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Contents

[1]This chapter is based on Cici, Hendriock, and Kempf (2020b).

[2]This chapter is based on Cici, Hendriock, and Kempf (2020a).

[3]This chapter is based on Hendriock (2020).

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Chapter 1

Introduction

This thesis consists of three essays on asset management. In particular, I focus on institutional investors in the form of active mutual funds and their ability to fulfill their mandate as delegated portfolio managers, which is to deliver the best risk-reward-trade-off, i.e., "performance", possible.

With 17.7 trillion U.S. dollars by the end of 2018, corresponding to a growth by a factor of 22 over the last three decades alone, the mutual fund industry in the United States witnessed substantial increases in assets under management. Active funds, with 64%, manage the largest part. Simultaneously, 45% of households are invested into mutual funds and ⅔ allocate more than half of their financial wealth to them, leaving 89% of the 17.7 trillion U.S. dollars on private investors' accounts.[1] These individuals rely on their mutual fund investments to meet long-term personal financial objectives, such as saving for education and retirement, purchasing real estate, and preparing for emergencies.[2] In consequence, large parts of economic prosperity depend on the weal and woe of the mutual fund industry, in particular, whether asset managers are able to deliver performance above their designated benchmark.

This question of fund manager skill has drawn the attention of both the public as well as research. One strand of literature on mutual fund managers' ability evolved with the focus on the identification of skill. Initially having examined fund returns, in an effort to increase the power of tests, it shifted the analysis to fund security

[1] Confer Investment Company Institute (2019).
[2] Confer Doellman, Huseynov, Nasser, and Sardarli (2020).

holdings and fund trades as well as more specialized tests intended to separate skill from luck.[3] Accepting that a subset of mutual funds appears to have skill, another strand of literature has turned to understanding which attributes of the three main parties involved in a mutual fund's production function - the fund itself, its managers, and the asset management company[4] - and their interrelations are associated with better performance.[5] The three essays of this thesis add to the latter strand of literature.

The first essay considers the contractual relationship between fund managers and their employer, the asset management company. With the design of the employment contract a company can shape the incentives of its workforce, which in turn impact its output. In the mutual fund industry, remuneration is characterized by distinctive explicit incentives, with managers receiving large parts of their compensation as a fraction of assets under management respectively in form of boni depending on their performance relative to their benchmark.[6] Besides, implicit incentives in form of general "career concerns" empirically have been shown to impact managers' risk taking.[7] While economic theory furthermore predicts that they also influence the first moment of labor output,[8] empirical studies, however, are scarce. In the first essay, we provide evidence consistent with theory.

Specifically, Cici, Hendriock, and Kempf (2020b) address the question, how labor mobility restrictions through non-compete clauses (NCCs) impact managerial

[3]Confer, e.g., Jensen (1968), Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (1999), Chen, Jegadeesh, and Wermers (2000), Wermers (2000), Kothari and Warner (2001), Pinnuck (2003), Barras, Scaillet, and Wermers (2010), Fama and French (2010), and Wermers (2020).

[4]In the following, this term is used interchangeably with the expression "fund family".

[5]As characteristics at the fund-level, e.g., Carhart (1997) studies the impact of expenses, whereas Bär, Kempf, and Ruenzi (2011) examine the impact of the management structure. Concerning manager characteristics, e.g., Golec (1996), Chevalier and Ellison (1999a), and Bai, Ma, Mullally, and Solomon (2019) study the impact of age, Costa and Porter (2003), Kempf, Manconi, and Spalt (2017), and Cici, Gehde-Trapp, Göricke, and Kempf (2018) that of experience, Gottesman and Morey (2006, 2019) and Andreu and Puetz (2017) the influence of education, and Atkinson, Baird, and Frye (2003), Beckmann and Menkhoff (2008), and Niessen-Ruenzi and Ruenzi (2019) the effect of gender. With respect to the influence of the asset management company, confer, e.g., Massa (2003), Gaspar, Massa, and Matos (2006), Kempf and Ruenzi (2008), Berk, van Binsbergen, and Liu (2017), and Evans, Prado, and Zambrana (2020). For a review, confer Elton and Gruber (2011) and Jones and Wermers (2011).

[6]Confer, e.g., Hu, Hall, and Harvey (2000), Elton, Gruber, and Blake (2003), and Ma, Tang, and Gómez (2019).

[7]Confer, e.g., Chevalier and Ellison (1999b) and Kempf, Ruenzi, and Thiele (2009).

[8]Confer, e.g., Fama (1980) and Andersson (2002).

actions.[9] NCCs prohibit a separating employee from competing with her former employer, either by working for a competing firm or by establishing one on her own, during a limited period of time and in a certain geographical area. As such, they not only impact career concerns in the most fundamental way possible but also enable companies to explicitly contract on them. How NCCs affect employees' incentives, however, neither is obvious ex-ante nor has it been investigated by research. There are at least two opposing effects. On the one hand, there potentially is a disciplining effect: NCCs impose costs on employees when they are fired because they have to stay unemployed for a certain period of time; this threat possibly incentivizes them to increase their effort and consequently their output to avoid termination. On the other hand, NCCs reduce outside options of managers in the external labor market, making it harder for them to exploit external promotion opportunities. This might reduce their incentives to signal their quality and consequently make them reduce their effort. Ultimately, it is an open empirical question which effect dominates.

Our identification strategy for measuring the impact of NCCs exploits exogenous shocks in form of legal amendments to the enforceability of NCCs.[10] Results from corresponding difference-in-differences regressions provide strong evidence of a positive association between increased NCC enforceability and fund performance. The evidence remains strong in robustness tests, where we, i.a., consider increases and decreases in NCC-enforceability separately to document exactly opposing effects, vary the size of the event window, and use a matched control group. Thus, the effort-increasing effect induced by a desire to avoid higher costs associated with being fired seems to be more important for fund managers than the effort-reducing effect arising from more-limited outside options.

To substantiate the effort channel by means of which increased NCC-enforceability leads to higher performance, we take into account differences in the relative impor-

[9] There is a growing literature that studies the impact of NCCs on economic activity at the state- and firm-level, in particular, on the innovation process, entrepreneurship, employee mobility, firm-sponsored versus employee-paid training, wages, firms' output, as well as firms' financial reporting choices. Bishara, Martin, and Thomas (2015), Bishara and Starr (2016), and Prescott, Bishara, and Starr (2016) provide a review of that literature.

[10] Scrutinized by legal researchers, they have frequently been employed in literature, confer, e.g., Conti (2014), Lou, Wang, and Zhou (2017), Yin, Hasan, Kobeissi, and Wang (2017), Aobdia (2018), Chen, Zhang, and Zhou (2018), He and Wintoki (2018), He (2018), and Ali, Li, and Zhang (2019).

tance of its effects (higher costs associated with termination versus more limited outside options) across fund managers. First, managers who consider themselves to be of low skill are likely to be more concerned about termination risk than about limited outside options relative to fund managers who consider themselves to be skilled; this would give larger importance to NCCs' threatening effect, resulting into even stronger increases in performance. Second, we hypothesize that concerns related to limited outside options are less relevant for fund managers employed by fund families with a larger internal labor market; as they offer more internal promotion opportunities, the effort-decreasing effect of NCCs is less important. Again, this would imply higher performance increases. Our results support both hypotheses.

In order to shed light on how managers achieve the increase in performance, we propose and test for a particular mechanism. Consistent with managers redirecting their effort to investments for which they are likely to have an information advantage, we find that the performance improvement is driven by stocks that treated managers overweight relative to their peers.

Finally, we focus on other actions fund managers might take in response to increased NCC enforceability. First, we look at actions of fund managers intended to make themselves useful to the organization in a way unrelated to fund performance, providing evidence that they increase window dressing in order to attract new investor flows; these increase the asset base of the family and consequently fee income for the fund company. Second, we find that stricter NCCs discipline managers' risk taking, as shown by noticeable reductions in their portfolio risk, portfolio deviations from their peers, and engagement in fund tournaments.

The findings from the first essay suggest restricting labor mobility, by means of the threat-induced discipline it elicits, has a positive effect on performance. This aspect, however, is just one of many facets labor mobility impacts employees' performance. In particular, from another perspective, restricting labor mobility confines the employee in her ability to test out different deployment areas in order to find that one whose demand profile best resonates with her skill set. According to occupational match theory,[11] however, this forms the essential basis to optimally employ

[11] Mortensen (1978, 1986), Jovanovic (1979), Diamond (1981), and Miller (1984) constituted oc-

labor and hence maximize its output.

In the second essay, which is based on Cici, Hendriock, and Kempf (2020a), we apply this idea to the mutual fund industry: to best utilize their labor, fund families need to match their portfolio managers' skills with the job requirements of different funds; thereby, uncovering the match necessitates managers testing different funds in a learning-by-trying-process. While previous studies show that personnel decisions by fund families on average create value,[12] we still lack an understanding of how families generate information about their managers' best deployment in the first place; our study tries to shed light on this question. Furthermore, whereas the effect of occupational matching on output is well described in theory, empirical research is confined to indirect tests.[13] In contrast, our study directly documents the productivity gains accruing to occupational match finding.

Thereby, the concept of different occupations is readily operationalized within the framework of the mutual fund industry. Funds typically are mandated to follow clearly delineated investment styles.[14] Fund managers operate within the boundaries of these styles and typically are viewed as being experts in a particular one. In order to identify the point in time when managers find their best match, we study the sequence of managerial moves to different styles during a manager's career. Occupational match theory predicts that a manager will move to a new style as long as she and her family consider another style to be a better fit than the current one; eventually, the manager would settle into a style where she achieves her optimal level of productivity. In this vein, we use the point in time when a fund manager returns to one of her previously-tried styles to identify the end point of the search process, i.e., when the match is found.[15]

cupational match theory. Recent work by Ortega (2001), Papageorgiou (2014, 2018), and Addison, Chen, and Ozturk (2018) developed the subject further.

[12]Confer, e.g., Cheng, Massa, Spiegel, and Zhang (2013), Berk, van Binsbergen, and Liu (2017), and Zambrana and Zapatero (2017).

[13]Relying on the premise of an underlying equilibrium model, it uses tenure to proxy for the likelihood that an employee has been matched and primarily examines its effects on turnover or wage; confer, e.g., McCall (1990), Jovanovic and Moffitt (1990), Eriksson and Ortega (2006), Kambourov and Manovskii (2008, 2009a,b), and Groes, Kircher, and Manovskii (2015).

[14]Confer Section 35d-1 of the U.S. Investment Company Act of 1940.

[15]Indeed, when managers return to a style, which happens on average at the midst of their career, in almost all (94%) cases, they never change styles again until they retire from the industry.

To test for the hypothesis that managers generate better performance after they found their style match, we compare the performance of a fund manager before and after she found her match, again employing a difference-in-differences framework. To control for possible self-selection issues of more-skilled managers towards fund families with higher resources,[16] we measure performance-effects following the manager's style match within the same family. Consistent with our hypothesis, annual performance of fund managers increases by about one percentage point after their style match is found. We aim to rule out the alternative explanation that mere task-specific experience through learning-by-doing drives the result via a matched-sample analysis; restricting the control group to only managers who have the same experience in each style as managers who found their match leads to the same conclusion. Yet another alternative explanation for our results poses managers just using their organizational power to return to their preferred style and divert more resources to their fund afterwards; such, the documented rise in performance were attributable to increases in resources instead of match finding. However, contradicting this hypotheses, performance does not improve more for managers with longer family tenure, which we use as a proxy for organizational power.

While returns to match finding constitute the back bone of our analysis, we continue to flesh out the whole anatomy of the match finding process. Examining the period before the match is found, we document that those managers find their match faster: who have more leeway in trying things out, because their employer offers more styles respectively they are not confined by NCCs; who have previous work experience outside the financial industry and hence an informational advantage for some sectors, which limits the numbers of styles required to try out; and who attended institutions with higher matriculate SAT scores, consistent with innate ability and networks established visiting university fostering match finding. Concerning the period after the match is found, managers exhibit a higher degree of conviction, both in their fund portfolios, as they deviate more from their peers, and personal portfolios, which to a larger extent are concentrated in their own funds.

[16]For literature on models of assortative matching, confer, e.g., Mayer (1960), Sattinger (1975, 1993), Rosen (1982), Gabaix and Landier (2008), and Terviö (2008).

Finally, we illustrate the implications of match finding for fund families. We document that they appear to utilize the higher productivity levels of their matched managers at a larger asset base, mirroring previous research of personnel decisions by fund families creating value. For instance, they delegate more responsibilities to managers after they have found their match by increasing the amount of assets under their management. Further, fund families exploit the investment ideas of these managers in other funds: ideas of a fund manager are followed more by affiliated managers after their colleague has reached her best style match. Moreover, fund families hiring practices reflect their ability to make the match discovery possible: whereas families with many style offerings also hire managers who have not yet found their match, families with only a few styles rather hire managers whose match is already known.

The first two essays consider how the organizational framework within which managers operate impacts their ability to deliver the best performance possible, which is their designated task and this thesis' research objective. Given this framework, the question arises, though, what a manager, to reach this goal, should actually consider as best practices for her core, day-to-day business; that is, what should a manager take into account when contemplating her investment strategy.

The third essay addresses this question, providing evidence that successful managers employ strategies based on the implied cost of capital (ICC) of their portfolio firms. Theoretically, ICC have been shown to be particularly apt to proxy for time-varying expected returns and there is ample evidence in empirical research for their capabilities predicting both returns as well as other measures for "performance" at the stock–level.[17] However, Esterer and Schröder (2014) conclude that transaction costs necessary to turn these paper gains into actual profits appear to be too high. Yet, with respect to transaction costs, active mutual fund managers, as institutional investors specialized on conducting financial transactions, arguably are in a preferential position. An issue yet unexplored is whether investors into funds, by means

[17] Confer, e.g., Claus and Thomas (2001), Botosan and Plumlee (2005), Easton (2007), Pástor, Sinha, and Swaminathan (2008), Botosan, Plumlee, and Wen (2011), Hou, van Dijk, and Zhang (2012), Li, Ng, and Swaminathan (2013), Li and Mohanram (2014), Esterer and Schröder (2014), Schröder (2018), and Bielstein and Hanauer (2019). The literature on ICC in general as well as its applications in research is extensive; Richardson, Tuna, and Wysocki (2010) provide a review.

of their reported holdings and respective ICCs, can turn the performance potential inherent to ICC-based strategies into actual profits.

Results in Hendriock (2020) suggest they can. Both portfolio sorts, excluding fund share classes with loads, resulting into a time series of returns entirely net of transactions costs, as well as panel regressions, allowing to control for confounding factors at the time-, investment style-, and fund-level, corroborate the notion that ICCs derived from a fund's stock holdings allow for a meaningful ex-ante classification of future under- and out-performers. The top ten percent of funds in terms of current ICC exhibit significant positive performance going forward and are the best among their peers; this also implies that investors would not need to short funds to profit from an ICC-based investment rule, which is practically obligatory with respect to investments into mutual funds, as they cannot be sold short. Panel regressions with, i.a., fund-by-manager fixed effects, controlling for unobserved, time-constant heterogeneity at the fund-, manager-, and fund-manager-match-level, corroborate the notion that a high-ICC strategy in itself constitutes a promising endeavor for fund managers to pursuit; this is additionally supported by analyses based on ICC-motivated trades. Further, ICC seem indicative for the fate of funds over a longer horizon, exhibiting associations with performance up to two years in the future. This potentially accommodates investors, as this spares them data-intensive computation of ICC each and every quarter anew and lowers turnover.

To learn about what determines whether mutual funds employ a high-ICC strategy, first, along the lines of transaction costs impeding the exploitation of performance potential inherent to ICC-based strategies, I consider the impact of the efficiency of a fund's trading desk. Results suggest that with higher efficiency and hence arguably lower transaction costs, funds indeed are more inclined to employ a high-ICC strategy. Second, regarding investments resting upon ICC reflecting skill, average matriculate SAT scores of the institutions managers received their bachelor's degrees from, again meant to proxy for innate ability, positively correlate with funds' ICC.

Finally, this essay investigates if market participants are aware of the positive association between current ICC and future fund performance and whether this association triggers corresponding responses. First, I document that managers who trail behind their peers in the middle of the year substantially temper risk shifting if they follow a high ICC-strategy. That is, they refrain from a behavior they in general were to engage in to catch up with their competitors. This is consistent with managers being both aware of the merits of a high-ICC strategy and indeed relying on it. Second, with regard to investors' awareness, however, only more sophisticated institutional ones seem to recognize and trade on the positive association between current ICC and future fund performance, as opposed to retail investors; while there is a positive association between current ICC and future fund flows among institutional funds, this association is absent from retail funds, consistent with retail investors' lack of "resources" necessary to gather relevant data and compute ICC.

Overall, the three essays reveal determinants of the extent to which active mutual funds can accomplish their task of delivering the best risk-reward trade-off possible. For example, by contracting on higher unemployment costs via NCCs, asset management companies potentially can elicit higher discipline from their managers, while by having them try out different styles, they can probe their optimal match to eventually exploit their labor input's full potential. Throughout, portfolio firms' ICC can viably be incorporated as one investment criterion into managers' strategies, as asset management companies offer the resources necessary to trade on the performance signal ICC imply.

Finally, I end the introduction to my thesis with a description of the input I provided to the three essays. For the first, the basic research idea was brought up by my coauthors. I reviewed the literature to refine the research idea and develop testable hypotheses; I also gathered and prepared the necessary data and run the empirical tests. The first draft of the paper was mainly written by my coauthors. We jointly revised the paper in several iterations according to the feedback we received from various conferences (among others from the Annual Meeting of the American Finance Association) and seminars.

The research idea of the second essay emerged from discussions we had together. In the process, we jointly developed research questions and derived hypotheses. I again reviewed the literature, collected and prepared the data, as well as designed and implemented the empirical analyses. This included finding an econometric identification strategy for the effect we had in mind. I wrote the first draft of the paper. The various revisions of the paper were jointly done by all three of us.

The third paper is solo-authored. I developed the research idea and the hypotheses on my own; I also did all the empirical work and the writing of the paper.

Chapter 2

The Impact of Labor Mobility Restrictions on Managerial Actions: Evidence from the Mutual Fund Industry*

2.1 Introduction

In the last few years, there has been an intense debate in the U.S. surrounding labor mobility restrictions and their impact on economic activity [e.g., White House (2016) and U.S. Department of the Treasury (2016)]. A supporting argument is that by preventing employees from transferring intellectual property and skills acquired on-the-job to rival firms, such restrictions protect trade secrets and thus encourage innovation and investment in employee training. A counter argument, however, is that labor mobility restrictions limit the labor market pool from which companies can hire, which can result in suboptimal matching of talent with available jobs;

*This chapter is based on Cici, Hendriock, and Kempf (2020b). For helpful comments and discussions we thank Alice Davison, Massimo Guidolin, Stefan Jaspersen, Peter Limbach, Gunter Loeffler, Daniel Metzger, Dirk Sliwka, Florian Sonnenburg, Tom Zimmermann, Eric Zitzewitz, seminar participants at the University of Arkansas, University of Basel, the University of Cologne, University of Glasgow, and the Technical University Munich, as well as participants at the AFA 2019 Annual Meeting, the 2019 EFMA Annual Conference, and the 25th Annual Meeting of the German Finance Association.

prevent employees from founding new companies; and stifle innovation by reducing the diffusion of knowledge and ideas among companies, all of which can potentially hinder economic growth.

Firms typically restrict labor mobility through non-compete clauses (NCCs) in employment contracts. Such clauses are heavily used in knowledge intensive industries [e.g., Starr, Prescott, and Bishara (2019)] and for highly skilled and highly paid employees [e.g., Bishara, Martin, and Thomas (2015)]. They prohibit a separating employee from competing with her former employer, either by working for a competing firm or by establishing one on her own during a limited period of time and in a certain geographical area. For example, Bishara, Martin, and Thomas (2015) document that 80% of CEOs are bound by NCCs, often with a broad geographic scope, that generally last from one to two years.

While the literature is advancing in its understanding of the impact that NCCs have on economic growth, innovation, and investments at the regional and firm level, the analysis has typically abstracted away from the economic agents whose actions are directly targeted by these labor restrictions.[1] The objective of our study is to fill this gap. In particular, we study how NCCs affect the behavior of labor force participants and their output. Theory suggests that employees respond to implicit incentives in addition to explicit incentives resulting from the compensation contract. For example, Fama (1980) argues that labor market forces can solve agency problems and efficiently discipline managers to a higher effort level, even in the absence of explicit incentive contracts, while Holmstrom (1982, 1999) incorporates and enlarges upon this intuition in a formalized setting. Along these lines, building on the framework of Holmstrom (1999), Andersson (2002) shows that managers increase their effort when career concerns are present (relative to when they are absent) even if their compensation contract provides them with effort-based explicit incentives. The reason is that career concerns create incentives that are not captured in compensation contracts.

How NCCs affect the incentives and behavior of employees is not obvious ex-ante.

