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Finding your calling: Matching skills with jobs in the mutual fund industry

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by

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Abstract

To best utilize labor, companies need to match employees' skills with jobs that best fit those skills. Exploiting unique features of the mutual fund industry, we identify instances when this matching happens for fund managers and study its consequences. After fund managers are matched, they improve their risk-adjusted performance significantly. Fund companies use this information to maximize company value by reallocating existing and directing new capital to their matched managers and by collecting higher fees from the matched managers' funds. In addition, they make the expertise of matched managers available to the other managers of the fund company.

Keywords: **human capital, mutual funds, occupational match finding**
JEL Classification: **G23, J24, J62, M50**

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1 Introduction

The skills of employees are a key factor for company success. To best exploit such skills, companies need to match them with jobs that are best suited to them, ensuring that employees operate at their highest level of productivity. In this paper, we analyze the effects of this match finding, shedding light on the extent to which it increases the productivity of employees and how employers use it to maximize company value.

We use the mutual fund industry as our laboratory for understanding the consequences of match finding. The main advantage is that here one does not need to approximate employees' productivity by their wages (as typically done in previous research) but can directly derive it from the performance of mutual funds, for which employees, i.e., mutual fund managers, are responsible. The fund industry offers additional advantages. First, it provides a sensible taxonomy of fund managers' skills and tasks. A mutual fund manager invests in accordance with a pre-specified investment style,[1] which largely determines the investment universe and, consequently, the skills required to invest in that universe.[2] Thus, one can think of different investment styles in which mutual fund managers operate as different jobs. Second, since fund companies typically offer various funds with different investment styles, we can observe the performance of funds in different styles within the same company. This allows us to observe how the performance of a fund manager changes within the same company when she finds her

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[1] Mutual funds are mandated to follow a clearly-defined investment style and have to invest at least 80% of their assets in accordance with the investment style suggested by their name under Section 35d-1 of U.S. Investment Company Act of 1940.

[2] For example, the most relevant skills of a fund manager operating under a value or income style mandate revolve around understanding the value of assets in place and the cash-flow generating capabilities of companies in the near future. A growth manager's skills, on the other hand, revolve around understanding the growth opportunities or growth options that the company has, the realization of which takes a longer time. In other words, a growth manager, as compared to a value manager, will try to assess outcomes, which have a higher level of uncertainty.

match relative to performance changes of other fund managers in the same fund company that have not found their match as of that point in time. This within-fund company analysis rules out that unobservable employer characteristics or self-selection issues drive the results and thus provides a particularly clear picture of the impact of match finding on performance.

To identify the point in time when a fund manager finds her match, we draw on occupational match theory. The basic idea is that when employees start their careers the positions that best match their skills are unknown to both, the employees and employers. The employees need to try out different jobs in a learning-by-trying fashion so that the employees and employers gather information that they can use to find the best match. At the end of this search and learning process the employees arrive at the positions that best match their skills, and from that point onwards they operate at their highest level of productivity.[3]

Applying these insights to our setting, when a fund manager is starting out her career, neither the fund manager nor the fund company typically know what particular investment style constitutes the best fit with the manager's skills. However, while the fund manager tries a particular style, both the fund manager and the fund company learn about the suitability of that particular style and update their beliefs about the match quality of various manager-style combinations. The manager will then move to a new investment style as long as the fund manager and the fund company think that the new style is a better match than the manager's current style. The learning that happens as the fund manager and the fund company observe the various pairwise manager-style combinations eventually leads to finding the best match

[3] See, e.g., Jovanovic (1979) and Miller (1984) for early job search models that treat jobs or occupations as "experience goods" and Papageorgiou (2014) for a more recent contribution to this literature.

(hereafter match) of the manager. Building on this intuition, we exploit instances when a fund manager that has tried different investment styles returns to one of the styles that she already tried in the past. Such occurrence suggests that the fund manager and the fund company adjusted their beliefs based on the public and private information they gathered during the search period to the point of considering this particular style to be the best fit.[4] Otherwise, if the fund company and the fund manager deemed that the best fit was not achieved, the fund manager would continue to try styles that are different from the ones already tried. Thus, we use the point in time when a manager returns to a previously-tried style to identify when matching occurs.

We acknowledge that there might be cases when the match of a fund manager is known to a fund company even without having the manager go through the process of trying various investment styles. For example, a fund company might hire an expert with experience outside the financial industry that is particularly useful in a specific investment style [e.g., Cici et al (2018)]. Given her special skills, the match might be obvious and the fund company might hire the expert as a fund manager in her best matching style right from the beginning of her career. In this case, the fund manager would not be classified as matched by our approach. Thus, our approach is likely to understate the extent to which matching happens, which might contribute to attenuation bias as some unidentified matches will end up in the control group.

[4] Papageorgiou (2014) documents that about a third of workers return to occupations they have tried before. He argues that workers returning to a previously-tried occupation reflects an upward adjustment of their beliefs about the match quality of that occupation or a downward adjustment of their beliefs about the match quality of the current occupation.

Identifying points in time when matching happens allows us to test our main hypothesis that match finding leads to an increase in fund company value, which we do by examining three direct mechanisms through which this happens. Improved performance of fund managers after they have arrived at their match is the first mechanism through which fund company value increases. Fund companies can also increase their value by assigning more assets to matched managers and by increasing the fees of funds managed by these managers. Together, these three mechanisms correspond to the factors (outperformance of a manager, assets assigned to a manager, and fees charged for these assets) that determine the value-added of a fund manager as defined by Berk and van Binsberg (2015). In addition, we also look at a fourth, less direct way fund companies use to increase their value, whereby they assign their matched managers to teams so that other fund managers can learn from them.

To test for the first value increasing mechanism, we measure fund manager performance by aggregating fund-specific performance at the manager level as done in Ibert et al. (2018). Then, we compare the performance of a fund manager before and after the manager is matched against other managers of the same fund company that are not matched, in a difference-in-differences setting. Our results show that matching improves the risk-adjusted performance of a fund manager by 139 to 193 basis points per year relative to her unmatched colleagues. This increase is economically significant given that the average sample fund manager generates a risk-adjusted performance slightly below zero.

We consider a number of alternative explanations for the observed performance improvement after managers find their match. First, we rule out the possibility that the performance improvement comes from these managers being assigned to higher quality funds for reasons that are unrelated to match finding. One example could be an assignment effect along the lines of Berk, van Binsbergen, and Liu (2017). Funds that managers try earlier on could be just lower quality funds that are used for fund manager training. After their training is complete, managers with proved skills get assigned to higher quality funds that are more important to the fund company and from which managers can extract more value from the securities market. Next, we rule out manager experience as an explanation for our results by controlling for different types of experience that a manager might have accumulated during her career. Finally, we rule out that matched managers might follow a distinct career path, perhaps due to innate unobservable characteristics. All these tests provide additional support for our hypothesis that match finding leads to better performance.

Next, we examine the other two direct mechanisms through which fund companies can increase their value in response to match finding. In particular, we test whether fund companies respond to match finding by reallocating existing or directing new capital to their matched managers and by extracting higher fees from the matched managers' funds. Indeed, we find strong evidence that fund companies take these actions and they do so fairly quickly after the discovery of their managers' match. For example, fund companies reallocate almost $3 billion towards a matched manager within two years after the match took place, which is about twice the size of the average fund. They also reallocate high-fee funds to the matched managers such that the management fees of these managers' funds increase by up to one quarter of the average management fee.

However, these are not the only ways in which fund companies exploit this advantage. We document that fund companies spread the expertise of matched managers to other managers. They do so by assigning matched managers to work in teams so that affiliated managers can interact with and learn from them. For this, they pick particularly big teams to allow for a larger number of affiliated managers to benefit from matched managers. Further, fund companies surround matched managers with more junior managers, which we interpret as evidence that these matched managers are being used to "train" their junior colleagues.

Our paper contributes to the literature on occupational match finding, especially to the empirical part of this literature. Prior empirical research in this area relies on the premise of an underlying equilibrium model that results in employees and occupations being matched after employees learn about the match quality of various "experienced" employee-occupation combinations. Building on this and using tenure as a proxy for the likelihood that an employee has been matched and wage as an approximation for productivity, these studies primarily examine tenure effects on turnover [e.g., McCall (1990)] or wage [e.g., Kambourov and Manovskii (2009)]. Our study contributes to this literature by directly documenting the productivity gains – as measured by performance improvement – that accrue once the match of an employee has been reached and the actions that employers take in response to it to maximize firm value.[5]

Our paper is also related to the literature that shows that fund companies assign fund managers to funds based on the private information they gather about their managers' abilities. This creates value for fund investors and for the companies themselves. Specifically, in Berk, van Binsbergen, and Liu (2017) fund companies identify which managers have investment skill

[5] In Section A of the Internet Appendix, we confirm previous findings from this literature on our sample by documenting that higher tenure is associated with higher productivity and lower probability of changing styles in the mutual fund industry.

and reallocate capital to those managers. In Zambrana and Zapatero (2021), fund companies learn whether fund managers have selection versus timing skills, based on which they assign managers to funds with specialized or general mandates. In this paper, we document a different type of value-creating private information that fund companies generate about their managers, whereby fund companies learn the investment styles that best fit their managers' skills. We make an additional contribution to this literature by documenting new value-increasing strategies that fund companies pursue to exploit the skills of their managers. In particular, we show that fund companies attract new capital to matched managers via increased distribution efforts and make the expertise of these managers available to other company managers.

Furthermore, our paper is related to the literature that studies how fund companies facilitate learning of their fund managers. For example, Cici et al. (2018) show that fund companies scale up the industry experience of their managers by making the expertise of managers with previous experience outside the financial industry available to affiliated fund managers. Cici, Kempf, and Peitzmeier (2022) show that fund companies hire away fund managers from competing companies to transfer valuable knowledge and expertise to their managers. Genc et al (2022) document that fund managers receive valuable investment ideas from other managers with whom they currently work or have worked in the past. Xu (2021) shows that fund managers learn capital-raising skills from their more senior colleagues. Our paper contributes to this literature by showing that fund companies assign matched managers to teams so that other managers, in particular more junior fund managers, can learn from their expertise.

