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

by

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Abstract

To best utilize labor, companies need to optimally match their employees' skills with job types that best fit those skills. We examine this optimal matching process in the mutual fund industry. Mutual fund families enable their managers to try out funds with different investment styles in a learning-by-trying fashion until they find their optimal match. After this has happened, managers operate at higher productivity levels and tend to stay in the same investment style. Fund families respond to this rationally by allocating more capital to the optimally matched managers, while the optimally matched managers respond by taking more active bets.

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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 arrange for employees' skills to match up with the job types that are best suited for those skills, ensuring that the employees operate at their highest level of productivity. Economic theories, in particular occupational match theory, suggest that optimal matching happens in a learning-by-trying fashion, whereby managers try out different types of jobs until they arrive at the job type that best matches their skills, where they operate at their highest level of productivity [e.g., Mortensen (1978, 1986), Jovanovic (1979), Diamond (1981), Miller (1984), Ortega (2001), Papageorgiou (2014, 2018), and Addison, Chen, and Ozturk (2017)].

We are the first to document that optimal matching in a learning-by-trying fashion takes place in the mutual fund industry and that this leads to significant productivity improvement. After a manager is matched to a fund following the investment style that optimally fits her skills, the manager's performance improves in an economically significant way. Both fund families and managers exploit the information that a manager has been optimally matched in highly rational ways. Fund families use this information to reallocate capital. They increase the assets under management assigned to optimally matched fund managers. They also benefit from affiliated family managers mimicking the trades of the matched managers. Fund managers seek to amplify the gains from the newly-found advantage by forming more active fund portfolios. Overall, our findings suggest that facilitating optimal matching in the fund industry benefits fund investors with better performance and contributes to greater efficiency in the stock market as fund families reallocate capital to managers whose productivity has increased and who take a more active stance after being optimally matched.

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The mutual fund industry provides an attractive setting to study optimal job matching and its effect on employee productivity for two reasons. First, this industry provides a sensible taxonomy of job types and skills. A mutual fund manager invests on behalf of investors in accordance with a pre-specified investment style, which largely determines the investment universe and, consequently, the skills required to invest in that universe.[1] Thus, we can think of investment styles as job types in the mutual fund industry. Anecdotal evidence also suggests that the reputation of fund managers is typically associated with a particular investment style. For example, Bill Miller, a former manager of Legg Mason Value Trust, was recognized as a famous "value" manager, whereas Thomas Rowe Price, Jr, a former fund manager and founder of T. Rowe Price, gained reputation as a successful "growth" manager. A second advantage of using the fund industry is that we can easily observe the productivity of a fund manager in the various job types by looking at the performance of the funds for which the manager was responsible.

For a fund manager that is starting out her career, neither the family nor the manager know what particular investment style constitutes the best match with the manager's skills. However, both the family and the manager can discover the manager's best match jointly over time as the manager tries different investment styles. While the manager is trying a particular style, both the fund family and the manager learn about the quality of the match. The manager will then move to a new investment style as long as the manager and the family think that the new style is a better fit to the manager's skills than the manager's current style. This process finds support in Jovanovic (1979), who "… predicts that workers remain on jobs in which their productivity is revealed to be relatively high and that they select themselves out of jobs in which their productivity is revealed to be low." Thus, in equilibrium, managers will eventually

[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.

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settle into jobs where they achieve the highest level of productivity, having no incentive to proceed with another job move henceforth. In light of this, the empirical predictions from theory are that employees (i) are more productive and (ii) do not switch jobs after they have found their optimal match.

Using tenure as a proxy for the likelihood of employees having reached their optimal match, previous research relates employees' tenure with wages (as a proxy for productivity) and with the likelihood of switching jobs.[2] We adopt this idea but use the performance of a fund manager as a more direct measure of her productivity instead of wage and tenure as the length of time a manager has been working in a given style. Our empirical analysis provides strong support for the above hypotheses as we find that fund managers with longer tenure exhibit significantly better performance and a lower likelihood of switching to another investment style.

This first set of results supports a general notion of the equilibrium described above. However, we cannot rule out that omitted factors cause the observed association between tenure and job turnover or productivity, no matter whether one proxies for productivity by fund performance or by wage, a common proxy in the literature. To study the consequences of optimal matching more directly, we identify points in time when this matching happens and look at changes in productivity around these events. Specifically, we identify when optimal matching happens by studying the sequence of managers' moves to different investment styles during their careers. Again, the underlying premise is that moving to a new investment style happens as long as the new style is expected to be a better fit than the manager's current style, a process that repeats until optimal matching. We argue that a manager has reached the optimal match after that manager has tried a number of styles and returns to one of the previously-tried

[2] See McCall (1990), Jovanovic and Moffitt (1990), Eriksson and Ortega (2006), Kambourov and Manovskii (2008), Kambourov and Manovskii (2009a, 2009b), and Groes, Kircher, and Manovskii (2015).

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styles. Presumably, both the manager and the family have realized that this style was the best match and facilitated the manager's return to that style. Thus, we use the point in time of a manager's return to a previously-tried style to identify when optimal matching occurs. Obviously, our approach is unable to identify all optimal matches. For example, a manager who starts her career in an investment style that happens to be her best match and stays in this style throughout her entire career would not be classified as optimally matched by our approach. Thus, our approach provides a lower bound of all optimal matches, which contributes to attenuation bias as some unidentified optimal matches will end up in the control group.

Identifying points in time when optimal matching happens allows us to test more directly the main hypothesis from occupational match theory that employees operate at a higher level of productivity after they arrive at their optimal match. We compare the performance of a fund manager before and after that manager is optimally matched in a difference-in-differences setting. In doing so, we control for possible self-selection issues as more-skilled managers might choose to move to fund families with more resources while their learning-by-trying takes place. Our findings support the hypothesis that productivity improves after a manager has found her best match by documenting a performance increase that ranges from 116 to 158 basis points per year. Additional tests rule out various alternative explanations for the performance improvement we document.

A closer look at the managers whom we have identified to be optimally matched shows that it takes them an average of about four different style tries over a time span of six years before optimal match, suggesting that the process is not trivial. The majority of them return to a style in which they had their best performance in the past. This indicates that the optimal match is in response to learning in which style the productivity of managers was the highest. After these fund managers reached their optimal match, about 94 percent of the managers

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stayed in the same style for the remainder of their careers.[3] This is rational from the career perspective of managers, who will switch only to positions that constitute a better fit with their skills, and from the perspective of fund families that will want to keep their employees' skills deployed to their best use. This evidence provides support that our approach performs reasonably well at identifying points of time when the optimal match takes place. We also study the determinants of optimal match finding. We document that managers who: have more opportunities to try different styles, graduate from institutions with higher SAT scores; are older; and have more experience are more likely to find their optimal match.