[1]See, e.g., Bishara, Martin, and Thomas (2015), Bishara and Starr (2016), and Prescott, Bishara, and Starr (2016) for recent reviews of the literature that looks at NCCs at the state and firm level.

Since NCCs are typically enforced not only when an employee leaves the company voluntarily but also when that employee is fired, there are two opposing effects.[2] On the one hand, there is a disciplining effect: NCCs impose costs on the employees when they are fired because they have to stay unemployed for a certain period of time. This incentivizes them to increase their effort and consequently their output to avoid termination. In addition, fund families could use their increased bargaining power following increased NCC enforceability to renegotiate their managers' contracts towards more performance sensitive compensation. This could also lead to an increased effort of fund managers. On the other hand, NCCs reduce the outside options of employees in the external labor market, which makes it hard for them to exploit external promotion opportunities. This reduces their incentives to signal their quality to the external labor market and consequently makes them reduce their effort. Ultimately, it is an open empirical question which effect dominates.

We use the mutual fund industry as a testing laboratory to examine the effect that NCCs have on the behavior of mutual fund managers and the output they deliver. The mutual fund industry represents an ideal setting for our investigation for several reasons. First, since this industry is knowledge-intensive and fund managers fit the income and industry profile of employees that are typically subject to such restrictions, we expect NCCs to be widely spread among mutual fund managers.[3] This is indeed supported by empirical evidence presented later in the paper showing that changes in enforceability of NCCs affect labor mobility among mutual fund managers as expected. Second, Barber, Scherbina, and Schlusche (2018) show that the fraction of fund managers who leave the mutual fund industry is really small, which makes the two opposing effects described above even more relevant. Third, for mutual fund managers, data availability allows us to directly observe their actions, i.e., their trades, as well as their production output, i.e., the performance of the funds that they manage. Fourth, given the relatively small number of players involved in the management of a mutual fund, we can more easily attribute production output

[2]During our sample period, NCCs were enforceable in the U.S. even when an employee was fired in all but the following six states [see, e.g., Garmaise (2011)]: Arkansas, District of Columbia, Georgia, Kentucky, Maryland, and New Mexico. Thus, for all the treated states in our analysis, NCCs were enforceable when an employee was fired.

[3]See Appendix to Chapter 2 for a discussion of the use of NCCs in the mutual fund industry.

to the actions of a mutual fund manager. The same cannot be said for corporations, where the output usually is the result of a complex network of interactions between a large set of production factors and economic agents. Finally, the granularity of information from fund trades and holdings allows us to analyze the different ways in which fund managers respond to changes in NCC enforceability.

Our identification strategy for measuring the impact of NCCs exploits well-documented exogenous shocks to the enforceability of NCCs that occurred in three states: Texas, Florida, and Louisiana. Based on the NCC survey of Malsberger (2004), these three cases were first identified and employed in Garmaise (2011) and are used in a large number of recent studies [e.g., Conti (2014), Lou, Wang, and Zhou (2017), Yin, Hasan, Kobeissi, and Wang (2017), Aobdia (2018), Chen, Zhang, and Zhou (2018), He and Wintoki (2018), He (2018), and Ali, Li, and Zhang (2019)]. This setting helps us handle endogeneity concerns because these changes were introduced by state governments or Supreme Court rulings and were thus unlikely to be caused by fund or manager characteristics.

Our first set of results unambiguously shows that increased enforceability of NCCs leads to better fund performance. This result holds regardless of whether we use different ways of measuring fund performance and employ control variables or not. The result is also economically significant, with increased NCC enforceability giving rise to performance improvement of affected mutual funds of 84 basis points per year (based on DGTW returns). This result remains robust in a battery of robustness tests. Thus, the effort-increasing effect induced by a desire to avoid higher costs associated with being fired seems to be more important for fund managers than the effort-reducing effect arising from more-limited outside options.

We propose and examine a particular mechanism for the documented performance improvement related to changes in NCC enforceability. The idea behind this mechanism is that fund managers respond to increased NCC enforceability by focusing their increased effort towards stocks where they have an information advantage. Stocks in which mutual funds have an information advantage are likely to be those that they overweight [e.g., van Nieuwerburgh and Veldkamp (2009)]. Consistent with this effort-redirecting mechanism, we find that the performance improvement we document comes from stocks that treated mutual funds overweight, in which they are likely to have an information advantage.

After having established our main result, we dig deeper by taking into account differences in the relative importance of the two effects (higher costs associated with termination vs. more limited outside options) across fund managers. For example, a fund manager who considers herself to be of low skill is likely to be more concerned about termination risk than about limited outside options relative to a fund manager who considers herself to be skilled. Therefore, we hypothesize that an increase in NCC enforceability increases the fund performance of the less-skilled manager more. Our empirical tests support this hypothesis. Furthermore, we hypothesize that concerns related to limited outside options are less important for fund managers employed by fund families with a larger internal labor market. The rationale is that families with a larger internal labor market offer fund managers more opportunities for promotion within the family, which should weaken the effort-reducing effect of limited outside options. Thus, we would expect an increase in NCC enforceability to improve the performance of funds more if they belong to families with large internal labor markets. Again, our results support the hypothesis.

Finally, we focus on other actions fund managers might take in response to increased NCC enforceability. First, we look at actions of fund managers intended to make themselves useful to the organization in a way that is unrelated to fund performance. In particular, we test whether fund managers engage in more window dressing - which helps attract new customers and thus generates additional fee income for the fund family - when NCCs become stricter. The rationale is that this can mitigate the concerns that arise from stricter NCCs for a number of reasons. First, the higher fee income reduces the fund managers' risk of being fired, which helps avoid the higher termination costs associated with stricter NCCs. Second, the larger asset base potentially increases the fund managers' compensation, and finally, by contributing more to the revenue of the fund family, managers increase the chances of being promoted in the internal labor market, both of which are important considerations in the face of limited outside options due to stricter NCCs. Our findings support the hypothesis developed above by showing that fund managers increase the amount of portfolio window dressing after an increase in NCC enforceability.

Furthermore, we hypothesize that stricter NCC enforceability causes fund managers to play it safe because they benefit less from taking risk when NCCs are stricter. If the risk taken leads to poor performance (in absolute terms or relative to their peers), fund managers might be fired and the costs associated with termination are higher in case of stricter NCC enforceability. At the same time, fund managers benefit less from risk taking even if it leads to great performance because they have limited outside options. Therefore, we hypothesize that in the face of increased NCC enforceability fund managers (i) reduce portfolio risk, (ii) engage less in tournament behavior, and (iii) herd more. We find evidence supporting all three hypotheses. Managers investing much more like their peers appears surprising at first and incompatible with the fact that a manager needs to deviate from her peers to outperform them. However, these results when combined with the documented effort-redirecting mechanism suggest a rational response by mutual fund managers: they direct more effort towards stocks where they are more likely to have an information advantage, i.e., their overweight positions, while herding with the rest of the portfolio stocks. This redirection of efforts towards parts of the stock universe where they have an advantage and away from stocks where they don't is what generates the performance improvement.

Our paper is related to a growing literature that studies the impact of NCCs on economic activity at the state and firm level. This literature looks at the effect of NCCs on the innovation process [e.g., Gilson (1999), Fallick, Fleischman, and Rebitzer (2006), Marx, Strumsky, and Fleming (2009), Samila and Sorenson (2011), Marx, Singh, and Fleming (2015), and Barnett and Sichelman (2016)], entrepreneurship [e.g., Stuart and Sorenson (2003a,b), Samila and Sorenson (2011), and Starr, Balasubramanian, and Sakakibara (2017)], employee mobility [e.g., Fallick, Fleischman, and Rebitzer (2006), Marx, Strumsky, and Fleming (2009), and Jeffers (2019)], firm-sponsored versus employee-paid training [e.g., Garmaise (2011), Starr, Ganco, and Campbell (2018), Starr (2019), and Starr, Prescott, and Bishara (2019)], wages [e.g., Mukherjee and Vasconcelos (2011), Starr (2019), and Balasubramanian, Chang, Sakakibara, and Starr (2020)], firms' output [e.g., Bishara (2011), Bishara and Orozco (2012), Amir and Lobel (2013), and Anand, Hasan, Sharma, and Wang (2018)], as well as on the firms' financial reporting choices [e.g., Chen, Zhang, and Zhou (2018)]. Our paper contributes to this literature by furthering our understanding of how participants of the labor force respond to NCCs. We find that, in response to increased NCC enforceability, managers not only increase their contribution to their employers' revenue by delivering better performance and window-dressing their portfolios, but also temper their risk-taking behavior. This represents a novel finding suggesting that NCCs have a disciplining impact, which contributes a new insight to the ongoing debate regarding the effect of NCCs on the economy.

Beyond the NCC literature, our paper also contributes to the literature on career concerns of fund managers. NCCs restrict labor mobility, limit outside labor market options, and increase unemployment costs, thus affecting career concerns. So far, the literature has focused on the impact of career concerns on risk-taking. Chevalier and Ellison (1999b) document that managers with stronger termination sensitivity to performance play it safe by reducing portfolio risk and herding more. Extending the Brown, Harlow, and Starks (1996) framework, Kempf, Ruenzi, and Thiele (2009) document that fund managers engage less in tournaments when the expected costs of unemployment are higher. In the context of this literature, our paper is the first to study how career concerns due to NCCs affect the performance of mutual fund managers. In particular, we document that stricter NCCs lead to better performance. An additional contribution of our paper is that we use an "exogenous shock" approach that allows us to draw causal inferences rather than inferences based on association.

The paper is organized as follows. In Section 2.2, we describe our data and methodology. In Section 2.3 we document that NCCs matter in the fund industry by showing that fund manager departure rates go down significantly when NCC enforceability becomes stricter. Section 2.4 presents the main result of our paper that an increase in NCC enforceability increases the performance fund managers deliver and shows for which fund managers this effect is particularly strong. Section

2.5 documents that fund managers also respond to increased NCC enforceability by doing more window dressing and taking less risk. Section 2.6 concludes.

2.2 Identification, Data, and Empirical Specification

2.2.1 Identification Strategy

Our identification strategy exploits well-documented shocks to examine the causal effect of changes of NCC enforceability on our variables of interest. These changes took place in Texas, Florida, and Louisiana. They were introduced by state governments or Supreme Court rulings and were thus unlikely to be caused by fund or manager characteristics. In all these states, NCCs apply to both cases, when an employee leaves the company voluntarily and also when the employee is fired.

In June 1994, Texas Supreme Courts redefined the legal standards for NCCs, making it more difficult to enforce NCCs.[4] For a NCC to be valid, the employment contract needed to explicitly mention the compensation the employee gets for signing the NCC. In late May 1996, Florida state legislature introduced a new law strengthening the employer's position enforcing NCCs. There were three major changes: First, there is a reversal of the burden of proof: the employee now has to prove that the NCC is not violated whereas before 1996 the employer had to prove the violation of the NCC. Second, courts must no longer consider "any individualized economic or other hardship that might be caused to the person against whom enforcement is sought".[5] Finally, in a move from a "red pencil" to "blue-pencil" doctrine, even if the NCC specifies an overbroad time period or geographic range, the contract is no longer considered illegal but is applied in a modified version deemed as reasonable. Louisiana experienced two opposing changes. In June 2001, Louisiana Supreme Court effectively banned NCCs largely by voiding all agreements not pertaining to

[4] *Light v. Centel Cellular Co. of Tex.*, 883 S.W.2d, 664-45 (Tex. 1994), https://www.courtlistener.com/opinion/1525150/light-v-centel-cellular-co-of-texas/.

[5] Florida State Law §542.335(g)(1), http://www.leg.state.fl.us/statutes/index.cfm?App_mode=Display_Statute&URL=0500-0599/0542/Sections/0542.335.html.

the case where the former employee seeks to establish a new business by herself.[6] However, in 2003 the former status quo was reestablished.[7]

A useful feature is that these changes have opposite effects on the enforceability of NCCs, i.e., increased enforceability for Florida and decreased enforceability for Texas. This way we can test the impact of an increase and a decrease of NCC enforceability separately, in effect using these opposite effects to check the construct validity of our main variable.

2.2.2 Sample Construction and Data Sources

Our sample period starts in 1992 and ends in 2004. The main reason for this choice is that, as described above, during this period three states faced substantial amendments to their legal standards related to enforcement of NCCs, while NCC enforceability stayed constant in all the other states.[8] In addition, a key variable that we collect from NSAR reports, advisors' "state of headquarter" (further discussed below) is not available before 1992 through the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system maintained by the SEC.

Our sample incorporates several data sets. From the Center for Research on Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database we get fund names, family names, monthly net returns, total nets assets under management, investment objectives, and further fund specific information such as expense and turnover ratios. For mutual funds with different share classes, we aggregate all

[6] *SWAT 24 Shreveport Bossier, Inc. v. Bond*, 808 So. 2d 294 (La. 2001), `http://caselaw.findlaw.com/la-supreme-court/1085030.html`.

[7] See, e.g., Terrell (2004) and Ecker (2015).

[8] A study by Ewens and Marx (2018) uses 14 more recent instances of NCC enforceability changes in a number of states. Two other studies by Jeffers (2019) and Kini, Williams, and Yin (2019) also use more recent changes. We considered using these more recent changes, but decided against doing so for the following reasons: (1) There is little agreement among these three studies as to what constitutes a valid NCC enforceability change. Specifically, all three papers fully agree only on the Star Direct, Inc. v. Dal Pra. (2009) case, which changed the NCC regime in Wisconsin. They also agree that NCC regimes changed in Colorado, Texas, and Illinois. However, in each of these three states several consecutive changes happened and the authors agree only on a subset of those changes that happened around the recent financial crisis. (2) For all the changes where the three papers are in full or partial agreement, we found that the parallel trends assumption does not hold. Thus, we decided to use our three cases detailed in Section 2.2.1, which have been used and vetted by a larger number of studies. Doing so also avoids potentially confounding effects that might have arisen during the recent financial crisis.

observations at the fund-level based on the asset value of the share classes. We limit the universe to include only diversified, domestic U.S. equity funds, thereby excluding index, balanced, bond, money market, and sector funds. 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.

NCC enforceability is governed by state law and changes in NCC enforceability take place at the state level. To determine the relevant state, we rely on N-SAR filings by mutual funds, which we retrieve through EDGAR. We download all N-SAR A and B filings and match them manually to our CRSP sample funds by name. The fund managers conducting the actual asset management are employees of the fund's "advisor" (item #8), and the advisor's "state of headquarter" (item #8.D), as opposed to the state of incorporation, is the relevant state, the laws of which govern the pertinent NCC law applicable to the fund managers.[9] Each fund with one unique advisor state is assigned one distinct NCC jurisdiction; we exclude all other funds without a unique advisor state from the sample.[10]

2.2.3 Descriptive Statistics

Our sample from 1992 to 2004 includes 2,063 funds from 616 families managed by 3,396 distinct managers. Out of the sample funds, 110 (5.3%) are from one of the treated states (Texas = 73 funds, Florida = 34 funds, Louisiana = 3 funds). Similarly, out of the 3,396 sample managers, 198 (5.9%) come from a state experiencing a change in NCC enforceability (Texas = 146 managers, Florida = 48 managers, Louisiana = 4 managers).

Table 2.1 provides descriptive statistics for the total sample as well as the treated and untreated subsamples separately. The average fund has almost $1 billion in as-

[9] This was most recently confirmed in *Ascension Insurance Holdings, LLC v. Underwood et al.* (January 28, 2015), whereby the Delaware Court of Chancery concluded that California law must be applied with respect to a non-compete agreement signed by a California-based employee despite a Delaware choice-of-law provision contained in the non-compete agreement.

[10] If a fund is subadvised, we assign the fund to the NCC jurisdiction which applies to the subadvisor.

Table 2.1: Descriptive Statistics

This table reports descriptive statistics for fund and family characteristics. Means are provided for the total sample; the group of treated funds, comprising funds where the fund adviser is headquartered in either Texas, Florida, or Louisiana; and the control group, comprising all remaining funds. The last two columns provide the difference between the mean value for the treated and for the control group and the corresponding t-statistic. *Fund Size* is given by the total net assets under management (AUM) in $ million. *Expense Ratio* is the annual expense ratio in percent. *Turnover Ratio* is the annual portfolio turnover ratio in percent. *Fund Age* is the age in years. *Family Size* [*$million*] measures the total net assets under management aggregated over the fund family in $ millions. *Family Size* [*#managers*] is the number of managers employed be the fund family. *Family Size* [*#funds*] is the total number of funds run by the family.

	Total Sample	Treated Group	Control Group	Difference	t-stat
Fund Size [$ million]	977.92	902.94	981.90	−78.96	−0.69
Expense Ratio [%/year]	1.40	1.56	1.40	0.16	5.98***
Turnover Ratio [%/year]	95.53	89.24	95.87	−6.63	−1.96*
Fund Age [years]	11.84	13.75	11.73	2.02	3.29***
Family Size [$ million]	23,685.56	15,487.75	24,123.30	−8,635.55	−6.49***
Family Size [#managers]	15.63	15.23	15.65	−0.43	−0.51
Family Size [#funds]	14.27	11.81	14.41	−2.60	−4.20***

sets, has an annual expense ratio of 1.4%, and turns over its portfolio approximately once per year (mean turnover ratio of 96%). On average, sample funds are 12 years old. The average sample family has about $24 billion in assets, manages 14 funds, and employs roughly 16 managers. In terms of assets, funds from the control and treated group are largely comparable. Treated funds exhibit slightly lower turnover than the control group (89% versus 96%). They are also two years older and charge 16 basis points higher in fees. Consistent with states in the control group housing large financial centers (e.g., New York, California, and Pennsylvania), which host disproportionately more large families, families from treated states are significantly smaller both in terms of totals assets and number of funds managed but not in terms of number of managers employed. Besides these differences, there are no other discernible differences between the subsamples.

2.2.4 Methodology

To test the hypotheses developed in the introduction, we estimate a generalized difference-in-differences regression model that resembles the one employed by Bertrand and Mullainathan (2003) to examine the effects of anti-takeover law changes:

$$y_{i,s,t} = \beta_0 + \beta_1 \cdot Treated_{i,s,t} \cdot Post_t + Controls + FE + \varepsilon_{i,s,t}, \tag{2.1}$$

where $y_{i,s,t}$ is the variable of interest for fund i from state s in period t. Following Garmaise (2011), we use the changes in the legal environment detailed above to generate our main independent variable, $Treated_{i,s,t} \cdot Post_t$, and assume that the legal changes affect managerial behavior starting in the year following their occurrence. Accordingly, this variable is set to -1 for funds in Texas from 1995 to 2004, +1 for funds in Florida from 1997 to 2004, and -1 for funds in Louisiana in 2002 and 2003, and is set to 0 otherwise. $Controls$ denotes fund-level control variables.[11] In particular, we include: $Expense\ Ratio$, fund's expense ratio; $Turnover\ Ratio$, fund's portfolio turnover ratio; $Flow$, fund's net flow computed as the change in fund assets not attributable to performance; $Log(Age)$, the natural logarithm of fund's age; and $Log(TNA)$, the natural logarithm of total net assets. We use fund fixed effects (FE) to control for time-invariant differences between treated and non-treated funds, time fixed effects to account for common time variant factors, and style fixed effects to control for commonalities within investment styles. $\varepsilon_{i,s,t}$ denotes the error term. We cluster standard errors at the state level in all specifications.[12]

2.3 Do NCCs Matter in the Fund Industry?

NCCs are very common in knowledge-intensive industries [e.g., Starr, Prescott, and Bishara (2019)].[13] Since mutual fund families almost exclusively consist of human

[11] We also calculate results without control variables to address the potential concern that the change in NCC enforceability might have an impact on the time-varying controls and lead to inconsistent estimates of the treatment effect. However, the results clearly show that this is not the case. The treatment effect is essentially the same with and without control variables.

[12] Although this choice follows the literature and guideline in Angrist and Pischke (2009), we test the robustness of our specification. As fund fixed effects potentially bias the coefficient estimates of fund size [see Pástor, Stambaugh, and Taylor (2015)], besides running the analysis without control variables, we repeat it with state fixed effects instead. Our results are also unaffected when we use style-by-time fixed effects. Further, we additionally cluster by state and time. Results essentially remain the same.

[13] The reach of NCCs has moved beyond high skill, high paying occupations, however, in recent years. Dougherty (2017) reports that in the last few years there has been a significant increase both in the use of NCCs by companies (to cover even non-technical workers such as sandwich makers

capital [e.g., Berk, van Binsbergen, and Liu (2017)], there is a strong rationale for the use of NCCs in the fund industry. They are intended to help with talent retention and keep fund managers from disseminating any trade secrets related to investment processes, investment strategies, and trading algorithms to competitors. In addition, another rationale for investment firms to use NCCs is to keep their portfolio managers from taking the firms' clients with them when they join a competitor or start their own firm.

