
	.	.	.	.	.	*1.155*	.	.	*1.147*
Obs.	1083	807	807	807	807	807	807	807	807

Appendix

A1. Variable definitions

This appendix provides a detailed description of the variables used in the analyses throughout the paper. All variables are computed as of the end of the prior month.

Foreign. A dummy variable indicating whether a manager attended at least one foreign college or university. If school information is missing, the variable is set to missing. Canadian colleges and universities are not considered to be foreign schools.

Foreign+Guess. A dummy variable indicating whether a manager attended at least one foreign college or university. Canadian colleges and universities are not considered to be foreign schools. If school information is missing, the variable is set to one if a manager has non-Anglo-Saxon sounding first and last names.

Top school. A dummy variable indicating whether a manager attended at least one top-ten college or university, a top-ten MBA program, or an Ivy-League university. The variable is set to missing for observations with missing school information.

Adv. Degree A dummy variable indicating whether a manager holds an MA, MBA, PhD, or Other Degree. The variable is set to missing for observations with missing school information.

Time in industry. The number of days since the manager first started managing funds.

Time at the fund. The number of days since the manager first started managing the fund.

Alpha. Style-adjusted CAPM alpha, if used as an outcome variable. Otherwise, a rank from 1 to 10 based on the monthly CAPM alphas computed within the fund's investment category. If a manager manages more than one fund, the individual funds' monthly alpha ranks are weighted by $\frac{1}{number\ of\ co\text{-}managers}$. $Alpha_{t-1}$, $Alpha_{t-2}$ and $Alpha_{t-3}$ are computed as the average rank over the trailing windows [-12,-1], [-24,-13], and [-36,-25], respectively.

FFlow. Style-adjusted fund flow, if used as an outcome variable. Otherwise, a rank from 1 to 10 based on the fund's monthly fund flow computed within the fund's investment objective category. If a manager manages more than one fund, the individual funds' monthly fund flow ranks are weighted by $\frac{1}{number\ of\ co\text{-}managers}$. $FFlow_{t-1}$, $FFlow_{t-2}$, and $FFlow_{t-2}$ are computed as the average rank over the trailing windows [-12,-1], [-24,-13], and [-36,-25], respectively.

Low Alpha dummy. A dummy variable indicating whether Alpha is below 2.

Low FFlow dummy. A dummy variable indicating whether FFlow is below 2.

Stdev. Standard deviation of a manager's alpha rank computed over the trailing window over which the manager's performance is measured.

Manager TNA. The natural logarithm of the dollar value of total assets managed by the manager. For co-managed funds, the fund's TNA is divided by the number of managers.

Num. funds managed. The total number of funds that a manager sole-manages or co-manages.

IOC Trend. For each investment category, the average fund flow into that investment objective category over a trailing 12-month period.

Early career. A dummy variable set to one if a manager has less than 10 years of industry experience and to zero otherwise.

Late career. A dummy variable set to one if a manager has more than 20 years of industry experience and to zero otherwise.

Table AI
Statistics on managers by investment objective categories

This table presents statistics on mutual fund managers by the investment objective categories of the funds they manage, as defined by Morningstar. The sample includes only category-month observations containing at least ten unique funds in a given month. The sample period is January 1992 – December 2016.