The discovery of managers' best match and subsequent performance improvement has implications for fund families and fund managers. Regarding fund families, we expect them to exploit the new information that one of their managers is optimally matched to maximize the performance for the entire family. Our findings support this. First, fund families allocate more capital to managers after they have arrived at their optimal match by increasing the amount of assets under their management. This is highly sensible and the most direct way for families to exploit this new information. Second, fund families benefit even more broadly from the investment ideas of the optimally matched managers. Specifically, we find that affiliated fund managers are more likely to use the investment ideas of their colleagues that have found their best match than those of other colleagues who have not been optimally matched. Fund managers also exploit the new information that they have achieved their optimal match. They do so by tilting their portfolios away from those of their peers and thus taking a more active stance in the market.

[3] This is consistent with a number of studies showing that the rate at which employees move to a different occupation declines with tenure. The rationale would be that because longer-tenured employees are more likely to have found their best occupation match, they would be less likely to move to another occupation, where productivity would be lower [e.g., Flinn (1986), Kambourov and Manovskii (2008, 2009b,) Antonovics and Golan (2012), and Papageorgiou (2014)].

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Our paper is related to the literature that studies the personnel decisions of mutual fund families. Cheng et al. (2013), Berk, van Binsbergen, and Liu (2017), and Zambrana and Zapatero (2020) show that personnel decisions made by mutual fund families on average create value for their investors. We contribute to this literature by documenting another way in which fund families create value for their investors, namely by figuring out the optimal match of their managers. We further add to this contribution by documenting how mutual fund families and fund managers exploit the information of having achieved optimal manager-style matches.

Our paper also contributes to a growing literature that examines the impact that fund managers' human capital has on their performance. For example, 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 findings contribute to this literature by suggesting that precise performance related inferences could be hampered by the fact that fund managers are not always optimally matched to the best positions given their skills. The discovery of their best match takes some time, meaning that they are not operating at their fullest productivity level before this happens. Thus, any true performance effects related to human capital would be harder to detect prior to the manager having reached her optimal match.

Finally, our paper contributes to the literature on occupational match finding, especially to the empirical part of this literature.[4] These empirical papers rely on the premise of an underlying equilibrium model that results in employees and jobs being matched after some learning has occurred about the match quality of different pairwise combinations tried.

[4] Theoretical papers include Mortensen (1978, 1986), Jovanovic (1979, 1984), Diamond (1981), Miller (1984), Ortega (2001), Papageorgiou (2014, 2018), and Addison, Chen, and Ozturk (2017). Empirical research was conducted in McCall (1990), Jovanovic and Moffitt (1990), Eriksson and Ortega (2006), Kambourov and Manovskii (2008), Kambourov and Manovskii (2009a, 2009b), and Groes, Kircher, and Manovskii (2015).

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Building on this and using tenure as a proxy for the likelihood that an employee has been matched, these studies primarily examine tenure effects on turnover or wage. Our study contributes to this literature by documenting directly the productivity gains that accrue once the occupational match is reached.

2 Data

2.1 Data Sources

We obtain fund and family names, monthly net returns, total nets 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 CRSP Style Code, which aggregates information from the previous Lipper, Strategic Insight, and Wiesenberger objective codes. We categorize funds based on the 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).

The 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 the CRSP stock data using stock CUSIPS. Portfolio holdings for each fund are either of quarterly or semi-annual frequency. Our sample spans the period from 1992 through 2016.

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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 classes 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.

2.2 Sample Descriptive Statistics

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

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 family in our sample manages $28 billion in assets.

3 Initial Tests of Occupational Match Theory

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The key empirical predictions from occupational match theory are that after employees have found their optimal match, they (i) exhibit greater productivity and (ii) are less likely to change jobs. Previous research used tenure as a proxy for the likelihood of employees having reached their optimal match and wages as a proxy for productivity. We follow this approach but use the performance of a fund manager as a more direct measure of productivity instead of wage.

To test the first hypothesis, we relate the manager's performance to $Tenure$, in a panel-regression at the manager-year level as specified in Equation (1):

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

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

$Tenure$ is computed as the natural logarithm of one plus the years a given manager has been in a given investment style. We employ four measures of performance: 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 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.[5] All performance measures are annualized by compounding the twelve monthly returns corresponding to each calendar year.

[5] 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.

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We include control variables measured at the manager, fund, and family level, all lagged by one year. Regarding the control variables measured at the manager level, we use the number of distinct job types that the manager has worked in ($\#Job\ Types\ Tried$) up to each particular point in time and her industry tenure ($Industry\ Tenure$) to control for the investment experience or human capital accumulated in a learning-by-doing fashion.

We aggregate all fund-specific performance and control variables at the manager level. To do so, we follow previous research [e.g. Ibert, Kaniel, van Nieuwerburgh, and Vestman (2018)] and divide a fund's total net asset value equally among all managers managing that fund to obtain per-manager assets. We then build a per-manager asset weighted sum of fund-level variables to obtain variables at the manager level. 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 natural logarithm of age ($Fund\ Age$); and the natural logarithm of total net assets ($Fund\ Size$). At the family level, we use the natural logarithm of family total net assets ($Family\ Size$) as a control variable.

For each performance measure, which is used as the dependent variable, 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-family 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 families. Selection issues can arise because higher ability managers might be more likely to join families with more resources where they are more likely to find their optimal match and also generate better performance in part due to greater family support.

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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 follow the guideline in Petersen (2009) and cluster standard errors at the manager-level.

Please insert Table II about here

Results are reported in Panel A of Table II. Our empirical findings provide strong support for the hypothesis that managers with longer tenure generate better performance. 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 0.92 percentage points. The evidence that managers who are more likely to have achieved their optimal match operate at a higher level of productivity confirms findings from previous research that use 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 as specified in Equation (2):

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

$Switch$ is an indicator variable that equals 1 for a given manager that moved to another investment style in year t and zero otherwise. All independent variables and controls are the same as in Equation (1).

Results reported in Panel B of Table II suggest that the longer the tenure of a given manager, the lower the likelihood of that manager switching to another job type. 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

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probability of style change. In sum, the findings from this section support the equilibrium view that managers enjoy a higher level or productivity and have no incentives to switch jobs after they are optimally matched.

4 Performance Change after Optimal-Match Discovery

The evidence from Section 3 is consistent with optimal matching taking place. However, we cannot rule out that omitted factors cause the observed association between tenure and job turnover or productivity, nor can we know the exact timing of when optimal matching happened to get a precise assessment of its consequences. To study the consequences of optimal matching more directly and measure the associated effects more precisely, in this section we identify points in time when optimal matching happens and look at changes in productivity around these events.

As discussed in the introduction, we use instances when a manager returns to a previously-tried style to identify points in time when optimal matching occurs. The idea is that as the manager tries different investment styles, both the manager and the family observe the quality of the various matches and learn about the skills of the manager. Thus, when a manager returns to a previously-tried style, such occurrence indicates that the family (and the manager) have realized that this style was the best match and facilitated the manager's return to that style.