There are no requirements for investment firms such as mutual fund families and affiliated entities to report information on the use and details of NCCs for their fund managers, thus detailed data on their use is unavailable. However, we can provide evidence on the use of NCCs in the mutual fund industry by documenting that labor mobility declines when NCC enforceability increases. To do so, we calculate the departure rate of fund managers from a given family in year t as the number of fund manager departures in that year scaled by the number of fund managers in that family. We apply the generalized difference-in-differences approach (2.1) and use the departure rate as the dependent variable. The control variables are as described in Section 2.2.4, but aggregated at the family level.

Table 2.2 clearly shows that the departure rate drops when NCCs enforceability becomes stricter. This holds, independent of whether we estimate the model with or without control variables. In both cases, the drop in departure rates due to increased NCC enforceability is about 6 percentage points, which is highly significant in statistical and economical terms. It constitutes 30% of the cross-sectional standard deviation of departure rates. The finding that NCCs affect the mobility of mutual fund managers suggests that NCCs are indeed used considerably by mutual fund families. However, since we are unable to observe the employment contracts of the fund managers, we cannot rule out that some fund managers in the treated states have no NCCs in their contract and therefore are unaffected by changes in NCC enforceability. This would create an attenuation bias in our analysis, which would make it more difficult to find significant effects on our variables of interest due to changes in NCC enforceability.

and hairstylists) and the number of NCC lawsuits brought by companies.

Table 2.2: Impact of Changes in NCC Enforceability on Departure Rates

This table presents results from pooled OLS regressions that relate average annual departure rates with changes in NCC enforceability at the state level. The analysis is done at the fund family and year level. We calculate the departure rate of fund managers from a given company in year t as the number of fund manager departures in that year scaled by the number of fund managers in that family. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. Family control variables are: *Expense Ratio*, expense ratio averaged across all family funds; *Turnover Ratio*, portfolio turnover ratio value-weighted across all family funds; *Flow*, fund's net flow computed as the change in fund assets not attributable to performance and value-weighted across all family funds; $Log(Age)$, the natural logarithm of the fund's age value-weighted across all funds in the family; and $Log(TNA)$, the natural logarithm of the sum of total net assets of all family funds. Regressions are run with family and calendar year fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Departure Rate	
Treated·Post	−0.0611***	−0.0650***
	(−4.70)	(−4.73)
Expense Ratio		−0.7380
		(−0.93)
Turnover Ratio		0.0031
		(0.82)
Flow		−0.000***
		(−6.33)
Log(Age)		−0.0034
		(−1.18)
Log(TNA)		0.0086
		(1.14)
Observations	2,344	2,344
Within R^2	0.001	0.004

2.4 The Impact of NCCs on Fund Managers' Performance

In this section, we analyze how changes in NCCs affect the performance of fund managers. As outlined in the introduction, there are two opposing effects. On the one hand, NCCs incur costs to employees when they are fired, thus incentivizing them to work harder and deliver better performance in order to avoid termination. On the other hand, NCCs limit the outside options of fund managers in the external labor market and thus reduce their incentives to work hard in order to achieve very good performance and make themselves marketable in the external job market. In Section 2.4.1 we show that the disciplining effect dominates and that an increase in NCC enforceability makes fund managers deliver better performance. In Section 2.4.2, we run various additional tests to provide further support for this finding and rule out alternative explanations. Section 2.4.3 examines a particular mechanism by means of which managers achieve the increase in performance. Finally, in Section 2.4.4 we analyze whether the relative importance of the two effects described above depends on characteristics of the fund manager and the fund family.

2.4.1 Main Result

To test how changes in NCC enforceability affect the performance of fund managers, we use model (2.1), but now with monthly fund performance as the dependent variable. We employ four measures of fund performance: raw return (*Return*); style-adjusted return ($Style - adj.\ Return$); risk-adjusted return (*Carhart*); and characteristic-adjusted return (*DGTW*). To measure style-adjusted returns, we subtract from the return of a given fund the mean return of all funds belonging to the same investment category. We calculate risk-adjusted returns using the Carhart (1997) approach as the difference between the actual return and the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns on the respective four factor-mimicking portfolios.[14] There are two potential concerns with the Carhart alpha even though it is a commonly used performance measure. First, it assumes that the risk factor model is linear, which has been shown to perform worse in explaining the cross section of stock returns than the nonlinear characteristic-based model of Daniel and Titman (1997) and Daniel, Grinblatt, Titman, and Wermers (1997). Second, the Carhart model (and also the Fama-French model) has been documented to produce biased alphas, as shown by the economically and statistically significant non-zero alphas it produces for passive benchmark indices [e.g., Cremers, Petajisto, and Zitzewitz (2013)].

To avoid the possibility that our inferences are affected by the issues highlighted above, we also employ characteristic-adjusted returns following Daniel and Titman (1997) and Daniel, Grinblatt, Titman, and Wermers (1997), which we calculate as

[14] Returns for the factor mimicking portfolios and the proxy for the risk-free rate are available via `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

follows. First, we determine a portfolio stock's characteristic-adjusted return in a given month by subtracting from its return the return of the benchmark portfolio, to which that particular stock belongs.[15] Each stock's benchmark portfolio is a value-weighted portfolio that includes all stocks that are part of the same size, book-to-market, and one-year past return quintile. Then, we calculate a fund-level DGTW measure as the value weighted sum of stock-level characteristic-adjusted returns.

Table 2.3 reports regression results with our four performance measures as dependent variables. The results provide strong evidence that increased enforceability leads to improved performance. This finding is consistent with Andersson (2002), who shows that managers increase their effort when career concerns increase even if their compensation contract provides them with effort-based explicit incentives, as is common in the mutual fund industry [e.g., Ma, Tang, and Gómez (2019)]. For each performance measure, the coefficient of $Treated_{i,s,t} \cdot Post_t$ is statistically significant at the 1% level and its magnitude implies a significant economic impact.[16] For example, results based on *DGTW* indicate that a change toward stricter enforcement of NCCs leads to an increase of 7 basis points per month, which corresponds to an 84 basis points improvement on an annual basis. To provide some context for the economic significance of these results, we compare them against the magnitude of the changes in NCC enforceability for our treated states. We rely on Garmaise's (2011) NCC enforceability index constructed for each state based on Malsberger's (2004) methodology. The values of this index range from 0 to 12 and its cross-sectional standard deviation is 2. The magnitude of the changes in the enforceability index ranges between 2 and 4 for our treated states.[17] This is at least as large as the cross-sectional standard deviation and suggests that the economic significance for the performance improvements we document is caused by economically large changes in NCC enforceability in our treated states.

In sum, the results from Table 2.3 suggest that an increase in NCC enforceability

[15] The DGTW benchmarks are available via `http://terpconnect.umd.edu/~wermers/ftpsite/Dgtw/coverpage.htm`.

[16] Coefficients continue to be statistically significant when we omit the control variables.

[17] The NCC enforceability index changes from 5 to 3 for Texas, 7 to 9 for Florida, and 4 to 0 and back for Louisiana.

Table 2.3: Impact of Changes in NCC Enforceability on Performance

This table presents results from pooled OLS regressions that relate performance measures with changes in NCC enforceability at the state level. The analysis is done at the fund and month level. Our performance measures include: The raw return (*Return*), style-adjusted return ($Style - adj.Return$), Carhart 4-factor alpha (*Carhart*), and DGTW-adjusted return (*DGTW*). Style adjusted return is computed by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective. Carhart 4-factor alpha is computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns on the four and five risk factors, respectively. DGTW-adjusted return is estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund portfolio level. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. Fund control variables are: *Expense Ratio*, fund's expense ratio; *Turnover Ratio*, fund's portfolio turnover ratio; *Flow*, fund's net flow computed as the change in fund assets not attributable to performance; $Log(Age)$, the natural logarithm of fund's age; and $Log(TNA)$, the natural logarithm of total net assets. Control variables are aggregated at the fund level. Regressions are run with fund, calendar month, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0014***	0.0016***	0.0015***	0.0007***
	(2.81)	(2.81)	(3.46)	(2.87)
Expense Ratio	−0.0007	0.0066	0.0059	0.0601*
	(−0.02)	(0.16)	(0.09)	(1.77)
Turnover Ratio	0.0004	0.0004	0.0002	0.0002
	(1.35)	(1.33)	(0.56)	(0.40)
Flow	0.0022**	0.0020***	0.0009	0.0024***
	(2.54)	(2.76)	(1.22)	(3.83)
Log(Age)	0.0033***	0.0021***	−0.0009	0.0028***
	(3.96)	(2.76)	(−1.21)	(5.95)
Log(TNA)	−0.0053***	−0.0046***	−0.0031***	−0.0025***
	(−13.49)	(−13.10)	(−8.63)	(−14.52)
Observations	104,043	104,043	70,656	95,011
Within R^2	0.008	0.008	0.004	0.002

makes fund managers deliver a better performance. This is consistent with the view that the effort-increasing effect of higher costs associated with being fired is more important for fund managers than the effort-reducing effect of limited outside options.

The reliability of causal inferences obtained from our difference-in-differences estimation hinges on the assumption that, in the absence of changes in NCC enforceability, changes in our variables of interest are the same for the treated and control group, i.e., these variables exhibit trends that are parallel between the treated and control groups before the treatment. To check the validity of this assumption, we

Table 2.4: Assessment of Parallel Trends in the Pre-Treatment Period

This table presents results from pooled OLS regressions utilized in Table 2.3 that have been augmented with additional variables to examine performance effects prior to the change in NCC enforceability. Specifically, we augment the regression with terms that interact an indicator variable for the first (second) year prior to the change in NCC enforceability, $Pre1$ ($Pre2$), with the treatment indicator. Fund controls are as in Table 2.3. Regressions are run with fund, calendar month, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Return	Style-adj. Return	Carhart	DGTW
Treated·Pre2	−0.0003	−0.0004	−0.0007	−0.0007
	(−0.40)	(−0.54)	(−0.85)	(−0.94)
Treated·Pre1	−0.0012	−0.0016	−0.0011	−0.0000
	(−0.73)	(−0.99)	(−1.16)	(−0.01)
Treated·Post	0.0015***	0.0007*	0.0015***	0.0018***
	(4.00)	(1.98)	(6.67)	(3.52)
Fund Controls	Yes	Yes	Yes	Yes
Observations	104,043	104,043	70,656	95,011
Within R^2	0.008	0.008	0.004	0.001

augment model (2.1) with two terms that interact indicator variables for each of the two years prior to the change in NCC enforceability ($Pre2_t$ and $Pre1_t$) with the treatment dummy. Given that the treatment for Texas funds starts in 1995 and our sample starts in 1992, we are able to look at two years prior to the treatment so that our benchmark period covers at least one year.

Results of corresponding regressions are presented in Table 2.4. They show that for none of the performance measures the interaction terms, $Treated_{i,s,t} \cdot Pre2_t$ and $Treated_{i,s,t} \cdot Pre1_t$, are economically or statistically significant. This evidence supports the assumption that treated and control group exhibited parallel trends prior to changes in the NCC enforceability.

2.4.2 Robustness Tests

To provide further support for our main finding in Table 2.3 and to rule out alternative explanations, we run various additional tests.

2.4.2.1 Single-State Analysis

Model (2.1) staggers changes in NCC enforceability in both directions, that is, it includes both increases and decreases in NCC enforceability. However, our data allow us to discern how fund managers react to opposite changes in NCC enforceability by looking separately at the effects of increased enforceability and decreased enforceability. Therefore, in our first robustness test, we re-estimate our main result separately for Florida (where NCC enforceability increased) and Texas (where NCC enforceability decreased).[18]

To run this test, we replace the variable $Treated_{i,s,t} \cdot Post_t$ in model (2.1) with $Increased_{i,s,t} \cdot Post_t$, which equals +1 for funds from Florida during 1997-2004 and 0 otherwise. When focusing on Texas, we replace the variable $Treated_{i,s,t} \cdot Post_t$ with $Decreased_{i,s,t} \cdot Post_t$, which equals +1 for funds with advisors headquartered in Texas from 1995-2004 and 0 otherwise. We hypothesize that increased or decreased enforceability of NCCs leads to effects on the left-hand side variable that have opposite signs. Table 2.5 presents results. In the interest of brevity, we report only the main coefficients of interest.

Table 2.5 clearly documents the robustness of our main result. All relevant coefficients have the hypothesized signs. For Florida, where NCC enforceability increased, we find that fund managers deliver better performance. In contrast, for Texas, where NCC enforceability decreased, we find the opposite effect. Regarding statistical and economic significance, the results are on par with the results of the aggregated analysis. This is sensible since the magnitude of the change in enforceability, as shown by Garmaise (2011), is the same in absolute terms for both states. Thus, our main finding does not only hold when we jointly look at all changes in NCC enforceability but also for each change in NCC enforceability separately. This increases the confidence that the effect we document indeed results from changes in NCC enforceability.

[18] We are unable to conduct a similar analysis for Louisiana given that there are only three treated funds in Louisiana.

Table 2.5: Impact of Changes in NCC Enforceability for each Treatment Group separately

In this table, we repeat our main analysis of changes in NCC enforceability for each treatment group separately. The construction of dependent variables and control variables is described in Table 2.3. Our main independent variables are $Increased \cdot Post$, which equals +1 for funds in Florida in 1997–2004 and 0 otherwise as well as $Decreased \cdot Post$, which equals +1 for funds in Texas in 1995–2004 and 0 otherwise. Regressions are run with fund, calendar month, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Return		Style-adj. Return		Carhart		DGTW	
	Florida	Texas	Florida	Texas	Florida	Texas	Florida	Texas
Increased /	0.0009^{***}	-0.0020^{***}	0.0012^{***}	-0.0023^{***}	0.0013^{***}	-0.0020^{***}	0.0005^{**}	-0.0008^{***}
Decreased · Post	(2.90)	(−5.61)	(3.49)	(−7.06)	(3.84)	(−5.93)	(2.09)	(−3.45)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,043	104,043	104,043	104,043	70,656	70,656	95,011	95,011
Within R^2	0.008	0.008	0.008	0.008	0.004	0.004	0.002	0.002

2.4.2.2 Switching Fund Managers

Manager turnover is another alternative explanation for our main result. Some managers might self-select to join or leave fund families that are affected by changes in NCC enforceability. To rule out this alternative explanation, we re-run our main test using only the subsample where the same fund manager was responsible for the fund before and after the change in NCC enforceability.

The results presented in Panel A of Table 2.6 rule out the alternative explanation that fund manager changes caused by self-selection drive our results. Using only constant manager-fund combinations, our result remains qualitatively unchanged.

The performance improvement we document might not only result from the increased effort in response to potentially higher termination costs but also from changes in compensation contracts after the increase in NCC enforceability. Fund families might have used their higher bargaining power due to higher NCC enforceability to change their managers' contracts towards more performance sensitive compensation. The unobservability of employment contracts makes it impossible for us to check whether and how the contracts actually change and, thus, to separate the two channels. Nonetheless, contract adjustments - in contrast to changes in NCC enforceability - might arguably not be instantaneous given the discussions and negotiations expected to take place between the parties involved. For this reason, contract changes should be less relevant when we look at shorter post-treatment periods, a consideration which leads us to use post-treatment periods ranging from three years to one year, respectively, in Panels B - D of Table 2.6. Evidence from these panels shows that the performance improvement gets indeed smaller when we look at shorter post-treatment periods. For example, based on $DGTW$, the performance improvement drops from 0.0027 for the three-year post treatment period to 0.0017 for the one-year post treatment period. This is consistent with the view that part of the performance improvement we document results from contract renegotiations due to NCC changes but the major part reflects an increased effort of fund managers in response to potentially higher termination costs.

Table 2.6: Constant Manager-Fund Pairs

In this table, we repeat our main analysis of changes in NCC enforceability using a subsample where the same fund manager was responsible for the fund before and after the change in NCC enforceability. The construction of dependent variables and control variables is described in Table 2.3. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. In Panel A, we utilize the complete sample period. In Panels B, C, and D, we repeat the analysis of Panel A, restricting the period to three, two, and one years around the change, respectively. Regressions are run with fund, calendar month, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Complete Sample Period

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0021***	0.0023***	0.0012***	0.0017**
	(3.08)	(2.80)	(2.70)	(2.13)
Fund Controls	Yes	Yes	Yes	Yes
Observations	101,255	101,255	68,954	92,336
Within R^2	0.008	0.007	0.004	0.002

Panel B: Three years around the change

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0024***	0.0027***	0.0020***	0.0027***
	(4.59)	(5.87)	(3.05)	(3.04)
Fund Controls	Yes	Yes	Yes	Yes
Observations	100,256	100,256	68,123	91,483
Within R^2	0.008	0.007	0.004	0.002

Panel C: Two years around the change

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0025***	0.0029***	0.0012**	0.0027***
	(4.81)	(4.34)	(1.97)	(8.04)
Fund Controls	Yes	Yes	Yes	Yes
Observations	99,906	99,906	67,905	91,161
Within R^2	0.008	0.007	0.004	0.002

Panel D: One year around the change

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0023***	0.0025***	0.0011	0.0017**
	(5.16)	(6.57)	(1.20)	(2.07)
Fund Controls	Yes	Yes	Yes	Yes
Observations	99,615	99,615	67,676	90,891
Within R^2	0.008	0.007	0.004	0.002

2.4.2.3 Propensity Score Matching

So far, we consider all untreated funds as the control group and take differences between treated and untreated funds (as documented in Table 2.1) into account by employing fund characteristics as control variables in our regressions. However, it could be that the results might reflect differences in fund characteristics that the linear model does not properly control for. To address this concern, we use a matching approach that selects the control group to consist of only non-treated funds that are matched to the treated funds. More specifically, following Agarwal, Mullally, Tang, and Yang (2015) and Agarwal, Vashishtha, and Venkatachalam (2018), in the last period before treatment we run three separate logistic regressions - one for each treated state - relating the probability of a fund being treated to the characteristics used as control variables in equation (2.1). Using the propensity scores from these regressions, we determine the nearest untreated neighbor for each treated fund. We then re-run our main test using only the treated and the matched untreated funds.

The results of Table 2.7 rule out the possibility that the way we control for differences in fund characteristics is responsible for our main result. When we use a propensity score matching approach, our main result remains unchanged.

Table 2.7: Propensity Score Match

In this table, we repeat our main analysis of changes in NCC enforceability using a subsample of treated and matched untreated funds. To construct the sample of matched untreated funds, we run a logistic regression that relates the probability of a fund being treated to fund characteristics. Using the propensity score from this regression, we determine the nearest untreated neighbor for each treated fund. The construction of dependent variables and control variables is described in Table 2.3. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. Regressions are run with fund, calendar month, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0022***	0.0027***	0.0021***	0.0012***
	(6.20)	(9.97)	(4.82)	(3.10)
Fund Controls	Yes	Yes	Yes	Yes
Observations	3,977	3,977	3,065	3,714
Within R^2	0.010	0.010	0.004	0.010

In summary, the findings of Section 2.4.2 provide further support for our main result and help rule out various alternative explanations for it.[19]

2.4.3 Mechanism

In this section, we propose and test for a particular mechanism that drives the performance effect arising due to changes in NCC enforceability. The mechanism entails fund managers responding to the abrupt increase in NCC enforceability and the associated looming higher costs of termination by focusing their increased effort towards stocks where they have an information advantage. Based on van Nieuwerburgh and Veldkamp (2009), stocks in which mutual fund managers have an information advantage are more likely to be the ones that they overweight. If this effort-redirecting mechanism is present, we would expect a bigger performance improvement in the subportfolio of stocks that represent large bets. We consider a stock to be overweighted in a given manager's portfolio if its portfolio weight belongs to the top quartile ($Q1$) of the peer managers' weights in the same stock. For comparison, we also identify stocks that fund managers underweight by looking for stocks with weights in the bottom quartile ($Q4$) of the peer manager weights.[20] These are the stocks for which they likely have no information advantage.

Table 2.8 reports results from regressions that relate the average performance of fund positions that separately fall in $Q1$ and $Q4$ to the change in NCC enforceability. Performance of the aggregated extreme positions is measured on a quarterly basis. Since the unit of analysis is a subset of the fund portfolio, we employ holdings-based raw returns and DGTW-adjusted returns as measures of performance. If fund managers direct more effort in stock picking towards their larger bets after NCC enforceability increases, we expect a positive effect of $Treated_{i,s,t} \cdot Post_t$ on the stocks managers overweight by a lot relative to their peers. This is indeed what Table 2.8 documents: the portfolio performance of the stocks in the extreme overweight bucket $Q1$ increases significantly more for treated funds. The DGTW-adjusted return of the sub-portfolio consisting of these stocks increases by 1.61 percentage points per

[19] In unreported analysis, we also find that our results are unaffected by whether the treated funds are managed by single managers or teams of managers.

[20] The results remain qualitatively unchanged when we use other cuts to classify extreme bets; they become even stronger when we use more extreme cuts, e.g., top decile and bottom decile.