Finally, our paper contributes to a growing literature that examines the impact that fund managers' human capital has on their performance. A number of studies have looked at the performance effects of human capital traits such as education, on the job-experience, and work experience outside the financial sector [e.g., Golec (1996), Chevalier and Ellison (1999), Greenwood and Nagel (2009), Fang, Kempf, and Trapp (2014), Kempf, Manconi, and Spalt (2017), and Cici et al. (2018)]. Our contribution to this literature is to show that the performance of a fund manager is not only driven by the manager's accumulated human capital, but also by the quality of the match between the manager's skills and the investment style in which the manager operates.

The paper is organized as follows. In Section 2 we describe the data and present descriptive statistics. We document the impact of match finding on the performance of fund managers in Section 3 and the various ways in which fund companies respond to match finding in Section 4. Section 5 concludes.

2 Data

We obtain fund and fund company names, monthly net returns, total net assets under management, investment styles, and further fund specific information such as expense and turnover ratios from the Center for Research on Security Prices Survivorship Bias Free Mutual Fund (CRSP MF) Database. For mutual funds with different share classes, we aggregate all observations at the fund-level based on the asset value of the share classes. We limit the universe to include only actively managed, domestic U.S. equity funds, thereby excluding index, international, balanced, bond, and money market funds. To categorize funds into styles, we use the CRSP Style Code, which aggregates information from the previous Lipper, Strategic

Insight, and Wiesenberger objective codes. We categorize funds based on funds' dominant objective code from the CRSP MF database, and the seven style categories used are: Sector (EDS), Mid Cap (EDCM), Small Cap (EDCS), Micro Cap (EDCI), Growth (EDYG), Growth & Income (EDYB), and Income (EDYI).

Portfolio holdings data come from the Thomson Financial Mutual Fund Holdings database, which we merge with the CRSP mutual fund data using the MFLINKS database and with CRSP stock data using stock CUSIPS. The portfolio holdings for each fund are either of quarterly or semi-annual frequency. Our sample spans the period from 1992 through 2016.

To obtain information on managerial fund employment records, we use Morningstar Direct. We merge Morningstar Direct with CRSP MF database by CUSIPs and dates. In case of missing CUSIPs, we use a fund's share class TICKER and date combination. If TICKER is also missing, funds are manually matched by name. A manager's tenure in the mutual fund industry is determined by her first appearance in the Morningstar Direct database. For biographical information on age and schooling, we employ several data sources. Besides Morningstar Principia CDs and managers' biographical information as provided via Morningstar Direct, we search through fund filings with the SEC (e.g., forms 485APOS/485BPOS and 497 and accompanying statements of additional information), Marquis Who's Who, as well as newspaper articles. We also use the web to search on Bloomberg, LinkedIn, and through university sources such as yearbooks, alumni, and donation pages.

Regarding the variables measured at the manager level, we use the number of distinct styles that the manager has worked in ($\#Styles\,Tried$) and her industry tenure

($Industry\ Tenure$) up to each particular point in time to control for investment experience or human capital accumulated in a learning-by-doing fashion. Fund level controls include: the fund's expense ratio ($Expense\ Ratio$); portfolio turnover ratio ($Turnover\ Ratio$); flows computed as the change in net assets not attributable to fund performance and normalized by beginning of period fund assets ($Flows$); the age ($Fund\ Age$); and the total net assets ($Fund\ Size$). At the fund company level, we use the fund company total net assets ($Fund\ Company\ Size$) as a control variable.

Table I provides descriptive sample statistics. The average sample manager has been in the mutual fund industry for about seven years and has worked in roughly two styles.

Please insert Table I about here

The average fund in our sample holds \$1.5 billion in assets, has an annual portfolio turnover of 83 percent, is about 15 years old, charges an expense ratio of 1.26%, and experiences monthly flows of 0.23%. The average fund company in our sample manages \$28 billion in assets.

About one third of the sample managers return to a previously-tried style (untabulated result), after which we classify these managers as being matched. Conditional on the managers that end up being matched, the average manager tries about four different styles before arriving at her match, but this number can range between two and five (based on 10th and 90th percentiles). It also takes about six years for the average manager to reach the match. The range is between two to eleven years, suggesting that for some managers discovery of their match happens much faster and for some others much slower.[6] Interestingly, we observe very little mobility after the match occurs, with 94% of the managers staying in the same investment style for the remainder of their careers. This suggests that the return to a previously-tried style is the end of the search process and thereafter the manager remains in the position that is her match, which is as predicted by occupational match theory [e.g., Jovanovic (1979)]. This finding supports our approach of using fund managers' returns to previously-tried styles to identify points in time when matching happens.

3 Impact of Match Finding on Fund Managers' Performance

In this section, we first analyze the impact of match finding on managers' performance using a difference-in-difference setting (Section 3.1). Then we test the underlying parallel-trend assumption (Section 3.2), and rule out various alternative explanations for our findings (Section 3.3).

3.1 Main Result

To study the performance effect due to match finding, we relate the manager's performance to our key variable, $Match$, in a difference-in-differences setting:

$$Performance_{i,t} = \alpha_{i,f} + \theta_t + \omega_s + \beta \cdot Match_{i,t} + \vec{\gamma}' \vec{c}_{i,t-1} + \epsilon_{i,t}. \quad (1)$$

Manager is denoted by i, fund company by f, style by s, and time by t. $\vec{\gamma}$ is the vector of coefficients associated with fund, fund manager, and fund company level covariates described in Table I, denoted by $\vec{c}$.

[6] In Section B of the Internet Appendix, we examine determinants of match finding using a linear probability model.

We construct our main independent variable, $Match$, by identifying the point in time when a manager returns to a previously-tried style. Then, we set $Match$ equal to one for all observations from that point on and zero for all observations before. $Match$ also equals zero for all observations belonging to all other managers who have not returned to a previously-tried style.

To capture the economic effect of match finding on performance, we need to compare the fund managers' performance in the post-match period in the style where they were matched with their performance in the pre-match period in other styles.[7] Our difference-in-differences Model (1) then compares the performance change of matched managers with performance changes of unmatched managers in the same fund company. As most of our analysis is at the manager-year level, to compute the performance of a manager in a given year, we aggregate the annual performance at the fund level. We employ four measures of performance at the fund level that are all based on net returns: raw return (Return); style-adjusted return (Style Return); Carhart (1997)-4-factor alpha (Alpha4); and Fama and French (2015)-5-factor alpha, augmented with the momentum factor (Alpha6) as used by Barillas and Shanken (2018), among others. To measure style-adjusted returns in period t, we subtract from the return of a given fund the mean return over the same period of all funds belonging to the same investment style. We compute alphas as the intercept of monthly regressions of a manager's monthly excess return over the risk free rate on a linear combination of the respective factors

[7] To capture this effect most precisely, for the matched managers we excluded funds with the same style as their matched style in the pre-match period and funds with styles that were different from the matched style in the post-match period. Even if we do not apply this restriction, our results remain both statistically and economically significant.

corresponding to each model.[8] All performance measures are annualized by compounding the twelve monthly returns corresponding to each calendar year.

We use the control variables introduced in Table I which are measured at the fund manager, fund, and fund company level, all lagged by one year. We use fund and fund company controls in addition to manager controls to capture the impact of the work environment on the performance of the fund manager. We aggregate all fund-specific performance and control variables at the manager level. To do so, we follow previous research [e.g., Ibert et al. (2018)] and divide a fund's total net asset value equally among all managers managing that fund to obtain per-manager assets. If a fund manager manages funds in multiple styles in a given year, we set her manager-level style for that year equal to the style of the majority of her assets under management. We then build a per-manager asset weighted sum of fund-level variables to obtain variables at the manager level. For $Fund\ Age$, $Fund\ Size$, and $Fund\ Company\ Size$ we use natural logarithms.

For all specifications, we include time fixed effects θ_t to account for common time variant factors, style fixed effects ω_s to control for commonalities within investment styles, and manager-by-fund company fixed effects, denoted by $\alpha_{i,f}$, to control for time-invariant unobserved manager characteristics and also for the endogenous selection of managers to fund companies. Given that our panel is characterized by a large number of individuals ($N = 8{,}647$ managers) but a small number of years ($T = 25$ years), we cluster standard errors at the manager level.

[8] We obtain monthly returns on US-T-bills and the factor mimicking portfolios from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Please insert Table II about here

Results are reported in Table II. The coefficients of our main variable, $Match$, are positive and statistically significant at the 1% level for all performance measures. Their magnitude also suggests a significant economic effect. For managers who reach their match, the subsequent performance improvement is 139 to 201 basis points per year relative to other fund managers who work in the same fund company but have not reached their match. This evidence suggests that finding the match of fund managers increases their performance significantly.

3.2 Parallel Trends Assessment and Impulse-Response Analysis

In Table III we provide a test of the identifying assumption for the diff-in-diff analysis that the managers that return to a previously-tried style and the control group exhibit parallel trends before the match takes place. Specifically, in the first column corresponding to each performance measure, we augment Model (1) with three indicator variables that identify the matched managers in each of the three years ($Pre1$ – $Pre3$) prior to their match happening. Results reported in Table III and corroborated visually in Figure 1 show that none of the variables $Pre1$, $Pre2$, or $Pre3$ is significantly different from zero, i.e., the performances of the two groups of managers show parallel trends prior to the match.

Please insert Table III about here

Please insert Figure I about here

We also examine the time pattern of performance improvement following the managers' matches. To do so, in the second column corresponding to each performance measure in Table III, we replace $Match$ with three indicator variables that identify matched managers in three periods subsequent to the point in time when the match is found, i.e., the first year, second year, and all years from the third year onwards.

Results show that the managers' performance starts improving right after the discovery of the match and this higher level of performance remains significant in all sub-periods that follow. This supports the view that arriving at their match provides fund managers with an immediate and long-lasting performance advantage relative to their unmatched colleagues.

3.3 Alternative Explanations

In this section we consider alternative explanations for the observed performance improvement of fund managers following matching. In Section 3.3.1, we start by ruling out the possibility that the performance improvement results from simply assigning these managers to funds with better performance. Then we proceed by ruling out that managers' experience (Section 3.3.2 and 3.3.3) and potentially unobservable fund mangers' traits (Section 3.3.4) could explain the performance improvement we document after match finding.