4.1 Main Result

To study the direct effect on productivity after a manager has been optimally matched, we relate the manager's performance to our key variable, $Match$, as specified in Equation (3):

$$Performance_{i,t} = \alpha_{i,f} + \theta_t + \omega_s + \beta \cdot Match_{i,t} + \vec{\gamma}'\vec{c}_{i,t-1} + \epsilon_{i,t}. \quad (3)$$

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We construct our main independent variable, $Match$, by identifying the point in time when a manager returns to a previously-tried style. Then, we code $Match$ as 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. The controls and fixed effects are the same as in Equation (1). Importantly, the use of manager-by-family fixed effects is crucial for our identification strategy, which focuses on matches that happen for the same manager within a given fund family, thus controlling for the innate abilities of fund managers and selection issues.

Please insert Table III about here

Results are reported in Table III. The coefficients of our main variable, $Match$, are positive and statistically significant at the 1% significance level for all performance measures. The magnitude of the coefficients also suggests a significant economic effect in terms of performance improvement following discovery of the managers' matches. Specifically, for managers who reach their optimal match, the subsequent performance improvement is 116 to 158 basis points per year relative to other fund managers who have not reached their optimal match. This evidence suggests that finding the best match of fund managers pays off for fund families and the fund managers, who both stand to benefit from the higher level of productivity that optimally matched managers can achieve.

4.2 Parallel Trends Assessment and Persistence of Performance Improvement

In order to support a causal interpretation of our inferences obtained from the difference-in-differences estimation, in Table IV we provide a test of the identifying assumption 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 (3) with three indicator

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variables that identify managers that attained match discovery—in each of the prior three years ($Pre1 \cdot Match$ – $Pre3 \cdot Match$). Results reported in Table IV and corroborated visually in Figure 1 show that none of the variables $Pre1 \cdot Match$, $Pre2 \cdot Match$, or $Pre3 \cdot Match$ are significantly different from zero, i.e., the performances of the two groups of managers show parallel trends prior to achievement of the match.

Please insert Table IV about here

Please insert Figure I about here

We also examine the persistence of the performance improvement following the managers' matches. To do so, in the second column corresponding to each performance measure in Table IV, we replace $Match$ with three indicator variables that identify managers that have reached optimal match — in three subsequent periods, i.e., the first year, second year, and all years from the third year onwards subsequent to match discovery.

Results show that performance improvement following the discovery of match exhibits persistence and becomes stronger over time. Performance improvement in the first subsequent year, although economically significant, is statistically significant only for two of the specifications. This is consistent with the manager not reaching an optimal level of productivity right away in the first year, possibly due to distractions that come from adopting to the change in responsibilities, adjusting to a new work environment (e.g., new colleagues), and communicating with new clients. In year 2 and beyond performance improvement gets much stronger both in an economic and statistical sense, which suggests that productivity gains coming from the best match become noticeable once the manager has gone through an initial period of adjustment.

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4.3 Alternative Explanations

4.3.1 Learning-by-Doing

It is possible that the performance improvement we document results from greater investment experience that the manager acquires as she tries more different styles [e.g., Golec (1996), Chevalier and Ellison (1999), Greenwood and Nagel (2009), and Kempf, Manconi, and Spalt (2017)]. That is why among the controls used in the regression we include the number of styles tried by the manager along with her industry tenure. Although the number of styles tried is not statistically significant in the linear model underlying Table III, it could be that it effects the dependent variable in a non-linear way. To rule that out, we proceed as follows. For each fund manager who has reached her best match, we identify a control manager, i.e., another manager from the same family that has tried the same styles and has the highest propensity score with respect to the length of time she tried the various styles. These pairs then constitute the observations on which we estimate Model (3).

Please insert Table V about here

Results are reported in Table V. Constructing the control group in the manner described above is restrictive, resulting in a much smaller sample of about 4,500 observations, relative to a sample of roughly 29 thousand observations in Table III. Nonetheless, despite the smaller sample used in Table V, the coefficients of the *Match* variable are still positive and exhibit similar levels of economic and statistical significance as those from Table III.[6]

In sum, our main finding that managerial productivity improves after a manager reaches her best style match continues to hold even after we control for experience in a more rigorous

[6] We come to the same conclusion when we use an even more restrictive approach to construct the control group. This alternative control group is constructed by ensuring that in addition to the conditions imposed in Table V, the control manager has the closest propensity score based on the manager and fund characteristics described in Table I (as the family characteristics, by construction, are equal, since we perform the matching within the same family). The results of this additional test are available from the authors upon request.

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way. This increases our confidence that the performance improvement we document is the result of optimal matching and not the result of greater experience (learning-by-doing) acquired by the manager in the process.

4.3.2 Managerial Preferences and Organizational Power

It is possible that the results documented above are caused by a combination of some managers' preferences for certain styles and their organizational power within their fund family. Since a manager's power within a fund family likely increases with her tenure with the family, a manager who has tried various styles is likely to have accumulated sufficient power, which she might use to first return to her preferred previously-tried style and afterwards to divert disproportionately more resources to her fund. To explore this possibility, we employ $HighFamilyTenure$, an indicator variable which equals one if the current family tenure of the respective manager is greater than the median family tenure of all managers in the same year, and zero otherwise. If organizational power is responsible for the performance improvement we document, we ought to see a positive and significant coefficient when we interact $Match$ with $HighFamilyTenure$.

Please insert Table VI about here

Table VI shows results from a model that augments Model (3) with $HighFamilyTenure$ and its interaction with *Match*. Results show that both $HighFamilyTenure$ and its interaction with *Match* are statistically insignificant. Thus, we are unable to find supporting evidence for the explanation that the return to a previously-tried style and the subsequent performance improvement are the product of these managers having more organizational power.

4. 4 Determinants of Optimal Matching

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We now take a closer look at the sample managers that returned to a previously-tried style. We document that this happens for one third of the sample managers, and focusing on these managers, we first provide some descriptive results.

From Panel A of Table VII we observe that, on average, a manager tries about four different styles before arriving at her best match, but the number of styles tried ranges between two and five (based on 10th and 90th percentiles). It takes about six years for the average manager to reach the optimal match. The range is between two to eleven years, suggesting that for some managers learning-by-trying of their best matches happens much faster and for some others much slower.

Please insert Table VII about here

In 70% of the times a manager returns to a style where she generated the best performance across all the styles that the manager tried in the past. Thus, having learned in which style a manager has the highest productivity, the family and the manager rationally decide for the manager to return to that particular style. Interestingly, we observe very little mobility after the best match has been discovered, 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 equilibrium outcome of a process that underlies the search for a best match [Jovanovic (1979)].