IOC	Female	Top school	Foreign	. MBA	MA	PhD	Other degree	CFA	. Age	Avg. no. of funds
Aggressive Allocation	0.12	0.66	0.07	0.33	0.07	0.03	0.01	0.55	46.2	39
Allocation - 15% - 30% Equity	0.12	0.39	0.10	0.34	0.16	0.04	0.04	0.36	49.0	94
Allocation - 30% - 50% Equity	0.09	0.36	0.06	0.42	0.14	0.06	0.02	0.52	47.0	333
Allocation - 50% - 70% Equity	0.11	0.29	0.04	0.46	0.14	0.04	0.02	0.51	46.7	649
Allocation - 70% - 85% Equity	0.09	0.38	0.05	0.39	0.17	0.05	0.02	0.46	47.9	240
Allocation - 85%+ Equity	0.10	0.56	0.07	0.35	0.14	0.07	0.07	0.46	46.3	79
Bank Loan	0.12	0.44	0.01	0.58	0.02	0.01	0.01	0.40	50.2	83
Bear Market	0.13	0.50	0.06	0.28	0.12	0.00	0.05	0.46	48.5	19
China Region	0.21	0.42	0.40	0.34	0.17	0.02	0.05	0.27	44.8	39
Commodities Broad Basket	0.06	0.50	0.05	0.37	0.11	0.06	0.01	0.27	44.1	75
Communications	0.07	0.21	0.10	0.40	0.16	0.00	0.01	0.54	43.8	17
Conservative Allocation	0.18	0.41	0.05	0.31	0.13	0.02	0.02	0.45	52.3	76
Consumer Cyclical	0.09	0.33	0.07	0.33	0.17	0.02	0.00	0.42	37.0	15
Convertibles	0.11	0.16	0.05	0.58	0.13	0.01	0.02	0.49	46.4	41
Corporate Bond	0.06	0.31	0.03	0.51	0.17	0.03	0.02	0.53	47.4	88
Diversified Emerging Mk	0.18	1.00	0.36	0.45	0.09	0.00	0.09	0.18	54.4	11
Diversified Emerging Mkts	0.14	0.38	0.30	0.35	0.22	0.07	0.04	0.38	45.3	414
Diversified Pacific/Asia	0.15	0.25	0.42	0.33	0.18	0.01	0.01	0.23	43.7	20
Emerging Markets - Local Currency Bond	0.09	0.65	0.14	0.23	0.14	0.13	0.06	0.37	42.5	26
Emerging Markets Bond	0.12	0.47	0.21	0.20	0.19	0.05	0.03	0.34	47.8	180
Energy Limited Partnership	0.01	0.34	0.04	0.37	0.13	0.04	0.08	0.27	49.5	42
Equity Energy	0.03	0.29	0.09	0.38	0.19	0.02	0.08	0.41	44.0	66
Equity Precious Metals	0.05	0.18	0.22	0.29	0.17	0.01	0.08	0.40	48.4	29
Europe Stock	0.14	0.33	0.33	0.24	0.21	0.03	0.02	0.27	43.4	76
Financial	0.14	0.25	0.08	0.45	0.16	0.02	0.01	0.33	44.6	54
Foreign Large Blend	0.14	0.38	0.28	0.39	0.21	0.06	0.03	0.43	47.0	554
Foreign Large Growth	0.09	0.33	0.30	0.41	0.27	0.03	0.04	0.36	46.3	213
Foreign Large Value	0.16	0.47	0.21	0.47	0.21	0.08	0.06	0.51	47.3	242
Foreign Small/Mid Blend	0.16	0.49	0.22	0.39	0.21	0.07	0.03	0.32	45.0	55
Foreign Small/Mid Growth	0.10	0.49	0.27	0.41	0.26	0.03	0.02	0.35	42.8	57
Foreign Small/Mid Value	0.12	0.34	0.21	0.46	0.21	0.05	0.04	0.39	45.3	49
Global Real Estate	0.09	0.38	0.21	0.47	0.12	0.03	0.03	0.36	47.1	161
Health	0.17	0.42	0.11	0.41	0.15	0.06	0.08	0.52	43.6	79
High Yield Bond	0.09	0.29	0.02	0.48	0.08	0.02	0.03	0.50	46.7	350
High Yield Muni	0.18	0.20	0.00	0.47	0.13	0.01	0.04	0.45	46.6	79
India Equity	0.04	0.47	0.63	0.49	0.23	0.01	0.14	0.38	40.2	19
Industrials	0.14	0.29	0.09	0.37	0.23	0.02	0.00	0.31	35.7	12
Inflation-Protected Bond	0.07	0.43	0.03	0.44	0.11	0.08	0.01	0.41	45.9	99
Infrastructure	0.07	0.35	0.12	0.37	0.19	0.02	0.14	0.40	53.4	35
Intermediate Government	0.11	0.24	0.05	0.45	0.15	0.03	0.01	0.39	44.3	186
Intermediate-Term Bond	0.09	0.25	0.03	0.48	0.11	0.02	0.01	0.47	46.5	768
Japan Stock	0.10	0.30	0.34	0.30	0.25	0.05	0.05	0.18	46.9	35
Large Blend	0.10	0.30	0.06	0.48	0.15	0.05	0.03	0.50	47.6	971
Large Growth	0.09	0.28	0.05	0.48	0.12	0.02	0.03	0.50	47.7	1101
Large Value	0.11	0.30	0.05	0.56	0.13	0.04	0.02	0.54	47.7	818