3.3.1 Does Matching Coincide with Assignment to Better Funds?

The performance improvement of fund managers after match finding might simply result from these managers being assigned to funds with better performance. For example, fund managers might run lower quality funds—which are used for training managers—at the beginning of their career, and eventually managers with proven superior investment skill might get assigned to funds of higher quality. The assignments motivated by this consideration are orthogonal to match finding, yet they could create the semblance of a performance improvement for the manager.

To rule this possibility out, we examine whether the performance of funds where managers achieve their style match improves after match finding takes place. More specifically, we estimate the diff-in-diff Model (1) at the fund level and include fund and time fixed effects so that we can compare the performance difference of the funds that were joined by a matched manager before and after the match relative to other funds. Our main independent variable, $Match$, is constructed as before but at the fund level. We identify the point in time when a manager returns to a previously-tried style and set $Match$ equal to one for all fund-year observations corresponding to that manager from that point on and zero for all observations before. We also set $Match$ equal to zero to all observations that correspond to control funds. To minimize any confounding effects related to changes in how fund companies allocate resources across funds, we restrict the analysis to one year before and after the match. We also include style fixed effects to control for fund investment styles.

Please insert Table IV about here

Results from the diff-in-diff regression at the fund level based on different control groups are reported in Panels A through D of Table IV. We start with the most general control group that includes all other funds in Panel A. In Panel B we restrict the control group to funds to which a new manager was assigned but that did not result in match finding; constructing the control group this way helps us isolate performance effects due to match finding while controlling for the general effect of capital allocation to managers with better investment skills as documented by Berk, van Binsbergen, and Liu (2017). In Panel C, to ensure greater comparability across treated and untreated funds, we further restrict the control fund set by assigning each treated fund to an untreated fund in the same year in the same style from the control set of Panel B, based on propensity score matching that utilizes the fund control variables of Table I as matching variables. Finally, in Panel D we construct the sample such that we can rule out that the fund's performance improvement resulted from replacing a poorly-performing manager. To do so, we first restrict both treated and control funds to only funds that did not face a change in team structure such that an existing manager was replaced, except for exactly one manager being added. Then, we conduct propensity score matching for the control funds as in Panel C.

Results from Table IV show that the coefficients on $Match$ are statistically and economically significant in all panels. These results suggest that funds that are joined by fund managers that find their style match experience performance in the subsequent year that is 98 to 202 bps points higher than in the previous year, relative to the performance change experienced by funds in the control group.[9] This confirms that the funds where managers find their style match experience performance improvement due to style match finding and rule out that the productivity improvement we documented for matched managers in Section 3.1 arises simply due to these managers being assigned to higher quality funds.

3.3.2 General Investment Experience Differences

Although our regressions include the manager's industry tenure and the number of styles tried by the manager to control for general investment experience, it is still possible that

[9] This result holds true no matter whether the style matched manager joins a fund he managed in the past or a different fund in that style segment. We find no statistically significant difference in the performance effect between these two cases, suggesting that style specific skills rather than fund specific skills explain our results.

general investment experience could affect the dependent variable in a non-linear way and thus impact our findings.

To rule this possibility out, we proceed as follows. For each fund manager who has reached her match, we identify an unmatched control manager, i.e., another manager from the same fund company that has comparable investment experience. We use three separate approaches to identify control managers. In the first approach, for each manager that reached her match we identify a control manager that is most similar with respect to industry tenure. In the second approach, we identify a control manager that has tried the same styles as the matched manager. Finally, for the last approach we require the control manager to be the most similar with respect to industry tenure among all managers that have tried the same styles. The resulting pairs from these three different approaches constitute the observations on which we estimate Model (1).

Please insert Table V about here

Panels A, B, and C of Table V report results for the various sets of control managers. Constructing the control groups in the manner described above is restrictive, resulting in much smaller samples ranging from about 7,500 observations in Panel A to about 5,100 observations in Panel C, relative to a sample of more than 29 thousand observations in Table II. Despite the smaller samples used in Table V, the coefficients on the $Match$ variable, which range from 101 to 200 basis points, exhibit similar levels of economic and statistical significance as those from Table II. Thus, our main finding that managerial performance improves due to match finding continues to hold even after we control for cross-sectional differences in general investment experience in a more rigorous way.

3.3.3 Style-Specific Experience Differences

In the previous section, we ruled out the concern that our results might be driven by different general investment experience for the matched managers in the presence of a non-linear performance effect of experience. However, a similar concern might be present with respect to style-specific investment experience.

To rule that out, we modify the control groups used in the various panels of Table V. For each of the three control groups in Table V, we impose an additional condition. Specifically, we require that each control manager has at least as much experience as the corresponding matched manager in the style where and at the time when matching happened.

Please insert Table VI about here

Results are reported in Table VI. Panels A, B, and C mirror those of Table V with the added restriction for the control managers to have at least as much style-specific experience as the matched managers. As expected, constructing the control groups in the manner described above reduces the number of observations further relative to Table V. Across the three panels the number of observations now ranges from 2,782 to 3,020.

The results of Table VI continue to support the hypothesis that matching leads to performance improvement. The coefficients on the $Match$ variable in all three panels are still significantly positive and economically important, ranging from 89 to 224 basis points. Thus, our main finding that match finding improves managerial performance continues to hold even after we control for style-specific experience in addition to controlling for general investment experience.

As mentioned in Section 2, there is very little mobility after managers are matched, with 94% of them staying in the same investment style for the remainder of their careers. This raises the possibility that in the post-match period these managers gain more style-specific investment experience by virtue of continuing to operate in the same style for a longer period of time than the managers in the control group. This style-specific post-match experience could still contribute to the performance effect documented in Table VI. To account for this possibility, we modify the analysis of Table VI by limiting the post-match period to only one year. Doing so avoids giving the matched manager credit for any performance improvements that result in the later years, which could be driven by style-specific investment experience gained in the post-match period.

Please insert Table VII about here

Results from these modified tests are reported in Table VII. The performance improvement after managers are matched relative to the control group continues to be significant and has about the same size as in Table VI. This finding helps rule out the concern that longer style-specific experience in the post-match period for the matched managers might drive our main result.

3.3.4 Unobservable Characteristics of Matched Managers

To account for the possibility that matched managers follow a different career path that is perhaps driven by unobservable traits, we estimate Model (1) only for the fund managers that were matched, excluding managers that were never matched. This ensures that for each matched manager, the control group includes only managers that have not reached their match yet but do so at a later point in time. Results reported in Panel A of Table VIII show that, even with this more homogenous set of control managers, match finding leads to statistically and economically significant improvement in managers' performance.

Please insert Table VIII about here

In another test, we control for unobservable characteristics of matched managers in an even stricter way. In particular, we exploit instances when a given manager manages multiple styles at the same time and compare her performance within the same year in styles where she is or will eventually be matched to styles where she will never be matched. Since fund managers typically manage funds in one style only at each point in time, we are only able to identify 146 managers that satisfy this condition. However, even based on this restricted sample, we find that managers perform significantly better in the style where they are or will be matched as documented in Panel B of Table VIII. This provides further support for the notion that managers are better at certain styles and matching them to those styles pays off.

In sum, our main finding that managerial performance improves after a manager reaches her style match continues to hold even after we account for the possibility of matched managers simply being assigned to better performing funds or account for the role of general or style-specific experience and for unobserved manager characteristics. This suggests that the performance improvement we document is indeed the result of match finding and not the result of these other factors.

4 How do Fund Companies Respond to Match Finding?

In the previous section, we documented the first way through which match finding contributes to company value, i.e., through better performance of the matched managers. In this section we examine additional ways through which match finding contributes to fund company value that have to do with how fund companies react to match discovery. In Section 4.1 we examine whether fund companies use the new information to reallocate existing capital or attract new capital to matched managers. In Section 4.2 we test whether fund companies charge higher fees in these managers' funds. In Section 4.3 we look at whether fund companies make the expertise of the matched managers available to other fund managers in the organization to benefit even more from match finding.

4.1 Allocating More Assets to Matched Managers

The simplest way in which fund companies can place more assets under the management of the matched managers is to simply reallocate existing capital towards them. This can be done by assigning additional funds or by assigning larger funds in exchange for smaller funds to the matched managers. Such reallocation of capital is sensible given that the fund company has learned that these managers are going to deliver better performance in the future, which will lead to higher revenue for the fund company both in the short and long term.

To test whether fund companies are acting in this manner, we estimate Model (1) subject to the following modification. The dependent variable is constructed for each manager-year observation as the difference in assets between the new funds assigned to a given manager and the old funds taken away from the manager in that year ($\Delta AssetNew\_Old$).

Similar to Section 3.2, we also estimate an augmented specification for each test, which includes six indicator variables that identify the matched managers in each of the three years prior to and in three periods subsequent to their match. This allows us to not only test the parallel-trends assumption underlying the difference-in-differences setting but also to see how quickly fund companies respond to match finding by reallocating capital.

Please insert Table IX about here

Results reported in Table IX show that indeed fund companies respond to match finding by assigning more assets to matched managers. Consistent with economic rationale, this reallocation happens immediately after the match is found as shown in Column (2). There is huge capital reallocation taking place in the first two years after the match. In the first year after discovery of their match, fund managers get assigned an additional $1.41 billion of assets and another $1.37 billion in the second year. The comparability of these numbers with the average sample fund size of $1.54 billion highlights the big economic magnitude of the capital reallocation. Furthermore, Column (2) shows that fund companies do not take any actions in the pre-match period that resemble their activity in the post-match period.[10] This suggests that fund companies take action to increase the share of revenue generated by their matched managers in response to learning of the match discovery of these managers, whom they now expect to deliver higher performance in the future.