We next examine possible determinants of managers finding their optimal match using a linear probability model. The dependent variable is $Match$, an indicator variable that identifies managers that have reached their optimal match. For this analysis, we employ Fama-MacBeth (1973) estimation, whereby we run cross-sectional regressions each year and report the time series average of coefficients, together with their time-series adjusted standard errors according to Newey and West (1987). Observations for each cross-sectional regression include

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managers that reached optimal match in that year and those managers that never reached their optimal match up to that point in time.

We first hypothesize that style matches are more likely when the manager has more opportunities to try different styles. We capture the size of a manager's opportunity set using two variables. First, we use the number of styles offered by the fund family to capture the options the manager has within the family. Second, we use the extent of labor mobility restrictions at the state level to measure how easily a manager can switch between employers and thereby try different styles. We measure these restrictions based on the strength of enforceability of non-compete clauses in employment contracts, which are used by firms to restrict labor mobility. Specifically, we add Garmaise's (2011) non-compete clause enforceability index constructed for each state based on Malsberger's (2004) methodology as an additional explanatory variable to our regression. The higher the index, the stricter non-compete clause enforceability is.

Next, we include the average student SAT score of the undergraduate institution that the manager attended. A higher college SAT score could suggest that the manager has a higher inherent ability and a better network of contacts in the financial industry [e.g., Chevalier and Ellison (1999)]. A manager who is inherently smarter is likely to figure out sooner her abilities and her best style match and a better network could benefit the manager by enlarging the opportunity set of positions that she can try.

Finally, we include a manager's age, industry tenure, and the number of jobs tried. Older managers presumably had opportunities to observe a larger number of market and industry cycles, providing them with a broader context to evaluate their different types of skills. Managers with more industry experience and managers that have tried a larger number of job

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types are likely to have acquired a better understanding of the different skills required for the different job types, thus making it more likely for them to find their optimal match.

Results from the linear probability model presented in Panel B confirm the reasoning presented above. We find that managers with more opportunities for learning-by-trying are more likely to find their optimal match. Our results also suggest a higher likelihood of optimal match finding for managers that graduated from higher-SAT institutions, older managers, and more experienced managers.

5 How do Fund Families Respond to Optimal-Match Discovery?

In this section we examine the implications that match discovery has for mutual fund families. In Section 5.1, we test whether fund families are more likely to allocate more capital to managers who have reached their optimal matches by increasing their assets under management. Then, we examine whether fund families extend the newly-found advantage to other funds in the family in Section 5.2. Both strategies are intended to maximize returns for the entire family.

5.1 Do Fund Families Reallocate Capital After Optimal-Match Discovery?

Consistent with fund families taking advantage of the information that a manager has found her best match, we hypothesize that fund families allocate more capital to the corresponding managers subsequent to their optimal match discovery. To test this hypothesis, we model the probability that a manager is promoted to a larger asset base as a function of the variables introduced in Equation (3) using a linear probability model. The dependent variable is $Asset\ Increase$, a binary variable that equals 1 if the fund family has assigned more assets under management to a manager. Such instances include the manager being assigned to an

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additional fund or the manager being moved out of the existing fund and into a different fund with larger assets under management.

Please insert Table VIII about here

Results are presented in Table VIII. They show that after arriving at her best match a manager is more likely to be promoted in the following period than before. The coefficient on the $Match$ variable is both statistically and economically significant. It suggests that the probability of promotion increases by 5.5 percentage points, which is roughly 11% of the unconditional probability of promotion. With this evidence we are able to provide a direct link from the match discovery process to the optimal deployment of managers' talent by fund families.

5.2 Do Fund Families Scale up the Information about Optimal-Match Discovery?

In the previous section we showed that fund families rationally exploit the information that a fund manager has reached her optimal match by allocating more capital to that manager. Another rational strategy would be to extend the benefits of this newly-found information to other funds in the family (hereafter, affiliated funds). If fund families follow this strategy, we would expect affiliated funds to utilize the investment ideas from a colleague who has discovered her best 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 family manager is followed by affiliated funds. The unit of observation is a trade of a given stock conducted by a manager in quarter *t*.

$$Trade\_Followed_{j,i,t} = \alpha_0 + \alpha_1 Matched\_Manager\_Trade_{ji} + \vec{\gamma}'\vec{c}_{j,t} + \varepsilon_{j,i,t}. \qquad (4)$$

The dependent variable $Trade\_Followed$ 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

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by at least one affiliated fund manager subsequently in quarter $t+1$ or $t+2$, and zero otherwise. The key independent variable $Matched\_Manager\_Trade$ is an indicator variable that equals one when the trade was conducted by a manager who has reached her optimal match and zero otherwise. If affiliated managers are more likely to follow the ideas of a manager who has found her optimal 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 family level and we also want to impose the restriction that only trades of managers that have the same investment style be considered, we employ family-by-style-by-report date fixed effects. Standard errors are clustered by fund family and style.

Please insert Table IX about here

Table IX reports the results. In the first column, we condition on trades that initiate a 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 $Matched\_Manager\_Trade$ variable in the first column is positive and statistically significant at the 5% level.[7] Its value suggests that when the new ideas are from a manager that has found her best match, they have a 1.2 percentage points higher

[7] 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.

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probability that they are subsequently utilized by the family's other fund 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 family's other fund managers follow the ideas of their colleagues in general. This evidence is consistent with affiliated managers paying greater attention to the investment ideas coming from an optimally matched manager than to those of other managers and being more likely to act on the matched managers' ideas. For completeness, in Column 2, we show results when we condition on the rest of stock purchases conducted by managers. The coefficient on the $Matched\_Manager\_Trade$ 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 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 $Matched\_Manager\_Trade$ variable continues to be positive and statistically significant, suggesting that the affiliated managers pay closer attention to the selling decisions of their colleagues that have reached their optimal match.

In sum, results from Section 5 suggest that fund families utilize the human capital of managers that operate at their optimal level of productivity by applying it to a larger asset base, which goes beyond funds managed by the managers that are at their best match themselves.

6 How do Fund Managers Respond to Optimal-Match Discovery?

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In this section we examine the implications that optimal matching has for fund managers, i.e., how fund managers respond to the discovery of their optimal match. Avery and Chevalier (1999) develop an equilibrium model, whereby managers with positive private information about their skills exhibit self-confidence by anti-herding, i.e., going against the trades of other managers. The predictions of this model are corroborated by Jiang and Verardo (2018) who document that more skilled managers herd less. This suggests that a manager who has reached her optimal match and knows where her productivity is highest is expected to exhibit a higher degree of conviction by investing differently from her peers. Thus, we expect a manager to tilt her portfolio away from the typical portfolio of her peers after she has arrived at her optimal match.