IOC	Female	Top school	Foreign	MBA	MA	PhD	Other degree	CFA	Age	Avg. no. of funds
Latin America Stock	0.22	0.35	0.34	0.44	0.20	0.04	0.00	0.39	44.6	29
Long Government	0.05	0.31	0.02	0.48	0.21	0.05	0.02	0.31	46.9	15
Long-Short Credit	0.09	0.40	0.04	0.36	0.12	0.04	0.01	0.12	44.6	37
Long-Term Bond	0.06	0.15	0.06	0.47	0.10	0.01	0.01	0.42	48.1	42
Long/Short Equity	0.04	0.29	0.06	0.38	0.13	0.04	0.02	0.46	47.5	232
Managed Futures	0.07	0.35	0.10	0.26	0.20	0.15	0.01	0.18	47.5	149
Market Neutral	0.06	0.33	0.06	0.34	0.17	0.10	0.02	0.36	46.9	103
Mid-Cap Blend	0.09	0.32	0.07	0.48	0.14	0.03	0.05	0.51	48.3	241
Mid-Cap Growth	0.10	0.29	0.04	0.50	0.12	0.02	0.03	0.54	46.6	484
Mid-Cap Value	0.10	0.31	0.04	0.55	0.13	0.03	0.03	0.48	49.1	273
Miscellaneous Region	0.07	0.31	0.23	0.37	0.23	0.04	0.07	0.19	47.6	21
Moderate Allocation	0.06	0.55	0.03	0.38	0.10	0.01	0.03	0.37	48.4	85
Multialternative	0.06	0.43	0.09	0.34	0.14	0.09	0.04	0.34	47.4	423
Multicurrency	0.08	0.64	0.18	0.25	0.30	0.18	0.04	0.19	43.5	27
Multisector Bond	0.07	0.24	0.07	0.46	0.11	0.04	0.02	0.42	47.1	181
Muni California Intermediate	0.17	0.23	0.00	0.37	0.04	0.01	0.00	0.29	45.0	57
Muni California Long	0.12	0.18	0.01	0.43	0.14	0.02	0.03	0.39	45.0	69
Muni Massachusetts	0.20	0.12	0.00	0.43	0.15	0.01	0.03	0.41	46.3	38
Muni Minnesota	0.21	0.11	0.00	0.46	0.11	0.00	0.02	0.43	46.0	36
Muni National Interm	0.19	0.15	0.01	0.37	0.07	0.01	0.01	0.39	46.0	175
Muni National Long	0.18	0.13	0.01	0.37	0.12	0.00	0.02	0.39	45.6	127
Muni National Short	0.20	0.16	0.01	0.35	0.09	0.01	0.01	0.31	45.3	105
Muni New Jersey	0.17	0.15	0.00	0.44	0.16	0.01	0.02	0.35	44.6	40
Muni New York Intermediate	0.21	0.20	0.01	0.34	0.11	0.00	0.02	0.32	47.6	38
Muni New York Long	0.12	0.09	0.01	0.38	0.16	0.02	0.04	0.41	45.3	57
Muni Ohio	0.15	0.14	0.00	0.40	0.14	0.00	0.02	0.46	45.2	37
Muni Pennsylvania	0.15	0.16	0.00	0.40	0.16	0.00	0.02	0.37	44.2	47
Muni Single State Interm	0.17	0.11	0.01	0.29	0.12	0.00	0.01	0.34	44.0	177
Muni Single State Long	0.18	0.09	0.01	0.37	0.16	0.02	0.03	0.35	42.3	206
Muni Single State Short	0.08	0.28	0.00	0.50	0.16	0.00	0.04	0.25	44.6	45
Natural Resources	0.08	0.31	0.13	0.34	0.13	0.03	0.03	0.44	42.7	60
Nontraditional Bond	0.05	0.32	0.06	0.41	0.09	0.03	0.03	0.42	48.2	195
Option Writing	0.01	0.31	0.07	0.38	0.10	0.07	0.04	0.39	49.2	65
Pacific/Asia ex-Japan Stk	0.18	0.29	0.45	0.25	0.21	0.02	0.05	0.24	44.3	54
Preferred Stock	0.07	0.06	0.11	0.42	0.17	0.00	0.00	0.30	45.4	20
Real Estate	0.06	0.41	0.02	0.50	0.14	0.02	0.01	0.41	46.3	124
Retirement Income	0.12	0.42	0.05	0.34	0.12	0.03	0.01	0.49	45.8	92
Short Government	0.13	0.23	0.01	0.45	0.10	0.02	0.00	0.40	43.7	133
Short-Term Bond	0.10	0.24	0.02	0.48	0.09	0.02	0.02	0.47	45.6	257
Small Blend	0.13	0.30	0.05	0.49	0.12	0.03	0.03	0.54	47.9	486
Small Growth	0.11	0.32	0.04	0.51	0.10	0.02	0.03	0.56	46.9	600
Small Value	0.08	0.24	0.06	0.53	0.17	0.06	0.03	0.53	48.0	311
Tactical Allocation	0.07	0.26	0.07	0.38	0.15	0.09	0.02	0.37	47.9	166
Target-Date 2000-2010	0.08	0.60	0.08	0.34	0.13	0.06	0.05	0.45	45.9	90
Target-Date 2015	0.11	0.58	0.10	0.31	0.14	0.05	0.06	0.50	47.7	94
Target-Date 2020	0.10	0.54	0.07	0.35	0.15	0.06	0.02	0.48	47.0	111
Target-Date 2021-2025	0.21	0.69	0.00	0.00	0.08	0.10	0.00	0.10	47.2	11
Target-Date 2025	0.10	0.58	0.10	0.31	0.14	0.05	0.05	0.49	47.5	99
Target-Date 2030	0.10	0.53	0.07	0.34	0.15	0.06	0.02	0.48	47.0	112
Target-Date 2031-2035	0.21	0.69	0.00	0.00	0.08	0.10	0.00	0.10	47.2	11
Target-Date 2035	0.11	0.57	0.11	0.30	0.14	0.05	0.05	0.50	47.3	98
Target-Date 2040	0.10	0.54	0.07	0.35	0.15	0.06	0.02	0.47	47.0	113
Target-Date 2041-2045	0.16	0.00	0.00	0.17	0.00	0.00	0.00	0.34	45.6	12

