CFR Working Paper NO. 19-05

Finding your calling: Skill matching in the mutual fund industry

G. Cici • M. Hendriock • A. Kempf

centre for financial Research cologne

Finding your calling: Skill matching in the mutual fund industry

by

Gjergji Cici, Mario Hendriock, and Alexander Kempf*

March 16, 2020

Abstract

To optimally utilize their labor, fund families need to match their portfolio managers' skills with the job requirements of different funds. Fund families make it possible for their managers to try out different funds in a learning-by-trying fashion until they find their best match. After they have reached their best match, managers operate at higher productivity levels, which then fund families utilize at a larger asset base. Moreover, fund families hire in accordance with their capability to make the match discovery possible. Managers exhibit a higher degree of conviction after their match discovery, both in their fund and personal portfolios.

* Cici (gjergji.cici@ku.edu) is from School of Business, University of Kansas. Hendriock (hendriock@wiso.uni-koeln.de) and Kempf (kempf@wiso.uni-koeln.de) are from Department of Finance, University of Cologne. All authors are members of the Centre for Financial Research (CFR), Cologne. For helpful comments and discussions we thank Stefan Jaspersen, Peter Limbach, Alexander Puetz, and seminar participants at the University of Cologne, Iowa State University, and University of Missouri.

1 Introduction

Managerial skill is a key factor for the success of mutual funds, which, with more than $17 trillion in assets under management, are important for millions of investors relying on them to achieve their financial goals (e.g., ICI 2019 Fact Book). To best exploit the skills of their fund managers, fund families need to optimally match managerial skills and job requirements demanded by the different fund types. How fund families and managers arrive at this optimal match is largely unknown, however. Occupational match theory suggests that one way in which the optimal match happens is through a learning-by-trying process, whereby managers try out different types of funds until their best match is found.[1] Consistent with this idea, some fund families (e.g., Fidelity Management & Research) try to facilitate the manager match discovery by instituting programs where junior portfolio managers serve as portfolio managers in certain funds for relatively short periods of time on a rotational basis.[2] Our paper is the first to study this learning-by-trying process in the fund industry and its implications for fund families and managers.

Within the U.S. mutual fund industry, funds are typically mandated to follow a clearly-defined investment style and are required to invest at least 80% of their assets in accordance with the investment style suggested by their name under Section 35d-1 of the U.S. Investment Company Act of 1940. Fund managers operate within the boundaries of these clearly-delineated investment styles and are typically viewed as being experts in a particular investment style. For example, Bill Miller, a former manager of Legg Mason Value Trust, was distinctly recognized as a "value" manager, whereas Thomas Rowe Price, Jr., a former fund manager and founder of T. Rowe Price, was recognized as a "growth" manager. However, for

[1] Seminal work by Mortensen (1978, 1986), Jovanovic (1979), Diamond (1981), and Miller (1984) lays the foundation of occupational match theory. More recent papers on this topic include Ortega (2001); Papageorgiou (2014, 2018); and Addison, Chen, and Ozturk (2018).
[2] See Huang (2014).

a fund manager that is starting out her career, neither the family nor the manager herself know what particular style she is best suited for. Nevertheless, they can discover the manager's best style match jointly over time while the manager tries different investment styles. This search process and the arrival of the manager at her best style match should finally lead to higher productivity of the fund manager in the form of better performance.

To identify points in time when managers arrive at their best style match, we study the sequence of managerial moves to different styles during a manager's career. Rationality suggests that a manager will move to a new style as long as the manager and the family think that the new style is a better fit than the manager's current style. Thus, the manager is expected to eventually settle into a style where she achieves her optimal level of productivity. This is in line with 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." Consistent with this, a fund manager who has tried a number of investment styles and has returned to one of her previously-tried styles has arguably reached her optimal style match. The idea is that both the manager and the family have likely realized that this previously-tried style was the best match for the manager and facilitated the manager's return to that style. Therefore, we use the point in time when a fund manager returns to one of her previously-tried styles to identify the end point of a search process that ended in ultimate discovery of the manager's best style match.

Conceivably, successful searches might happen even when a manager does not return to a previously-tried style. For example, the best style fit of a manager might have been discovered when the manager was a senior analyst while supporting portfolio managers operating in different investment styles. However, ex-ante it is impossible to distinguish these cases from instances whereby the manager did not return to a previously-tried style and her style match discovery did not happen. Therefore, our approach provides a lower bound of all the style match discoveries, which contributes to attenuation bias as some of these other successful searches we cannot identify will end up in the control group.

We start our analysis by providing an anatomy of the learning-by-trying process, uncovering a number of interesting facts. The average manager tries four styles over a time span of six years before she finds her best style match. In 70 percent of these cases, the fund manager returns to the style in which she delivered the best performance in the past. This supports the notion that returning to a previously-tried style is in response to learning in which style a manager has the highest productivity. After having discovered their best style match, about 94 percent of those managers stay in the same style for the remainder of their careers.[3] This is sensible from the career perspective of the manager, who will rationally switch only to positions that constitute a better fit with her style type, eventually settling into more stable positions closer to her optimal level of productivity and compensation. Taken together, these initial findings suggest that learning-by-trying of manager style types happens and that the search for the best style fit takes a long time and a considerable number of tries. Furthermore, the stability observed afterwards is highly suggestive of the notion that the return to a previously-tried style by a fund manager is the equilibrium outcome of a process that underlies the search for a best style match.

In order to further understand the process of best style match discovery, we explore a number of factors that can potentially affect the speed with which it happens. We find that a manager who has more opportunities to try different styles is quicker to find her style match. This is the case when a manager works in fund families that offer a larger number of styles and in states with weaker labor mobility restrictions, which enable the manager to try different

[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, Kambourov and Manovskii 2009b, Antonovics and Golan 2012, and Papageorgiou 2014).

styles across different fund families. In addition, we find that managers with prior work experience outside the financial industry find their best style match sooner than other managers. This is consistent with these managers having an informational advantage in some sectors or styles (e.g., Cici et al 2018), which reduces the number of styles they need to try before they find their best match. Finally, managers that attended institutions with higher student SAT scores take significantly less time to find their best style match. One possible reason is that such managers are inherently smarter, which helps them figure out their style type sooner; another one is that they have a better network of connections that facilitates this process either through more opportunities to try different jobs or through mentoring.