Besides reallocating existing capital, fund companies can try to attract new capital to the matched managers by distributing the products managed by these managers more aggressively. To test whether fund companies are putting more distribution effort behind the funds of the matched managers, we employ three proxies for distribution effort on the part of fund companies. The first one is the 12b-1 fee, which is an annual fund fee covering marketing

[10] This lack of significance in the pre-match period also supports the parallel-trends assumption underlying our analysis.

and distribution activities ($12b-1$). A higher 12b-1 fee indicates more effort in selling the underlying mutual fund. The second and third measures are the number of share classes offered per fund ($\#Share\ Classes$) and the number of separate accounts managed by the manager ($\#Separate\ Accounts$).[11] A larger number of share classes in a fund suggests that the fund company is employing more distribution channels for the fund and a larger number of separate accounts suggests the company is targeting more institutional or wealthy retail clients.

To examine whether match finding makes fund companies distribute the funds of matched managers more aggressively, we estimate a variation of Model (1) separately for each measure of distribution effort discussed above used as a dependent variable. We aggregate each fund-level measure ($12b-1,\ \#Share\ Classes$) at the manager-year level by taking its asset-weighted average across all funds run by a given manager in a given year. Similar to Table IX, we also estimate an augmented specification for each distribution measure, which allows us to test the parallel-trends assumption and to examine when the change in distribution efforts by the fund companies in response to match finding happens and whether the distribution effect is permanent or limited to certain years.

Please insert Table X about here

The first two columns of Table X are dedicated to the specification with $12b-1$ as the dependent variable. Column (1) shows an increase in 12b-1 fees of three basis points in response to match finding. This effect is statistically significant at the one percent level and economically relevant given that the 12b-1 fee for the average sample fund is 37 basis points. Column (2) documents that the fund company increases its distribution effort right after the

[11] We obtain data on separate accounts from Morningstar Direct.

manager's match has been found and keeps this higher level of 12b-1 fees constant over time – a highly sensible strategy given that the fund company expects the matched manager to deliver a higher performance permanently.[12]

The results of the specifications with $\#Share\ Classes$ and $\#Separate\ Accounts$ as the dependent variables, reported in Columns (3) – (6) of Table X, tell a similar story: Fund companies increase the number of share classes per fund and the number of separate accounts of their matched managers. They start doing so right after discovery of the match and keep these higher numbers of share classes and separate accounts during the entire post-match period.

In sum, the results of this section provide strong evidence that fund companies respond to the match discovery of their fund managers in a highly rational manner. Consistent with pursuit of profit-maximization, they actively seek to maximize revenue from deploying their matched managers to a larger asset base and they work fairly quickly towards that goal.

4.2 Charging Higher Fees on Funds of Matched Managers

The revenue of the fund company is determined by the assets under management and the fees charged on those assets. Therefore, the fund company can increase the revenue delivered by matched managers not only by increasing their asset base (as documented in the previous section) but also by increasing the fees of their funds.

To test whether fund companies increase the fees of the funds managed by matched managers, we conduct an initial test by estimating a variation of Model (1) with fee variables

[12] This expectation is confirmed by our results in Table III.

as dependent variables. For this analysis, the dependent variables are the asset-weighted average expense ratio ($Expense\ Ratio$) and the asset-weighted average management fee ($Mgmt\ Fee$) of all funds managed by a manager in a given year. We use management fees in addition to the expense ratio because the expense ratio is made up of management fees and 12b-1 fees. The latter fees are used to support marketing of the fund and compensate brokers that help sell the fund and, thus, have less direct impact on the fund company's profitability. Similar to the previous sections, we also estimate an augmented specification for each fee measure.

Please insert Table XI about here

Results presented in Table XI indeed confirm that fund companies charge higher fees for the funds managed by matched managers in the post- vs. pre-match period in comparison to other managers from the same fund company. This effect is highly significant in both statistical and economic terms. The increase is 21 basis points for the total expense ratio and 11 basis points for the management fee. These increases are notable given that the expense ratio and management fee for the average sample are 126 and 44 basis points, respectively. Furthermore, we find that these increases happen in the first year following the match and the fees are kept at about the same higher level in the following years, suggesting that fund companies react fairly quickly in order benefit from the anticipated higher productivity of their managers.

The analysis presented above shows that fund companies are collecting higher fees from the funds managed by their matched managers in the post-match period, but it does not reveal how fund companies do it. There are two possible non-mutually exclusive strategies fund companies can pursue. They can either swap higher-fee funds for lower-fee funds under the matched managers in the post-period or they can increase fees charged by funds that these managers continue to manage in the post-match period.

To test for the first strategy, we construct dependent variables similar to Table IX. For each manager in each year of the sample period, we calculate the dependent variables as the differences in asset-weighted average expense ratio or management fee between the new funds assigned to a given manager and the old funds that she stopped managing, respectively denoted by $\Delta Expense\ Ratio_{New\_Old}$ and $\Delta Mgmt.Fee_{New\_Old}$. To test for the second strategy, the dependent variables are constructed as the asset-weighted average expense ratio or management fee of funds that the manager continues to carry over in the post-match period from before the match happened, respectively denoted as $Expense\ Ratio_{Old}$ and $Mgmt.Fee_{Old}$.

Please insert Table XII about here

Results are reported in Table XII. Columns (1) – (4) provide strong evidence that fund companies are indeed pursuing a "swapping" strategy after managers are matched whereby they replace these managers' funds with other funds that charge both higher total expense ratios (+ 34 basis points) and higher management fees (+ 13 basis points). Given that the expense ratio and management fee for the average sample fund are 126 and 44 basis points, respectively, these increases are economically large. Consistent with starting the reallocation of capital in the first year of the post-match period, Columns (2) and (4) document significant changes in expense ratios and management fees from the first year of the post-match period onwards.

There is no such effect in the pre-period supporting the view that the "swapping" strategy is caused by the match finding.

We next turn to the second strategy fund companies can use to generate higher fee income, which is by increasing the fees of funds that managers continue to manage after they have found their match. To test for this strategy, we employ $Expense\ Ratio_{Old}$ and $Mgmt.Fee_{Old}$, described above, as dependent variables. Results from these specifications are presented in Columns (5) – (8) of Table XII. They suggest that fund companies indeed respond to match finding by increasing the expense ratio and management fees of the funds that matched managers keep on managing by a significant six and four basis points, respectively, relative to other managers from the same fund company. Again, this increase is mainly happening in the first-year of the post-match period and the fees are kept at the increased level through the entire post-match period. Thus, not only are fund companies increasing their revenue by assigning the matched managers to funds that charge higher fees than the funds from which they were removed but they are also raising the fees of the funds these managers keep on managing.

4.3 Spreading the Expertise of Matched Managers to Other Managers

In the previous section we studied direct actions taken by fund companies aimed at generating higher revenue from the matched managers. Fund companies can benefit from the expertise of matched managers in yet another way by spreading their expertise to other fund managers, who can potentially use it to generate better performance in their funds. This increases the fund companies' revenue even further. Fund companies can do so by making matched managers work in teams so that a larger number of affiliated managers interact and learn from them. On top of that, fund companies might change the composition of the teams in two ways. They might increase the number of team members to let even more managers learn from the matched manager or might surround matched managers with more junior managers, who stand to benefit even more from such expertise.

We first look at whether fund companies are more likely to assign managers to teams after these managers have found their match. We model the probability that a manager is promoted to a team as a function of the variables introduced in Model (1) using a linear probability model. The dependent variable is $Team$, a binary variable that equals 1 if a fund manager operates in a team and 0 otherwise. Using $Team$ as the dependent variable, we then estimate Model (1) using the same fixed effects as before. We also estimate an augmented specification, which allows us to examine the effects for the various years of the pre- or post-match periods separately.

Please insert Table XIII about here

Results presented in Table XIII show that fund companies are indeed more likely to assign fund managers to teams after they have found their match. The coefficient on the $Match$ variable is both statistically and economically significant. It suggests that the probability of being in a team increases by 16 percentage points in response to match finding relative to other managers from the same fund company. The effect starts right after the manager has found her match and the higher likelihood remains throughout the entire post-period.

We next examine whether fund companies change the composition of fund management teams in response to match finding. In particular, we test the hypotheses that fund companies place their matched managers in larger teams and in teams with more junior managers. For this analysis, we condition on fund managers that ran at least one team-managed fund in the pre-match period.[13] Not doing so would cause the documented effects to be driven in part by managers being moved to teams after their match is found.

To assess whether fund companies pursue these actions, we modify Model (1) by introducing new dependent variables that capture the actions of the fund company discussed above. The first dependent variable measures the asset-weighted average management team size across all the team-managed funds a manager is responsible for ($Team\ Size$). The second variable, intended to capture the seniority of a manager relative to other team members, is constructed for each manager-year observation as the difference of the industry tenure of that manager and the average industry tenure of the other managers that are part of the same team ($Relative\ Seniority$).

Please insert Table XIV about here

Results are reported in Table XIV. The positive and significant coefficients on the $Match$ variable suggest that fund companies assign fund managers—after they have found their match—to larger teams and teams with more junior colleagues in comparison to other managers from the same fund company. This reallocation of managers starts happening just after the managers have found their match.[14]

In summary, our findings from this section support the notion that fund companies try to capitalize on the known expertise of the matched managers by seeking to spread their

[13] In our sample, 75% of the fund managers ran at least one team-managed fund in the pre-match period.

[14] To further support the idea that matched managers are used as trainers for more junior colleagues, we checked whether the junior colleagues are replaced after some years of learning. We indeed find support for such a rotation mechanism. The junior colleagues of the matched manager are replaced regularly by new junior colleagues so that the average age of the fellow team members of matched managers does not increase as time goes by.

capabilities widely across the organization so that other managers can acquire similar skills. In Section C of the Internet Appendix we uncover evidence that this strategy is indeed having the desired effect from the perspective of the fund company. Specifically, we document that the investment ideas of matched managers are more widely used in the organization by other company managers than the ideas of managers that are not matched.

5 Conclusion

Using the mutual fund industry as a testing laboratory and the performance a fund manager generates as a direct measure of her productivity, our paper studies the economic consequences resulting from the matching of employees' skills with jobs that best fit those skills. Our study sheds new light on the importance of matching as our methodological innovation to identify the points in time when matching actually happens allows us to directly quantify its effect on performance.