IOC	Female	Top school	Foreign	. MBA	MA	PhD	Other degree	CFA	. Age	Avg. no. of funds
Target-Date 2045	0.11	0.58	0.10	0.30	0.15	0.04	0.06	0.48	47.5	97
Target-Date 2050	0.10	0.58	0.06	0.35	0.16	0.05	0.03	0.50	47.9	110
Target-Date 2051+	0.11	0.45	0.04	0.37	0.09	0.04	0.00	0.49	45.2	26
Target-Date 2055	0.10	0.71	0.13	0.31	0.16	0.05	0.10	0.51	49.5	85
Target-Date 2060+	0.09	0.65	0.04	0.42	0.15	0.02	0.01	0.55	50.5	69
Technology	0.09	0.31	0.05	0.40	0.19	0.02	0.02	0.39	43.6	162
Trading-Inverse Debt	0.03	0.66	0.02	0.36	0.02	0.00	0.00	0.27	30.6	10
Trading-Leveraged Equity	0.22	0.45	0.11	0.00	0.11	0.00	0.00	0.20	42.7	50
Ultrashort Bond	0.14	0.20	0.02	0.43	0.14	0.02	0.01	0.36	44.1	113
Utilities	0.19	0.32	0.04	0.53	0.09	0.05	0.01	0.55	46.0	30
Volatility	0.08	0.60	0.08	0.50	0.25	0.00	0.00	0.50	47.8	12
World Allocation	0.09	0.39	0.12	0.38	0.18	0.09	0.02	0.43	48.1	307
World Bond	0.11	0.35	0.22	0.33	0.22	0.09	0.02	0.32	44.9	201
World Stock	0.12	0.40	0.19	0.41	0.19	0.05	0.06	0.43	46.4	618

Table AII
Descriptive statistics on mutual fund managers of mainstream active domestic equity funds

This table presents descriptive statistics for the sample on managers of mainstream active domestic equity funds. The table corresponds to Table II.

Panel A: Statistics on promotions and demotions (monthly probabilities)

Promotion - gain additional sole-managed fund(s)	0.00458
Promotion - gain additional co-managed fund(s)	0.01955
Total probability of promotion	0.02413
Demotion - lose sole-managed fund(s)	0.00594
Demotion - lose co-managed fund(s)	0.01762
Total probability of demotion	0.02356

Panel C: Statistics on employment gaps and firings (monthly probabilities)

Gap in employment over 6 months	0.00146
Fired (leave the industry <55 y.o. or <25 yrs experience)	0.00645

Panel B: Male vs. female managers

			Difference	
	Male	Female	Female - male	*t*-statistic
Fraction of manager-months	0.903	0.097		
Number of unique managers	5,870	700		
Years in industry	10.101	9.137	-0.964	(-34.73)
Age	48.787	46.287	-2.500	(-37.99)
Age first started	32.389	32.366	-0.023	(-0.05)
Under 35 y. o.	0.056	0.056	-0.000	(-0.18)
Over 55 y. o.	0.250	0.143	-0.106	(-37.80)
Foreign	0.042	0.054	0.012	(1.34)
MBA	0.458	0.391	-0.066	(-3.39)
MA	0.118	0.130	0.012	(0.92)
PhD	0.028	0.024	-0.003	(-0.53)
Other degree	0.032	0.016	-0.016	(-3.08)
Top school	0.408	0.406	-0.002	(-0.10)
CFA	0.472	0.433	-0.039	(-1.96)
No. of sole-managed funds	0.445	0.403	-0.043	(-9.56)
No. of co-managed funds	2.111	2.221	0.109	(8.55)
Managed TNA (millions of $)	1,203.778	969.279	-234.50	(-14.87)
No. of managers in fund family	40.449	47.740	7.291	(33.95)
Alpha rank	4.547	4.542	-0.006	(-0.33)
Fund flow rank	4.395	4.337	-0.059	(-1.91)
Prob. employment gap over 6 months	0.001	0.001	-0.000	(-0.95)
Length of empl. gap (yrs)	2.241	2.141	-0.100	(-0.50)
Prob. fired	0.006	0.009	0.003	(5.50)
Prob. demoted	0.022	0.023	0.001	(1.08)
Prob. promoted	0.020	0.022	0.001	(1.85)