Having documented how learning-by-trying takes place, we next test the main hypothesis of the paper: Fund managers generate better performance after they have reached their best style match. To do so, we compare the performance of a fund manager before and after she has found her style match in a difference-in-differences setting. In doing so, we also control for possible self-selection issues that arise due to the possibility that more-skilled managers decide to move to fund families with more resources while their learning-by-trying takes place. This form of self-selection would lead us to overestimate the performance improvement that results from the manager reaching her best style match. To address this concern, we measure performance effects following the manager's style match within the same family, i.e., we include manager-by-family fixed effects in our regressions. Our findings support our hypothesis that performance improves after a manager has found her best style match by documenting a performance improvement that ranges from 116 to 158 basis points per year.

The performance improvement we document is also consistent with two alternative explanations. First, it is possible that performance improves because the manager is simply enhancing her human capital in a learning-by-doing or on-the-job training fashion (e.g., Golec

1996, Chevalier and Ellison 1999, Greenwood and Nagel 2009, and Kempf, Manconi, and Spalt 2017).[4] Simply put, the larger the number of different styles the manager has managed, the more investment knowledge she has acquired, which then translates into superior performance. However, we rule out this alternative explanation in a matched-sample analysis, whereby we compare a manager who has reached her best match with another manager from the same family that has tried the same styles and had the highest propensity score with respect to amount of time spent in the various styles. Second, perhaps some managers who have tried various styles are likely to have accumulated a certain amount of organizational power, which they use to first return to their preferred previously-tried style and afterwards to divert disproportionately more resources to their funds. If organizational power is responsible for the performance improvement we document, we ought to see a stronger performance improvement for managers with longer family tenure, which we use as a proxy for organizational power, relative to managers with shorter family tenure. We find no such difference and thus rule out organizational power as a possible explanation.

The discovery of managers' best style match and subsequent performance improvement raises various implications for fund families and fund managers. With regards to fund families, we expect them to exploit their new information regarding the style match of their managers to maximize the performance for the entire family. We document support for this in a number of findings. First, we find that fund families are more likely to promote managers after they have arrived at their best style match by increasing the amount of assets under their management. This is highly sensible and the most direct way for families to exploit the information they have about the skills of their managers. Second, fund families exploit the investment ideas of these managers in other funds managed by affiliated managers. Specifically, we find that the ideas

[4] Using French matched employer-employee data, Nagypal (2007) finds that firms place greater importance on the learning about the quality of the match between employee skills and jobs than on-the-job learning by employees.

of a fund manager are followed more by affiliated fund managers after the fund manager has reached her best style match. We also expect fund families to tailor their hiring strategies to their capabilities for making the discovery of their managers' style matches possible. Specifically, we find that larger families, which enjoy the benefits of larger internal labor markets, are more likely to hire managers that have not yet found the best style fit. This is highly sensible, since the size of the internal labor market determines the number of opportunities they can offer their managers to try different styles. Thus, larger families can better figure out their managers' types.

Armed with information about their style type and being matched to that style, fund managers are expected to exploit this information to their own advantage. We find that the extent of managers' conviction increases after they have found their best style match: these managers tilt their portfolios away from those of their peers after discovery of their style match and exploit this newly-found information in their personal investment decision making. Specifically, managers significantly increase their ownership in the funds that they manage after they have found their best style fit.

Our paper is related to the literature that studies the personnel decisions of mutual fund families. Cheng, Massa, Spiegel, and Zhang (2013) and Berk, van Binsbergen, and Liu (2017) show that personnel decisions by mutual fund families on average create value for their investors. Zambrana and Zapatero (2017) show that fund families assign "Stock Pickers" to manage funds focused on a particular style and "Market Timers" to manage funds across different styles, which is consistent with these managers being put to their best uses. However, to make these decisions, fund families need to know the types of their managers. We add to this literature by showing that fund families can figure out the managers' types in a learning-by-trying fashion that is consistent with occupation match theory. In addition, we document that the outcome of this learning-by-trying process has important implications for the behavior of mutual fund families and managers.

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 has 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 1999a, 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 style fit 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 style match.

Finally, our paper contributes to the large literature on occupational matching, especially to the empirical part of this literature.[5] These empirical papers rely on the premise of an underlying equilibrium model that results in employees and firms being matched after some learning has occurred about the match quality of different pairwise combinations tried. 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. The empirical prediction being tested is that an employee with longer tenure, who is more likely to be optimally matched to a job, will be less likely to leave that job and should have a higher salary

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

that is reflective of her higher productivity. Our study contributes to this literature by documenting directly the productivity gains that accrue once the occupational match is reached.

The rest of the paper is organized as follows. In Section 2, we discuss our data sources, describe our main methodology, and provide descriptive information about our sample managers. In Section 3, we provide details on the process that leads to optimal style match. We examine the impact that the discovery of optimal style match has on subsequent managerial productivity in Section 4. Sections 5 and 6 examine implications for fund families and fund managers, respectively. Section 7 concludes.

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.

To obtain information on managerial fund employment records, we use Morningstar Direct. We merge Morningstar Direct with the 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 Methodology

In our main tests we relate the manager's performance or other variables of interest to our key variable, $Style\ Match$, in a yearly panel-regression at the manager level as specified in equation (1):

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

$y_{i,t+1}$ denotes either the performance or another variable of interest for manager i at time $t+1$. $\vec{\gamma}$ is the vector of coefficients associated with fund, manager, and family level covariates described in the following and Table I, which are stacked into vector $\vec{c}$. ε denotes the error term.

We construct our $Style\ Match$ variable as follows. First, we identify the point in time when a manager has returned to a previously-tried style. Then, we code $Style\ Match$ as equal to one for all observations the manager manages that style from that point on and zero else, in particular for all observations before. $Style\ Match$ also equals zero for all observations belonging to all other managers who have not returned to a previously-tried style.

It is important that we control for the endogenous relation between style match discovery and innate manager characteristics and also the endogenous selection of managers to mutual fund families. For example, higher ability managers might be more likely to find their best style match in the first place. At the same time, higher ability managers might be more likely to join families with more resources where they are more likely to find their best fit and also generate better performance in part due to greater family support. To control for that, our identification strategy focuses on style matches that happen for the same manager within a given fund family by including manager-by-family fixed effects denoted by $\alpha_{i,f}$. We also include time fixed effects θ_t to account for common time variant factors and style fixed effects ω_s to control for commonalities within investment styles.

We include control variables measured at the manager, fund, and family level. Regarding the control variables measured at the manager level, we use the number of distinct styles that the manager has worked in ($\#Styles\ Tried$) up to each particular point in time and the natural logarithm of her industry tenure [$Log(\ Industry\ \ Tenure)$] to control for the investment experience or human capital accumulated in a learning-by-doing fashion.