Table 2.8: Extreme Bets of Fund Managers

This table presents results from pooled OLS regressions relating the performance of subportfolios of fund holdings that capture extreme bets with changes in NCC enforceability at the state level. The analysis is done at the fund and quarterly level. We consider a stock to be overweighted in a given manager's portfolio if its portfolio weight belongs to the top quartile ($Q1$) of the peer managers weights in the same stock. Similarly, we consider a stock to be underweighted in a given manager's portfolio if its portfolio weight belongs to the bottom quartile ($Q4$) of the peer managers weights in the same stock. *Return* $Q1$ ($Q4$) denotes the value-weighted return of stocks in the respective subportfolios formed at the end of the previous quarter. *DGTW* $Q4$ ($Q1$) denotes the value-weighted DGTW-adjusted return of stocks in the respective subportfolios formed at the end of the previous quarter. Fund controls are as in Table 2.3. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. Regressions are run with fund, calendar quarter, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Return Q1	Return Q4	DGTW Q1	DGTW Q4
Treated·Post	0.0112***	−0.0010	0.0041**	−0.0001
	(3.01)	(−0.93)	(2.04)	(−0.14)
Fund Controls	Yes	Yes	Yes	Yes
Observations	25,106	25,106	24,693	24,647
Within R^2	0.013	0.001	0.005	0.000

year. Compared to the overall annual performance effect of 0.84 percentage points (see fourth column of Table 2.3), this suggests that the increase in performance due to increased NCC enforceability is particularly strong in stocks that fund managers overweight by a lot. For the stocks that fund managers underweight, we see that the coefficients are negative but they are not statistically significant.[21]

2.4.4 Cross-Sectional Differences in the Behavior of Fund Managers

After having established our main result, we examine factors that we hypothesize to affect the relative strength of the two opposing effects, i.e., the effort-increasing effect caused by costs associated with termination vs. the effort-reducing effect due to limited outside options. To this end, we consider managerial skill in Section 2.4.4.1 and the size of the internal labor market in a fund family in Section 2.4.4.2.

[21] Although in unreported results the coefficients for stocks in the $Q2$ and $Q3$ buckets are positive and suggest a monotonic increase when compared with the coefficient $Q4$, they are statistically insignificant. This suggests that the overall performance effect results from the stocks the fund managers overweight heavily.

2.4.4.1 Low- versus High-Skilled Managers

We expect that the relative importance of the two effects associated with an increase in NCC enforceability depends on a fund manager's perception of her skill. A fund manager who considers herself to be of lower skill is likely to be more concerned about termination risk than about limited outside options relative to a fund manager who considers herself to be more skilled. Therefore, we hypothesize that the performance impact of increased NCC enforceability is stronger for less-skilled than for more-skilled managers.

We measure a manager's perception of her skill as the average SAT score of matriculates at the institution where the manager obtained her bachelor degree. We first collected information on which universities managers obtained their degree from using Morningstar Direct, Morningstar Principia, SEC filings, LinkedIn, and the websites of the fund companies. Then, from the College Scorecard provided by the U.S. Department of Education, we obtained the average SAT scores of the institutions from where managers graduated.[22]

To test the prediction that an increase in NCC enforceability leads to greater performance increases for lower-skilled managers, we augment model (2.1) with two variables: $SAT_{i,s,t}$, the average SAT score of the school from which the manager graduated, and the interaction of $Treated_{i,s,t} \cdot Post_t$ with $SAT_{i,s,t}$ (scaled by 1,000). Consistent with our discussion above, we expect the interaction term to be negative.

The results provided in Table 2.9 support our hypothesis. The coefficient of the interaction term is negative and statistically significant. This suggests that the performance improvement due to increased NCC enforceability intensifies for lower-SAT managers. For example, lower skilled managers at the 25-percentile of the SAT distribution increase $DGTW$ by 6 basis points per month, which constitutes a performance improvement that is 10 basis points higher than that of managers with median SAT scores. This is consistent with the view that for managers with lower skill, the effort-increasing effect due to higher costs associated with termination dominates the effort-reducing effect due to limited outside options to a greater extent

[22] See `https://collegescorecard.ed.gov/`.

Table 2.9: Manager Skill and NCC Impact on Fund Performance

This table presents results from pooled OLS regressions that relate fund performance measures with changes in NCC enforceability at the state level and their interaction with the skill level of the manager. The analysis is done at the fund and monthly level. The construction of dependent variables and control variables is described in Table 2.3. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. We interact $Treated \cdot Post$ with our skill measure SAT, the average matriculates' SAT score at the institution where the manager obtained her bachelor degree, divided by 1,000. Regressions are run with fund, calendar month, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0133***	0.0158***	0.0225***	0.0118***
	(5.26)	(3.87)	(3.19)	(7.95)
SAT	0.0001	−0.0005	−0.0039	0.0032
	(0.02)	(−0.17)	(−1.18)	(1.35)
Treated·Post·SAT	−0.0113***	−0.0130***	−0.0169***	−0.0093***
	(−5.94)	(−3.81)	(−3.09)	(−5.07)
Fund Controls	Yes	Yes	Yes	Yes
Observations	59,889	59,889	38,699	51,551
Within R^2	0.010	0.009	0.005	0.003

than for managers with higher skill.[23]

2.4.4.2 Managers in Families with Large versus Small Internal Labor Markets

We next test whether the reaction of fund managers to changes in NCC enforceability depends on how developed the internal labor markets are in which managers operate. Managers that work for larger fund families are expected to benefit from the presence of more developed internal markets, which allow them to replace restricted across-family mobility with within-family mobility [Papageorgiou (2014, 2018)]. In more developed internal labor markets, managers still face the risk of being fired, but at the same time, they have more opportunities to be internally promoted. Thus,

[23]We also examined whether increases in NCC enforceability have a different performance impact for younger vs. older managers. Chevalier and Ellison (1999b) argue that the likelihood of being fired due to poor performance is higher for younger managers than for older managers. This suggests that an increase in the costs of being fired due to stricter NCCs is more relevant for younger managers than for older managers. At the same time, an opposing effect is also likely: limited outside options due to stricter NCCs are likely to be more important for younger managers since they are just starting their career in the fund business. Unreported results suggest that manager age does not affect the performance impact of changes in NCC enforceability significantly, which is consistent with the two effects offsetting each other.

Table 2.10: Size of the Internal Labor Market and NCC Impact on Fund Performance

This table presents results from pooled OLS regressions that relate fund performance measures with changes in NCC enforceability at the state level and their interaction with the size of the internal labor market. The analysis is done at the fund and monthly level. The construction of dependent variables and control variables is described in Table 2.3. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. We interact $Treated \cdot Post$ with $FamilySize$, which is given by the total number of funds in the family to which the fund belongs. Regressions are run with fund, calendar month, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Return	Style-adj. Return	Carhart	DGTW
Treated·Post	0.0004	0.0005*	0.0009**	0.0006**
	(1.34)	(1.73)	(2.58)	(2.33)
FamilySize	0.0000	0.0000	−0.0000	−0.0000
	(0.57)	(1.00)	(−0.56)	(−0.10)
Treated·Post·FamilySize	0.0001***	0.0001***	0.0001***	0.0000
	(3.70)	(4.13)	(4.20)	(0.86)
Fund Controls	Yes	Yes	Yes	Yes
Observations	103,308	103,308	71,184	94,324
Within R^2	0.008	0.008	0.004	0.002

the managers' concerns of a limited upside after increased NCC enforceability are mitigated in larger families. This weakens the relative importance of the effort-reducing effect in favor of the disciplining effect. Therefore, we expect the positive performance effect of increased NCC enforceability to be greater in larger families than in smaller families.

We measure the size of the internal labor market in a fund family by the number of family funds. To quantify the effect of family size on the performance impact of changes in NCC enforceability, we augment equation (2.1) with two variables: $FamilySize_{i,s,t}$, the number of family funds, and the interaction of $Treated_{i,s,t} \cdot Post_t$ with $FamilySize_{i,s,t}$. Consistent with our discussion above, we expect the interaction term to be positive.

Results from this regression are reported in Table 2.10. They show that, as expected, $FamilySize_{i,s,t}$ interacts positively with $Treated_{i,s,t} \cdot Post_t$. Except for the $DGTW$ specification, the coefficient of the interaction term is statistically significant at the 1 percent level in all specifications. Overall, the evidence from Table 2.10 supports our hypothesis: Fund managers in larger families increase their performance more than fund managers in smaller families following increased enforceability of NCCs. This is consistent with the notion that the effort-reducing effect of limited outside options is less important in larger families where managers have more opportunities to be promoted internally.

2.5 Other Actions of Fund Managers in Response to NCCs

So far, we have shown that one action managers take in response to increased NCC enforceability is to increase their output, i.e., deliver better performance. This makes fund managers more valuable for their fund families and thus reduces their likelihood of being fired. In this section, we document other actions fund managers take that are not intended to deliver a better performance. In Section 2.5.1, we document that managers also make themselves valuable to the fund family by window dressing their portfolios, which can help attract new money and consequently generate more income for the fund family. In Section 2.5.2, we show that fund managers respond to increased NCC enforceability by taking less risk.

2.5.1 The Impact of NCCs on Window Dressing

We hypothesize that fund managers increase window dressing to attract new customers and thus generate additional fee income for the fund family when NCCs become stricter. Agarwal, Gay, and Ling (2014) document that window dressing by mutual fund managers influences investment flows.[24] Thus, by window dressing with the intention of attracting more flows and inflating assets under management, fund managers can potentially improve the profitability of their fund family and consequently increase their standing and job security in the fund family. At the same time, this higher contribution of fund managers to the profitability of the fund management company is likely to increase their compensation as well as their

[24] Seminal papers on window dressing by institutional investors are Scharfstein and Stein (1990), Lakonishok, Shleifer, Thaler, and Vishny (1991), and Sias and Starks (1997).

chances of being promoted in the internal labor market, which is more important when outside options due to stricter NCCs are limited.

To test this hypothesis, we estimate model (2.1) with the two measures of window dressing developed by Agarwal, Gay, and Ling (2014) and Solomon, Soltes, and Sosyura (2014) as dependent variables. The first one, *Rank Gap*, measures the gap between a fund's return rank and a rank based on its stock holdings. The latter is calculated as the average of a rank based on the proportion of winners (the higher the proportion of winners, the higher the rank) and losers (the lower the proportion of losers, the higher the rank). The intuition is that if a fund's return was low relative to other funds, despite its portfolio covering a relatively high amount of winners and low amount of losers, this is interpreted as evidence of window dressing. The second measure of window dressing is the Backwards Holding Return Gap ($BHRG$).[25] It is measured as the difference between the quarterly return, net of expenses and trading costs, of a hypothetical portfolio consisting of a fund's end-of-quarter holdings assumed to have been held through the whole quarter up until the next report date and the fund's actual quarterly return. As with *Rank Gap*, high values of $BHRG$ indicate that reported holdings suggest higher returns than actually realized, consistent with window dressing. Results from these regressions are presented in Table 2.11.

In Table 2.11, the positive coefficients of $Treated_{i,s,t} \cdot Post_t$, statistically significant at the 1%-level, are consistent with managers increasing their window dressing behavior after an increase in NCC enforceability. These results are also economically significant. For example, a coefficient of 0.0035 in the regression using $BHRG$ as the dependent variable corresponds to an increase in window dressing behavior that amounts to 61% of the sample mean for $BHRG$. The increased window-dressing that we document suggests that fund managers respond to increased NCC enforceability by making themselves more useful to the fund family in ways that go beyond changes in fund performance.

[25] Other studies that use $BHRG$ include Brown, Sotes-Paladino, Wang, and Yao (2017) and Chuprinin and Sosyura (2018). Bai, Ma, Mullally, and Solomon (2019) additionally employ *Rank Gap*.

Table 2.11: Impact of Changes in NCC Enforceability on Window Dressing

This table presents results from pooled OLS regressions that relate window dressing measures with changes in NCC enforceability at the state level. The analysis is done at the fund and quarter level. Our two window dressing measures are the *Rank Gap* by Agarwal, Gay, and Ling (2014) and the Backwards Holding Return Gap (*BHRG*) by Solomon, Soltes, and Sosyura (2014). Fund control variables are calculated as described in Table 2.3. Our main independent variable is $Treated \cdot Post$, which equals 1 for firms in Florida in 1997-2004, -1 for firms in Texas in 1995-2004 and for firms in Louisiana in 2002-03, and 0 otherwise. Regressions are run with fund, calendar quarter, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Rank Gap	BHRG
Treated·Post	0.0180***	0.0035***
	(6.89)	(8.02)
Expense Ratio	−0.0447	−0.2661
	(−0.09)	(−0.95)
Turnover Ratio	0.0006	0.0016**
	(0.23)	(2.04)
Flow	−0.0011	0.0010
	(−0.32)	(0.53)
Log(Age)	0.0008	0.0019
	(0.13)	(1.02)
Log(TNA)	0.0174***	0.0019**
	(6.72)	(2.29)
Observations	24,998	24,973
Within R^2	0.009	0.002

2.5.2 The Impact of NCCs on Risk Taking

We now move to our final hypothesis: stricter NCC enforceability causes fund managers to play it safe by (i) reducing portfolio risk, (ii) deviating less from their peers, and (iii) engaging less in tournament behavior. The rationale underlying this hypothesis is that fund managers benefit less from taking risk (in absolute terms or relative to their peers) when NCCs are stricter. If the risky actions that fund managers take lead to poor performance, fund managers run the risk of being fired and the costs associated with termination are higher in case of stricter NCC enforceability. At the same time, when NCC enforceability is stricter, fund managers benefit less from risky actions even if they lead to great performance simply because their outside options are more limited.

To test the predictions (i) and (ii), we run model (2.1) with risk and herding measures as dependent variables. These are volatility ($Volatility$), return semi-deviation ($Semi - Deviation$), downside beta ($Downside - Beta$), and portfolio herding ($Herding$). We compute return volatility as the standard deviation of a fund's past twelve months' net returns. The next two variables measure downside risk. $Semi-Deviation$, which also uses a fund's past twelve months' returns, reflects deviations from the mean for returns that were below the mean. We follow Whaley (2002) and compute $Downside - Beta$ based on the covariance with the market only when the excess fund and market returns are both below the zero threshold. To compute $Herding$, we first calculate a stock-level based herding measure following Lakonishok, Shleifer, and Vishny (1992), which we then aggregate at the fund level by value-weighting it over all stocks in a fund's portfolio. The results of our regressions are presented in Table 2.12.

Panel A of Table 2.12 shows that, as expected, increased enforceability of NCCs leads to a decrease in portfolio risk taking and an increase in herding. Specifically, an increase in NCC enforceability leads to a decrease in $Volatility$ of 15 basis points, in $Semi - Deviation$ of 36 basis points, and a decrease in $Downside - Beta$ of more than 0.09, which are all sizable relative to the sample means of these variables. For example, the decrease of 0.09 in $Downside - Beta$ corresponds to a reduction of about 9% of the sample mean. The positive and significant coefficient of $Treated_{i,s,t} \cdot Post_t$ in regressions with $Herding$ as dependent variable suggests that an increase in NCC enforceability leads to more herding by the affected fund managers. This increase in herding is of striking economic magnitude, in that the coefficient of $Treated_{i,s,t} \cdot Post_t$ amounts to 172% of the sample mean for the herding measure. Thus, evidence from Panel A clearly supports hypotheses (i) and (ii).

Managers investing much more like their peer group appears surprising at first blush and at odds with the fact that a fund manager needs to deviate from her peers to outperform them. However, when combined with the results of Section 2.4.3, these results suggest that although fund managers take fewer risky bets relative to their peers, which is consistent with increased herding, at the same time they redirect more effort towards stocks where they have an information advantage, which helps deliver better performance.

Table 2.12: Impact of Changes in NCC Enforceability on Risk Taking

This table presents results from pooled OLS regressions that relate risk taking measures with changes in NCC enforceability at the state level. The analysis is done at the fund and yearly level. Our risk measures of Panel A are $Volatility$, $Semi-Deviation$, $Downside-Beta$ following Whaley (2002), and $Herding$, the holdings value weighted sum of the Lakonishok, Shleifer, and Vishny (1992) herding measure. In Panel B, we relate the risk adjustment ratio defined by equation (2.2) to performance of the first part of the year ($Perf^{First}$), measured as either style-adjusted return or as ranks based on raw returns. Ranks are calculated for each market segment and year separately. They are normalized so that they are equally distributed between zero and one, with the best fund manager in its respective segment getting assigned the rank of one. Fund control variables are calculated as described in Table 2.3. Regressions are run with fund, calendar year, and investment objective fixed effects. T-statistics, based on standard errors clustered at the state level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Portfolio risk and herding

	Volatility	Semi-Deviation	Downside-Beta	Herding
Treated·Post	−0.0015**	−0.0035**	−0.0926**	1.2528***
	(−2.00)	(−2.28)	(−2.24)	(4.54)
Expense Ratio	0.0925	0.1680	1.8942**	52.176
	(0.62)	(0.58)	(2.15)	(0.21)
Turnover Ratio	0.0004	0.0004	−0.0174**	−0.0151
	(1.41)	(0.56)	(−2.03)	(−0.19)
Flow	0.0000**	0.0000**	0.0000**	0.0040***
	(2.35)	(2.05)	(2.00)	(2.95)
Log(Age)	−0.0018*	−0.0021	−0.0633***	−0.2335
	(−1.69)	(−0.98)	(−3.00)	(−0.92)
Log(TNA)	0.0022***	0.0044***	0.1179***	−0.1211
	(3.27)	(3.31)	(9.72)	(−1.17)
Observations	8,514	8,514	8,514	2,227
Within R^2	0.010	0.008	0.032	0.005

We now move on to hypothesis (iii), i.e., the tournament hypothesis. Brown, Harlow, and Starks (1996) are the first to examine the risk taking incentives of fund managers in a tournament setting. They show that fund managers with poor interim performance increase their risk taking in the second half of the year to catch up with the interim winners. However, since an increase in NCC enforceability increases the costs associated with being fired, we expect fund managers to cut back on their tournament-driven actions in the face of increased NCC enforceability. To test this hypothesis, we use the risk adjustment ratio of Kempf, Ruenzi, and Thiele (2009)

Table 2.12: Impact of Changes in NCC Enforceability on Risk Taking (Continued)

Panel B: Tournament behavior

	Rank	Style-adj. Return
$\text{Perf}^{\text{First}}$	−0.0191**	−0.3856***
	(−2.14)	(−3.46)
Treated·Post	0.0041	0.0257*
	(0.26)	(1.82)
$\text{Perf}^{\text{First}}$·Treated·Post	0.0512***	0.4394***
	(5.8)	(9.11)
Expense Ratio	0.1828	0.2915
	(0.58)	(0.89)
Turnover Ratio	0.0027	0.0027
	(0.23)	(0.23)
Flow	−0.0025	−0.0019
	(−0.66)	(−0.49)
Log(Age)	0.0187*	0.0171*
	(1.94)	(1.77)
Log(TNA)	−0.0058	−0.0036
	(−1.65)	(−1.05)
Observations	4,244	4,244
Within R^2	0.007	0.014

as the dependent variable in our regression:

$$RAR_{i,s,t} = \frac{\sigma_{i,s,t}^{(2),int}}{\sigma_{i,s,t}^{(1)}}. \tag{2.2}$$

$RAR_{i,s,t}$ captures how much fund managers change their risk in the second half of the year relative to the first half. $\sigma_{i,s,t}^{(1)}$ denotes the realized portfolio risk of fund i in state s in the first half of year t. It is calculated using the actual portfolio holdings and the actual volatility of the corresponding portfolio returns in the first half of the year. The intended portfolio risk, $\sigma_{i,s,t}^{(2),int}$, in the second half of year t is calculated using the actual portfolio holdings in the second half and the forecast of the volatility of the corresponding portfolio returns in the second half of the year (which is proxied by the realized stock volatility of that same portfolio in the first half of the year).[26] Our regression model to test for the impact of changes in NCC enforceability on tournament behavior reads as:

$$\begin{aligned} RAR_{i,s,t} = \beta_0 &+ \beta_1 \cdot Perf^{First}_{i,s,t} + \beta_2 \cdot Treated_{i,s,t} \cdot Post_t \\ &+ \beta_3 \cdot Perf^{First}_{i,s,t} \cdot Treated_{i,s,t} \cdot Post_t + Controls + FE + \epsilon_{i,s,t}, \end{aligned} \tag{2.3}$$

where $Perf^{First}_{i,s,t}$ denotes performance of fund i in state s during the first half of year t. We measure performance as style-adjusted returns or as ranks based on raw returns. Ranks are calculated for each market segment and year separately. They are normalized so that they are equally distributed between zero and one, with the best fund manager in its respective segment getting assigned the rank of one. According to the traditional tournament literature, we expect a negative coefficient of $Perf^{First}_{i,s,t}$ ($\beta_1 < 0$), i.e., the lower the performance in the first half of the year, the more fund managers increase risk in the second half of the year. Like in model (2.1), $Treated_{i,s,t} \cdot Post_t$ captures the change in enforceability of NCCs, $Controls$ denotes fund-level controls, and FE the various fixed effects; $\epsilon_{i,s,t}$ denotes the error term. The main variable of interest is the interaction term. The coefficient β_3 shows how a change in enforceability impacts tournament behavior. Since we expect that fund managers engage less in tournaments when enforceability of NCCs increases, we expect β_3 to have the opposite sign of β_1, i.e., $\beta_3 > 0$.