Table AIII
Explaining raw style-adjusted returns

This table presents the results of OLS regressions explaining raw style-adjusted returns. The sample and variable definitions correspond to those in Table III.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001	-0.0002	-0.0002	-0.0001	-0.0002	-0.0002
	(-1.29)	(-1.21)	(-1.73)	(-0.81)	(-1.32)	(-1.29)	(-1.28)	(-0.94)	(-1.32)	(-1.28)
Time in industry	.	.	.	.	.	.	.	.	.	-0.0000
	.	.	.	.	.	.	.	.	.	(-0.45)
Time in industry^2	.	.	.	.	.	.	.	.	.	-0.0000
	.	.	.	.	.	.	.	.	.	(-0.16)
Foreign	.	.	.	.	.	.	0.0000	0.0001	0.0000	-0.0001
	.	.	.	.	.	.	(0.20)	(0.57)	(0.19)	(-0.39)
Foreign×female	.	.	.	.	.	.	.	-0.0008	.	.
	.	.	.	.	.	.	.	(-1.48)	.	.
MBA	.	.	.	.	.	.	0.0000	0.0000	0.0000	0.0001
	.	.	.	.	.	.	(0.30)	(0.32)	(0.30)	(0.58)
MA	.	.	.	.	.	.	-0.0000	-0.0000	-0.0000	-0.0000
	.	.	.	.	.	.	(-0.36)	(-0.40)	(-0.34)	(-0.22)
PhD	.	.	.	.	.	.	0.0001	0.0001	0.0001	0.0001
	.	.	.	.	.	.	(0.33)	(0.35)	(0.30)	(0.43)
Other degree	.	.	.	.	.	.	.	.	.	0.0007
	.	.	.	.	.	.	.	.	.	(2.60)
CFA	.	.	.	.	.	.	.	.	.	0.0001
	.	.	.	.	.	.	.	.	.	(0.82)
Top school	.	.	.	.	.	.	.	.	.	-0.0001
	.	.	.	.	.	.	.	.	.	(-0.77)
Time at the fund	.	.	.	.	.	.	.	.	-0.0000	.
	.	.	.	.	.	.	.	.	(-1.06)	.
Obs.	257,370	262,724	258,901	257,443	257,443	257,370	220,456	220,456	220,456	220,456
	.	.	.	.	.	.	.	.	.	.
Adj. RSq.	0.0161	0.0152	0.0098	0.0092	0.0088	0.0160	0.0175	0.0175	0.0175	0.0175

Table AIV
Explaining style-adjusted fund flows and CAPM alphas for mainstream active domestic equity funds

This table presents the results of OLS regressions explaining style-adjusted fund flows (Panel A) and style-adjusted CAPM alphas (Panel B) for mainstream active domestic equity funds. The variable definitions correspond to those in Table III.

Panel A: Style-adjusted fund flows

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	0.0001	0.0004	-0.0003	0.0002	0.0000	0.0001	0.0007	0.0006	0.0006	0.0006
	(0.20)	(0.54)	(-0.37)	(0.34)	(0.07)	(0.21)	(0.90)	(0.82)	(0.76)	(0.76)
Time in industry	.	.	.	.	.	.	.	.	.	-0.0000
	.	.	.	.	.	.	.	.	.	(-3.88)
Time in industry^2	.	.	.	.	.	.	.	.	.	0.0000
	.	.	.	.	.	.	.	.	.	(3.37)
Foreign	.	.	.	.	.	.	0.0024	0.0023	0.0024	0.0023
	.	.	.	.	.	.	(2.20)	(2.06)	(2.13)	(1.94)
Foreign×female	.	.	.	.	.	.	.	0.0028	.	.
	.	.	.	.	.	.	.	(0.49)	.	.
MBA	.	.	.	.	.	.	-0.0000	-0.0000	0.0001	0.0000
	.	.	.	.	.	.	(-0.03)	(-0.03)	(0.18)	(0.08)
MA	.	.	.	.	.	.	0.0001	0.0001	0.0001	0.0003
	.	.	.	.	.	.	(0.09)	(0.09)	(0.17)	(0.39)
PhD	.	.	.	.	.	.	0.0028	0.0028	0.0028	0.0030
	.	.	.	.	.	.	(2.55)	(2.55)	(2.55)	(2.66)
Other degree	.	.	.	.	.	.	.	.	.	-0.0009
	.	.	.	.	.	.	.	.	.	(-0.70)
CFA	.	.	.	.	.	.	.	.	.	-0.0004
	.	.	.	.	.	.	.	.	.	(-0.79)
Top school	.	.	.	.	.	.	.	.	.	0.0003
	.	.	.	.	.	.	.	.	.	(0.51)
Time at the fund	.	.	.	.	.	.	.	.	-0.0000	.
	.	.	.	.	.	.	.	.	(-3.08)	.
Fund flow controls	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Fund return controls	Y	Y	N	Y	Y	Y	Y	Y	Y	Y
Fund controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
IOC dummy	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
Fund family dummy	Y	Y	Y	N	N	Y	Y	Y	Y	Y
Fund family controls	N	N	N	Y	Y	N	N	N	N	N
Obs.	114,781	117,413	115,678	114,781	114,781	114,781	96,509	96,509	96,509	96,509
Adj. RSq.	0.1284	0.0747	0.1106	0.1215	0.1195	0.1282	0.1293	0.1293	0.1294	0.1294