This matching process is highly important because the performance gains of fund managers after they are matched are economically significant, making this a worthwhile quest for fund companies. This effect of match finding remains robust to controlling for a number of potentially confounding factors including assignment effects, different forms of experience that the matched managers have acquired, and unobservable manager characteristics. This finding has important implications for fund companies. It suggests that by offering more opportunities for their fund managers to try different investment styles, fund companies can increase the likelihood that their portfolio managers get matched to styles that best fit their skills, and thus better utilize the human capital of their portfolio managers.

Fund companies respond rationally to the information that their managers are matched. To maximize company value, fund companies reallocate existing capital to their matched managers, direct new capital to them, and charge higher fees in the funds managed by these managers. Underscoring the importance of the private information fund companies generate during the search process, fund companies take actions to utilize the expertise of their matched managers in funds managed by other fund company managers. In particular, fund companies restructure the working arrangements of the matched managers so that other managers have the opportunity to learn from the expertise of the matched managers.

To what extent the performance improvement of matched fund managers and the additional capital fund companies make available to these managers either directly (e.g., more assets under their management) or indirectly (e.g., their expertise used by other company managers) contributes to higher efficiency in the stock market is an interesting venue for future research.

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Table I: Descriptive Statistics

This table reports statistics for our sample ranging from 1992 through 2016. It reports the mean, standard deviation (std), as well as the 10th, 50th, and 90th percentiles (p10, p50, and p90, respectively). Industry Tenure is the number of years a manager spent in the mutual fund industry. #Styles Tried is the number of styles a manager has worked for. Fund Size is given by the total net assets under management (AUM) per fund in $ millions. Turnover Ratio is the annual portfolio turnover ratio in percent. Fund Age is the age of the fund in years. Expense Ratio is the annual expense ratio in percent. Flow is the monthly percentage growth in net assets under management unrelated to fund performance. Fund Company Size is the fund company AUM in $ millions.

	mean	std	p10	p50	p90
Industry Tenure [years]	7.13	6.22	0.99	5.43	15.76
#Styles Tried	1.76	0.99	1.00	1.00	5.00
Fund Size [$ million]	1,541	4,433	21	315	3,534
Turnover Ratio [%/year]	82.56	111.68	18.47	61.00	156.10
Fund Age [years]	14.74	12.79	2.99	11.45	30.06
Expense Ratio [%/year]	1.26	0.77	0.80	1.19	1.79
Flow [%/month]	0.23	1.55	-0.21	-0.01	0.62
Fund Company Size [$ million]	28,082	70,744	83	6,635	59,102

Table II: Performance Change after Match Discovery

This table presents results from pooled OLS regressions that relate performance measures with changes in the match status of a manager. The analysis is done at the manager and year level. To capture the economic effect of match finding more precisely, for a given matched manager in the pre-match period we excluded funds with the same style as her matched style and excluded funds in the post-match period with styles that were different from her matched style. To compute the performance of a manager, we aggregate her performance at the fund level. The performance measures at the fund level include: The raw return (Return), style-adjusted return (Style Return), Carhart (1997) 4-factor alpha (Alpha4), and Fama and French (2015)-5-factor alpha, augmented with the momentum Factor [Barillas and Shanken (2018)] (Alpha6). To measure style-adjusted returns in period t, we subtract from the return of a given fund the mean raw return over the same period of all funds belonging to the same investment objective. We compute alphas as the intercept of monthly regressions of a manager's monthly excess return over the risk free rate on a linear combination of the respective factors corresponding to each model. All performance measures are annualized by compounding the twelve monthly returns corresponding to each calendar year. Our main independent variable is Match, constructed as described in Section 3.1. Control variables at the manager, fund, and fund company level are constructed as in Table I. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Match	0.0201***	0.0193***	0.0139***	0.0170***
	(3.97)	(4.22)	(3.81)	(3.73)
#Styles Tried	-0.0023	-0.0015	-0.0009	-0.0015
	(-0.92)	(-0.65)	(-0.44)	(-0.68)
Industry Tenure	-0.0041**	-0.0059***	-0.0036***	-0.0018
	(-2.37)	(-3.80)	(-2.63)	(-1.07)
Fund Age	0.0306***	0.0257***	0.0118***	0.0074*
	(8.10)	(7.47)	(3.84)	(1.95)
Fund Size	-0.0318***	-0.0283***	-0.0177***	-0.0163***
	(-21.39)	(-20.29)	(-14.17)	(-11.43)
Expense Ratio	0.1245	0.3614	1.4902***	0.1316
	(0.33)	(0.64)	(2.89)	(0.19)
Turnover Ratio	-0.0027**	-0.0024**	-0.0003	0.0010
	(-2.13)	(-1.98)	(-0.35)	(0.69)
Flow	-0.0066***	-0.0053***	-0.0041***	-0.0050***
	(-6.59)	(-6.09)	(-4.15)	(-4.11)
Fund Company Size	-0.0046**	-0.0039**	0.0003	-0.0022
	(-2.49)	(-2.33)	(0.17)	(-1.29)

Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	29,688	29,688	29,512	29,512
Adjusted R^2	0.739	0.068	0.116	0.122

Table III: Parallel Trends Assessment Impulse-Response Analysis

In this table, we modify our main analysis of Table II in order to test for parallel trends and examine the time pattern of performance effects. In the first column corresponding to each performance measure in Table III, we augment Model (1) with three indicator variables that identify managers that attained match discovery—in each of the prior three years (Pre3 – Pre1). In the second column corresponding to each performance measure, we replace Match with three indicator variables that identify how the performance of managers that have reached their match changes in three subsequent periods, i.e., the first year (Post1), second year (Post2), and all years from the third year onwards subsequent to match discovery (Post3+). All dependent variables and the other independent variables are like in Table II. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table III (continued): Parallel Trends Assessment Impulse-Response Analysis

	Return		Style-Return		Alpha4		Alpha6	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Pre3	0.0033	0.0033	0.0000	0.0000	-0.0034	-0.0034	0.0056	0.0057
	(0.50)	(0.50)	(0.00)	(0.01)	(-0.63)	(-0.63)	(0.88)	(0.88)
Pre2	-0.0084	-0.0082	-0.0013	-0.0011	0.0020	0.0020	-0.0007	-0.0007
	(-1.20)	(-1.18)	(-0.18)	(-0.16)	(0.40)	(0.39)	(-0.11)	(-0.10)
Pre1	-0.0024	-0.0023	-0.0010	-0.0009	-0.0001	-0.0002	-0.0031	-0.0030
	(-0.40)	(-0.38)	(-0.18)	(-0.16)	(-0.03)	(-0.04)	(-0.64)	(-0.63)
Match	0.0193***		0.0190***		0.0139***		0.0168***	
	(3.84)		(4.16)		(3.76)		(3.54)	
Post1		0.0161**		0.0160***		0.0140***		0.0142**
		(2.55)		(2.91)		(2.85)		(2.35)
Post2		0.0142**		0.0163***		0.0165***		0.0167***
		(2.22)		(2.58)		(3.15)		(2.61)
Post3+		0.0235***		0.0221***		0.0128***		0.0185***
		(4.05)		(4.23)		(2.87)		(3.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,688	29,688	29,688	29,688	29,512	29,512	29,512	29,512
Adjusted R^2	0.739	0.739	0.068	0.068	0.116	0.116	0.122	0.122

Table IV: Fund Performance Change after Match Discovery

This table presents results from pooled OLS regressions that relate fund performance measures with changes in the match status of a manager. The analysis is done at the fund and year level. Our performance measures include: The raw return (Return), style-adjusted return (Style Return), Carhart (1997) 4-factor alpha (Alpha4), and Fama and French (2015)-5-factor alpha, augmented with the momentum Factor [Barillas and Shanken (2018)] (Alpha6). To measure style-adjusted returns in period t, we subtract from the return of a given fund the mean raw return over the same period of all funds belonging to the same investment objective. We compute alphas as the intercept of monthly regressions of a fund's monthly excess return over the risk free rate on a linear combination of the respective factors corresponding to each model. All performance measures are annualized by compounding the twelve monthly returns corresponding to each calendar year. Our main independent variable, *Match*, is constructed as before but at the fund level. We identify the point in time when a manager returns to a previously-tried style and set Match equal to one for all fund-year observations corresponding to that manager from that point on and zero for all observations before. We only consider the performance one year before the match and the performance in the year after the match. Control variables at the manager, fund, and fund company level are constructed as in Table I. In Panel A, control funds contain the complete set of other funds. In Panel B, funds in the control group are restricted to funds to which a new manager was assigned but that did not result in match finding. For Panel C, we restrict the control funds from Panel B further by assigning each treated fund to an untreated fund in the same year in the same style, based on propensity score matching utilizing the fund control variables of Table I as matching variables. Finally, in Panel D, before conducting propensity score matching, we restrict both treated and control funds to such kind of funds which did not face a change in team structure, except for exactly one manager being added. Regressions are run with time, style, and fund-fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table IV (continued): Fund Performance Change after Match Discovery

Panel A: Control Set Includes all Other Funds

	(1) Return	(2) Style Return	(3) Alpha4	(4) Alpha6
Match	0.0195**	0.0179***	0.0124***	0.0135***
	(2.16)	(2.85)	(3.87)	(3.16)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	13,848	13,848	13,479	13,479
Adjusted R^2	0.669	-0.043	0.003	-0.005

Panel B: Control Set Includes all Other Funds with Managerial Turnover

	(1) Return	(2) Style Return	(3) Alpha4	(4) Alpha6
Match	0.0179***	0.0183***	0.0098***	0.0131***
	(3.74)	(3.03)	(5.86)	(4.26)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	5,318	5,318	5,184	5,184
Adjusted R^2	0.678	-0.053	0.013	0.016

Panel C: Control Set Includes Funds from Panel B Matched on Propensity Scores

	(1) Return	(2) Style Return	(3) Alpha4	(4) Alpha6
Match	0.0182***	0.0177***	0.0107***	0.0137***
	(3.49)	(3.70)	(4.64)	(3.31)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	2,598	2,598	2,512	2,512
Adjusted R^2	0.767	0.002	-0.002	-0.018

Table IV (continued): Fund Performance Change after Match Discovery

Panel D: Control Set Includes Funds with no Manager Replacement Matched on Propensity Scores