Panel B of Table 2.12 presents the results. It clearly shows that an increase in NCC enforceability mitigates the tournament behavior of fund managers. Whereas we observe a general tendency for tournament-like behavior ($\beta_1 < 0$), we see that this behavior changes when NCC enforceability is increased ($\beta_3 > 0$). This change is strong, both in statistical and economic terms. β_3 is statistically significant at the 1%-level in each model specification. Furthermore, the size of β_3 is larger than the size of β_1 in absolute terms, i.e., the change effect dominates the baseline tournament effect. This implies that an increase in NCC enforceability prevents fund managers from engaging in tournaments. They no longer increase the risk of their portfolio in

[26]This approach for measuring intended risk is the same as the one used in Kempf, Ruenzi, and Thiele (2009) and Ma, Tang, and Gómez (2019). For more details, please see the appendix of Kempf, Ruenzi, and Thiele (2009).

response to poor interim performance but instead play it safe. This finding again highlights the importance of career concerns resulting from NCCs.

In summary, the results from Table 2.12 clearly show that fund managers play it safe when NCC enforceability increases. This is highly sensible since increased NCC enforceability leads to higher potential costs and lower potential benefits from risk taking.

2.6 Conclusion

In the last few years, non-compete clauses in employment contracts, intended to restrict labor mobility, have received growing attention from academics, regulators, politicians, companies, and the public at large. While the focus of this debate has been on how these restrictions affect overall state or firm economic activity, we know little about how the targeted members of the labor force respond to such restrictions. Our paper contributes to this ongoing debate through a unified examination of the effect that NCCs have on the behavior of managers by looking at a number of possible actions that managers can undertake.

Using the mutual fund industry as a testing laboratory, we show that managers respond to increased NCC enforceability by increasing their contribution to the revenue of their fund company. They do so by improving their performance through a concentration of their increased effort towards stocks where they have an information advantage, while at the same time they increase window dressing in order to attract new investor flows, which increase the asset base of the family and consequently the fee income for the fund company. In addition, we find that stricter NCCs discipline managers' risk taking, as shown by noticeable reductions in their portfolio risk, portfolio deviations from their peers, and engagement in fund tournaments. All these behavioral changes of fund managers are highly sensible given that stricter NCCs increase their costs associated with being fired and reduce their options in the external labor market.

Our findings also inform the regulatory debate regarding possible courses of action with respect to enforceability of NCCs by providing a micro-view on how employees adjust their behavior in response to changes in NCC enforceability. Both fund management companies and fund investors are affected by how fund managers react to increased NCC enforceability. On one hand, fund management companies might benefit from an alignment of incentives, whereby employees increase contribution to the firm's revenue, but on the other hand, they might have to pay higher compensation to entice managers to accept stricter labor mobility restrictions. Given that detailed compensation data for mutual fund managers is not available, this makes the net effect of stricter NCC enforceability on fund families unknown. This alignment of incentives proves beneficial to fund investors, however, who stand to gain from the improved fund performance.

At a macro level, the fact that employees face greater incentives to reign in their risk-taking behavior could contribute to reduced systemic risk. Whether and to what extent similar effects extend to other important financial institutions such as banks, insurance companies, or hedge funds is an interesting venue for future research.

Chapter 3

Finding your calling: Skill matching in the mutual fund industry[†]

3.1 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., Investment Company Institute (2019)]. 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

[†]This chapter is based on Cici, Hendriock, and Kempf (2020a). 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]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).

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 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

[2]See Huang (2014).

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 different 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.[3] After having discovered their best style match, about 94 percent of those managers stay in the same style for the remainder of their careers. 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

[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)].

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 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, Gehde-Trapp, Göricke, and Kempf (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 (1999a), 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 the 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 in-

[4] Using French matched employer-employee data, Nagypál (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.

vestment ideas of these managers in other funds managed by affiliated managers. Specifically, we find that the ideas 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, Gehde-Trapp, Göricke, and Kempf (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 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 3.2, we discuss our data sources, describe our main methodology, and provide descriptive information about our sample managers. In Section 3.3, 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 3.4. Sections 3.5 and

[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, 2009a,b), and Groes, Kircher, and Manovskii (2015).

3.6 examine implications for fund families and fund managers, respectively. Section 3.7 concludes.

3.2 Data

3.2.1 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.

3.2.2 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 (3.1):

$$y_{i,t+1} = \alpha_{i,f} + \theta_t + \omega_s + \beta \cdot Style\ Match_{i,t} + \vec{\boldsymbol{\gamma}} \cdot \vec{\boldsymbol{c}}_{i,t} + \varepsilon_{i,t+1}. \tag{3.1}$$

$y_{i,t+1}$ denotes either the performance or another variable of interest for manager i at time $t+1$. $\vec{\boldsymbol{\gamma}}$ is the vector of coefficients associated with fund, manager, and family level covariates described in the following and Table 3.1, which are stacked into vector $\vec{\boldsymbol{c}}$. 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 managers 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 natural logarithm of age [*Log*(*Fund Age*)]; the natural logarithm of total net assets [*Log*(*Fund Size*)]; the fund's expense ratio (*Expense Ratio*); portfolio turnover ratio (*Turnove Ratio*); and flows computed as the change in net assets not attributable to fund performance and normalized by beginning of period fund assets (*Flows*). 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.

3.2.3 Sample Descriptive Statistics

Table 3.1 provides descriptive statistics for our sample. The average sample manager has worked in roughly two distinct styles and has been in the mutual fund industry for about seven years.

The average fund in our sample is about 15 years old, holds \$1.5 billion in assets,

Table 3.1: Descriptive Statistics

This table reports descriptive statistics for the total sample. The sample period is from 1992 through 2016. Besides the mean, this table reports the standard deviation (std) as well as the 10th, 50th, and 90th percentile (p10, p50, and p90, respectively). *#Styles Tried* is the number of styles a manager has worked for throughout her career. *Industry Tenure* is the time managers spent in the mutual fund industry in years. *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]	1,540.90	4,433.38	21.20	314.60	3,534.28
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]	28,082.41	70,744.42	82.60	6,635.23	59,101.50

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.

3.3 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.

From Table 3.2 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 10th and 90th 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

Table 3.2: 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, 50th, and 90th percentile (p10, p50, and p90, respectively). *#Styles Tried* and *#Funds Tried* are, respectively, the number of styles and number of funds 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
#Styles Tried	3.6	1.1	2.0	3.0	5.0
#Funds Tried	4.4	3.5	2.0	4.0	9.0
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		

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, Gehde-Trapp, Göricke, and Kempf (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 otherwise. We categorize a fund manager as having outside work experience like in Cici, Gehde-Trapp, Göricke, and Kempf (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 insti-

[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.

Table 3.3: 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 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

tution 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 3.3. Since Garmaise's (2011) non-compete clause enforceability index is available only until 2004, we report results

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

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.

Evidence from Table 3.3 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 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.

3.4 Performance after Discovery of Style Match

3.4.1 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 (3.1) 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 (*Alpha*4); and Fama and French (2015)-5-factor alpha, augmented with the momentum factor (*Alpha*6) [Fama and French (2018) and Barillas and Shanken (2018)]. To measure style-adjusted returns in period t, we subtract from the return of

Table 3.4: 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 (*Alpha*4), and Fama and French (2015)-5-factor alpha, augmented with the momentum Factor [Fama and French (2018) and Barillas and Shanken (2018)] (*Alpha*6). 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 3.2.2. Control variables at the manager, fund, and family level are constructed as in Table 3.1. 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
Manage×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

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 3.2.2. 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.

Results are reported in Table 3.4. 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.

3.4.2 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 3.5 we provide a test of the identifying assumption that managers returning 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 (3.1) 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 3.5 and corroborated visually in Figure 3.1 show that none of the variables $Pre1 \cdot Style\ Match$, $Pre2 \cdot Style\ Match$, and $Pre3 \cdot Style\ Match$ are significantly different from zero, i.e., performance of the two groups of managers shows parallel trends prior to achievement of style match.

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 3.5, we replace $Style\ Match$ with three indicator variables that identify managers that reached style match discovery - in three

[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`.

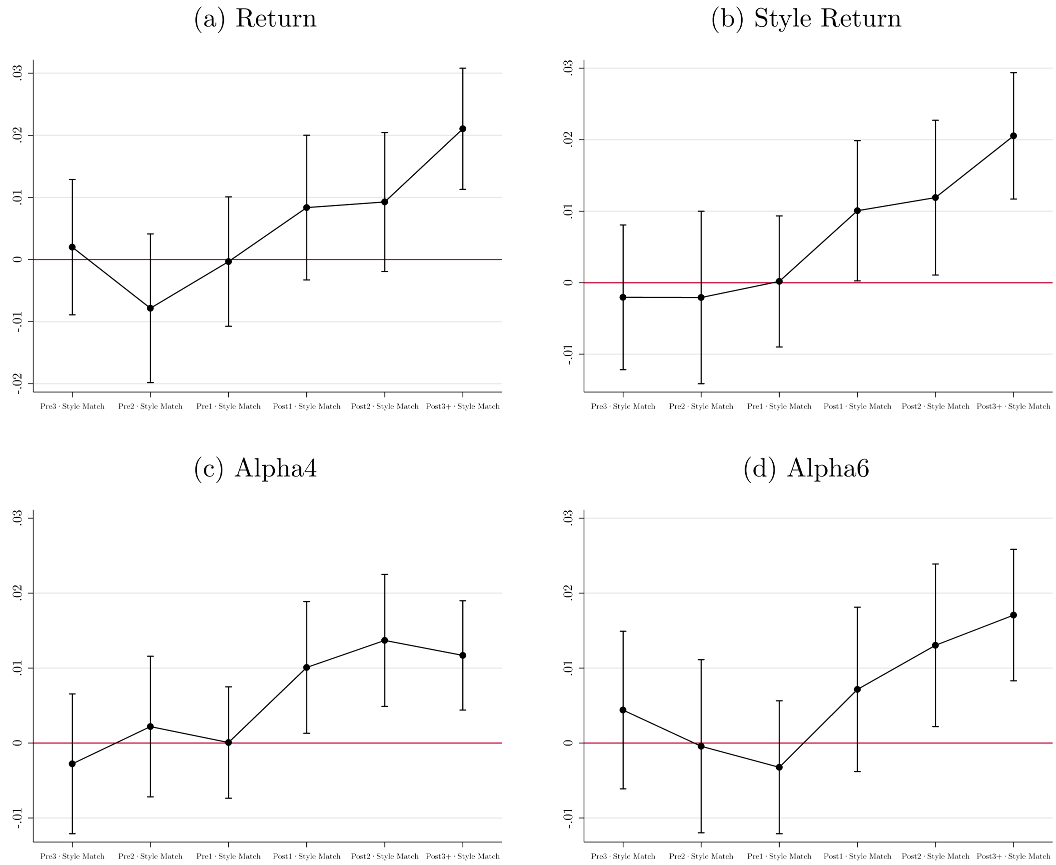
Table 3.5: Parallel Trends Assessment and Persistence of Performance

In this table, we modify our main analysis of Table 3.4 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 3.5, we augment model (3.1) 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 3.4. 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)	(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)
Manager Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund 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

Figure 3.1: Parallel Trends Assessment and Persistence of Performance

In this figure, we plot the regression coefficients from Table 3.5, along with their 95%-confidence interval error bands.



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.

3.4.3 Alternative Explanations

3.4.3.1 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 [Golec (1996), Chevalier and Ellison (1999a), 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 3.4, 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 (3.1).

Results are reported in Table 3.6. 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 3.4. Nonetheless, despite the smaller sample used in Table 3.6, the coefficients on the *Style Match* variable are still positive and exhibit similar levels of economic and statistical significance as those from Table 3.4.[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

[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 3.6, the control manager has the closest propensity score based on the manager and fund characteristics described in Table 3.1 (as the family characteristics, by construction, are equal, since we perform the matching within the same family).

Table 3.6: Matched Sample Analysis of Performance after Discovery of Style Match

In this table, we repeat our main analysis of Table 3.4 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 3.4. 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	−12.207
	(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
Manage×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

in a more rigorous 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.

3.4.3.2 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 $High\ Family\ Tenure$.

Table 3.7 shows results from a model that augments model (3.1) 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.

3.5 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 3.5.1, 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 3.5.2. Both strategies would be intended to maximize

Table 3.7: Managerial Preferences and Organizational Power

In this table, we augment our main analysis of Table 3.4 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 3.4. 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**	0.0265***	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)
Manager Controls	Yes	Yes	Yes	Yes
Fund 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

returns for the entire family. Finally, in Section 3.5.3 we explore the broader hiring implications for families with more versus less developed internal labor markets.

3.5.1 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 (3.1) using a linear probability model. 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

Table 3.8: 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 3.4. 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)
Manager Controls	Yes
Fund Controls	Yes
Family Controls	Yes
Time FE	Yes
Style FE	Yes
Manager× Family FE	Yes
Observations	27,314
Adj. R^2	0.268

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.

Results are presented in Table 3.8. 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.

3.5.2 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, Gehde-Trapp, Göricke, and Kempf (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.

$$trade\ followed_{j,i,t} = \chi_{f,s,t} + \alpha \cdot SM\ Trade_{j,i,t} + \vec{\boldsymbol{\gamma}} \cdot \vec{\boldsymbol{c}}_{i,t} + \epsilon_{j,i,t}. \tag{3.2}$$

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 $\vec{\boldsymbol{c}}$, 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.

Table 3.9 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

Table 3.9: 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

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

[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.

consistent with affiliated managers paying greater attention to the 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.

3.5.3 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

Table 3.10: 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 3.1. 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

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 3.2.2 and cluster standard errors at the family level.

Results reported in Table 3.10 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.

3.6 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 3.6.1 we examine whether managers adjust their investment behavior and in Section 3.6.2 whether they change the level of personal investments in the mutual funds that they manage.

3.6.1 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

$$Active\ Peer\ Share_{i,t} = \sum_{j=1}^{M} |w_{j,i,t} - w_{j,peer_i,t}|, \tag{3.3}$$

Table 3.11: 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 3.6.1 Our main independent variable is *Style Match*, constructed as in Section 3.2.2. Control variables at the manager, fund, and family level are constructed as in Table 3.1. 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)
Manager Controls	Yes
Fund Controls	Yes
Family Controls	Yes
Time FE	Yes
Style FE	Yes
Manager×Family FE	Yes
Observations	28,506
Adj. R^2	0.908

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 (3.1).

Results are reported in Table 3.11. 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.

3.6.2 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 (3.1). It is important to note

[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.

Table 3.12: 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 3.2.2. Control variables at the manager, fund, and family level are constructed as in Table 3.1. 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)
Manager Controls	Yes
Fund Controls	Yes
Family Controls	Yes
Time FE	Yes
Style FE	Yes
Manager×Family FE	Yes
Observations	6,795
Adj. R^2	0.801

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, Tufano, and Wedge (2007), and Taylor (2011)] with our fixed effects structure.

Results are reported in Table 3.12. 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 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 3.6 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.

3.7 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.

Chapter 4

Implied Cost of Capital and Mutual Fund Performance[‡]

4.1 Introduction

For a long time, finance researchers have been trying to discern, whether mutual fund managers, as a large and important class of institutional investors, have skill when it comes to picking stocks. This quest by scholars has been at the heart of understanding important concepts in finance, such as the efficient market hypothesis or how information advantages are developed and exploited by market participants. However, research on the ability of active mutual fund managers to beat their benchmark, i. e., generate positive active returns after costs commonly referred to as "alpha",[1] unanimously provides evidence for the scarcity of this skill. Fama and French (2010) conclude that "true alpha [...] is negative for most if not all active funds". Yet, the U.S. mutual fund industry has seen enormous growth, having decupled over the past 25 year alone, with 17.7 trillion U.S. dollar under management by the end of 2018 [Investment Company Institute (2019)]. This mismatch between the track record of the mutual fund industry's performance and its growth gave rise

‡This chapter is based on Hendriock (2020). For helpful comments and discussions I thank Alexander Kempf and Alexander Puetz.

[1] A different topic is active managers' ability to extract money from the market and generate positive value for their firms, confer Berk and van Binsbergen (2015), Berk, van Binsbergen, and Liu (2017), and van Binsbergen, Kim, and Kim (2019).

to the "mutual fund puzzle" put forth by Gruber (1996).

In this paper, I try to add a piece to this puzzle and examine the ability of funds' holdings' implied cost of capital (ICC) to ex-ante identify funds with positive alpha and thereby inform the capital allocation process of financial decision makers. Hereof, research documents that it is mainly guided by past performance[2] - yet, on average, funds outperforming in one period do not repeat their achievement in the next. Persistence documented in early studies was later explained by recently successful managers holding stocks with high past performance - i.e., momentum; further, persistence seems to be entirely absent in recent times.[3] Thus, research turned towards analyzing whether fund characteristics help discern future "winners" from "losers", documenting associations of performance with, e.g., fund age, flows, and expenses.[4] While these findings are important to further our understanding of the nature of skill in the mutual fund industry, we still lack an understanding of what strategies managers in their day-to-day business (should) employ and how fund investors can turn mere correlations into implementable investment strategies with real profits.

This study aims to document the extent to which ICC of a fund can serve as a building block for such kind of a strategy. The main insight of this paper is that current ICC appear to map into future fund performance in a way that lets investors profit from the small fraction of mutual fund managers which indeed seems to have skill picking stocks. That is, ICC seem to be one information advantage successfully exploited by skilled managers.

The focus on ICC is motivated by literature on their return-predictive capabilities. Conceptually, ICC of a firm equate its current market value of equity to present value of expected future cash flows. Pástor, Sinha, and Swaminathan (2008) show theoretically how ICC are particularly apt as a proxy for time-varying expected

[2]Confer, e.g., Ippolito (1992), Sirri and Tufano (1998), Guercio and Tkac (2008), Barber, Huang, and Odean (2016), and Berk and van Binsbergen (2016).

[3]Carhart (1997) attributes persistence as documented in Grinblatt and Titman (1992) and Hendricks, Patel, and Zeckhauser (1993) to momentum; Choi and Zhao (2020) do not find evidence for persistence between 1994 and 2018.

[4]Confer Howell (2001) and Ferson and Schadt (1996), Rakowski and Wang (2009), as well as Carhart (1997) and Russell (2010), respectively. For a review of studies on the association between characteristics both at the manager as well as fund level and fund performance, confer Jones and Wermers (2011).

returns; based on theoretically justifiable valuation models, ICC take into consideration future growth opportunities and, as a function of current market values, are inherently forward looking. Empirically, ICCs indeed have been documented to positively predict future returns and other measures for "performance".[5] When it comes to exploiting this association between current ICC and future performance, however, Esterer and Schröder (2014) underline the detrimental effect of transaction costs necessary, stating profit potentials "revealed by the ICC [were] not large enough to allow for substantial trading opportunities using diversified equity portfolios."

Regarding transaction costs and implementation opportunities, active mutual funds arguably are in a preferential position; as part of potentially large institutions specialized on financial transactions, respective costs are comparably low [Frazzini, Israel, and Moskowitz (2018)]. Further, whereas ICC-based investment rules analyzed in literature either simply value-, though mostly equal-weight stocks, mutual fund managers can - both to the detriment as well as advantage - exert their discretion in portfolio selection. An issue yet unexplored is whether investors, by means of funds' reported holdings and respective ICCs, can turn paper gains of ICC-based strategies into actual profits.

This study provides empirical evidence that they can. On the onset, it conducts a portfolio-based analysis to study the relation between fund-level ICC and future performance. Each quarter, a fund-level ICC is calculated as the value-weighted average of the ICCs of the stocks in the fund's portfolio, which in turn are computed as the mean over eight commonly used metrics. Proxies for expected earnings used to calculate ICCs obtain from analysts respectively the three most widely used cross-sectional earnings prediction models [Hou, van Dijk, and Zhang (2012) and Li and Mohanram (2014)]. Consecutively, funds are sorted into equally-weighted portfolios, based on ICC-quintiles. Over a horizon of 25 years, a $1 investment into bottom portfolios led to a seven-fold increase from 1992 to 2016. In comparison, $1 invested in top portfolios would have grown to $15.

[5] Confer, e.g., Claus and Thomas (2001), Botosan and Plumlee (2005), Easton (2007), Pástor, Sinha, and Swaminathan (2008), Botosan, Plumlee, and Wen (2011), Hou, van Dijk, and Zhang (2012), Li, Ng, and Swaminathan (2013), Li and Mohanram (2014), Esterer and Schröder (2014), Schröder (2018), and Bielstein and Hanauer (2019). The literature on ICC in general as well as its applications in research is extensive; Richardson, Tuna, and Wysocki (2010) provide a review.