Our control variables measured at the fund and family level are standard in the mutual fund literature. To aggregate fund level variables at the manager level, 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 [$Log(Fund\ Age)$]; and the natural logarithm of total net assets [$Log(Fund\ Size)$]. At the family level, we use the natural logarithm of family total net assets [$Log(Family\ Size)$] as a control variable.

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.

2.3 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 distinct styles.

Please insert Table I about here

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

3 An Anatomy of Learning-by-Trying

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. Then, we explore factors that can potentially affect the speed with which these managers find their best style match.

Please insert Table II about here

From Table II we observe that, on average, a manager tries about four different styles before arriving at her best style match, but the number of styles tried ranges between two and five (based on 10^{th} and 90^{th} percentiles). During this process, managers end up working, on average, for about four different funds. It takes about six years for the average manager to reach the optimal style match, which constitutes more than half of her industry tenure. The range is between two to eleven years, suggesting that for some managers learning-by-trying of their best style matches happens much faster and for some others much slower – an issue that we will analyze in more detail later in this section.

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 style match has been discovered, with 94% of the managers staying in the same style for the remainder of their careers.

Summing up, the considerable number of styles and funds tried as well as the considerable length of time spent in the process suggest that learning-by-trying of managers' style types is not a trivial process. Most importantly, stability observed afterwards is consistent with the return to a previously-tried style by a fund manager being the equilibrium outcome of a process that underlies the search for a best style match (Jovanovic 1979).

Given the cross-sectional variation in the length of time it takes to find the optimal style match, we next examine its possible determinants using a linear regression model. In other words, focusing on the managers that achieve their optimal style match, we examine what drives the speed with which that happens. The dependent variable is the time between when the manager first showed up in the database and the first day when she returned to a previously-tried style, measured in days. The independent variables included for this analysis are motivated by hypotheses developed below.[6]

We first hypothesize that style matches are reached faster 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 ($\#Family\ Styles$) 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 ($NCC - Index$) 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 hypothesize that fund managers with prior work experience outside the financial industry find their optimal style match faster. The idea is that this outside work experience offers managers an informational advantage in some sectors, which makes them more suitable for some styles than for others (e.g., Cici et al 2018). Therefore, the fund manager needs to try fewer styles before achieving her best style fit. To capture this effect in our regression, we include the dummy variable $Practical\ Experience$ that equals one if a fund manager has worked outside the financial industry before she became a fund manager, and zero

[6] Results are similar when we use a Cox proportional hazard model (Cox 1972), which estimates the relation between the hazard rates and the independent variables.

otherwise. We categorize a fund manager as having outside work experience like in Cici et al (2018) but do not limit our sample to managers of diversified funds as we also include sector fund managers.

Finally, 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 1999a). 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. Thus, we expect that higher-SAT managers are able to find their optimal match faster. We employ a dummy variable SAT, which equals one if the manager obtained her bachelor degree from an institution at which the average matriculates' SAT score is above median. We obtain SAT scores from the College Scorecard provided by the U.S. Department of Education.[7]

The regression results are provided in Table III. Since Garmaise's (2011) non-compete clause enforceability index is available only until 2004, we report results from univariate regressions (Columns 1-4) as well as from a regression that includes all independent variables (Column 5). For this latter regression, the sample period is limited to 1992 – 2004, during which period we observe 415 fund managers returning to a previously-tried style.

Please insert Table III about here

Evidence from Table III is in line with our predictions. When the manager has more opportunities to try different styles and when the manager has attended institutions with a higher average student SAT score, that manager can find her optimal style match sooner. In addition, managers with prior work experience outside the financial industry find their best

[7] See https://collegescorecard.ed.gov/.

style match sooner than other managers. This is consistent with these managers having an information advantage in certain sectors or styles, which reduces the number of styles they need to try before they find their best match.

4 Performance after Discovery of Style Match

4.1 Main Result

The economic rationale for finding the style match of a fund manager is for that manager to operate at the highest possible level of productivity, which is an optimal outcome for both the fund family and the manager. It is optimal for the fund family because by deploying the fund manager at her best style match it can generate higher fund performance and consequently higher fee revenue. It is optimal for the fund manager because in competitive labor markets we would expect her compensation to increase to a higher level that reflects her higher level of productivity.

To test the hypothesis that the performance of the fund manager improves after her best style match has been realized, we estimate equation (1) with manager performance as the dependent variable. 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 ($Alpha6$) (Fama and French 2018 and Barillas and Shanken 2018). 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 aggregate fund-level returns and style-adjusted returns to the manager-level by the method described in Section 2.2. 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.[8] All performance measures are annualized by compounding the twelve monthly returns corresponding to each calendar year.

Please insert Table IV about here

Results are reported in Table IV. The coefficients on our main variable, $Style\ Match$, 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' style matches. Specifically, for managers who reach their best style match, the subsequent performance improvement is 116 to 158 basis points per year relative to other funds. This evidence suggests that finding the style match of fund managers pays off for the fund family and the manager, who both stand to benefit from the higher level of productivity that a best matched manager 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 V 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 style match discovery. Specifically, in the first column corresponding to each performance measure, we augment model (1) with three indicator variables that identify managers that attained style match discovery—in each of the prior three years ($Pre1 \cdot Style\ Match$, $Pre2 \cdot Style\ Match$, and $Pre3 \cdot Style\ Match$). Results reported in Table V and corroborated visually in Figure 1 show that none of the variables $Pre1 \cdot Style\ Match$, $Pre2 \cdot$

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

$Style\ Match$, and $Pre3 \cdot Style\ Match$ are significantly different from zero, i.e., the performance of the two groups of managers shows parallel trends prior to achievement of style match.

Please insert Table V about here

Please insert Figure I about here

We also examine the persistence of the performance improvement following the managers' style match discovery. To do so, in the second column corresponding to each performance measure in Table V, we replace $Style\ Match$ with three indicator variables that identify managers that reached style match discovery—in three subsequent periods, i.e., the first year, second year, and all years after the second year (third year or later) subsequent to style match discovery ($Post1 \cdot Style\ Match$, $Post2 \cdot Style\ Match$, and $Post3 + \cdot Style\ Match$).