	(1) Return	(2) Style Return	(3) Alpha4	(4) Alpha6
Match	0.0183***	0.0195***	0.0093***	0.0096***
	(2.78)	(3.21)	(2.88)	(2.72)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	761	761	746	746
Adjusted R^2	0.809	0.051	0.059	0.033

Table V: Control Managers with Similar General Investment Experience

In this table, we repeat our main analysis of Table II using a subsample of managers that found their style match (treated managers) and a control group of managers that did not find their match (untreated managers). For each fund manager who has reached her match, we identify a control manager, i.e., another manager from the same fund company that prior to the match has the closest propensity score with respect to total fund industry tenure (Panel A), has tried the same styles (Panel B) or has both the closest propensity score with respect to total fund industry tenure and has tried the same styles (Panel C). The construction of all dependent and independent variables is described in Table II. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Match on Industry Tenure				
	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Match	0.0200***	0.0191***	0.0109***	0.0133***
	(3.94)	(4.22)	(2.98)	(2.84)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	7,606	7,606	7,562	7,562
Adjusted R^2	0.751	0.054	0.113	0.143

Panel B: Match on Same Styles Tried				
Match	0.0196***	0.0183***	0.0102***	0.0119**
	(3.82)	(3.94)	(2.74)	(2.53)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	6,076	6,076	6,046	6,046
Adjusted R^2	0.754	0.046	0.125	0.125

Panel C: Match on Industry Tenure and Same Styles Tried				
Match	0.0200***	0.0192***	0.0101***	0.0141***
	(3.87)	(4.12)	(2.85)	(2.98)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	5,167	5,167	5,139	5,139
Adjusted R^2	0.766	0.047	0.145	0.152

Table VI: Control Managers with Similar Style-Specific Investment Experience

In this table, we repeat our main analysis of Table II using a subsample of managers that found their style match (treated managers) and a control group of managers that did not find their match (untreated managers). For each fund manager who has reached her match, we identify a control manager, i.e., another manager from the same fund company that in the pre-match period has spent at least the same amount of time as the matched manager in the match style and has the closest propensity score with respect to total fund industry tenure (Panel A), has tried the same styles (Panel B) or has both the closest propensity score with respect to total fund industry tenure and has tried the same styles (Panel C). The construction of all dependent and independent variables is described in Table II. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Match on Industry Tenure

	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Match	0.0195***	0.0212***	0.0099**	0.0160***
	(3.66)	(4.18)	(2.46)	(3.15)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	3,020	3,020	2,986	2,986
Adjusted R^2	0.769	0.062	0.210	0.161

Panel B: Match on Same Styles Tried

	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Match	0.0190***	0.0224***	0.0100**	0.0160***
	(3.50)	(4.29)	(2.44)	(3.08)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	2,918	2,918	2,890	2,890
Adjusted R^2	0.778	0.061	0.231	0.146

Panel C: Match on Industry Tenure and Same Styles Tried

	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Match	0.0184***	0.0219***	0.0089**	0.0156***
	(3.33)	(4.14)	(2.08)	(2.89)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	2,811	2,811	2,782	2,782
Adjusted R^2	0.774	0.056	0.215	0.146

Table VII: Control Managers with Similar Style-Specific Investment Experience and Using Shorter Post Period

This table replicates the analysis of Table VI with the added restriction that we include only one year in the post-match period. The control managers are selected as in Table VI and the construction of all dependent and independent variables is described in Table II. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Match on Industry Tenure				
	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Match	0.0226***	0.0260***	0.0168***	0.0262***
	(2.99)	(3.55)	(2.84)	(3.76)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	2,121	2,121	2,100	2,100
Adjusted R^2	0.745	0.066	0.204	0.169

Panel B: Match on Same Styles Tried				
Match	0.0210***	0.0266***	0.0157***	0.0251***
	(2.75)	(3.56)	(2.67)	(3.57)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	2,051	2,051	2,033	2,033
Adjusted R^2	0.758	0.063	0.234	0.153

Panel C: Match on Industry Tenure and Same Styles Tried				
Match	0.0208***	0.0264***	0.0147**	0.0255***
	(2.62)	(3.45)	(2.38)	(3.42)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	1,944	1,944	1,924	1,924
Adjusted R^2	0.751	0.055	0.212	0.150

Table VIII: Unobservable Characteristics of Managers that Reach their Match

Panel A of this table replicates the analysis of Table II using only the subset of managers that find their match. All variables and fixed effects (FE) are as in Table II. Panel B presents results from pooled OLS regressions that consider only manager-year observations where the managers simultaneously work in a style where they are or will be matched and in other styles where they are never matched in the future. All performance measures and control variables at the fund level are constructed as in Table II. In Panel A, regressions are run with time, style, and manager-by-fund company fixed effects, whereas in Panel B they are run with manager-by-time fixed effects. In both panels, t-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Replication of Table II based on the Subset of Matched Managers

	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Match	0.0257***	0.0241***	0.0218***	0.0329***
	(4.46)	(4.58)	(5.57)	(6.87)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	5,210	5,210	5,161	5,161
Adjusted R^2	0.759	0.060	0.226	0.149

Panel B: Within-Manager Comparisons

	(1) Return	(2) Style Return	(3) Alpha4	(4) Alpha6
Matched Style	0.0115**	0.0121***	0.0134***	0.0254***
	(2.43)	(2.82)	(4.75)	(7.66)
Fund Age	-0.0030	-0.0041	-0.0065*	-0.0009
	(-0.49)	(-0.85)	(-1.75)	(-0.18)
Fund Size	0.0003	0.0001	0.0016	0.0003
	(0.14)	(0.03)	(1.05)	(0.16)
Expense Ratio	2.1012	0.3602	0.4745	1.3247
	(1.06)	(0.25)	(0.54)	(1.28)
Turnover Ratio	0.0067	-0.0023	0.0022	-0.0027
	(1.11)	(-0.47)	(0.56)	(-0.43)
Flow	0.0055***	0.0085***	-0.0009**	0.0013**
	(9.06)	(13.90)	(-2.42)	(2.14)
Manager×Time FE	Yes	Yes	Yes	Yes
Observations	946	946	922	922
Adjusted R^2	0.900	0.494	0.550	0.462

Table IX: More Assets under Management after Match Discovery

This table presents results from pooled OLS regressions that relate changes in assets under management (AUM) that result from capital reallocation to funds with changes in the match status of a manager. The analysis is done at the manager and year level. The dependent variable, Δ AssetNew_Old, is constructed for each manager-year observation as the difference in assets between the new funds assigned to a given manager and the old funds taken away from the manager in that year. Our main independent variables and controls are defined as in Table III. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	$\Delta\ Asset_{New\_Old}$	
	(1)	(2)
Pre3		-69.6790
		(-0.37)
Pre2		199.7605
		(1.35)
Pre1		382.6840
		(1.37)
Match	744.4323***	
	(2.67)	
Post1		1413.3616***
		(3.13)
Post2		1371.6616**
		(2.23)
Post3+		304.7836
		(1.62)
Controls	Yes	Yes
Time FE	Yes	Yes
Style FE	Yes	Yes
Manager × Fund Company FE	Yes	Yes
Observations	1,455	1,455
Adjusted R^2	0.227	0.227

Table X: Distribution Efforts after Match Discovery

This table presents results from pooled OLS regressions that relate 12b-1 fees [Columns (1) and (2)], the average number of share classes [Columns (3) and (4)], and the number of separate accounts [Column (5) and (6)] with changes in the match status of a manager. The analysis is done at the manager and year level. Our main independent variables and controls are defined as in Table III. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	12b-1 Fees		# Share Classes		# Separate Accounts	
	(1)	(2)	(3)	(4)	(5)	(6)
Pre3		-0.0000		0.0717		0.1451
		(-0.00)		(1.19)		(0.92)
Pre2		-0.0000		-0.0072		0.1665
		(-0.52)		(-0.15)		(1.17)
Pre1		-0.0000		0.0364		0.2025
		(-0.63)		(0.88)		(1.04)
Match	0.0003***		0.2442***		0.2160***	
	(3.57)		(3.68)		(3.08)	
					0.2160***	
Post1		0.0003***		0.2587***		0.2168***
		(3.15)		(4.23)		(3.36)
Post2		0.0003***		0.2279***		0.2147***
		(2.90)		(3.75)		(2.79)
Post3+		0.0003***		0.2544***		0.1979**
		(3.19)		(2.82)		(2.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,1244	2,1244	29,152	29,152	29,375	29,375
Adjusted R^2	0.826	0.826	0.863	0.863	0.985	0.985

Table XI: Fund Fees after Match Discovery

This table presents results from pooled OLS regressions that relate total expense ratio [Columns (1) and (2)] and management fee [Columns (3) and (4)] with changes in the match status of a manager. The analysis is done at the manager and year level. Our main independent variables and controls are defined as in Table III. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Expense Ratio		Management Fee	
	(1)	(2)	(3)	(4)
Pre3		0.0007		-0.0004
		(1.11)		(-1.39)
Pre2		-0.0009		0.0004
		(-1.36)		(1.49)
Pre1		-0.0001		0.0001
		(-0.15)		(0.60)
Match	0.0021***		0.0011***	
	(4.09)		(6.32)	
Post1		0.0025***		0.0008***
		(4.58)		(4.05)
Post2		0.0019**		0.0008***
		(2.37)		(3.85)
Post3+		0.0018**		0.0009***
		(2.47)		(3.97)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	28,708	28,708	25,232	25,232
Adjusted R^2	0.896	0.896	0.775	0.775

Table XII: Fund Fees after Match Discovery – Fund Reassignments and Remaining Funds

This table presents results from pooled OLS regressions that relate different fee measures with changes in the match status of the manager. The analysis is done at the manager and year level. In Columns (1) – (4), for each manager in each year of the sample period, we calculate the dependent variables as the differences in asset-weighted average expense ratio or management fee between the new funds assigned to a given manager and the old funds that she stopped managing. In Columns (5) – (8), the dependent variables are constructed as the asset-weighted average expense ratio or management fee of funds that the manager continues to carry over in the post-match period from before the match happened. Our main independent variables and controls are defined as in Table III. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table XII (continued): Fund Fees after Match Discovery – Fund Reassignments and Remaining Funds