Considering adjustments for factor tilts respectively investment styles, funds in bottom quintile portfolios show average one and six factor alphas of around -30 to -20 basis points per month, whereas top portfolios deliver alphas between zero and ten basis points, resulting in a significant spread. In terms of loadings according to the six factor model in Fama and French (2018), high-ICC managers appear to place bets on small and value firms as well as gross profitability and against stock momentum, consistent with both ICCs being used as part of an investment strategy based on fundamental analysis and a "mechanical" effect owing to ICCs' computational properties.

Although quintile-based analyses are parsimonious and such widely used in literature, they cannot serve as basis for a viable outperforming investment strategy. While reported individual fund returns are net of transaction costs, portfolio turnover, which amounts to approximately 30% in the top quintile, necessitates additional payments of front-end loads for entering new positions and back-end loads to sell off funds leaving the portfolio. Additionally, only the spread-portfolio's performance is significant, which is infeasible, as mutual funds cannot be shorted. Further, given the small fraction of funds being able to generate alpha in the first place, quintiles are hardly fine enough. Also after excluding load-funds, yielding a time series of returns purely net of costs, and stratification based on ICC-deciles the positive difference in performance between top and bottom portfolio remains. Additionally, top decile portfolios exhibit positive one and six factor alphas of roughly 25 basis points per month, resolving the necessity to short funds.

The portfolio analysis provides evidence for positive factor alphas, corroborating the notion that returns from an ICC-based strategy do not simply reflect investment styles respectively originate from factor tilts. However, it does not allow to control for other fund characteristics potentially associated with future performance. Hence, I relate current ICC to future fund performance in panel regressions. Results provide evidence of a close to one-to-one correspondence between changes in ICC and future performance, independent of what earnings estimates enter the calculation of ICCs. Also holding fund-manger-matches fixed to control for unobserved time-invariant heterogeneity at the fund-manager-level, ICCs continue to be positively correlated with future performance, corroborating the notion that a high-ICC strategy in itself is associated with high fund performance; this association is not explained by high-ICC funds being systematically concentrated in particular styles at certain times either. With regard to persistence of this association, ICCs are strongly correlated with performance up to two years in the future.

After documenting this baseline result, this study seeks to delve deeper into trading mechanisms associated with an ICC strategy. Relating trading decisions with ex-post realized fund performance, it tries to shed light on whether fund managers' active decisions altering their funds' ICC correlate with contemporaneous performance. It documents that the larger the fraction of a manager's buys (sells) was in firms with increasing (decreasing) ICC, the higher was contemporaneous fund performance. A complete "correct" trading decision on average translated into roughly 2.5 percentage points higher quarterly fund performance, reinforcing that ICC-based strategies seem to pay off.

Next, this study turns towards possible determinants of managers employing such kind of strategies. A main motivation for combining return predictability via ICCs and identification of skilled managers is based on evidence for, on the one hand, transaction costs preventing effective utilization of ICCs for portfolio selection and, on the other hand, managers' alleged access to a more efficient trading apparatus [Frazzini, Israel, and Moskowitz (2018)]. Along these lines, cross-sectional heterogeneity among funds potentially correlates with their likelihood of adopting high-ICC strategies. Whereas trading costs are not reported, Cici, Dahm, and Kempf (2018) construct a proxy for the efficiency of a mutual fund family's trading desk, expected to be negatively correlated with transaction costs. Consistent with funds facing lower transaction costs being more likely to employ a high-ICC strategy, funds with higher trading desk efficiency exhibit higher ICCs, corroborating the notion that favorable transaction costs are part of the explanation for why mutual funds are able to gather rents of a strategy based on ICC. With regard to manager characteristics, in accordance to successfully implementing strategies based on ICCs representing a form of skill, managers who received their bachelor's degree from universities with high average matriculate SAT scores, meant to proxy for innate abilities, display above average ICCs.

To learn more about possible implications of ICC-based strategies, this study examines, whether they change incentives faced by managers. If they consider ICCs for portfolio allocation and are aware of the potential performance consequences, ICCs in particular add to the repertoire of how managers can react to being ranked unfavorable relative to their peers and such might influence risk-taking. Brown, Harlow, and Starks (1996) are the first to document how fund managers with poor interim performance increase risk in the second half of the year to catch up with interim winners. A high ICC, however, provides another means to close the gap towards their peers. Consistent with managers relying on this strategy paying off, this study provides evidence that mid-year losers with high ICCs increase risk less relative to their peers with low ICCs.

Finally, this study closes with an analysis of whether investors respond towards funds' ICCs. Given the positive association between current ICC and future performance, investors might direct their money accordingly. A fund's ICC, however, is not reported in its prospectus; instead, an investor would need to collect both market and fundamental information to compute ICCs by herself. Given evidence for limited resources, attention, and financial literacy of less sophisticated retail investors,[6] they might be insensitive to a fund's ICC. In contrast, institutional investors with both the means and knowledge to determine its value and uncovering its positive association with future fund performance potentially respond to it. In this vein, this study documents that retail share classes do not receive additional money based on ICCs, whereas institutional investors appear to reward funds with high ICC with higher flows, consistent with awareness of and confidence in ICCs' association with future fund performance.

This study contributes to the literature on delegated asset management, specifically with regard to the question of whether there exists skill in the active mutual fund industry and if so, how it can be identified. Previous studies evolved in an ef-

[6]For studies suggesting retail respectively individual investors being less sophisticated than institutional, confer, e.g., Hand (1990), Lee, Shleifer, and Thaler (1991), Walther (1997), Balsam, Bartov, and Marquardt (2002), Bonner, Walther, and Young (2003), Asthana, Balsam, and Sankaraguruswamy (2004), Franco, Lu, and Vasvari (2007), Mikhail, Walther, and Willis (2007), Hirshleifer, Myers, Myers, and Teoh (2008), and Kaniel, Liu, Saar, and Titman (2012).

fort to increase the power of tests, shifting the focus of analysis from fund returns to more specialized tests intended to separate skill from luck. Accepting that a subset of mutual fund managers appears to have skill, research has turned to understanding which characteristics of mutual funds and their managers are associated with better performance.[7] This study provides evidence that funds implementing a theoretically motivated strategy backed by research based on ICCs generate outperformance and are identifiable ex-ante.

Further, this study adds to the literature on managerial incentives in the mutual fund industry. In particular, compensation schemes based on assets under management and asymmetric performance-based boni [Elton, Gruber, and Blake (2003) and Ma, Tang, and Gómez (2019)], paired with a convex performance-flow relation [e.g., Sirri and Tufano (1998) and Ferreira, Keswani, Miguel, and Ramos (2012)], according to which investors punish bad performance less by disinvestment than they reward good performance by inflows, give rise to an option-like pay-off, incentivizing managers to engage into “tournament” behavior [Nalebuff and Stiglitz (1983) and Rosen (1986)]. Brown, Harlow, and Starks (1996) document evidence for tournaments in the fund industry per se, whereas Kempf and Ruenzi (2008) find evidence for tournaments within fund families. Kempf, Ruenzi, and Thiele (2009) show how career concerns due to higher unemployment risk during recessions alleviate tournament behavior, as the option-like pay-off is distorted because of managers facing more severe consequences of bad performance. This paper provides evidence that another determinant of how managers respond towards trailing their peers is which investment strategies they follow and how much they (can) rely on them by documenting that managers with high ICC temper their tournament behavior.

This paper also contributes to the literature on determinants of investors’ capital allocation. Previous research documents strong evidence for mutual fund investors catering to past performance [Ippolito (1992), Sirri and Tufano (1998), Guercio

[7]Respective studies start from Jensen (1968), who, using a market model, denies the existence of skill, and continue over, e.g., Lehmann and Modest (1987), Ippolito (1989), Grinblatt and Titman (1989, 1992, 1993), Malkiel (1995), Gruber (1996), Carhart (1997), Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (1999), Chen, Jegadeesh, and Wermers (2000), Wermers (2000), Kothari and Warner (2001), Pinnuck (2003), Barras, Scaillet, and Wermers (2010), Fama and French (2010), and Wermers (2020), who all, to varying degree, document some sort of skill.

and Tkac (2008), Barber, Huang, and Odean (2016), and Berk and van Binsbergen (2016)], despite its limited use forecasting future performance. This study documents that sophisticated investors able to identify funds with high ICC steer their investments accordingly, whereas there appears to be no such behavior for an investor class less well equipped.

Finally, this study adds to the literature on ICCs and their association with future realized returns (see above). Whereas there is mixed evidence at the individual stock- respectively strong evidence for return predictability at the stock-portfolio-level, in either regard, ICC-based strategies appear to fail being monetizable owing to underlying costs. This paper provides evidence for mutual fund managers being able to seize the potential of an ICC-based strategy, in particular due to their access to efficient trading opportunities.

The results of this study potentially have both theoretical and practical implications. Theoretically, the opportunity to ex-ante identify investments going to generate positive performance unexplained by pertinent factor models opens questions with regard to market efficiency and the correct specification of performance measurement. The two most obvious implications were that markets lack a form of semi-strong efficiency or performance attribution is ill-specified, i.e., ICCs capture a risk factor not accounted for. Retail investors' insensitivity towards a fund's ICC, as they potentially lack the necessary capabilities to detect it, would speak towards the former, such that performance can persist. Hence, as a potential practical implication, disseminating information about a fund's ICC, e.g., via incorporation into ratings investors are shown to respond to,[8] could help increasing awareness and such drive flows, with the potential to eliminate performance opportunities, i.e., increase efficiency of markets. Yet still, the concept of ICC might be hard to communicate or "sell" to an investor group with low involvement and financial training. For asset managers, this study's findings might serve as positive evidence for the viability of ICC-based investments.

[8]In particular, Evans and Sun (2018) provide evidence for modifications of how "Morningstar Stars" are calculated implicitly changing the asset pricing respectively style attribution model investors cater to. Hartzmark and Sussman (2019) show how investors respond to newly introduced sustainability ratings. The general effect of Morningstar ratings on flows is studied by Guercio and Tkac (2008).

The remainder of the paper is organized as follows. Section 4.2 describes the sample and how earnings estimates and ICCs of firms and ultimately funds are calculated. Section 4.3 presents the main result, portfolio- and regression-based evidence for the ability of ICC to forecast fund performance. In Section 4.4, I explore possible determinants of funds employing a high-ICC strategy, analyzing the impact of trading efficiency at the family- and innate ability at the manager-level. Section 4.5 considers whether the positive association between ICC and fund performance triggers responses by market participants, analyzing managers' incentives to engage into tournament-like behavior and how investors react to ICCs. Finally, Section 4.6 concludes.

4.2 Data

4.2.1 Sources

The data in this study are collected from several sources. 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, as well as loads for years 1992 to 2016 are obtained from the Center for Research on Security Prices Survivorship Bias Free Mutual Fund (CRSP MF) Database. For mutual funds with different share classes, all observations are aggregated at the fund-level. In case of quantitative information, aggregation is performed based on the asset value of share classes; qualitative information on investment style and family is the same across all share classes. A fund's age is determined by the initial offering date of its oldest share class. I limit the universe to include only actively managed, diversified, domestic U.S. equity funds, thereby excluding index, international, balanced, bond, money market, and sector funds.

To obtain information on managerial fund employment records, I use Morningstar Direct [confer, e.g., Berk, van Binsbergen, and Liu (2017) and Patel and Sarkissian (2017)], which is merged with the CRSP MF database by CUSIPs and dates. In case of missing CUSIPs, I use a fund share class's TICKER and date combination. If TICKER is also missing, funds are manually matched by name.

Portfolio holdings data come from the Thomson Financial Mutual Fund Holdings database, which are merged with 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 semi-annual or quarterly frequency.[9] Data on firm fundamentals come from COMPUSTAT. I obtain consensus analyst forecasts for earnings and earnings' growth rates from I/B/E/S.

4.2.2 ICC and Expected Earnings Proxies

The central metric used in this study derives from firms' ICC. Based on a certain corporate valuation model, they represent the rate of return implied by current price and forecasts of future pay-offs, which in turn are determined by earnings and their growth.[10] Such, most generally, ICC solve

$$P_{i,t} = \sum_{\tau=0}^{T} \frac{\mathbb{E}_t(X_{i,t+\tau})}{(1 + r_{i,t+\tau})^{\tau}}, \tag{4.1}$$

where $P_{i,t}$ denotes market value of equity of firm i at time t, $\mathbb{E}_t(X_{i,t+\tau}) =: \mathbb{E}(X_{i,t+\tau}|\Psi_t)$ the expected value, conditional on the information set available at time t, Ψ_t, of "pay-off", reified within the respective model framework, of firm i τ periods ahead, and $r_{i,t+\tau}$ are the cost of equity, i.e., just ICC, of firm i for the τth period ahead. T represents the end point of business activities. More specifically, according to the going-concern principle, T is assumed to converge to infinity and the term structure of equity rates to be flat, such that $r_{i,t+\tau} = r_{i,t}\ \forall\ \tau$. Hence, for one firm, $r_{i,t}$ is still allowed to vary over time, but for one point in time, is constant.

Over the last 25 years, literature developed numerous models to obtain ICCs, which can be grouped into dividend discount models (DDMs), residual income models (RIMs), and abnormal earnings growth models (AEGMs). Under the assumptions inherent to all of them,[11] however, they are mere algebraic reformulations of

[9] Confer SEC rule RIN 3235-AG64, effective date May 10, 2004.

[10] This is analogous to internal rates of return calculated from the market price of a bond and coupon payments, commonly referred to as "yield to maturity".

[11] Heinrichs et al. (2013), employing the principle of financial statement articulation, extend the

each other, which lend themselves to expose certain economic concepts.

In a first step, following literature [e.g., Hou, van Dijk, and Zhang (2012), Li and Mohanram (2014), and Hess, Meuter, and Kaul (2019)], a firm's ICC obtains as the average over commonly used ICCs.[12] In particular, I employ the two DDMs employed by Pástor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Li, Ng, and Swaminathan (2013) respectively Gordon and Gordon (1997). The two RIMs used in this study are the three-phase model by Gebhardt, Lee, and Swaminathan (2001) respectively two-phase model in Claus and Thomas (2001). Finally, the four AEGMs I employ are the model introduced by Ohlson and Juettner-Nauroth (2005) as well as the modified price earnings growth (MPEG) model [Easton (2004)], the price earnings growth (PEG) model, and ICCs based on the forwarded price earnings ratio (PE). Appendix to Chapter 4 provides details on how each of these eight models is specified and their empirical implementation.

In a second step, firm-level ICCs are aggregated at the fund-quarter-level computing a value-weighted average of the respective ICCs corresponding to the stocks in a fund's portfolio,

$$ICC_{f,t} = \sum_{n=1}^{N_{f,t}} w_{f,i,t} \cdot ICC_{i,t}, \tag{4.2}$$

where $ICC_{f,t}$ denotes the ICC associated with fund f at time t, $N_{f,t}$ the number of stocks the fth fund holds at time t, and $w_{f,i,t}$ the weight of fund f in stock i at time t. $ICC_{i,t}$ denotes the ICC of stock i at time t.

While market value of equity is observable to the econometrician, the numerator in equation (4.1), expected pay-off, is not. Historically, literature used analysts' forecasts as a proxy for market expectations of future earnings to derive expected pay-offs, one venue also followed in this paper. However, these forecasts come with certain restrictions. There is evidence for systematic biases, resulting from, e.g., career concerns to curry favor with target firms' executives to secure future investment banking business respectively not be excluded from certain meetings [e.g., McNichols and O'Brien (1997), Lin and McNichols (1998), Dechow, Hutton, and Sloan (2000),

standard models to establish empirical equivalence under non-ideal conditions.

[12]Theoretically, forecasts combination is motivated by a diversification motive with regard to specification respectively model error. Empirically, "simple", "robust" estimation schemes tend to work well [Timmermann, Granger, and Elliott (2006)].

Westphal and Clement (2008), Mohanram and Gode (2013), and Larocque (2013)]. Further, coverage by analysts is limited, especially for earlier years and smaller firms.

As a response, research developed cross-sectional or "mechanical" earnings forecasts [e.g., Fama and French (2000), Gerakos and Gramacy (2012), Hou, van Dijk, and Zhang (2012), and Li and Mohanram (2014)], which are also used in this study. Literature documents that related earnings surprises exhibit higher earnings response coefficients than surprises with regard to analysts' forecasts. This suggests that they better reflect market expectations and such better align the left-hand-side of equation (4.1) with the numerator on its right-hand-side.

To obtain cross-sectional earnings forecasts, in pooled OLS-regressions,[13] a constant and current accounting data are related to earnings τ periods ahead. This results into coefficient estimates for each regressor, which subsequently are multiplied with current accounting data and summed to obtain an estimate for earnings in $t + \tau$. Following literature, I use rolling regressions with a window of ten years and assume a reporting lag of minimum three and maximum fourteen months. As fund holdings are reported every quarter, four separate regression specifications are run each year in March, June, September, and December.

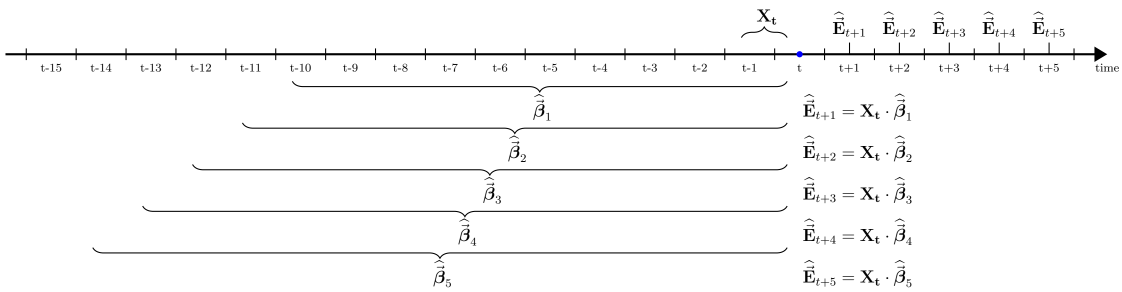
Figure 4.1 shall illustrate the estimation procedure in June of year t. For example, to obtain an earnings estimate for June $t + 1$, first, using the past ten years of data, a pooled OLS-regression of earnings one year ahead on current accounting information is performed (i.e., earnings in $t, ..., t - 9$ are regressed on accounting information in $t - 1, ..., t - 10$, avoiding look-ahead bias). Second, for each firm in t, resulting coefficients are multiplied with its accounting data in t to obtain an earnings forecast. That way, firms for which earnings estimates in t can be computed do not have to have entered the previous regression; coefficients are the same for all firms and applied to all with relevant accounting data in t, which reduces survivorship requirements and distinguishes the cross-sectional from a time series approach, where regressions are run for each firm separately.[14] Appendix to Chapter 4 pro-

[13] Recent research examines the usefulness of quantile regressions, in particular median regressions, confer Konstantinidi and Pope (2016) and Easton, Kapons, Kelly, and Neuhierl (2020).

[14] Empirical evidence is in favor of analyst over time series forecast, confer Ball and Brown (1968), Brown, Richardson, and Schwager (1987), O'Brien (1988), Lobo (1992), and Bradshaw, Drake, Myers, and Myers (2012).

Figure 4.1: Illustration of Cross-Sectional Earnings Estimation Procedure

This figure illustrates the procedure of how cross-sectional earnings estimates are obtained, by way of example for forecasts made in June. Each year t, depicted on the time-axis, under consideration of minimum three and maximum fourteen months reporting lag, denoted by the overbrace, a constant and firms' latest balance sheet information are collected in matrix $\mathbf{X_t}$, where each row corresponds to one firm-year. Based on ten years of accounting data, pooled cross-sectional OLS regressions are run of τ periods ahead realized earnings, $\tau \in \{1, \ \ldots, \ 5\}$, on balance sheet information, specified according to EP (2014), RI (2014), and HvDZ (2012), respectively. Underbraces depict the interval of data points entering the respective regressions. Resulting estimated coefficients are stacked into column vectors $\widehat{\vec{\boldsymbol{\beta}}}_\tau \ \forall \ \tau$. Post-multiplication with $\mathbf{X_t}$ results into forecasts, $\widehat{E}_{i,t+\tau}$, for each firm, stacked into column-vectors $\widehat{\vec{\mathbf{E}}}_{t+\tau}$.



vides an overview of the three models used in this paper: The earnings persistence (EP) model, as the most reduced model, and residual income (RI, to distinguish from ICC-models) model by Li and Mohanram (2014) as well as the pioneer, most comprehensive model by Hou, van Dijk, and Zhang (2012) (HvDZ).