Results show that performance improvement following the discovery of style 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 research infrastructure of the new fund, adjusting to a new work environment (e.g., new colleagues), and communicating with new clients. In year two and beyond performance improvement gets much stronger both in an economic and statistical sense, which suggests that productivity gains coming from the best style match become noticeable once the manager has gone through an initial period of adjustment.

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 1999a; Greenwood and Nagel 2009; 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 IV, 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 (1).

Please insert Table VI about here

Results are reported in Table VI. 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 IV. Nonetheless, despite the smaller sample used in Table VI, the coefficients on the $Style\ Match$ variable are still positive and exhibit similar levels of economic and statistical significance as those from Table IV.[9]

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

[9] 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 VI, 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.

way. This increases our confidence that the performance improvement we document is the result of learning-by-trying of style matches 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 will likely increase with her tenure with the family, a manager who has tried various styles is likely to have accumulated sufficient power, which she uses 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 $High\ Family\ Tenure$, 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 $Style\ Match$ with $High\ Family\ Tenure$.

Please insert Table VII about here

Table VII shows results from a model that augments model (1) with $High\ Family\ Tenure$ and its interaction with $Style\ Match$. Results show that both $High\ Family\ Tenure$ and its interaction with $Style\ Match$ 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.

5 How do Families Respond to Optimal Style Discovery?

In this section we examine the implications that style match discovery has for mutual fund families. We explore three possible ways in which fund families exploit the information they acquired after a manger has reached her best style match. In Section 5.1, we test whether fund families are more likely to promote managers who have reached their best style match 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 would be intended to maximize returns for the entire family. Finally, in Section 5.3 we explore the broader hiring implications for families with more versus less developed internal labor markets.

5.1 Do Families Promote Managers who Reach their Style Match?

Consistent with fund families taking advantage of the information they acquire after the style match of a manager has been found, we expect that fund families will be more likely to promote the corresponding managers by increasing their assets under management. To test this hypothesis, we model the probability that a manager is promoted as a function of the variables introduced in equation (1) using a linear probability model. The dependent variable is $Promotion$, a binary variable that equals 1 if a manager is promoted in a given year and zero otherwise. We determine that a manager has had a promotion if the reshuffling of her responsibilities resulted in greater assets under management than before. 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.

Please insert Table VIII about here

Results are presented in Table VIII. They show that after arriving at her best style match a manager is more likely to be promoted in the following period than before. The coefficient on the $Style\ Match$ 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 style match discovery process and the resulting private information that families generate about the skills of their managers to the optimal deployment of managers' talent by fund families.

5.2 Do Families Further Scale up the New Information?

In the previous section we showed that fund families rationally exploit the information they acquire about managerial skill after the manager has reached her best style 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 style 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 *j* conducted by a manager *i* in quarter *t*.

$$trade\ followed_{j,i,t} = \chi_{f,s,t} + \alpha \cdot SM\ Trade_{j,i,t} + \vec{\gamma}'\vec{c}_{j,t} + \epsilon_{j,i,t}. \tag{2}$$

The dependent variable $trade\ followed_{j,i,t}$ 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 subsequently in quarter $t+1$ or $t+2$, and zero otherwise. The key independent variable $SM\ Trade$ is an indicator variable that equals one when the trade was conducted by a manager who has reached her style match and zero otherwise. If affiliated managers are more likely to follow the ideas of a manager who is operating at her best style match than those of managers who have not reached this point, then we expect the coefficient on this variable to be positive. $\epsilon_{j,i,t}$ denotes the error term.

Our control variables, stacked into vector $\vec{c}$, include: the natural logarithm of market capitalization [$Log(Firm\ Size)$]; 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 style be considered, we employ family-by-style-by-report date fixed effects, denoted by $\chi_{f,s,t}$. 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 $SM\ Trade$ variable in the first column is positive and statistically significant at the 5% level.[10] Its value suggests that when the new ideas are from a manager that operates at her best style match, they have a 1.2 percentage points higher probability that they are subsequently utilized by the family's other funds. 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 funds follow the ideas of their colleagues in general. This evidence is consistent with affiliated managers paying greater attention to the

[10] Because it only considers the following of ideas with a time lag, 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.

investment ideas coming from a manager that is at her best style match than those of other managers and being more likely to act on those 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 $SM\ Trade$ 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 operating at their best style match 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 $SM\ Trade$ variable continues to be positive and statistically significant, suggesting that the affiliated managers pay closer attention to the selling decisions of their colleagues operating at their best style match.

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

5.3 Implications for the Hiring Decisions of Fund Families

Our findings have broad implications for how families approach hiring of new managers. Fund families with developed internal markets, e.g., larger families, have a larger opportunity set of style offerings for their managers to work in during their learning-by-trying process. This makes it more likely for managers working for larger families to try out more different styles and find their best style match faster than managers working for smaller families, consistent with occupation match theory (e.g., Papageorgiou 2018). For this reason, we expect that larger families tend to hire managers that are not yet at their best style match because such families have more opportunities to facilitate the style match discovery of these managers. Conversely, we expect that smaller families, which have fewer style offerings and are therefore less able to facilitate style match discovery, tend to hire managers who have already reached their style match.

To test this hypothesis, we first identify all hires within our sample, with accompanying information as to which manager was hired and in which family the hiring took place. The dependent variable is whether the manager hired has already reached her style match ($SM\ Manager$), coded as a (1/0) indicator variable. The main independent variable is size of the internal labor market measured by the number of styles offered by the fund family ($\#Family\ Styles$). We regress $SM\ Manager$ on $\#Family\ Styles$ along with manager and family controls introduced in Section 2.2 and cluster standard errors at the family level.

Please insert Table X about here

Results reported in Table X show that the likelihood that the hired manager is a manager who has already reached her style match is significantly negatively related with the size of the internal labor market. This finding supports our hypothesis that fund families with larger internal labor markets are in a position to hire managers who have not yet discovered their best style match.

Overall, the findings from this section suggest that fund families respond to the outcome of the style match discovery process in two key ways: First, they utilize the productivity gains that follow the discovery of the style match of their managers to a large asset base, and second, they follow hiring practices that reflect their ability to make the optimal style match discovery of their managers possible.

6 How do Managers Respond to Style Match Discovery?

In this section we examine the implications that the outcome of learning-by-trying has for fund managers, i.e., how fund managers respond to the discovery of their best style fit. In Section 6.1 we examine whether managers adjust their investment behavior and in Section 6.2 whether they change the level of personal investments in the mutual funds that they manage.