To test this hypothesis, we examine the extent to which the difference of a manager's portfolio relative to the average peer portfolio increases after the manager has found the best match. The dependent variable, $Active\ Peer\ Share$, which measures this difference, is constructed as follows. Similar to Cremers and Petajisto (2009) and Petajisto (2013), we calculate

$$Active\ Peer\ Share_{i,t} = \sum_{i=1}^{N} \left| w_{j,i,t} - w_{peer_j,i,t} \right|, \tag{5}$$

where $w_{j,i,t}$ and $w_{peer_j,i,t}$ are, respectively, the portfolio weights of stock j held by manager i and in manager i's benchmark based on her peer portfolio at time t. The sum is taken over the universe of all N stocks. If a manager holds exactly the peer portfolio, her $Active\ Peer\ Share$ will be zero, whereas if she invests only into one stock and the corresponding peer weight is to zero, $Active\ Peer\ Share$ will be 2. We employ the same independent variables, controls, and fixed effects as in our estimation of Equation (3).

Please insert Table X about here

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Results are reported in Table X. They show that $Active\ Peer\ Share$ increases after managers have reached their optimal matches relative to other fund managers. This result is statistically significant at the 1% significance level and also economically significant. The coefficient on the $Match$ variable suggests an increase in $Active\ Peer\ Share$ of 0.6648 after optimal-match discovery, which is economically meaningful given that the maximum value $Active\ Peer\ Share$ can take is 2. This evidence suggests that fund managers use the information they acquire about their best match in a way that is consistent with them exhibiting a higher level of conviction.

7 Conclusion

Matching employees to jobs that best fit their skills is important for productivity. Our paper is the first to study this optimal matching process in the mutual fund industry. Using fund performance as a direct measure of productivity, our findings provide supporting evidence for the occupation match theory.

We show that employees gravitate towards job types that optimally match their skills, from which point they operate at their highest level of productivity and thus have no incentives to try other job types. Our methodological innovation to identify the points in time when optimal matching actually happens allows us to provide even more direct evidence on the optimal matching that takes place in the mutual fund industry by precisely quantifying its effect on productivity and to study its implications for fund families and fund managers.

We find that arriving at the optimal match is involved for fund managers, requiring a significant number of tries and considerable time. These obvious hurdles notwithstanding, the optimal matching process is highly important because the productivity gains of fund managers

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after their optimal match has been discovered are economically significant, making this a worthwhile quest for both fund managers and fund families.

The findings of our study have important implications for fund families and fund managers. These implications are related to how these players respond following discovery of managers' optimal match. Fund families respond rationally after they discover the optimal match of their managers. To maximize returns for the entire family, they allocate more capital to the optimally matched managers who are operating at a higher level of productivity. Beyond this capital reallocation centrally decided at the family level, additional capital flows to the ideas of the optimally matched managers as affiliated family managers mimic the trades of the optimally matched managers. Managers also respond rationally to learning that they are optimally matched by exhibiting a higher level of investment conviction. Specifically, they tilt their portfolio away from the typical portfolio of their peer managers to amplify the gains from their higher productivity. These findings contribute to furthering our understanding of how fund families and fund managers interact when it comes to talent development and deployment. More generally, our study sheds light on the importance of match finding between employees and companies by documenting sizable productivity gains that happen as a result of this process. Furthermore, our findings have implications for market efficiency. The optimal matching of managers, who become more productive, is likely to contribute to market efficiency, which is further amplified by the reallocation of capital by fund families towards their matched managers.

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References

Addison, John T; Chen, Liwen and Orgul D. Ozturk (2017): Occupational Match Quality and Gender over Two Cohorts, in: *Industrial and Labor Relations Review (forthcoming)*.

Antonovics, Kate and Limor Golan (2012): Experimentation and Job Choice, in: *Journal of Labor Economics*, Vol. 30, No. 2, pp. 333–366.

Barillas, Francisco and J. A.Y. Shanken (2018): Comparing Asset Pricing Models, in: *The Journal of Finance*, Vol. 73, No. 2, pp. 715–754.

Berk, Jonathan B; van Binsbergen, Jules H. and Binying Liu (2017): Matching Capital and Labor, in: *The Journal of Finance*, Vol. 72, No. 6, pp. 2467–2504.

Carhart, Mark M. (1997): On Persistence in Mutual Fund Performance, in: *The Journal of Finance*, Vol. 52, No. 1, pp. 57–82.

Cheng, Si; Massa, Massimo; Spiegel, Matthew and Hong Zhang (2013): Human Capital and the Structure of the Mutual Fund Industry, *Working Paper*.

Chevalier, Judith and Glenn Ellison (1999): Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance, in: *The Journal of Finance*, Vol. 54, No. 3, pp. 875–899.

Cici, Gjergji; Gehde-Trapp, Monika; Göricke, Marc-André and Alexander Kempf (2018): The Investment Value of Fund Managers' Experience outside the Financial Sector, in: *Review of Financial Studies*, Vol. 31, No. 10, pp. 3821–3853.

Cremers, K. J.M. and Antti Petajisto (2009): How Active Is Your Fund Manager? A New Measure That Predicts Performance, in: *Review of Financial Studies*, Vol. 22, No. 9, pp. 3329–3365.

Diamond, Peter A. (1981): Mobility Costs, Frictional Unemployment, and Efficiency, in: *Journal of Political Economy*, Vol. 89, No. 4, pp. 798–812.

Electronic copy available at: https://ssrn.com/abstract=3732930

Eriksson, Tor and Jaime Ortega (2006): The Adoption of Job Rotation: Testing the Theories, in: *ILR Review*, Vol. 59, No. 4, pp. 653–666.

Fama, Eugene F. and Kenneth R. French (2015): A five-factor asset pricing model, in: *Journal of Financial Economics*, Vol. 116, No. 1, pp. 1–22.

Fama, Eugene F. and James d. Macbeth (1973): Risk, Return, and Equilibrium: Empirical Tests, in: *Journal of Political Economy*, Vol. 81, pp. 607–636.

Fang, Jieyan; Kempf, Alexander and Monika Trapp (2014): Fund Manager Allocation, in: *Journal of Financial Economics*, Vol. 111, No. 3, pp. 661–674.

Flinn, Christopher J. (1986): Wages and Job Mobility of Young Workers, in: *Journal of Political Economy*, Vol. 94, No. 3, 88-110.

Garmaise, M. J. (2011): Ties that Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment, in: *Journal of Law, Economics, and Organization*, Vol. 27, No. 2, pp. 376–425.

Golec, Joseph H. (1996): The effects of mutual fund managers' characteristics on their portfolio performance, risk and fees, in: *Financial Services Review*, Vol. 5, No. 2, pp. 133–147.

Greenwood, Robin and Stefan Nagel (2009): Inexperienced investors and bubbles, in: *Journal of Financial Economics*, Vol. 93, No. 2, pp. 239–258.

Groes, F; Kircher, P. and I. Manovskii (2015): The U-Shapes of Occupational Mobility, in: *The Review of Economic Studies*, Vol. 82, No. 2, pp. 659–692.