Panel B: Style-adjusted CAPM alphas

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.0001	-0.0001	-0.0001	0.0001	0.0000	-0.0001	-0.0002	-0.0002	-0.0002	-0.0002
	(-0.35)	(-0.35)	(-0.24)	(0.30)	(0.23)	(-0.35)	(-0.60)	(-0.62)	(-0.66)	(-0.79)
Time in industry	.	.	.	.	.	.	.	.	.	-0.0000
	.	.	.	.	.	.	.	.	.	(-1.55)
Time in industry^2	.	.	.	.	.	.	.	.	.	0.0000
	.	.	.	.	.	.	.	.	.	(1.06)
Foreign	.	.	.	.	.	.	0.0003	0.0003	0.0003	0.0002
	.	.	.	.	.	.	(0.87)	(0.82)	(0.84)	(0.49)
Foreign×female	.	.	.	.	.	.	.	0.0004	.	.
	.	.	.	.	.	.	.	(0.20)	.	.
MBA	.	.	.	.	.	.	0.0000	0.0000	0.0001	0.0001
	.	.	.	.	.	.	(0.22)	(0.21)	(0.31)	(0.78)
MA	.	.	.	.	.	.	-0.0001	-0.0001	-0.0001	-0.0001
	.	.	.	.	.	.	(-0.59)	(-0.59)	(-0.56)	(-0.35)
PhD	.	.	.	.	.	.	-0.0002	-0.0002	-0.0002	-0.0001
	.	.	.	.	.	.	(-0.55)	(-0.55)	(-0.55)	(-0.27)
Other degree	.	.	.	.	.	.	.	.	.	0.0002
	.	.	.	.	.	.	.	.	.	(0.51)
CFA	.	.	.	.	.	.	.	.	.	0.0000
	.	.	.	.	.	.	.	.	.	(0.18)
Top school	.	.	.	.	.	.	.	.	.	-0.0003
	.	.	.	.	.	.	.	.	.	(-1.44)
Time at the fund	.	.	.	.	.	.	.	.	-0.0000	.
	.	.	.	.	.	.	.	.	(-1.41)	.
Fund flow controls	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Fund return controls	Y	Y	N	Y	Y	Y	Y	Y	Y	Y
Fund controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month dummy	Y	Y	Y	Y	Y	N	Y	Y	Y	Y
IOC dummy	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
Fund family dummy	Y	Y	Y	N	N	Y	Y	Y	Y	Y
Fund family controls	N	N	N	Y	Y	N	N	N	N	N
Obs.	114,855	117,799	115,757	114,855	114,855	114,855	96,576	96,576	96,576	96,576
Adj. RSq.	0.0185	0.0180	0.0128	0.0106	0.0103	0.0183	0.0198	0.0198	0.0198	0.0199

Table AV

Explaining manager firings and career advancement: Later sample start date

This table presents the results of linear probability regressions explaining firings, and OLS regressions explaining managers' career changes. The sample starts in January 2006. Panels A and B correspond to Panels A1 of Tables IV and Table V, respectively.

Panel A: Firings

	Years of fund management experience									
	All observations				$\geq$ 1 year		$\geq$ 5 years		$\geq$ 10 years	
Female	0.0028	0.0028	0.0024	0.0024	0.0028	0.0022	0.0029	0.0023	0.0028	0.0025
	(8.40)	(8.59)	(7.07)	(7.07)	(8.21)	(6.58)	(7.42)	(5.85)	(5.81)	(4.97)
Foreign+Guess	.	.	.	-0.0000	.	-0.0001	.	0.0005	.	0.0006
	.	.	.	(-0.15)	.	(-0.31)	.	(1.30)	.	(1.11)
$Alpha_{t-1}$	.	.	.	.	.	-0.0010	.	-0.0010	.	-0.0008
	.	.	.	.	.	(-7.94)	.	(-6.66)	.	(-4.38)
$Alpha_{t-2}$	.	.	.	.	.	.	.	-0.0004	.	-0.0006
	.	.	.	.	.	.	.	(-2.62)	.	(-2.95)
$Alpha_{t-3}$	.	.	.	.	.	.	.	-0.0001	.	-0.0001
	.	.	.	.	.	.	.	(-0.87)	.	(-0.27)
$FFlow_{t-1}$	.	.	.	.	.	-0.0010	.	-0.0007	.	-0.0008
	.	.	.	.	.	(-14.38)	.	(-6.19)	.	(-5.49)
$FFlow_{t-2}$	.	.	.	.	.	.	.	-0.0001	.	0.0001
	.	.	.	.	.	.	.	(-0.86)	.	(0.34)
$FFlow_{t-3}$	.	.	.	.	.	.	.	-0.0000	.	-0.0001
	.	.	.	.	.	.	.	(-0.35)	.	(-0.81)
Stdev	.	.	.	.	.	-0.0415	.	-0.0241	.	0.0101
	.	.	.	.	.	(-2.51)	.	(-1.03)	.	(0.35)
Manager TNA	.	.	-0.0025	-0.0025	.	-0.0024	.	-0.0025	.	-0.0022
	.	.	(-33.56)	(-33.52)	.	(-31.82)	.	(-25.51)	.	(-17.88)
Num. funds managed	.	.	-0.0001	-0.0001	.	-0.0001	.	-0.0001	.	-0.0001
	.	.	(-3.71)	(-3.72)	.	(-4.46)	.	(-3.64)	.	(-2.28)
Trend	.	.	0.0004	0.0004	.	0.0028	.	0.0035	.	0.0016
	.	.	(0.41)	(0.42)	.	(2.66)	.	(2.57)	.	(0.89)
Exp. ratio	.	.	-0.0001	-0.0001	.	-0.0001	.	-0.0002	.	-0.0002
	.	.	(-1.39)	(-1.39)	.	(-2.41)	.	(-3.15)	.	(-1.95)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	534,716	534,716	527,693	527,693	531,393	524,281	363,645	322,194	211,583	187,996
Adj. RSq.	0.0025	0.0003	0.0054	0.0054	0.0025	0.0059	0.0027	0.0067	0.0034	0.0069