6.1 Investment Behavior

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 learned her best style match and knows where her skill is highest is expected to exhibit a higher degree of conviction by investing differently from her peers. Thus, we would expect a manager to tilt her portfolio away from the typical portfolio of her peers after she has arrived at her style 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 finds the best style 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

$$Active\ Peer\ Share_{i,t} = \sum_{j=1}^{M} \left| w_{j,i,t} - w_{j,peer_i,t} \right|, \tag{3}$$

where $w_{j,i,t}$ and $w_{j,peer_i,t}$ 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 M 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 zero, $Active\ Peer\ Share$ will be two. We employ the same independent variables, controls, and fixed effects as in our estimation of equation (1).

Please insert Table XI about here

Results are reported in Table XI. They show that $Active\ Peer\ Share$ increases after managers reach their style match relative to other funds. This result is statistically significant at the 1% level and also economically significant. The coefficient on the $Style\ Match$ variable suggests an increase in $Active\ Peer\ Share$ of 0.6648 after style match discovery, which is economically meaningful given that the maximum value $Active\ Peer\ Share$ can take is two. This evidence suggests that fund managers use the information they acquire about their best style fit to amplify the utilization of these skills where their productivity is highest in a way that is consistent with them exhibiting a higher level of conviction.

6.2 Managerial Fund Ownership Changes

The finding that managers exhibit significant improvement in performance after they have found their best style match could suggest yet another way in which fund managers exploit their newly-found advantage. In particular, fund managers could increase their personal investments in the funds that they manage in order to personally benefit from the better performance that follows. A similar investment motive is supported by Gupta and Sachdeva (2019), who show that hedge fund managers invest strategically in the funds that they manage, an action that contributes sizable returns to their personal wealth. On the other hand, there is reason to believe that managers might not want to increase their personal investments in the funds that they manage following their style match discovery. The idea is that in a competitive labor market, the manager should experience increased compensation that is commensurate with her new, higher level of productivity. This would mean that the manager would have a larger fraction of her wealth tied to the fortunes of the fund family and she might prefer to counter this from a diversification perspective. Ex-ante it is not clear which of these two effects dominates.

We obtain data on managerial ownership mutual funds have to disclose per SEC Rule S7-12-04 for the 2004-2012 period.[11] Mutual fund managers are not required to report the actual level of their mutual fund ownership but they have to report whether their ownership falls in one of six ranges.[12] Given the compensation levels of mutual fund managers, we consider the distinction among lower ranges as trivial and therefore introduce a binary variable, $High\ Ownership$, which equals one if the manager's ownership in the fund was above \$500,000 and zero otherwise.[13]

To examine whether fund managers increase ownership in the funds they manage after reaching their style match, we model the likelihood of a fund manager being in the high ownership group, i.e., $High\ Ownership$ being equal to one, as a function of the independent variables employed in equation (1). It is important to note that we are able to control for unobserved heterogeneity in managerial ownership at the family level due to internal policies requiring family managers to invest certain amounts into the funds they manage (see, e.g., Laise 2006; Khorana, Servaes, and Wedge 2007; and Taylor 2011) with our fixed effects structure.

Please insert Table XII about here

Results are reported in Table XII. They show that managers are more likely to be in the $High\ Ownership$ category after they have reached their best style match. This result is highly significant, with statistical significance at the 1% level. It is also economically significant, as finding the manager's best style match leads to an increase in the likelihood that the manager

[11] We thank Florian Sonnenburg for kindly providing us with the managerial ownership data used in Martin and Sonnenburg (2015).
[12] The six ranges are: \$1-\$10,000; \$10,001-\$50,000; \$50,001-\$100,000; \$100,001-\$500,000; \$500,001-\$1,000,000; and above \$1,000,000.
[13] Results are robust when we define $High\ Ownership$ to denote a managerial ownership level at above \$1,000,000.

will be in the $High\ Ownership$ group by about 10 percentage points, which constitutes 100 percent of the unconditional probability that a manager will be in the $High\ Ownership$ group. This finding suggests that managers exploit their newly-found information in their personal investment decision making.

Overall, the evidence from Section 6 suggests that fund managers change their behavior in two significant ways following discovery of their best style match, which highly supports the notion that the learning-by-trying process has important implications for fund managers.

7 Conclusion

Our paper is the first to study how mutual fund managers arrive at the point where they are optimally matched to investment styles. We find that, consistent with occupational match theory, this process happens in a learning-by-trying fashion, whereby managers try different styles until they arrive at their optimal style match. Learning of the style match of fund managers is involved, requiring a significant number of tries and considerable time. These challenges notwithstanding, some fund managers are able to arrive at their style match discovery much faster than others. These managers had more opportunities to try different styles, had prior industry work experience outside of asset management, and attended institutions with higher student SAT scores. This process is highly important because the productivity gains of fund managers after their best style 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' best style matches. Fund families respond rationally after they discover the best style match of their managers. To maximize returns for the entire family, they try to increase the asset base footprint of the investment ideas of their best-style-matched managers who are operating at a higher level of productivity. In addition, depending on the size of their internal labor market their hiring decisions reflect their capabilities to make optimal style matches possible. Thus, if their internal labor market is small, which diminishes their capabilities for identifying managers' style matches, they do not spend resources on the discovery of their managers' best style matches but rather hire external managers whose style match has already been discovered. Managers also respond rationally to learning that they are optimally matched to an investment style 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 in that particular style, and they also utilize this information for their personal gain by increasing ownership in the funds where they are optimally matched by style. These findings contribute to furthering our understanding of how fund families and fund managers interact when it comes to talent acquisition, 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.

References

Addison, John T; Chen, Liwen and Orgul D. Ozturk (2018): 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.

Avery, Christopher N. and Judith A. Chevalier (1999): Herding over the career, in: *Economics Letters*, Vol. 63, No. 3, pp. 327-333.

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.

Cox, D. R. (1972): Regression Models and Life-Tables, in: *Journal of the Royal Statistical Society. Series B (Methodological)*, Vol. 34, No. 2, pp. 187-220.

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.

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 Kenneth R. French (2018): Choosing factors, in: *Journal of Financial Economics*, Vol. 128, No. 2, pp. 234-252.

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.

Gupta, Arpit and Kunal Sachdeva (2019): Skin or Skim? Inside Investment and Hedge Fund Performance, *NBER Working Paper Series*.

Huang, Nellie (2014): 10 Best Funds for Aggressive Investors, in: Kiplinger, November 12.