	ΔExpense Ratio$_{New_Old}$		ΔManagement Fee$_{New_Old}$		Expense Ratio$_{Old}$		Management Fee$_{Old}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre3		-0.0004		-0.0000		0.0001		-0.0002
		(-0.26)		(-0.06)		(0.81)		(-1.26)
Pre2		0.0000		0.0044		-0.0003		0.0002
		(0.01)		(1.62)		(-1.55)		(1.48)
Pre1		-0.0012		-0.0061		-0.0002		0.0000
		(-0.81)		(-1.25)		(-1.07)		(0.39)
Match	0.0034***		0.0013**		0.0006***		0.0004***	
	(2.87)		(2.16)		(3.68)		(5.35)	
Post1		0.0058***		0.0037***		0.0007***		0.0003***
		(2.80)		(2.77)		(3.76)		(3.07)
Post2		0.0044*		0.0021***		0.0005**		0.0003***
		(1.91)		(2.74)		(2.08)		(3.40)
Post3+		0.0027*		0.0012*		0.0006***		0.0004***
		(1.86)		(1.84)		(2.76)		(3.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,335	1,335	976	976	28,444	28,444	25,027	25,027
Adjusted R^2	0.263	0.263	0.506	0.506	0.896	0.896	0.775	0.774

Table XIII: Team Assignment after Match Discovery

This table presents results from pooled OLS regressions that relate the likelihood of operating in teams with changes in the match status of a manager. The analysis is done at the manager and year level. Our main independent variable is Match, constructed as described in Section 4.1. Control variables at the manager, fund, and fund company level are constructed as in Table II. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Team	
	(1)	(2)
Pre3		-0.0543
		(-1.14)
Pre2		-0.0102
		(-0.23)
Pre1		0.0178
		(0.52)
Match	0.1640***	
	(4.33)	
Post1		0.1757***
		(3.24)
Post2		0.1115**
		(2.54)
Post3+		0.2007***
		(4.60)
Controls	Yes	Yes
Time FE	Yes	Yes
Style FE	Yes	Yes
Manager × Fund Company FE	Yes	Yes
Observations	28,708	28,708
Adjusted R^2	0.896	0.896

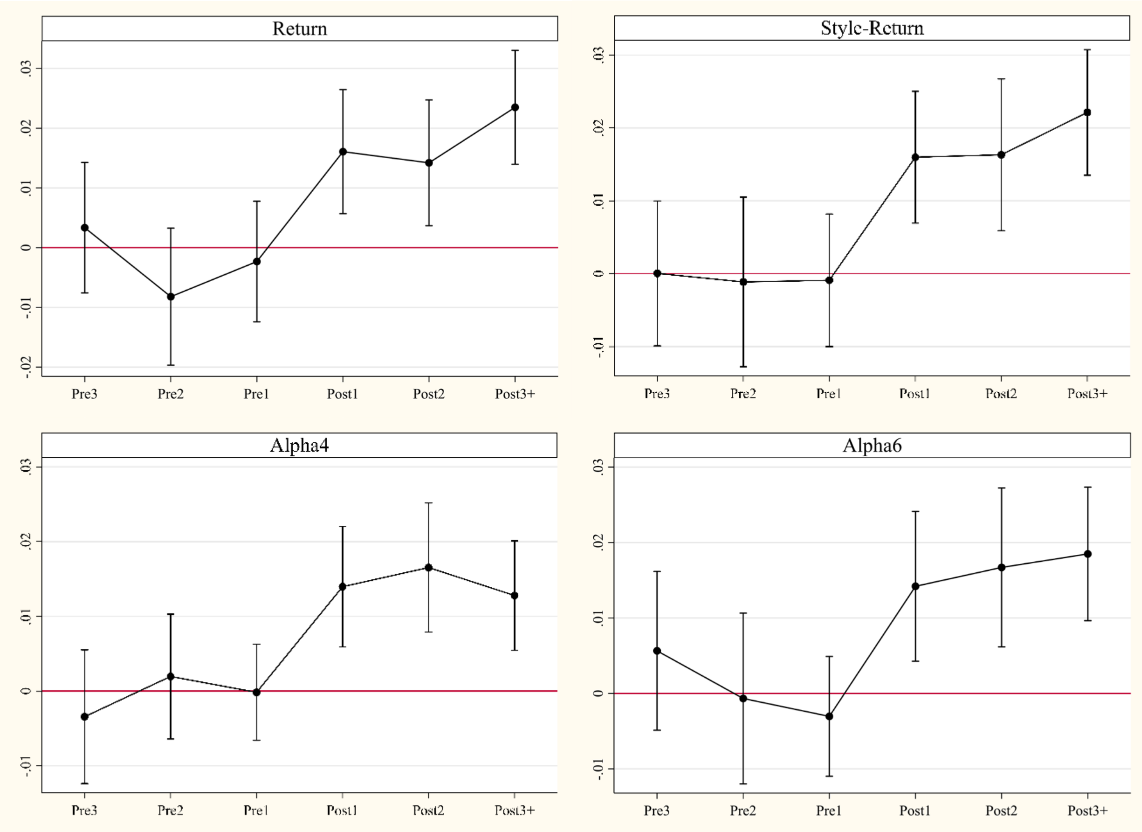
Table XIV: Dissemination of Expertise after Match Discovery

This table presents results from pooled OLS regressions that relate team size [Columns (1) and (2)] and Relative Seniority [Columns (3) and (4)] with changes in the match status of a manager. The analysis is done at the manager and year level. In Columns (1) and (2), the dependent variable measures the asset-weighted average management team size across all the team-managed funds a manager is responsible for. In Column (3) and (4) the dependent variable is constructed for each manager-year observation as the difference of the industry tenure of that manager and the average industry tenure of the other managers that are part of the same team. Our main independent variable is Match, constructed as described in Section 4.1. Control variables at the manager, fund, and fund company level are constructed as in Table II. Regressions are run with time, style, and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Team Size		Relative Seniority	
	(1)	(2)	(3)	(4)
Pre3		0.1244		-0.1723
		(0.88)		(-1.56)
Pre2		0.0296		-0.0296
		(0.33)		(-0.22)
Pre1		0.0095		0.0785
		(0.11)		(0.79)
Match	0.4307***		1.3243***	
	(4.59)		(5.80)	
Post1		0.4360***		0.5986***
		(5.15)		(3.13)
Post2		0.4113***		1.0384***
		(3.11)		(4.63)
Post3+		0.3960***		1.3291***
		(3.37)		(4.50)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	27,083	27,083	27,830	27,830
Adjusted R^2	0.865	0.865	0.862	0.862

Figure I: Parallel Trends Assessment and Persistence of Performance

In this figure, we plot the regression coefficients from Table III, along with their 95%-confidence interval error bands.



Internet Appendix for

"Finding your calling: Matching skills with jobs in the mutual fund industry"

Appendix A: Traditional Tests of Occupational Match Theory

The key empirical predictions from occupational match theory are that after employees find their match, they (i) exhibit greater productivity and (ii) are less likely to change jobs. Using tenure as a proxy for the likelihood of employees having reached their match and wages as a proxy for productivity, previous research has provided evidence consistent with the above hypotheses [see e.g., Kambourov and Manovskii (2009)]. To confirm that our mutual fund setting is not that different from other settings used in the previous literature, we check whether we find similar results in our sample when we adopt this approach but use the performance of a fund manager rather than wage as a more direct measure of productivity.

To test the first hypothesis, we relate the manager's performance to $Tenure$, in a panel-regression at the manager-year level:

$$Performance_{i,t} = \alpha_{i,f} + \theta_t + \omega_s + \beta \cdot Tenure_{i,t} + \vec{\gamma}'\vec{c}_{i,t-1} + \epsilon_{i,t}. \qquad \text{(A.1.)}$$

$Tenure$ is computed as the natural logarithm of one plus the years a given manager has been in a given investment style. All performance measures, controls, and fixed effects are as in Model (1) of the main text.

Please insert Table IA.1 about here

Results are reported in Panel A of Table IA.1 of this internet appendix. They provide strong support for the hypothesis that a manager generates better performance as her tenure increases. The coefficients on $Tenure$ are statistically significant in all specifications at a significance level of 5% or higher. They are also economically significant: A one-standard deviation increase in $Tenure$ is associated with a performance gain of up to 92 basis points.

The evidence that managers who are more likely to have achieved their match operate at a higher level of productivity confirms findings from previous research that uses wages as a measure of productivity.

To test the second hypothesis, we relate the likelihood that a fund manager changes her job type to $Tenure$ using a linear probability model:

$$Switch_{i,t} = \alpha_{i,f} + \theta_t + \omega_s + \beta \cdot Tenure_{i,t} + \vec{\gamma}'\vec{c}_{i,t-1} + \epsilon_{i,t}. \quad \text{(A.2.)}$$

$Switch$ is an indicator variable that equals 1 for a given manager that moved to another investment style in year t and 0 otherwise. The controls and fixed effects are the same as in Model (1) of the main text.

Results reported in Panel B of Table IA.1 of this internet appendix suggest that the longer the tenure of a given manager, the lower the likelihood of that manager switching to another investment style. This result is highly significant both in a statistical and economic sense. The coefficient on $Tenure$ is significant at the 1% significance level. In terms of economic magnitude, the size of the coefficient suggests that a one-standard-deviation increase of tenure reduces the likelihood of switching to another investment style by approximately 27% of the average unconditional probability of style change. In sum, the findings from this section are consistent with the key predictions from occupational match theory: managers enjoy a higher level or productivity and have no incentives to switch jobs after they are matched.

Appendix B: Determinants of Match Finding

In this appendix, we examine possible determinants of match finding using a linear probability model. The dependent variable is $Match$, an indicator variable that identifies managers that have reached their match. We employ Fama-MacBeth (1973) estimation, running cross-sectional regressions each year and reporting the time series average of coefficients together with their t-statistics based on time-series adjusted standard errors according to Newey and West (1987). Observations for each cross-sectional regression include managers that reached their match in that year and those that never did up to that point.