Jiang, H. A. and Verardo, Michela (2018): Does Herding Behavior Reveal Skill? An Analysis of Mutual Fund Performance, in: *The Journal of Finance*, Vol. 73, pp. 2229–2269

Jovanovic, Boyan (1979): Job Matching and the Theory of Turnover, in: *Journal of Political Economy*, Vol. 87, No. 5, pp. 972–990.

Jovanovic, Boyan (1984): Matching, Turnover, and Unemployment, in: *Journal of Political Economy*, Vol. 92, No. 1, pp. 108–122.

Electronic copy available at: https://ssrn.com/abstract=3732930

Jovanovic, Boyan and Robert Moffitt (1990): An Estimate of a Sectoral Model of Labor Mobility, in: *Journal of Political Economy*, Vol. 98, No. 4, pp. 827–852.

Kambourov, Gueorgui and Iourii Manovskii (2008): Rising Occupational And Industry Mobility In The United States: 1968-97, in: *International Economic Review*, Vol. 49, No. 1, pp. 41–79.

Kambourov, Gueorgui and Iourii Manovskii (2009a): Occupational Mobility and Wage Inequality, in: *Review of Economic Studies*, Vol. 76, No. 2, pp. 731–759.

Kambourov, Gueorgui and Iourii Manovskii (2009b): Occupational Specifity of Human Capital, in: *International Economic Review*, Vol. 50, No. 1, pp. 63–115.

Kempf, Elisabeth; Manconi, Alberto and Oliver G. Spalt (2017): Learning by Doing: The Value of Experience and the Origins of Skill for Mutual Fund Managers, *Working Paper*.

Malsberger, B.M., (2004), *Covenants not to compete: A state-by-state survey*, 4th ed., Bureau of National Affairs, Washington, DC.

Martin, Thorsten and Florian Sonnenburg (2015): Managerial Ownership Changes and Mutual Fund Performance, *Working Paper*.

McCall, Brian P. (1990): Occupational Matching: A Test of Sorts, in: *Journal of Political Economy*, Vol. 98, No. 1, pp. 45–69.

Miller, Robert A. (1984): Job Matching and Occupational Choice, in: *Journal of Political Economy*, Vol. 92, No. 6, pp. 1086–1120.

Mortensen, Dale T. (1978): Specific Capital and Labor Turnover, in: *The Bell Journal of Economics*, Vol. 9, No. 2, p. 572.

Mortensen, Dale T. (1986): Job search and labor market analysis, in: Handbook of Labor Economics, Vol. 2, pp. 849–919.

Electronic copy available at: https://ssrn.com/abstract=3732930

Newey, Whitney K. and Kenneth D. West (1987): A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, in: *Econometrica*, Vol. 55, pp. 703–708.

Ortega, Jaime (2001): Job Rotation as a Learning Mechanism, in: *Management Science*, Vol. 47, No. 10, pp. 1361–1370.

Papageorgiou, Theodore (2014): Learning Your Comparative Advantages, in: *The Review of Economic Studies*, Vol. 81, No. 3, pp. 1263–1295.

Papageorgiou, Theodore (2018): Large firms and within firm occupational reallocation, in: *Journal of Economic Theory*, Vol. 174, pp. 184–223.

Petajisto, Antti (2013): Active Share and Mutual Fund Performance, in: *Financial Analysts Journal*, Vol. 69, No. 4, pp. 73–93.

Petersen, Mitchell A. (2009): Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, in: *Review of Financial Studies*, Vol. 22, No. 1, pp. 435–480.

Zambrana, Rafael and Zapatero, Fernando (2020): A Tale of Two Types: Generalists vs. Specialists in Mutual Funds Asset Management, in: *Journal of Financial Economics* (*forthcoming*).

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Table I: Descriptive Statistics

This table reports statistics for the total sample. The sample period is from 1992 through 2016. This table 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. #Job Types 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. Family Size is given by family AUM in $ millions.

	mean	std	p10	p50	p90
Industry Tenure [years]	7.13	6.22	0.99	5.43	15.76
#Job Types 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
Family Size [$ million]	28,082	70,744	83	6,635	59,102

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Table II: Initial Tests of Match Finding Theory

This table presents results from initial 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. 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 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. In Panel B, the dependent variable is an indicator (1/0) variable capturing whether a manager changes her job type (Switch). Control variables at the manager, fund, and family level are constructed as in Table I and lagged by one year. Regressions are run with time, style and manager-by-family 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)
#Job Types Tried	-0.0039	-0.0031	-0.0033	-0.0003*
	(-1.50)	(-1.29)	(-1.63)	(-1.70)
Industry Tenure	-0.0059***	-0.0072***	-0.0054***	-0.0003**
	(-3.19)	(-4.40)	(-3.94)	(-2.01)
Expense Ratio	0.0295***	0.0261***	0.0109***	0.0005*
	(7.56)	(7.33)	(3.55)	(1.83)
Turnover Ratio	-0.0313***	-0.0282***	-0.0172***	-0.0012***
	(-20.48)	(-19.61)	(-13.20)	(-10.73)
Flow	0.3134	0.5450	1.5751***	0.0340
	(0.96)	(0.86)	(2.58)	(0.60)
Fund Age	-0.0022	-0.0017	0.0007	0.0001
	(-1.51)	(-1.15)	(0.87)	(1.00)
Fund Size	-0.0069***	-0.0052***	-0.0039***	-0.0003***
	(-6.55)	(-5.87)	(-3.88)	(-3.59)
Family Size	-0.0066***	-0.0058***	-0.0009	-0.0002
	(-3.53)	(-3.40)	(-0.56)	(-1.61)
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Family FE	Yes	Yes	Yes	Yes
Observations	29,699	29,759	29,582	29,582
Adjusted R^2	0.743	0.068	0.124	0.107

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Panel B: Impact of Tenure on the Likelihood of Switching Job Types

	(1)	(2)
Tenure	-0.2261***	-0.3354***
	(-26.10)	(-35.57)
#Job Types Tried		-0.3038***
		(-33.63)
Industry Tenure		0.0851***
		(17.02)
Expense Ratio		0.0408***
		(4.72)
Turnover Ratio		0.0313***
		(10.15)
Flow		1.3630**
		(2.17)
Fund Age		0.0004
		(0.28)
Fund Size		-0.0050***
		(-3.33)
Family Size		-0.0057
		(-1.43)
Time FE	Yes	Yes
Style FE	Yes	Yes
Manager × Family FE	Yes	Yes
Observations	30,398	30,398
Adjusted R^2	0.177	0.339

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Table III: Performance Change after Discovery of Optimal Match