4.2.3 Descriptive Statistics

Table 4.1 reports summary statistics for the 3,699 funds analyzed in this study. The sample period spans from 1992 to 2016. Panel A provides information about the distribution of fund characteristics. It reports 25th, 50th, and 75th percentiles, alongside the mean and standard deviation, for the main covariates used in regression analyses as well as fund-level ICC. The average fund is 13 years old, oversees approximately 1 billion U.S. dollars, has an expense ratio of 1.3 percent per year, and turns over its portfolio slightly less than once on an annual basis. Flows, net of the impact of returns, amount to 2.22% per quarter, on average. Over half of funds are managed by a team. Fund-level ICCs are distinguishable between analyst-based ICCs on the one hand and ICCs with mechanical earnings forecasts as inputs on the other; whereas the latter, with means of roughly 6.5%, closely resemble each other, ICCs based on analysts are approximately 50% larger. This is consistent with the

Table 4.1: Descriptive Statistics

This table shows descriptive statistics for the quarterly sample of 3,699 mutual funds during 1992-2016. Panel A presents 25, 50, and 75 percentiles (p_{25}, p_{50}, and p_{75}, respectively), as well as the mean ($\overline{x}$) and standard deviation (Std) of fund characteristics. *Age* denotes fund age in years. *TNA* denotes fund size, measured as fund total net assets in $ million. *Exp. Ratio* is the fund expense ratio in % p.a. *Turn. Ratio* is the fund turnover ratio in % p.a. *Flow* is the percentage quarterly growth in funds' new money, net of the effect of returns. *I(Team)* is an indicator variable equal to one if the fund is managed by a team and zero else. *ICC*, for every fund every quarter, obtains as a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, as described in Section 4.2.2. Panel B reports average cross-sectional Pearson correlation coefficients below and Spearman rank correlation coefficients above the diagonal between fund-level ICCs. Panel C provides autocorrelation coefficients of fund-level ICCs up to a lag length of eight quarters.

Panel A: Fund Characteristics

	p_{25}	p_{50}	p_{75}	$\overline{x}$	Std
Control variables					
Age [years]	4.67	9.50	16.75	13.23	13.15
TNA [$ million]	45.60	181.10	708.90	1,042.48	3,523.40
Exp. Ratio [%]	0.98	1.21	1.50	1.30	1.35
Turn. Ratio [%]	34.00	63.00	108.00	87.07	117.60
Flow [%]	−3.85	−0.75	3.99	2.22	15.96
I(Team) [%]	0.00	100.00	100.00	59.93	49.00
Fund-level ICC					
Analyst [%]	8.24	9.01	9.93	9.15	1.52
EP (2014) [%]	5.09	6.00	7.09	6.28	2.25
RI (2014) [%]	5.06	6.13	7.34	6.33	1.89
HvDZ (2012) [%]	4.75	5.96	7.28	6.15	1.99

Panel B: Pearson and Spearman Correlations between Fund-level ICC

	Analyst	EP (2014)	RI (2014)	HvDZ (2012)
Analyst	1.00	0.65	0.63	0.56
EP (2014)	0.58	1.00	0.82	0.78
RI (2014)	0.59	0.79	1.00	0.95
HvDZ (2012)	0.53	0.74	0.93	1.00

Panel C: Autocorrelation of Fund-Level ICC

	1	2	3	4	5	6	7	8
Analyst	0.83	0.73	0.64	0.61	0.57	0.54	0.50	0.49
EP (2014)	0.85	0.73	0.66	0.61	0.55	0.50	0.47	0.44
RI (2014)	0.92	0.85	0.80	0.77	0.73	0.70	0.67	0.64
HvDZ (2012)	0.93	0.87	0.82	0.78	0.75	0.72	0.70	0.69

positive analyst forecast bias documented in literature [e.g., Lim (2001), Hou, van Dijk, and Zhang (2012), Mohanram and Gode (2013), and Larocque (2013)], as, ceteris paribus, higher expected pay-offs in equation (4.1) imply higher ICC. Cross-sectional variation seems to be considerable, as the interquartile range amounts to ⅓ of the median.

Panel B informs about cross-sectional correlations between different ICC measures; below the diagonal, it reports Pearson correlation coefficients and Spearman rank correlation coefficients above.[15] Again, a stratification into analyst- and model-based ICCs is recognizable; whereas correlations with analyst-based ICCs amount to roughly 0.60, correlations between model-based ICCs are never below 0.79. ICCs based on RI and HvDZ show the highest correlation (0.93 respectively 0.95), consistent with the high similarity between the underlying models' inputs.

Finally, Panel C reports autocorrelation coefficients for lags up to eight quarters, i.e., two years. Although it is lowest for EP-based ICCs, persistence in general appears to be high, with coefficients of around 0.85 for one lag and still above 0.60 for eight lags in case of the two more complex earnings models and below 0.50 for analyst- and EP-based ICCs. These findings may be relevant for persistence of possible performance-predicting capabilities of ICCs and, related, turnover in portfolio-based analyses I turn to in the next section.

4.3 ICC and Fund Performance

This section is concerned with the main research object of this paper, the association between current ICC and future fund performance. It starts with a portfolio-based analysis in Section 4.3.1. Thereafter, in Section 4.3.2, it transitions to a regression-based approach in an aim to control for possible confounding covariates. Within this framework, Section 4.3.3 studies trading mechanisms related to ICCs.

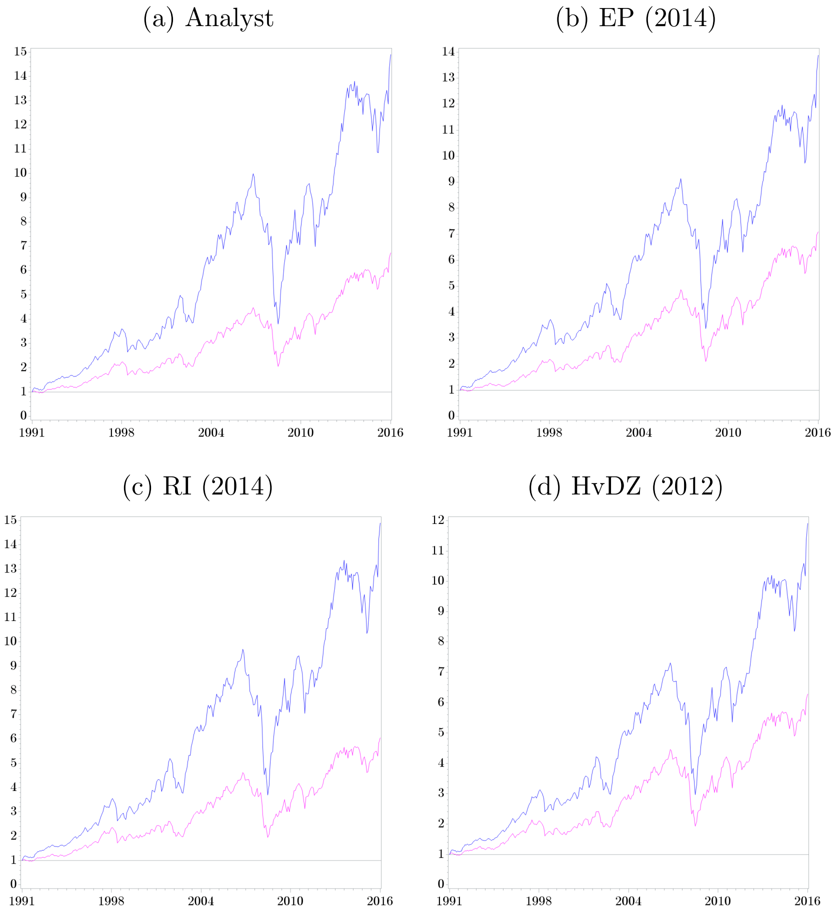
4.3.1 Portfolio Approach

The portfolio analysis is specified in following manner. Each quarter, funds are sorted into quintile portfolios, based on their current holdings' implied ICC. Funds with the lowest ICC enter portfolio 1 (bottom portfolio), whereas funds with the highest ICC are allocated to portfolio 5 (top portfolio). Within portfolios, funds are equally weighted. The five portfolios are held for three months, until the next holdings' report date, when the sorting procedure is repeated. The first sort is based

[15] All correlation coefficients are statistically significant at the 1%-level.

Figure 4.2: Cumulative Fund Returns of ICC-Percentile-Portfolios.

This figure plots cumulative returns of equally-weighted fund-portfolios corresponding to the bottom (magenta) and top (blue) quintiles of fund-level ICCs. These obtain as value-weighted ICCs of the funds' portfolios' constituents, based on four different proxies for expected earnings, constructed for every fund every quarter as described in Section 4.2.2. Each quarter, funds are sorted based on their holdings' implied ICC and quintiles are determined. According to these quintiles, equally-weighted portfolios are built and held over the subsequent quarter.



on holdings in December 1991, the last on holdings in September 2016. This results into a return series over 300 months (25 years à 12 months) and 98 rebalances.

For a first impression of ICCs' discriminating capabilities in terms of future fund performance, Figure 4.2 plots cumulative returns of the bottom (magenta) and top (blue) portfolio for each of the four earnings specifications. Values are all in the same ball park; whereas bottom portfolios never show more than a seven-fold increase, top portfolios reach values twice as large. No strategy, however, seems to be charmed against recessions. Losses during the 2008/2009-crisis are particularly high. As ICCs are based on market prices, which during "extraordinary" periods potentially are less informative,[16] this finding seems to be less of a surprise.

Although Figure 4.2 provides evidence for ICCs being able to discern funds with high returns from funds with low returns, differences could be attributable to differences in risk (or factor respectively style exposure), leaving ICCs useless to discriminate skillful managers. Hence, in addition to returns (*Return*), besides style-adjusted returns (*SReturn*), which obtain by subtracting from a fund's return in one month the mean return of all funds in the same investment category in the same month, I calculate two performance measures based on linear factor models: Jensen-Alpha ($Alpha1$), the intercept from a regression of fund-portfolio excess returns over the risk-fee rate on a proxy for the market factor, and $Alpha6$, the Fama and French (2015) 5-factor alpha, augmented with the momentum factor [Barillas and Shanken (2018) and Fama and French (2018)], calculated analogously to $Alpha1$.[17] While $Alpha1$ has been documented as the performance measure a large fraction of investors and hence fund customers, whose investment and divestment decisions determine fund managers' career outcomes, care for most [Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016)], $Alpha6$ is meant to capture additional risk or investment styles mutual fund managers follow and more "sophisticated", like institutional, investors may "correct" for. Finally, I adjust returns as in Daniel, Grinblatt, Titman, and Wermers (1997) (*DGTW*), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of its benchmark portfolio, which is a value-weighted portfolio of all stocks in the same size, book-to-market, and one-year past return quintile. These adjusted returns are then value-weighted at the fund-portfolio-level. To asses statistical significance for *Return*, *SReturn*, and *DGTW*, their time series are regressed on a constant; corresponding t-values are based on Newey and West (1987)-adjusted standard errors accounting for a lag length of twelve months.

[16] Literature argues mainly based on insights from behavioral finance. For a review, confer Hirshleifer (2015). E.g., crises are seen as periods with strong negative emotions alleviating existing biases as well as particularly bad news, to which investors appear to systematically falsely react to [e.g., Chopra, Lakonishok, and Ritter (1992) and Hong, Lim, and Stein (2000)]. Veronesi (1999) provides a dynamic, rational expectations equilibrium model where prices underreact to good news in bad times. In all cases, the gap between prices and fundamental values widens.

[17] Returns for factor mimicking portfolios and a proxy for the risk-free rate are obtained from `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

Table 4.2: ICC and Mutual Fund Performance: Portfolio Sorts

This table presents results from portfolio sort analyses of funds' ICC and future fund performance. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, *ICC*, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2. Each quarter, funds are sorted according to their most recent ICC. Panel A presents average monthly returns (*Return*), style-adjusted returns (*SReturn*), Jensen Alpha (*Alpha*1), the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), and characteristics adjusted returns (*DGTW*), described in Section 4.3.1, of equally-weighted ICC quintile portfolios, stratified according to which earnings estimates entered the calculation of *ICC*. Besides quintile porfolio performance measures, the bottom row reports the top-minus-bottom-performance of the corresponding spread portfolio. Panel B presents factor loadings corresponding to regressions underlying *Alpha*6. Finally, Panel C reports the top and bottom portfolio performance as well as the spread portfolio performance for decile portfolios based on no-load fund share classes. Performance measures are reported in % per month. T-statistics [according to Newey and West (1987), considering 12 monthly lags, in case of *Return*, *SRetun*, and *DGTW*] are reported in parentheses. Throughout the table, ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Performance of Quintile Portfolios.

	Analyst					EP (2014)				
ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.60**	−0.12**	−0.19***	−0.22***	−0.07	0.57**	−0.13***	−0.25***	−0.31***	−0.08
	(2.48)	(−2.36)	(−3.27)	(−3.76)	(−1.32)	(2.28)	(−3.34)	(−4.72)	(−5.63)	(−1.46)
2	0.72***	−0.01	−0.08**	−0.14***	−0.02	0.68***	−0.03	−0.12***	−0.2***	−0.00
	(3.12)	(−0.33)	(−2.02)	(−4.18)	(−0.51)	(2.91)	(−0.85)	(−2.83)	(−5.28)	(−0.04)
3	0.77***	0.04	−0.03	−0.14***	0.01	0.77***	0.03	−0.03	−0.15***	0.02
	(3.18)	(1.20)	(−0.6)	(−3.97)	(0.25)	(3.19)	(0.96)	(−0.55)	(−4.21)	(0.59)
4	0.85***	0.06	0.03	−0.15***	0.08	0.89***	0.09	0.09	−0.10*	0.03
	(3.41)	(0.93)	(0.40)	(−2.63)	(1.54)	(3.65)	(1.49)	(1.10)	(−1.83)	(0.63)
5	0.90***	0.07	0.05	−0.14*	0.05	0.93***	0.07	0.10	−0.04	0.07
	(3.17)	(0.89)	(0.42)	(−1.91)	(0.83)	(3.37)	(0.93)	(0.84)	(−0.72)	(1.33)
5-1	0.29**	0.19*	0.25*	0.08	0.12*	0.36***	0.20**	0.35***	0.26***	0.15**
	(2.18)	(1.86)	(1.81)	(0.83)	(1.80)	(2.95)	(2.11)	(2.81)	(3.94)	(2.32)

Table 4.2: ICC and mutual fund performance: Portfolio Sorts (Continued)

Panel A: Performance of Quintile Portfolios (Continued).

	RI (2014)					HvDZ (2012)				
ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.55**	−0.15***	−0.25***	−0.29***	−0.10*	0.57**	−0.15***	−0.26***	−0.30***	−0.09*
	(2.27)	(−3.93)	(−5.68)	(−6.27)	(−1.86)	(2.24)	(−4.30)	(−4.98)	(−5.66)	(−1.68)
2	0.68***	−0.05	−0.12***	−0.20***	−0.01	0.69***	−0.05	−0.12***	−0.21***	−0.00
	(2.91)	(−1.41)	(−2.87)	(−5.45)	(−0.35)	(2.92)	(−1.44)	(−2.69)	(−5.39)	(−0.08)
3	0.77***	0.02	−0.04	−0.16***	0.01	0.76***	0.02	−0.05	−0.16***	−0.00
	(3.12)	(0.46)	(−0.76)	(−4.51)	(0.13)	(3.06)	(0.62)	(−1.08)	(−4.52)	(−0.02)
4	0.88***	0.09	0.06	−0.12**	0.05	0.89***	0.11*	0.09	−0.10*	0.05
	(3.49)	(1.48)	(0.70)	(−2.17)	(1.01)	(3.66)	(1.74)	(1.15)	(−1.93)	(0.94)
5	0.96***	0.13	0.14	−0.01	0.10*	0.95***	0.11	0.13	−0.02	0.09
	(3.57)	(1.52)	(1.26)	(−0.18)	(1.67)	(3.56)	(1.41)	(1.22)	(−0.41)	(1.50)
5-1	0.40***	0.28***	0.39***	0.28***	0.2***	0.38***	0.27***	0.39***	0.28***	0.18**
	(3.4)	(2.70)	(3.28)	(3.68)	(2.80)	(3.51)	(2.71)	(3.54)	(3.90)	(2.48)

Table 4.2: ICC and Mutual Fund Performance: Portfolio Sorts (Continued)

Panel B: Factor Loadings of Regressions underlying Alpha6.

Analyst

ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	−0.22***	0.95***	0.00	0.04	0.05**	0.03	−0.04***
	(−3.76)	(58.39)	(−0.13)	(1.46)	(1.97)	(0.83)	(−3.06)
2	−0.14***	0.96***	0.01	0.05***	0.10***	0.01	−0.02***
	(−4.18)	(104.6)	(0.99)	(3.07)	(6.61)	(0.43)	(−3.34)
3	−0.14***	0.97***	0.11***	0.10***	0.13***	0.03	−0.02***
	(−3.97)	(100.44)	(9.25)	(6.43)	(7.71)	(1.31)	(−3.03)
4	−0.15***	1.00***	0.28***	0.14***	0.18***	0.06*	−0.04***
	(−2.63)	(63.35)	(14.44)	(5.28)	(6.59)	(1.68)	(−3.63)
5	−0.14*	0.99***	0.56***	0.19***	0.20***	0.04	−0.08***
	(−1.91)	(49.42)	(21.9)	(5.59)	(5.94)	(0.76)	(−5.08)
5-1	0.08	0.04	0.56***	0.15***	0.15***	0.00	−0.04*
	(0.83)	(1.61)	(16.17)	(3.24)	(3.19)	(0.06)	(−1.91)

EP (2014)

ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	−0.31***	1.01***	0.01	0.02	0.08***	0.01	0.01
	(−5.63)	(67.67)	(0.38)	(0.69)	(3.09)	(0.15)	(1.17)
2	−0.2***	0.98***	0.01	0.06***	0.11***	0.02	−0.02**
	(−5.28)	(93.5)	(0.73)	(3.47)	(6.26)	(0.72)	(−2.35)
3	−0.15***	0.98***	0.10***	0.10***	0.14***	0.04*	−0.03***
	(−4.21)	(102.69)	(8.31)	(6.42)	(8.76)	(1.87)	(−3.69)
4	−0.10*	0.97***	0.28***	0.15***	0.17***	0.08**	−0.05***
	(−1.83)	(66.94)	(15.82)	(6.34)	(6.92)	(2.28)	(−5.05)
5	−0.04	0.95***	0.57***	0.18***	0.16***	0.03	−0.11***
	(−0.72)	(60.01)	(28.43)	(6.75)	(5.89)	(0.94)	(−9.7)
5-1	0.26***	−0.06***	0.56***	0.16***	0.08**	0.03	−0.13***
	(3.94)	(−3.17)	(24.17)	(5.25)	(2.57)	(0.69)	(−9.3)

RI (2014)

ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	−0.29***	0.97***	0.01	0.01	0.07***	−0.02	0.01
	(−6.27)	(77.08)	(0.56)	(0.43)	(3.06)	(−0.78)	(1.35)
2	−0.20***	0.98***	0.04***	0.06***	0.13***	0.00	−0.02***
	(−5.45)	(95.01)	(3.38)	(3.29)	(7.23)	(0.18)	(−2.69)
3	−0.16***	0.99***	0.14***	0.12***	0.13***	0.04	−0.02***
	(−4.51)	(98.8)	(11.37)	(7.39)	(7.63)	(1.52)	(−3.06)
4	−0.12**	1.00***	0.28***	0.16***	0.18***	0.04	−0.05***
	(−2.17)	(63.98)	(14.55)	(6.33)	(6.75)	(1.15)	(−4.43)
5	−0.01	0.94***	0.48***	0.17***	0.16***	0.10**	−0.12***
	(−0.18)	(53.65)	(21.79)	(5.71)	(5.41)	(2.49)	(−9.11)
5-1	0.28***	−0.03	0.47***	0.16***	0.10***	0.12***	−0.13***
	(3.68)	(−1.51)	(18.18)	(4.59)	(2.73)	(2.6)	(−8.56)

Table 4.2: ICC and Mutual Fund Performance: Portfolio Sorts (Continued)

Panel B: Factor Loadings of Regressions underlying Alpha6 (Continued).

	HvDZ (2012)						
ICC-rank	Alpha6	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
1	−0.30*** (−5.66)	0.99*** (68.43)	0.08*** (4.53)	−0.01 (−0.56)	0.08*** (3.08)	−0.03 (−0.88)	0.02 (1.43)
2	−0.21*** (−5.39)	0.98*** (92.29)	0.07*** (5.17)	0.06*** (3.49)	0.13*** (7.2)	0.00 (0.18)	−0.02** (−2.5)
3	−0.16*** (−4.52)	0.99*** (100.78)	0.12*** (9.81)	0.11*** (6.97)	0.13*** (8.01)	0.02 (1.05)	−0.04*** (−5.08)
4	−0.10* (−1.93)	0.98*** (68.62)	0.26*** (14.35)	0.15*** (6.37)	0.18*** (7.31)	0.08** (2.33)	−0.05*** (−4.49)
5	−0.02 (−0.41)	0.95*** (59.97)	0.44*** (22.2)	0.20*** (7.64)	0.14*** (5.24)	0.09** (2.48)	−0.11*** (−9.26)
5-1	0.28*** (3.9)	−0.04** (−2.21)	0.36*** (14.74)	0.21*** (6.66)	0.07** (1.97)	0.12*** (2.69)	−0.12*** (−8.64)

Table 4.2, Panel A, reports performance measures for each of the five quintile portfolios separately as well as the hypothetical top-minus-bottom-portfolio short in the bottom and long in the top portfolio. Consistent with previous research on ICC at the stock-level, spreads are highest and always statistically significant at the 1%-level for ICCs based on mechanical earnings forecasts. Alphas and returns are approximately of same magnitude (30 to 40 basis points per month), indicating that spread returns do not simply originate from factor exposure. Values for $DGTW$, which are based on a fund's holdings, are, with on average 15 basis points, the lowest. An adjustment of returns for which investment category the funds belong to reduces the spread by 10 basis points, leaving it still statistically significant, though.