Ibert, Markus; Kaniel, Ron; van Nieuwerburgh, Stijn and Roine Vestman (2018): Are Mutual Fund Managers Paid for Investment Skill?, in: *Review of Financial Studies*, Vol. 31, No. 2, pp. 715–772.

Jiang, H. A.O. and Michela Verardo (2018), Does Herding Behavior Reveal Skill? An Analysis of Mutual Fund Performance, in: *The Journal of Finance*, Vol. 73, No. 5, 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.

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*.

Khorana, Ajay; Servaes, Henri and Lei Wedge (2007): Portfolio manager ownership and fund performance, in: *Journal of Financial Economics*, Vol. 85, No. 1, pp. 179–204.

Laise, Eleanor (2006): Another Way to Assess a Mutual Fund, in: *Wall Street Journal*, 2006.

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. (1978): Job search and labor market analysis, in: Handbook of Labor Economics, Vol. 2, pp. 849–919.

Nagypál, Éva (2007): Learning by Doing vs. Learning about Match Quality: Can We Tell Them Apart?, in: *The Review of Economic Studies*, Vol. 74, No. 2, pp. 537–566.

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.

Taylor, Chris (2011): Analysis: Why some fund managers don't invest in their own funds, in: 2011, available at: https://www.reuters.com/article/us-mutualfunds-managers-idUSTRE7935BJ20111004.

Table I: Descriptive Statistics

This table reports descriptive statistics for the total sample. Besides the mean, this table reports the standard deviation (std) as well as the 10th, 50th, and 90th percentile (p10, p50, and p90, respectively). Industry Tenure is the time managers spent in the mutual fund industry in years. #Styles Tried is the number of styles a manager has worked for throughout her career. Fund Age is the age of the fund in years. Fund Size is given by the total net assets under management (AUM) per fund in $ millions. Expense Ratio is the annual expense ratio in percent. Turnover ratio is the annual portfolio turnover 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
#Styles Tried	1.76	0.99	1.00	1.00	5.00
Industry Tenure [years]	7.13	6.22	0.99	5.43	15.76
Fund Age [years]	14.74	12.79	2.99	11.45	30.06
Fund Size [$ million]	1,541	4,433	21	315	3,534
Expense Ratio [%/year]	1.26	0.77	0.80	1.19	1.79
Turnover Ratio [%/year]	82.56	111.68	18.47	61.00	156.10
Flow [%/month]	0.23	1.55	-0.21	-0.01	0.62
Family Size [$ million]	28,082	70,744	83	6,635	59,102

Table II: Managers that Reach Style Match

This table reports statistics for the managers that return to a previously-tried style during the 1992-2016 sample period. Besides the mean, this table reports the standard deviation (std) as well as the 10th, 50^{th}, and 90th percentile (p10, p50, and p90, respectively). #Funds Tried and #Styles Tried are, respectively, the number of funds and number of styles a manager tried before returning to a previously-tried style. Time until Style Match represents the length of time (in years) until style 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 (% Return to best performing style) and the fraction of managers that stayed in the same style after reaching style match (% Stay in same style afterwards).

	mean	std	p10	p50	p90
#Funds Tried	4.4	3.5	2.0	4.0	9.0
#Styles Tried	3.6	1.1	2.0	3.0	5.0
Time until Style Match [years]	5.7	3.6	2.0	5.0	10.6
% Return to best performing style			70		
% Stay in same style afterwards			94		

Table III: Determinants of Style Match Discovery Speed

This table reports results from pooled OLS regressions that relate the speed of best style match discovery with a number of characteristics. The sample period for this table is from 1992 through 2004. The focus of analysis is on the managers that during the sample period returned to one of their previously-tried styles. The dependent variable is the time between when the manager first showed up in the database and the first day when she returned to a previously-tried style, measured in days. The independent variables include: #Family Styles, the number of different styles the family a manager is currently working for offers; NCC-Index, an index by Garmaise (2011) quantifying the strength of non-compete clause (NCC) enforceability ranging from 0 (weakest) to 12 (strongest) and available for the 1992-2004 period; Practical Experience, which equals one if a fund manager has worked outside the financial industry before he became a fund manager, and zero otherwise; and SAT, which equals one if the manager obtained her bachelor degree from an institution at which the average matriculates' SAT score is above median, and 0 otherwise. The regression is run with time and style 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.

	Time until Match Discovery				
	(1)	(2)	(3)	(4)	(5)
#Family Styles	-27.8033*				-43.0025**
	(-1.69)				(-2.10)
NCC-Index		54.8846***			55.7421***
		(3.43)			(-3.25)
Practical Experience			-329.8996**		-289.4539**
			(-2.10)		(-2.37)
SAT				-104.3887*	-199.1915***
				(-1.87)	(-2.82)
Time FE	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes
Observations	2,296	527	1,561	2,042	415
Adj. R^2	0.086	0.016	0.001	0.001	0.045

Table IV: Performance after Discovery of Style Match

This table presents results from pooled OLS regressions that relate performance measures with changes in style 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 (Fama and French 2018 and Barillas and Shanken 2018) (Alpha6). To measure style-adjusted returns in period t, we subtract from the raw 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 Style Match, constructed as in Section 2.2. 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
Style Match	0.0153***	0.0158***	0.0116***	0.0135***
	(2.77)	(3.24)	(3.05)	(2.83)
#Styles Tried	-0.0016	-0.0012	-0.0008	-0.0013
	(-0.61)	(-0.52)	(-0.39)	(-0.58)
Log(Industry Tenure)	-0.0042**	-0.0060***	-0.0037***	-0.0016
	(-2.43)	(-3.86)	(-2.73)	(-0.95)
Log(Fund Age)	0.0305***	0.0252***	0.0109***	0.0063*
	(8.04)	(7.26)	(3.46)	(1.65)
Log(Fund Size)	-0.0315***	-0.0280***	-0.0173***	-0.0158***
	(-21.04)	(-19.95)	(-13.62)	(-11.05)
Exp. Ratio	0.0440	0.2950	1.4000***	0.0564
	(0.12)	(0.52)	(2.66)	(0.08)
Turn. 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)
Log(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
Adj. R^2	0.737	0.065	0.115	0.120

Table V: Parallel Trends Assessment and Persistence of Performance

In this table, we modify our main analysis of Table IV 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 (1) with three indicator variables that identify managers that attained style match discovery—in each of the prior three years. In the second column corresponding to each performance measure, we replace Style Match with three indicator variables that identify managers that reached style match discovery—in three subsequent periods, i.e., the first year, second year, and all years after the second year (third year or later) subsequent to style match. The construction of all dependent and independent variables is described in Table IV. 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.