Matching is presumably more likely when the manager has more opportunities to try different styles. We proxy for these opportunities in two ways. First, we use the number of investment styles offered by the fund company. This determines how many styles a fund manager can try out at the fund company in which she is currently employed. Second, we use Garmaise's (2011) non-compete enforceability index constructed for each state based on the Malsberger's (2004) methodology. This index captures restriction in external labor market mobility. The higher the index, the stricter non-compete clause enforceability is and the harder it is for a manager to switch between employers and, therefore, try different investment styles.

Next, we include the average student SAT score of the undergraduate institution that the manager attended. The university SAT score can proxy for a manager's inherent ability [e.g., Chevalier and Ellison (1999)]. For a smarter manager, both the fund company and the manager herself, are likely to figure out her abilities and her style match sooner.

Finally, we include a manager's age, industry tenure, and the number of jobs tried as proxies for experience. Managers with more experience are likely to have acquired a better understanding of the different skills required for the different styles, thus making it more likely for them to find their match. At the same time, fund companies might acquire more private information about the abilities and style suitability of managers that have been around for a longer time.

Insert Table IA.2 about here

Results from the linear probability model presented in Table IA.2 of this internet appendix confirm the reasoning presented above. We find that managers with more opportunities to try out different investment styles are more likely to find their match. Our results also suggest a higher likelihood of match finding for managers that graduated from higher-SAT institutions and for more experienced managers.

Appendix C: Utilization of Matched Manager's Ideas in Other Funds of the Fund Company

In Section 4.3 of the main paper we showed that fund companies exploit the information that a fund manager has reached her match by disseminating the expertise of the matched managers to other managers in the fund company. Therefore, we would expect affiliated funds to utilize the investment ideas from a colleague who has discovered her match more than those of other colleagues who have not done so.

Following the methodology of Cici et al. (2018), we employ a linear probability model where we model the likelihood that a trade conducted by a company fund manager is followed by affiliated funds. The unit of observation is a trade of a given stock conducted by a manager in quarter *t*.

$$TradeFollowed_{j,i,f,t} = \alpha_{f \cdot s \cdot t} + \beta \cdot MatchedManagerTrade_{i,j,f,t} + \vec{\gamma}' \vec{c}_{j,t-1} + \varepsilon_{j,i,f,t}. \quad \text{(C.1.)}$$

The dependent variable $TradeFollowed$ is a dummy variable, which equals one if a trade conducted in stock j by manager i in quarter *t* is followed by a trade in the same direction by at least one affiliated fund manager in the same fund company f subsequently in quarter $t + 1$ or $t + 2$, and zero otherwise. The key independent variable $MatchedManagerTrade$ is an indicator variable that equals one when the trade was conducted by a manager who has reached her match and zero otherwise. If affiliated managers are more likely to follow the ideas of a manager who has found her match than those of managers who have not reached this point, then we expect the coefficient on this variable to be positive.

Our control variables, stacked into vector $\vec{c}$, include: the natural logarithm of market capitalization ($Firm\ Size$); past 12-month compounded stock return ($Past\ Return$); past 12-

month stock return volatility ($Past\ Volatility$); and book-to-market ratio ($Book - to - Market$). Because the analysis is at the fund company level and we also want to impose the restriction that only trades of managers that have the same investment style be considered, we employ fund company -by-style-by-report date fixed effects. Standard errors are clustered by fund company and style.

Please insert Table IA.3 about here

Table IA.3 of this internet appendix reports the results. In the first column, we condition on trades that initiate a long position in the portfolio of managers in stocks that are not concurrently held by any of the affiliated managers. Stocks that appear for the first time in the portfolio of a particular manager, but not in those of affiliated managers, are most likely to have been the product of ideas generated by that manager.

The coefficient on the $MatchedManagerTrade$ variable in the first column is positive and statistically significant at the 5% level.[16] Its value suggests that when the new ideas are from a manager that has found her match, they have a 1.2 percentage points higher probability that they are subsequently utilized by the fund company's other managers. This is economically significant as it constitutes more than a 12% increase in probability relative to the baseline probability (not reported in the table) that the fund company's other managers follow the ideas of their colleagues in general. Thus, affiliated managers seem to pay greater attention to the investment ideas coming from a matched manager than to those of other managers and are more likely to act on the matched managers' ideas. For completeness, in Column (2), we show

[16] Since our approach only considers the following of ideas with a time lag in order to attribute the ideas more precisely, this likely underestimates the economic effect given that fund managers can observe the trades of affiliated managers in the same quarter and thus adopt their ideas sooner.

results when we condition on the rest of stock purchases conducted by managers. The coefficient on the $MatchedManagerTrade$ variable continues to be significant.

Finally, in the last two columns, we condition on the stock sales of managers. Mutual fund managers typically face short-selling constraints. This would prevent affiliated funds from acting on negative information on a specific stock that was generated by their colleagues unless they currently own that stock. For this reason, we apply a filter to the stock sales by keeping only those that correspond to stocks that were held by at least one affiliated fund manager at the beginning of t.

In Column (3), the observations comprise all sales that terminate a position and in Column (4) they comprise the rest of the sales. The coefficient on the $MatchedManagerTrade$ variable continues to be positive and statistically significant, suggesting that affiliated managers pay closer attention to the selling decisions of their colleagues that have reached their match.

Table IA.1: Traditional Tests of Occupational Match Theory

This table presents results from traditional tests of occupation match theory. The analysis is done at the manager and year level. Our main independent variable is Tenure, computed as the natural logarithm of one plus the years a manager spent in a given style. Panel A presents results from pooled OLS regressions that relate performance measures with Tenure. Performance is measured as described in Section 3 of the main text. In Panel B, the dependent variable is an indicator (1/0) variable capturing whether a manager changes her job type. Control variables at the manager, fund, and fund company level are constructed as in Table II of the main text. Regressions are run with time, style and manager-by-fund company fixed effects (FE). T-statistics, based on standard errors clustered at the manager level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Impact of Tenure on Productivity

	(1) Return	(2) Style-Return	(3) Alpha4	(4) Alpha6
Tenure	0.0103***	0.0064***	0.0075***	0.0005**
	(4.04)	(2.99)	(3.43)	(2.30)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Fund Company FE	Yes	Yes	Yes	Yes
Observations	29,759	29,759	29,582	29,582
Adjusted R^2	0.743	0.068	0.124	0.107

Panel B: Impact of Tenure on the Likelihood of Switching Investment Styles

	(1)	(2)
Tenure	-0.2261***	-0.3354***
	(-26.10)	(-35.57)
Controls	No	Yes
Time FE	Yes	Yes
Style FE	Yes	Yes
Manager × Fund Company FE	Yes	Yes
Observations	30,398	30,398
Adjusted R^2	0.177	0.339

Table IA.2: Determinants of Match Finding

This table reports results from a linear probability model that examines determinants of managers finding their match. The dependent variable, Match, is a (1/0) indicator variable, which identifies managers that have reached their match. Fama-MacBeth (1973) estimation is conducted such that we run cross-sectional regressions each year and report the time series average of coefficients, together with t-stats based on Newey and West (1987)-adjusted time-series standard errors. Observations for each cross-sectional regression include managers that reached their match in that year and those managers that never reached their match up to that point in time. Independent variables, include: #Fund Company Styles, the number of styles in a manager's fund company; NCC-Index, an index by Garmaise (2011) quantifying the strength of non-compete (NCC) enforceability ranging from 0 (weakest) to 12 (strongest) and available for the 1992-2004 period; SAT, the average SAT-score of the institution the manager received her Bachelor's degree from; Age, manager's age in years; #Styles Tried and Industry Tenure, as defined in Table I of the main text. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
#Fund Company Styles	0.0035**						0.0019*
	(2.66)						(2.17)
NCC-Index		-0.0014**					-0.0020***
		(-2.44)					(-3.44)
SAT			0.0001***				0.0001***
			(5.55)				(4.43)
Age				0.0581***			0.0343***
				(7.39)			(5.73)
Industry Tenure					0.0140***		0.0036**
					(10.50)		(2.86)
#Styles Tried						0.1043***	0.1000***
						(15.98)	(15.46)
Observations	8,786	8,786	8,786	8,786	8,786	8,786	8,786
R^2	0.061	0.059	0.067	0.064	0.066	0.132	0.144

Table IA.3: Utilization of Trade Ideas by Affiliated Managers

This table presents results from pooled OLS regressions that relate the probability that a trade by a manager who has found her match is followed subsequently by affiliated managers. The analysis is done at the stock-fund company-style and quarter level. The observations for the Initiating Buys are identified as stocks that are held for the first time by a manager having found her match and not held concurrently by an affiliated fund in the same style at time t. Remaining Buys are identified as increases in shares held and exclude initiating buys. For Terminating Sales, the dependent variable equals one if there is at least one other fund within the same fund company in the same style at t+1 or t+2 selling the stock off. Remaining Sales are identified as reductions in shares held and exclude terminating sales. Our main independent variable is MatchedManagerTrade, an indicator variable that equals one when the trade was conducted by a manager who has reached her match and zero otherwise. Our control variables include the natural logarithm of market capitalization (Firm Size); past 12-month compounded stock return (Past Return); past 12-month stock return volatility (Past Volatility); and book-to-market ratio (Book-to-Market). Regressions are run with fund company-by-style-by-report-date fixed effects (FE). T-statistics, based on standard errors clustered at the fund company and style level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Initiating Buys	(2) Remaining Buys	(3) Terminating Sales	(4) Remaining Sales
MatchedManagerTrades	0.0122**	0.0129**	0.0121***	0.0313**
	(2.03)	(2.01)	(8.81)	(2.17)
Firm Size	0.0374**	0.0850***	0.0438**	0.0888***
	(2.97)	(5.43)	(3.43)	(5.13)
Past Return	0.0088**	0.0178**	0.0042	0.0081
	(2.57)	(2.91)	(1.25)	(1.37)
Past Volatility	0.4854**	0.9988**	0.7483**	1.1224**
	(2.48)	(2.76)	(2.85)	(2.77)
Book-to-Market	-0.0035	-0.0101	-0.0105	-0.0197
	(-0.79)	(-0.69)	(-1.56)	(-1.16)
Fund Company × Style × Report-Date FE	Yes	Yes	Yes	Yes
Observations	486,998	2,023,244	964,073	1,627,854
Adjusted R^2	0.155	0.250	0.184	0.341

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