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. 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 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 4.1. Control variables at the manager, fund, and family level are constructed as in Table I. Regressions are run with time, style and manager-by-family 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	0.0153***	0.0158***	0.0116***	0.0135***
	(2.77)	(3.24)	(3.05)	(2.83)
#Job Types Tried	-0.0016	-0.0012	-0.0008	-0.0013
	(-0.61)	(-0.52)	(-0.39)	(-0.58)
Industry Tenure	-0.0042**	-0.0060***	-0.0037***	-0.0016
	(-2.43)	(-3.86)	(-2.73)	(-0.95)
Expense Ratio	0.0440	0.2950	1.4000***	0.0564
	(0.12)	(0.52)	(2.66)	(0.08)
Turnover. Ratio	-0.0027**	-0.0023*	-0.0002	0.0011
	(-2.12)	(-1.96)	(-0.30)	(0.72)
Flow	-0.0067***	-0.0053***	-0.0041***	-0.0051***
	(-6.62)	(-6.12)	(-4.22)	(-4.16)
Fund Age	0.0305***	0.0252***	0.0109***	0.0063*
	(8.04)	(7.26)	(3.46)	(1.65)
Fund Size	-0.0315***	-0.0280***	-0.0173***	-0.0158***
	(-21.04)	(-19.95)	(-13.62)	(-11.05)
Family Size	-0.0049***	-0.0042**	0.0001	-0.0024
	(-2.64)	(-2.50)	(0.04)	(-1.38)
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Family FE	Yes	Yes	Yes	Yes
Observations	29,699	29,759	29,582	29,582
Adjusted R^2	0.737	0.065	0.115	0.120

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Table IV: Parallel Trends Assessment and Persistence of Performance

In this table, we modify our main analysis of Table III in order to test for parallel trends and the persistence of the performance effect. In the first column corresponding to each performance measure in Table IV, we augment Model (3) with three indicator variables that identify managers that attained match discovery—in each of the prior three years (Pre3·Match – Pre1·Match). 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 optimal match changes in three subsequent periods, i.e., the first year (Post1·Match), second year (Post2·Match), and all years from the third year onwards subsequent to match discovery (Post3+·Match). The construction of all dependent and independent variables is described in Table II. Regressions are run with time, style and manager-by-family 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.

	Return		Style-Return		Alpha4		Alpha6	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Pre3·Match	0.0019	0.0020	-0.0021	-0.0020	-0.0028	-0.0028	0.0043	0.0044
	(0.29)	(0.30)	(-0.34)	(-0.33)	(-0.49)	(-0.49)	(0.68)	(0.69)
Pre2·Match	-0.0081	-0.0078	-0.0023	-0.0021	0.0022	0.0022	-0.0006	-0.0004
	(-1.11)	(-1.08)	(-0.31)	(-0.28)	(0.39)	(0.39)	(-0.08)	(-0.06)
Pre1·Match	-0.0005	-0.0003	0.0000	0.0002	0.0001	0.0001	-0.0033	-0.0032
	(-0.08)	(-0.05)	(0.01)	(0.03)	(0.02)	(0.02)	(-0.62)	(-0.60)
Match	0.0147***		0.0155***		0.0116***		0.0132***	
	(2.72)		(3.21)		(3.05)		(2.69)	
Post1·Match		0.0084		0.0101*		0.0101*		0.0072
		(1.18)		(1.69)		(1.89)		(1.07)
Post2·Match		0.0093		0.0119*		0.0137**		0.0130**
		(1.36)		(1.81)		(2.56)		(1.98)
Post3+·Match		0.0211***		0.0205***		0.0117***		0.0171***
		(3.55)		(3.82)		(2.64)		(3.20)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family 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 × Family FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,699	29,699	29,759	29,759	29,582	29,582	29,582	29,582
Adjusted R^2	0.737	0.737	0.065	0.065	0.115	0.115	0.120	0.120

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Table V: Matched Sample Analysis of Performance Change after Discovery of Optimal Match

In this table, we repeat our main analysis of Table III using a subsample of manager that found their style match (treated) and a control group of managers that did not find their match (untreated) managers. For each fund manager who has reached her best match, we identify a control manager, i.e., another manager from the same family that has tried the same styles and has the highest propensity score with respect to the length of time she tried the various styles. The construction of all dependent and independent variables is described in Table II. Regressions are run with time, style and manager-by-family 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	0.0215***	0.0201***	0.0116***	0.0126***
	(3.91)	(3.99)	(3.13)	(2.72)
#Job Types Tried	0.0048	0.0033	-0.0001	-0.0012
	(1.58)	(1.23)	(-0.06)	(-0.47)
Industry Tenure	-0.0044**	-0.0061***	-0.0039**	-0.0009
	(-2.05)	(-3.04)	(-2.42)	(-0.46)
Expense Ratio	0.7647	-0.2046	0.1427	-1.2207
	(1.17)	(-0.36)	(0.24)	(-1.21)
Turnover Ratio	-0.0020	-0.0019	-0.0002	0.0003
	(-1.25)	(-1.55)	(-0.44)	(0.48)
Flow	-0.0085***	-0.0061***	-0.0047**	-0.0051***
	(-4.74)	(-3.85)	(-2.51)	(-2.65)
Fund Age	0.0236***	0.0210***	0.0095**	0.0035
	(5.14)	(5.09)	(2.58)	(0.84)
Fund Size	-0.0252***	-0.0239***	-0.0150***	-0.0135***
	(-12.89)	(-13.29)	(-9.55)	(-7.77)
Family Size	-0.0007	0.0037*	0.0057***	0.0038*
	(-0.28)	(1.71)	(3.20)	(1.95)
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Family FE	Yes	Yes	Yes	Yes
Observations	4,608	4,622	4,519	4,519
Adjusted R^2	0.761	0.044	0.164	0.142

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Table VI: Managerial Preferences and Organizational Power

In this table, we augment our main analysis of Table III to test for the impact of managerial preferences and managers' organizational power. We employ HighFamilyTenure, an indicator variable which equals one if the current family tenure of the respective manager is greater than the median family tenure of all managers in the same year, and zero otherwise and interact this variable with Match. The construction of all dependent and independent variables is described in Table II. Regressions are run with time, style and manager-by-family 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	0.0215**	0.0265***	0.0175***	0.0150**
	(2.37)	(2.94)	(3.12)	(2.29)
HighFamilyTenure	-0.0018	-0.0009	-0.0005	-0.0020
	(-0.82)	(-0.43)	(-0.28)	(-0.83)
HighFamilyTenure × Match	-0.0074	-0.0128	-0.0074	-0.0019
	(-0.91)	(-1.55)	(-1.40)	(-0.32)
Fund Controls	Yes	Yes	Yes	Yes
Manager Controls	Yes	Yes	Yes	Yes
Family Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Manager × Family FE	Yes	Yes	Yes	Yes
Observations	29,699	29,759	29,582	29,582
Adjusted R^2	0.737	0.065	0.115	0.120

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Table VII: Managers that Reach Optimal Match