	Ret.		Style-Ret.		Alpha4		Alpha6	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre3 · Style 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 · Style 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 · Style 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)
Style Match	0.0147***		0.0155***		0.0116***		0.0132***	
	(2.72)		(3.21)		(3.05)		(2.69)	
Post1 · Style Match		0.0084		0.0101*		0.0101*		0.0072
		(1.18)		(1.69)		(1.89)		(1.07)
Post2 · Style Match		0.0093		0.0119*		0.0137**		0.0130**
		(1.36)		(1.81)		(2.56)		(1.98)
Post3+ · Style 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
Adj. R^2	0.737	0.737	0.065	0.065	0.115	0.115	0.120	0.120

Table VI: Matched Sample Analysis of Performance after Discovery of Style Match

In this table, we repeat our main analysis of Table IV 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 IV. 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
Style Match	0.0215***	0.0201***	0.0116***	0.0126***
	(3.91)	(3.99)	(3.13)	(2.72)
#Styles Tried	0.0048	0.0033	-0.0001	-0.0012
	(1.58)	(1.23)	(-0.06)	(-0.47)
Log(Industry Tenure)	-0.0044**	-0.0061***	-0.0039**	-0.0009
	(-2.05)	(-3.04)	(-2.42)	(-0.46)
Log(Fund Age)	0.0236***	0.0210***	0.0095**	0.0035
	(5.14)	(5.09)	(2.58)	(0.84)
Log(Fund Size)	-0.0252***	-0.0239***	-0.0150***	-0.0135***
	(-12.89)	(-13.29)	(-9.55)	(-7.77)
Exp. Ratio	0.7647	-0.2046	0.1427	-1.2207
	(1.17)	(-0.36)	(0.24)	(-1.21)
Turn. 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)
Log(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
Adj. R^2	0.761	0.044	0.164	0.142

Table VII: Managerial Preferences and Organizational Power

In this table, we augment our main analysis of Table IV to test for the impact of managerial preferences and managers' organizational power. We employ High Family Tenure, 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 Style Match. The construction of all dependent and independent variables is described in Table IV. 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) Ret.	(2) Style-Ret.	(3) Alpha4	(4) Alpha6
Style Match	0.0215**	0.0265***	0.0175***	0.0150**
	(2.37)	(2.94)	(3.12)	(2.29)
High Family Tenure	-0.0018	-0.0009	-0.0005	-0.0020
	(-0.82)	(-0.43)	(-0.28)	(-0.83)
High Family Tenure ·	-0.0074	-0.0128	-0.0074	-0.0019
Style Match	(-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
Adj. R^2	0.737	0.065	0.115	0.120

Table VIII: Promotion of Managers that Reached their Style Match

This table presents results from pooled OLS regressions that relate promotion probability with changes in style match status of a manager. The analysis is done at the manager- and year-level. The dependent variable is Promotion, a binary variable that equals one if a manager is promoted in a given year and zero otherwise. We determine that a manager has had a promotion if the reshuffling of her responsibilities resulted in greater assets under management than before. 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 IV. 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.

	Promotion
Style Match	0.0545**
	(2.43)
Fund Controls	Yes
Manager Controls	Yes
Family Controls	Yes
Time FE	Yes
Style FE	Yes
Manager × Family FE	Yes
Observations	27,314
Adj. R^2	0.268

Table IX: 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 style match is followed subsequently by affiliated managers. The analysis is done at the stock-family-style- and quarter-level. The observations for Initiating Buys are identified as stocks that are held for the first time by a manager having found her style 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 SM Trade, an indicator variable that equals one when the trade was conducted by a manager who has reached her style match and zero otherwise. Our control variables include the natural logarithm of market capitalization [Log(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
SM Trade	0.0122**	0.0129**	0.0121***	0.0313**
	(2.03)	(2.01)	(8.81)	(2.17)
Log(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
Adj. R^2	0.155	0.250	0.184	0.341

Table X: Implications for the Hiring Decisions of Fund Families.

This table presents results from pooled OLS regressions that relate manager characteristics of hires to the number of funds in the hiring fund family. The analysis is done at the level of hires. The dependent variable is whether the manager hired has already reached her style match (SM Manager), coded as a (1/0) indicator variable. The main independent variable is #Family Styles, measured by the number of different styles in the family. Control variables include manager and family controls described in Table I. T-statistics, based on standard errors clustered at the family level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	SM Manager
#Family Styles	-0.0057**
	(-2.35)
Manager Controls	Yes
Family Controls	Yes
Observations	9,183
Adj. R^2	0.023

Table XI: Investment Behavior

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 6.1. Our main independent variable is Style Match, constructed as in Section 2.2. 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.

	Active Peer Share
Style Match	0.6648***
	(2.63)
Fund Controls	Yes
Manager Controls	Yes
Family Controls	Yes
Time FE	Yes
Style FE	Yes
Manager × Family FE	Yes
Observations	28,506
Adjusted R^2	0.908