Panel B: Career advancement

	Years of fund management experience									
	All observations				$\geq$ 1 year		$\geq$ 5 years		$\geq$ 10 years	
Female	-0.0044	-0.0041	-0.0053	-0.0054	-0.0042	-0.0049	-0.0028	-0.0027	-0.0017	-0.0017
	(-2.25)	(-2.14)	(-2.69)	(-2.71)	(-2.14)	(-2.45)	(-1.86)	(-1.83)	(-0.84)	(-0.89)
Foreign+Guess	.	.	.	0.0009	.	0.0010	.	-0.0008	.	-0.0026
	.	.	.	(0.47)	.	(0.52)	.	(-0.52)	.	(-1.24)
$Alpha_{t-1}$	.	.	.	.	.	0.0016	.	0.0023	.	0.0033
	.	.	.	.	.	(2.23)	.	(4.12)	.	(4.78)
$Alpha_{t-2}$	.	.	.	.	.	.	.	0.0026	.	0.0018
	.	.	.	.	.	.	.	(4.48)	.	(2.50)
$Alpha_{t-3}$	.	.	.	.	.	.	.	0.0005	.	-0.0002
	.	.	.	.	.	.	.	(0.91)	.	(-0.22)
$FFlow_{t-1}$	.	.	.	.	.	0.0027	.	0.0015	.	0.0021
	.	.	.	.	.	(6.36)	.	(3.77)	.	(4.08)
$FFlow_{t-2}$	.	.	.	.	.	.	.	0.0014	.	0.0012
	.	.	.	.	.	.	.	(2.94)	.	(2.07)
$FFlow_{t-3}$	.	.	.	.	.	.	.	-0.0006	.	-0.0000
	.	.	.	.	.	.	.	(-1.62)	.	(-0.06)
Stdev	.	.	.	.	.	0.0882	.	0.2626	.	0.2684
	.	.	.	.	.	(0.90)	.	(3.02)	.	(2.51)
Manager TNA	.	.	-0.0021	-0.0021	.	-0.0022	.	-0.0011	.	-0.0007
	.	.	(-4.83)	(-4.80)	.	(-5.07)	.	(-3.01)	.	(-1.49)
Num. funds managed	.	.	-0.0007	-0.0007	.	-0.0007	.	-0.0004	.	-0.0005
	.	.	(-4.87)	(-4.85)	.	(-4.33)	.	(-3.84)	.	(-3.94)
Trend	.	.	0.0116	0.0115	.	0.0053	.	-0.0009	.	0.0001
	.	.	(1.88)	(1.87)	.	(0.85)	.	(-0.18)	.	(0.01)
Exp. ratio	.	.	-0.0013	-0.0013	.	-0.0012	.	-0.0005	.	-0.0005
	.	.	(-3.86)	(-3.86)	.	(-3.47)	.	(-1.79)	.	(-1.36)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	534,716	534,716	527,693	527,693	531,393	524,281	363,645	322,194	211,583	187,996
Adj. RSq.	0.0018	0.0027	0.0037	0.0020	0.0018	0.0021	0.0037	0.0049	0.0045	0.0061

Table AVI

Explaining firings and career advancement for managers of mainstream active domestic equity funds

This table presents the results of regressions explaining manager firings, demotions and promotions. The sample of managers includes only managers of mainstream active domestic equity funds. Panels A and B correspond to Panels A1 of Tables IV and Table V, respectively.