This table reports statistics for the managers that return to a previously-tried style during the 1992-2016 sample period. In Panel A we report the mean, the standard deviation (std) as well as the 10th, 50th and 90th percentile (p10, p50, and p90, respectively). #Job Types Tried is the number styles a manager tried before returning to a previously-tried style. Time until Match represents the length of time (in years) until the manager has reached her optimal match.The last two rows, respectively, report the fraction of managers that return to a style where they generated the best performance across all styles tried and the fraction of managers that stayed in the same style after reaching style match. In Panel B, we report results from a linear probability model that examines determinants of managers finding their optimal. The dependent variable, Match, is a (1/0) indicator variable, which identifies managers that have reached their optimal match. Fama-MacBeth (1973) estimation is conducted whereby we run cross-sectional regressions each year and report the time series average of coefficients, together with their Newey and West (1987)-adjusted time-series standard errors. Observations for each cross-sectional regression include managers that reached optimal match in that year and those managers that never reached their optimal match up to that point in time. Independent variables, include: #Fam Styles, the number of styles in a manager's fund family; 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; #Job Types Tried", defined above, and "Industry Tenure", the time spent in the mutual fund industry in years. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Descriptive Statistics

	Mean	std	p10	p50	p90
#Job Types Tried	3.6	1.1	2	3	5
Time until Match	5.7	3.6	2	5	10.6
% Return to best performing style			70%		
% Stay in the same style afterwards			94%		

Panel B: Determinants of Match Finding

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
#Family 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)
#Job Types 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

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Table VIII: Capital Reallocation after Discovery of Optimal Match

This table presents results from pooled OLS regressions that relate the probability that a manager gets assigned more assets under management with changes in match status of a manager. The analysis is done at the manager and year level. The dependent variable is Asset Increase, a binary variable that equals 1 if a manager gets assigned more assets under management in a given year and zero otherwise. Such instances include the manager being assigned to an additional fund or the manager being moved out of the existing fund and into a different fund with larger assets under management. The construction of the independent variables is described in Table II. Regressions are run with time, style and manager-by-family fixed effects. 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.

	Asset Increase	Asset Increase
Match	0.0272***	0.0545**
	(10.63)	(2.43)
Fund Controls	No	Yes
Manager Controls	No	Yes
Family Controls	No	Yes
Time FE	Yes	Yes
Style FE	Yes	Yes
Manager × Family FE	Yes	Yes
Observations	27,314	27,314
Adjusted R^2	0.181	0.268

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Table IX: Utilization of Trade Ideas by Affiliated Managers after Discovery of Optimal Match

This table presents results from pooled OLS regressions that relate the probability that a trade by a manager who has found her optimal match is followed subsequently by affiliated managers. The analysis is done at the stock-family-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 optimal 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 family 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 Matched_Manager_Trade, an indicator variable that equals one when the trade was conducted by a manager who has reached her optimal 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 family-by-style-by-report-date fixed effects (FE). T-statistics, based on standard errors clustered at the family 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
Matched_Manager_Trades	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)
Family × 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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Table X: Change in Investment Behavior after Discovery of Optimal Match

This table presents results from pooled OLS regressions that relate how far a manager's portfolio deviated from that of her peers with changes in the style match status of a manager. The analysis is done at the manager and year level. The dependent variable is Active Peer Share, constructed as described in Section 6. The independent variables are the same as in Table II. Regressions are run with time, style and manager-by-family 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.

	Active Peer Share	Active Peer Share
Match	0.6418***	0.6648***
	(2.53)	(2.63)
Fund Controls	No	Yes
Manager Controls	No	Yes
Family Controls	No	Yes
Time FE	Yes	Yes
Style FE	Yes	Yes
Manager × Family FE	Yes	Yes
Observations	28,506	28,506
Adjusted R^2	0.907	0.908

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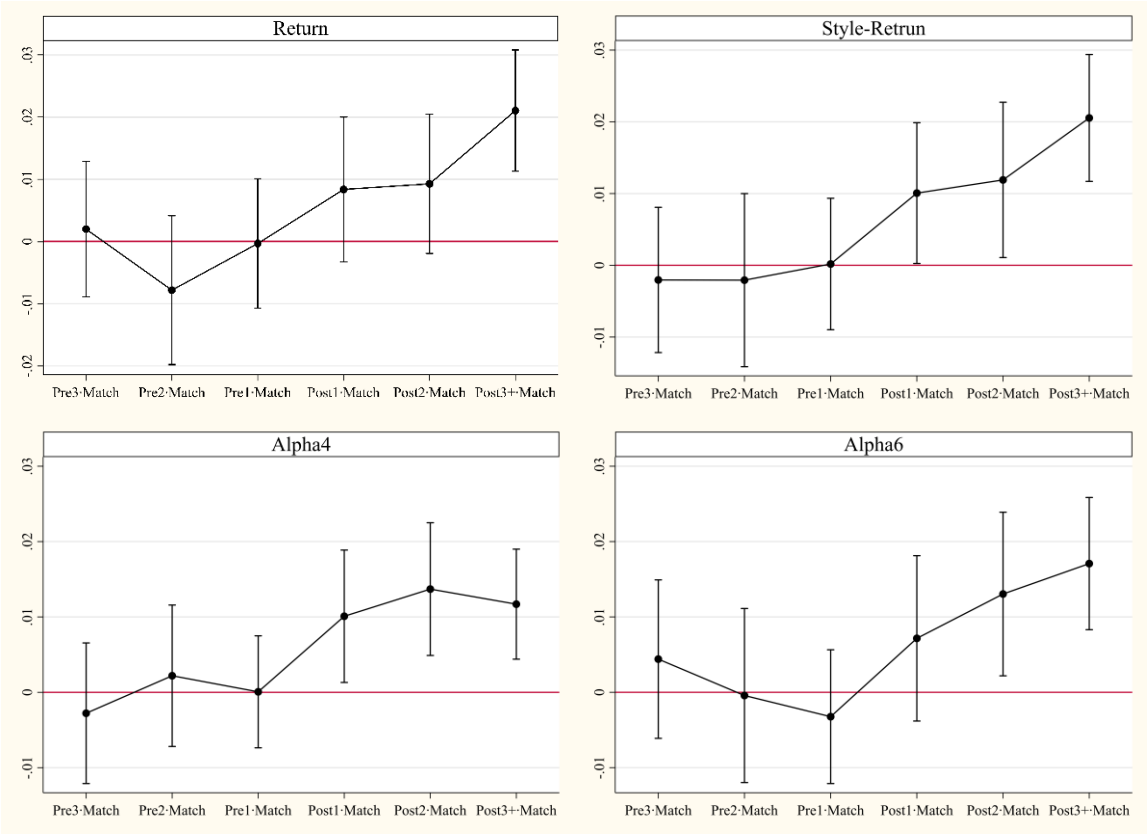
Figure I: Parallel Trends Assessment and Persistence of Performance

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



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