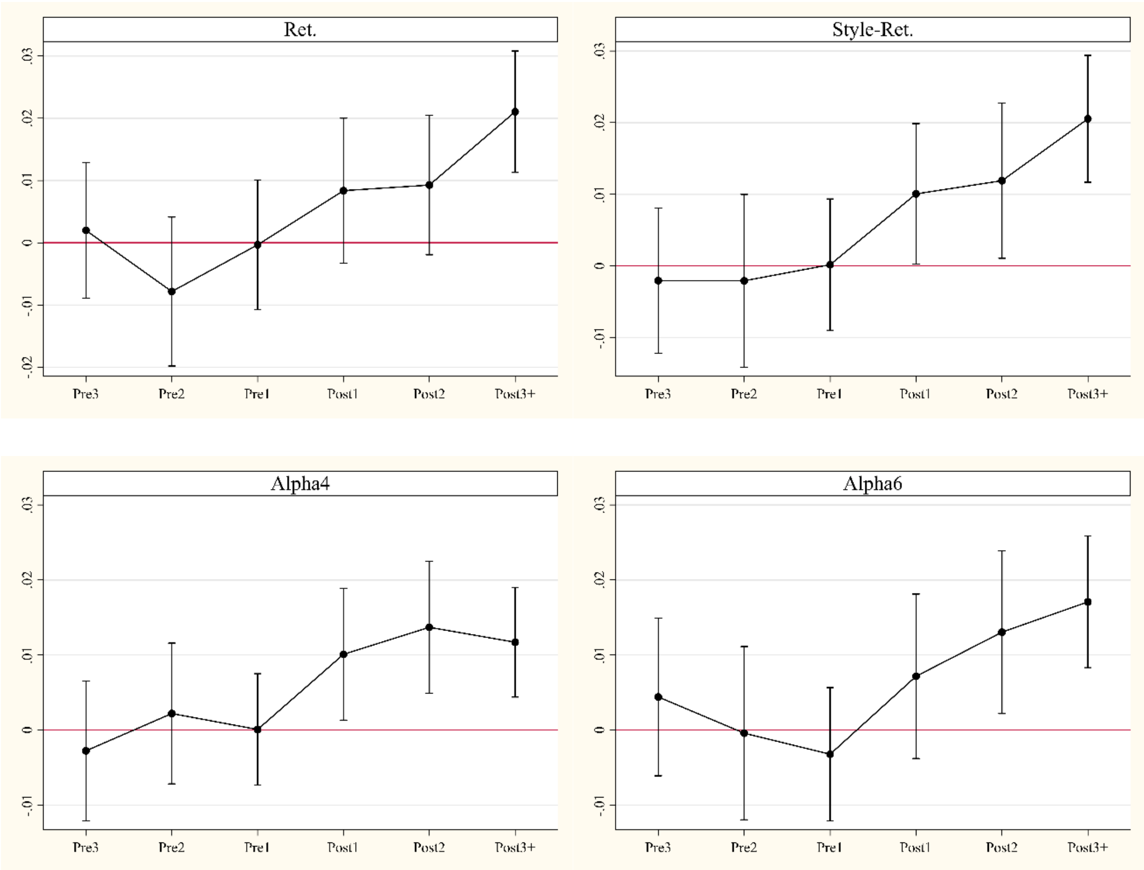
Table XII: Managerial Fund Ownership

This table presents results from pooled OLS regressions that relate how much a manager is personally invested into the fund she manages with changes in the style match status of a manager. The analysis is done at the manager- and year-level. The dependent variable is High Ownership, an indicator variable, which equals one if the manager's ownership in the fund was above $500,000 and zero otherwise. Our main independent variable is Style Match, constructed as in Section 2.2. 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.

	High Ownership
Style Match	0.1125***
	(4.29)
Fund Controls	Yes
Manager Controls	Yes
Family Controls	Yes
Time FE	Yes
Style FE	Yes
Manager × Family FE	Yes
Observations	6,795
Adjusted R^2	0.801

Figure I: Parallel Trends Assessment and Persistence of Performance

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



centre for financial research
cologne

cfr working papers are available for download from www.cfr-cologne.de.

2020

No.	Author(s)	Title
20-10	J. Fink, Stefan Palan, E. Theissen	Earnings Autocorrelation and the Post-Earnings-Announcement Drift – Experimental Evidence
20-09	E. Theissen, C. Yilanci	Momentum? What Momentum?
20-08	V. Agarwal, L. Jiang, Q. Wen	Why Do Mutual Funds Hold Lottery Stocks?
20-07	V. Agarwal, S. Ruenzi, F. Weigert	Unobserved Performance of Hedge Funds
20-06	M. Ammann, S. Fischer, F. Weigert	Factor Exposure Variation and Mutual Fund Performance
20-05	P. Limbach, P. R. Rau, H. Schürmann	The Death of Trust Across the Finance Industry
20-04	A. Y. Chen, T. Zimmermann	Open Source Cross-Sectional Asset Pricing
20-03	L. Ahnert, P. Vogt, V. Vonhoff, F. Weigert	Regulatory Stress Testing and Bank Performance
20-02	P. Schuster, E. Theissen, M. Uhrig-Homburg	Finanzwirtschaftliche Anwendungen der Blockchain-Technologie
20-01	S. Ruenzi, M. Ungeheuer, F. Weigert	Joint Extreme Events in Equity Returns and Liquidity and their Cross-Sectional Pricing Implications

2019

No.	Author(s)	Title
19-06	S. Greppmair, E. Theissen	Small Is Beautiful? How the Introduction of Mini Futures Contracts Affects the Regular Contract
19-05	G. Cici, M. Hendriock, A. Kempf	Finding your calling: Skill matching in the mutual fund industry
19-04	O. Korn, P. M. Möller, Ch. Schwehm	Drawdown Measures: Are They All the Same?

19-03	G. Cici, M. Hendriock, S. Jaspersen, A. Kempf	#MeToo Meets the Mutual Fund Industry: Productivity Effects of Sexual Harassment
19-02	T. Johann, S. Scharnowski, E. Theissen, C. Westheide, L. Zimmermann	Liquidity in the German Stock Market
19-01	A. Betzer, P. Limbach, P. Raghavendra Rau, Henrik Schürmann	Till death (or divorce) do us part: Early-life family disruption and investment behavior

2018

No.	Author(s)	Title
18-06	M. Goergen, P. Limbach, M. Scholz-Daneshgari	On the Choice of CEO Duality: Evidence from a Mandatory Disclosure Rule
18-05	F. Brochet, P. Limbach, D. Bazhutov, A. Betzer, M. Doumet	Where Does Investor Relations Matter the Most?
18-04	G. Cici, A. Kempf, C. Peitzmeier	Knowledge Spillovers in the Mutual Fund Industry through Labor Mobility
18-03	T. Rischen, E. Theissen	Underpricing in the Euro Area Corporate Bond Market: New Evidence from Post-Crisis Regulation and Quantitative Easing
18-02	S. Lesmeister, P. Limbach, M. Goergen	Trust and Shareholder Voting
18-01	G. Cici, M. Hendriock, A. Kempf	The Impact of Labor Mobility Restrictions on Managerial Actions: Evidence from the Mutual Fund Industry

2017

No.	Author(s)	Title
17-04	G. Cici, P.B. Shane, Y. S. Yang	Do Connections with Buy-Side Analysts Inform Sell-Side Analyst Research?
17-03	G. Cici, S. Gibson, R. Moussawi	Explaining and Benchmarking Corporate Bond Returns
17-02	S. Jaspersen, P. Limbach	Screening Discrimination in Financial Markets: Evidence from CEO-Fund Manager Dyads
17-01	J. Grammig, E.-M. Küchlin	A two-step indirect inference approach to estimate the long-run risk asset pricing model

This document only covers the most recent cfr working papers. A full list can be found at www.cfr-cologne.de.

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de