Panel A: Firings

	Years of fund management experience									
	All observations				$\geq$ 1 year		$\geq$ 5 years		$\geq$ 10 years	
Female	0.0030	0.0033	0.0026	0.0026	0.0030	0.0024	0.0031	0.0026	0.0025	0.0024
	(7.52)	(8.28)	(6.36)	(6.35)	(7.36)	(5.99)	(6.18)	(4.82)	(3.62)	(3.28)
Foreign+Guess	.	.	.	0.0008	.	0.0009	.	0.0005	.	0.0000
	.	.	.	(1.40)	.	(1.58)	.	(0.64)	.	(0.01)
$Alpha_{t-1}$	.	.	.	.	.	-0.0011	.	-0.0013	.	-0.0012
	.	.	.	.	.	(-7.76)	.	(-6.70)	.	(-4.75)
$Alpha_{t-2}$	.	.	.	.	.	.	.	-0.0007	.	-0.0011
	.	.	.	.	.	.	.	(-3.72)	.	(-4.33)
$Alpha_{t-3}$	.	.	.	.	.	.	.	-0.0001	.	0.0000
	.	.	.	.	.	.	.	(-0.64)	.	(0.18)
$FFlow_{t-1}$	.	.	.	.	.	-0.0010	.	-0.0007	.	-0.0007
	.	.	.	.	.	(-13.08)	.	(-5.23)	.	(-3.50)
$FFlow_{t-2}$	.	.	.	.	.	.	.	-0.0003	.	-0.0001
	.	.	.	.	.	.	.	(-1.62)	.	(-0.30)
$FFlow_{t-3}$	.	.	.	.	.	.	.	-0.0001	.	-0.0002
	.	.	.	.	.	.	.	(-0.72)	.	(-1.29)
Stdev	.	.	.	.	.	-0.0971	.	-0.1372	.	-0.0976
	.	.	.	.	.	(-4.61)	.	(-4.03)	.	(-2.12)
Manager TNA	.	.	-0.0019	-0.0019	.	-0.0018	.	-0.0018	.	-0.0020
	.	.	(-21.51)	(-21.45)	.	(-20.77)	.	(-14.59)	.	(-12.01)
Num. funds managed	.	.	-0.0009	-0.0009	.	-0.0009	.	-0.0009	.	-0.0007
	.	.	(-13.66)	(-13.66)	.	(-14.26)	.	(-12.00)	.	(-7.35)
Trend	.	.	-0.0003	-0.0003	.	0.0029	.	0.0044	.	0.0016
	.	.	(-0.26)	(-0.25)	.	(2.12)	.	(2.25)	.	(0.57)
Exp. ratio	.	.	-0.0001	-0.0001	.	-0.0000	.	-0.0001	.	-0.0001
	.	.	(-0.97)	(-0.95)	.	(-0.53)	.	(-1.42)	.	(-0.72)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	388,517	388,517	384,073	384,073	385,652	380,998	241,302	208,045	123,499	108,684
Adj. RSq.	0.0030	0.0004	0.0059	0.0057	0.0030	0.0065	0.0038	0.0096	0.0087	0.0112

Panel B: Career advancements

	Years of fund management experience									
	All observations				≥ 1 year		≥ 5 years		≥ 10 years	
Female	-0.0041	-0.0039	-0.0048	-0.0049	-0.0039	-0.0047	-0.0014	-0.0015	-0.0000	-0.0005
	(-1.58)	(-1.55)	(-1.87)	(-1.88)	(-1.52)	(-1.81)	(-0.71)	(-0.77)	(-0.01)	(-0.18)
Foreign+Guess	.	.	.	0.0077	.	0.0077	.	-0.0038	.	-0.0022
	.	.	.	(2.09)	.	(2.08)	.	(-1.31)	.	(-0.52)
$Alpha_{t-1}$	.	.	.	.	.	0.0013	.	0.0031	.	0.0044
	.	.	.	.	.	(1.37)	.	(4.40)	.	(4.90)
$Alpha_{t-2}$	.	.	.	.	.	.	.	0.0032	.	0.0029
	.	.	.	.	.	.	.	(4.40)	.	(3.19)
$Alpha_{t-3}$	.	.	.	.	.	.	.	0.0003	.	0.0006
	.	.	.	.	.	.	.	(0.51)	.	(0.63)
$FFlow_{t-1}$	.	.	.	.	.	0.0030	.	0.0017	.	0.0015
	.	.	.	.	.	(5.93)	.	(3.40)	.	(2.33)
$FFlow_{t-2}$	.	.	.	.	.	.	.	0.0014	.	0.0011
	.	.	.	.	.	.	.	(2.38)	.	(1.52)
$FFlow_{t-3}$	.	.	.	.	.	.	.	-0.0000	.	0.0011
	.	.	.	.	.	.	.	(-0.00)	.	(1.88)
Stdev	.	.	.	.	.	-0.1221	.	0.2265	.	0.4738
	.	.	.	.	.	(-0.90)	.	(1.83)	.	(2.97)
Manager TNA	.	.	-0.0018	-0.0018	.	-0.0019	.	-0.0020	.	-0.0018
	.	.	(-3.24)	(-3.18)	.	(-3.27)	.	(-4.41)	.	(-3.09)
Num. funds managed	.	.	-0.0027	-0.0027	.	-0.0028	.	-0.0011	.	-0.0008
	.	.	(-6.68)	(-6.68)	.	(-6.70)	.	(-4.01)	.	(-2.18)
Trend	.	.	0.0224	0.0224	.	0.0154	.	-0.0028	.	0.0069
	.	.	(2.60)	(2.60)	.	(1.76)	.	(-0.40)	.	(0.73)
Exp. ratio	.	.	-0.0018	-0.0018	.	-0.0018	.	-0.0011	.	-0.0015
	.	.	(-4.24)	(-4.21)	.	(-4.08)	.	(-3.33)	.	(-3.31)
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund family dummy	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	388,517	388,517	384,073	384,073	385,652	380,998	241,302	208,045	123,499	108,684
Adj. RSq.	0.0015	0.0013	0.0028	0.0017	0.0015	0.0019	0.0028	0.0039	0.0051	0.0062