The spread, however, does not inform about general discriminating power of ICCs. Even absent a steady increase in performance from bottom to top portfolios, it could potentially be significant. Hence, Panel A also reports performance of the respective quintile portfolios. For illustration, Figure 4.3 plots the five performance measures for all quintile portfolios based on ICCs derived from earnings forecasts according to the model by HvDZ. It shows that for all measures, performance increases from bottom to top portfolio. Style or factor adjusted measures are all (statistically significant) below zero in the lower part and increase to values of around 10 basis points for $SReturn$, $Alpha1$, and $DGTW$, respectively -2 basis points for $Alpha6$.

Table 4.2: ICC and Mutual Fund Performance: Portfolio Sorts (Continued)

Panel C: Performance of Decile Portfolios.

Analyst

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.61**	−0.16**	−0.23**	0.00	−0.34
	(2.08)	(−2.21)	(−2.09)	(0.01)	(−1.36)
10	1.07***	0.20**	0.24**	0.37***	0.17**
	(3.9)	(2.29)	(2.3)	(3.06)	(2.07)
10-1	0.47***	0.35***	0.47***	0.37**	0.50*
	(3.46)	(3.08)	(3.50)	(2.22)	(1.95)

EP (2014)

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.62**	−0.14**	−0.25***	−0.13	−0.13*
	(2.57)	(−2.50)	(−3.12)	(−0.93)	(−1.70)
10	1.06***	0.19**	0.26**	0.21**	0.17**
	(3.76)	(2.02)	(2.06)	(2.46)	(2.23)
10-1	0.43***	0.34***	0.51***	0.34**	0.28***
	(2.92)	(3.07)	(3.82)	(2.20)	(2.79)

RI (2014)

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.58	−0.14**	−0.29***	−0.10	−0.32
	(1.60)	(−2.19)	(−3.22)	(−0.72)	(−1.58)
10	1.01***	0.19**	0.27**	0.21**	0.37**
	(3.22)	(2.04)	(2.4)	(2.49)	(2.03)
10-1	0.42**	0.33***	0.56***	0.31**	0.68***
	(2.17)	(2.79)	(4.31)	(2.07)	(2.63)

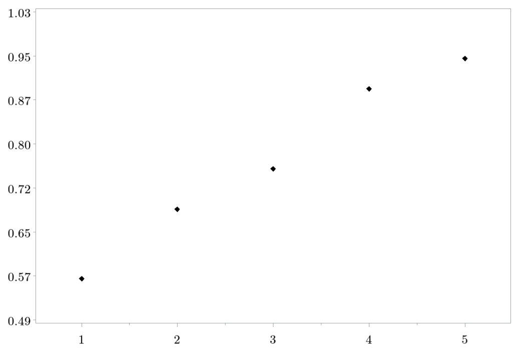
HvDZ (2012)

ICC-rank	Return	SReturn	Alpha1	Alpha6	DGTW
1	0.64**	−0.18*	−0.23	−0.26*	−0.05
	(2.18)	(−1.76)	(−1.54)	(−1.68)	(−0.35)
10	1.05***	0.23**	0.32**	0.19*	0.23***
	(3.82)	(2.02)	(2.11)	(1.75)	(3.87)
10-1	0.41***	0.41***	0.55***	0.46**	0.28**
	(3.10)	(2.69)	(3.92)	(2.59)	(1.97)

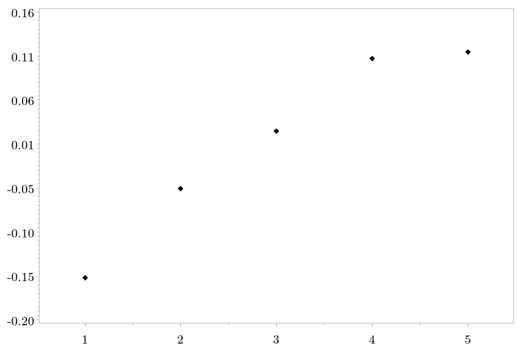
Figure 4.3: Average Monthly Performance of ICC-Percentile-Portfolios.

This figure plots, for all quintile portfolios indicated on the x-axis, average performance measures in % per month, denoted on the y-axis, corresponding to the analysis in Table 4.2, Panel A, for ICCs derived from earnings forecasts according to HvDZ (2012). In particular, for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on proxies for expected earnings following HvDZ (2012), is constructed as described in Section 4.2.2. Each quarter, funds are sorted based on their holdings' implied ICC and quintiles are determined. According to these quintiles, equally-weighted portfolios are built and held over the subsequent quarter. Performance measures include average monthly returns (*Return*), style-adjusted returns (*SReturn*), Jensen Alpha (*Alpha*1), the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), and characteristics adjusted returns (*DGTW*), described in Section 4.3.1.

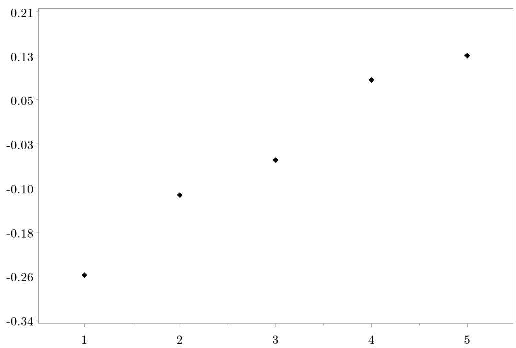
(a) Return



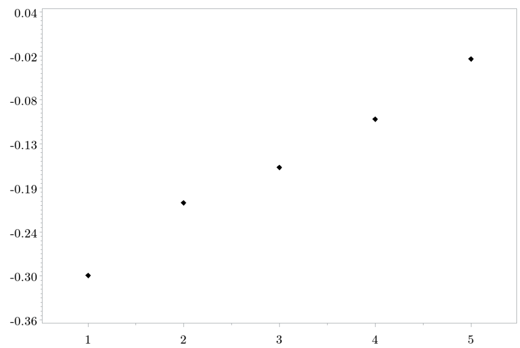
(b) SReturn



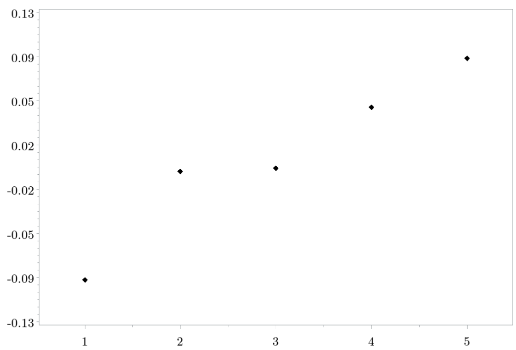
(c) Alpha1



(d) Alpha6



(e) DGTW



This could be interpreted as evidence that ICCs do not simply show extreme results at the tails but no (or even perverse) discriminating power in-between.

To shed light on which factor tilts are associated with which ICC strategy, Panel

B tabulates the whole set of coefficients in regressions underlying *Alpha*6, β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA}, and β_{UMD}, i.e., loadings corresponding to the market, small-minus-big (size), high-minus-low (value), robust-minus-weak (profitability), conservative-minus-aggressive (investment), and up-minus-down (momentum) factor-mimicking portfolio, respectively. In comparison to funds with low ICCs, high-ICC funds show larger exposure to firms which behave like small value-firms with high operating profitability; in addition, they show a negative exposure to the momentum portfolio. Value and profitability tilts are consistent with a fundamental investment approach, which screens firms with "cheap" valuations in relation to their profitability prospects. However, size and momentum exposures could also simply reflect how ICCs are calculated. If the market value of equity is relatively low, which tends to be the case for small firms or firms with recent losses in terms of stock returns, ceteris paribus, the larger the ICC needed to equate it to discounted expected pay-offs. Further, high current profitability, considering the regressors in earnings regression equations, tends to translate into comparably high future earnings, which, ceteris paribus, also increase a firm's ICC.

Cut-offs based on quintiles reveal a certain sorting pattern. However, only returns, but none of the top portfolios' risk- or style-adjusted performance measures, are statistically significant different from zero, necessary for a feasible investment approach. Additionally, considering portfolio turnover (not reported), on average 70% of the funds remain in the top portfolio from one period to the next (in line with autocorrelations reported in Table 4.1, Panel B), such that investors potentially need to pay back-end and front-end loads concerning the remnant 30%. Further, provided evidence in previous research for managers able to beat their benchmark after costs being scarce, 20%-percentiles might simply be too coarse.

In an aim to address these issues, the sorting-exercise, now based on decile portfolios, is repeated for no-load share classes. Panel C reports performance measures for bottom and top as well as corresponding spread portfolios. In general, spreads increase; further, investors could realize a return of 1% per month. More importantly, top portfolios now exhibit statistically significant risk respectively style adjusted performance measures. Alphas range between 19 basis points and 37 basis points, statistically significant at the 5%-level, on average. Hence, feasible investments into mutual funds with high ICC had led to entirely net-of-cost alphas for investors free from any assumptions on trading costs, not readily reconstructed for analyses at the stock-level.

4.3.2 Regression Analysis

Whereas portfolio sorts seem to provide first evidence for a positive association between current ICC and future fund performance, possibilities to control for confounding characteristics at the fund level are limited. Hence, for the rest of the paper, I turn towards panel regressions at the fund-quarter-level of the form

$$y_{f,t+1} = \beta \cdot ICC_{f,t} + \vec{\boldsymbol{\gamma}} \cdot \vec{\boldsymbol{c}}_{f,t} + \vec{\boldsymbol{\iota}} \cdot \vec{\boldsymbol{\varphi}} + \varepsilon_{f,t+1}, \tag{4.3}$$

where $y_{f,t+1}$ denotes one of the five performance measures of fund f in quarter $t+1$.[18] $ICC_{f,t}$ is a fund's quarterly[19] ICC at time time t, calculated as described in Section 4.2.2. $\vec{\boldsymbol{\gamma}}$ is the vector of coefficients associated with fund-level covariates, which are described in Section 4.2.3 respectively Table 4.1 and stacked into vector $\vec{\boldsymbol{c}}_{f,t}$. Thereby, following literature, Age and TNA are log-transformed to reduce skewness. The specification of fixed effects is captured by $\vec{\boldsymbol{\varphi}}$, which denotes a vector of length h, where h equals the number of fixed effects included in the model. $\vec{\boldsymbol{\iota}}$ is the corresponding vector of ones and hence also of length h. $\varepsilon_{f,t+1}$ denotes the error term, while $\cdot$ symbolizes the scalar product. The main variable of interest is β, the coefficient of a fund's ICC, where a positive coefficient were consistent with ICCs being able to positively predict future performance.

Table 4.3 shows results for regression (4.3), estimated with three different specifications of fixed effects, separately for each of the four earnings specifications. Throughout, given a "large" N (3,699) relative to a "small" T (100), standard er-

[18] In quarterly regressions, $Alpha1$ and $Alpha6$ are obtained as follows. First, for a given fund, monthly alphas are computed as the difference between actual returns and expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns on a constant and proxies for the respective factor(s). Second, these monthly alphas are aggregated to the quarterly level using compounding.

[19] To obtain quarterly ICCs with matching maturities to ease interpretation, I subtract one from $\sqrt[4]{1 + ICC_{f,t}}$.

Table 4.3: ICC and Mutual Fund Performance: Panel Regressions

This table presents results from pooled OLS regressions that relate future, quarterly fund performance with most recent fund-level ICC. The analysis is performed at the fund-quarter-level. The five analyzed performance measures are return ($Return$), style-adjusted return ($SReturn$), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha ($Alpha1$) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor ($Alpha6$), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns ($DGTW$), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the quarterly level using compounding. The main independent variable is ICC; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2. Controls are described in Table 4.1. Regressions are run with time and style [columns (1) to (5)], time-by-style [columns (6) to (10)], and time-by-style and fund fixed effects (FE) [columns (11) to (15)], respectively. The four panels correspond to the four earnings specifications used to obtain stock-level ICCs. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 4.3: ICC and Mutual Fund Performance: Panel Regressions (Continued)

Analyst

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	2.0715***	1.5225***	1.4616	0.2157*	0.4956***	1.2985***	1.1014***	0.7188***	0.3709***	0.4933***	1.6527***	1.4006***	1.2999***	0.8570***	0.7004***
	(18.17)	(14.24)	(14.25)	(1.88)	(4.21)	(11.52)	(9.83)	(6.40)	(2.60)	(3.63)	(9.72)	(8.26)	(6.76)	(4.03)	(3.38)
Log(Age)	−0.0003	−0.0002	−0.0005**	−0.0005**	0.0001	−0.0008***	−0.0007***	−0.0007***	−0.0006***	−0.0001	0.0002	−0.0001	−0.0006	−0.0014*	0.0017***
	(−1.37)	(−0.99)	(−2.34)	(−2.35)	(0.57)	(−4.07)	(−3.28)	(−3.32)	(−2.84)	(−0.56)	(0.27)	(−0.16)	(−0.83)	(−1.90)	(3.22)
Log(TNA)	−0.0005***	−0.0006***	−0.0004***	−0.0002**	−0.0004***	−0.0003***	−0.0004***	−0.0001*	−0.0001*	−0.0003***	−0.0054***	−0.0053***	−0.0047***	−0.0032***	−0.0032***
	(−5.37)	(−6.29)	(−3.84)	(−2.17)	(−5.22)	(−3.38)	(−4.56)	(−1.87)	(−1.79)	(−4.14)	(−27.10)	(−26.73)	(−23.41)	(−18.89)	(−19.65)
Exp. Ratio	−0.3043***	−0.2869***	−0.2996***	−0.2579***	−0.0254	−0.2889***	−0.2758***	−0.2877***	−0.2562***	−0.0190	−0.2157***	−0.2070***	−0.2222***	−0.2691***	−0.0107
	(−14.44)	(−17.42)	(−12.19)	(−17.08)	(−0.68)	(−16.25)	(−19.18)	(−12.21)	(−16.43)	(−0.50)	(−7.13)	(−5.21)	(−11.57)	(−7.91)	(−0.25)
Turn. Ratio	−0.0007**	−0.0007**	−0.0008***	−0.0007***	−0.0008***	−0.0007***	−0.0006**	−0.0010***	−0.0007***	−0.0007***	0.0003	0.0003	−0.0005	−0.0003	−0.0004
	(−2.35)	(−2.30)	(−2.68)	(−2.98)	(−3.58)	(−2.68)	(−2.34)	(−3.65)	(−3.24)	(−3.23)	(0.75)	(0.78)	(−1.43)	(−1.01)	(−1.08)
Flow	−0.0000**	0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000**	−0.0000	−0.0000**	0.0000
	(−2.05)	(0.49)	(−1.48)	(−0.08)	(−1.52)	(−0.86)	(0.10)	(−1.02)	(−1.23)	(−0.35)	(0.16)	(2.09)	(−0.79)	(−2.17)	(0.18)
I(Team)	0.0002	0.0002	0.0000	−0.0004	−0.0002	0.0001	0.0001	−0.0001	−0.0004*	−0.0003	−0.0001	0.0002	−0.0003	−0.0003	−0.0006*
	(0.61)	(0.78)	(0.02)	(−1.57)	(−0.79)	(0.42)	(0.54)	(−0.26)	(−1.66)	(−1.36)	(−0.36)	(0.63)	(−0.86)	(−0.70)	(−1.77)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,371	124,371	114,618	114,618	118,823	124,371	124,371	114,618	114,618	118,823	124,371	124,371	114,618	114,618	118,823
Adj. R^2	0.785	0.014	0.110	0.081	0.111	0.865	0.233	0.426	0.166	0.270	0.869	0.251	0.441	0.184	0.282

EP (2014)

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	1.0728***	0.6747***	0.9108***	0.4925***	0.0888	0.6128***	0.5551***	0.5712***	0.6413***	0.2290	1.0707***	0.9715***	1.1198***	1.0451***	0.6935**
	(6.41)	(5.65)	(6.20)	(4.87)	(0.36)	(4.60)	(4.46)	(4.83)	(4.95)	(0.70)	(5.95)	(5.70)	(6.13)	(6.22)	(2.06)
Log(Age)	−0.0003	−0.0002	−0.0005**	−0.0005**	0.0001	−0.0008***	−0.0007***	−0.0007***	−0.0006***	−0.0001	0.0003	0.0000	−0.0005	−0.0014*	0.0017***
	(−1.18)	(−0.84)	(−2.32)	(−2.44)	(0.71)	(−4.07)	(−3.31)	(−3.49)	(−3.11)	(−0.45)	(0.52)	(0.04)	(−0.70)	(−1.88)	(3.32)
Log(TNA)	−0.0005***	−0.0006***	−0.0003***	−0.0001	−0.0004***	−0.0002***	−0.0003***	−0.0001	−0.0001	−0.0003***	−0.0053***	−0.0053***	−0.0047***	−0.0031***	−0.0032***
	(−4.95)	(−6.23)	(−3.22)	(−1.32)	(−4.71)	(−2.92)	(−4.18)	(−1.11)	(−0.76)	(−3.20)	(−26.64)	(−26.43)	(−22.79)	(−17.79)	(−17.25)
Exp. Ratio	−0.3120***	−0.2881***	−0.3009***	−0.2611***	−0.0313	−0.2908***	−0.2801***	−0.2852***	−0.2642***	−0.0305	−0.2261***	−0.2186***	−0.2246***	−0.2756***	−0.0206
	(−12.18)	(−18.11)	(−11.57)	(−20.34)	(−0.77)	(−14.90)	(−18.52)	(−13.34)	(−23.49)	(−0.67)	(−13.02)	(−9.20)	(−13.28)	(−11.59)	(−0.40)
Turn. Ratio	−0.0006*	−0.0006*	−0.0007**	−0.0007***	−0.0007***	−0.0006**	−0.0005**	−0.0009***	−0.0007***	−0.0006***	0.0002	0.0003	−0.0006*	−0.0004	−0.0004
	(−1.83)	(−1.89)	(−2.15)	(−2.86)	(−3.44)	(−2.39)	(−2.04)	(−3.33)	(−2.98)	(−3.07)	(0.55)	(0.59)	(−1.66)	(−1.23)	(−1.07)
Flow	−0.0000***	−0.0000	−0.0000***	−0.0000	−0.0000	−0.0000*	−0.0000	−0.0000**	−0.0000**	−0.0000	−0.0000	0.0000*	−0.0000	−0.0000**	−0.0000
	(−3.24)	(−1.11)	(−2.74)	(−0.75)	(−1.45)	(−1.77)	(−0.67)	(−2.10)	(−2.23)	(−0.58)	(−0.34)	(1.78)	(−1.35)	(−2.56)	(−0.03)
I(Team)	0.0000	0.0001	−0.0001	−0.0004	−0.0003	0.0000	0.0001	−0.0001	−0.0004	−0.0003	−0.0003	0.0001	−0.0004	−0.0003	−0.0006*
	(0.13)	(0.34)	(−0.32)	(−1.46)	(−1.10)	(0.07)	(0.26)	(−0.38)	(−1.57)	(−1.52)	(−0.70)	(0.33)	(−1.13)	(−0.87)	(−1.84)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,429	124,429	114,663	114,663	118,868	124,429	124,429	114,663	114,663	118,868	124,429	124,429	114,663	114,663	118,868
Adj. R^2	0.784	0.010	0.109	0.082	0.109	0.865	0.231	0.425	0.168	0.265	0.868	0.249	0.440	0.185	0.278

Table 4.3: ICC and Mutual Fund Performance: Panel Regressions (Continued)

RI (2014)

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	1.8835***	1.3627***	1.6200***	0.5290***	0.4765***	1.2893***	1.2117***	0.8511***	0.6960***	0.6436***	1.7995***	1.6212***	1.3281***	1.1927***	0.9658***
	(19.86)	(14.64)	(19.31)	(5.46)	(4.69)	(14.32)	(12.97)	(9.90)	(6.15)	(5.27)	(13.12)	(10.83)	(9.59)	(6.44)	(5.27)
Log(Age)	−0.0001	−0.0001	−0.0004*	−0.0004**	0.0002	−0.0007***	−0.0006***	−0.0006***	−0.0005***	−0.0001	0.0002	−0.0001	−0.0005	−0.0014*	0.0017***
	(−0.47)	(−0.30)	(−1.76)	(−2.15)	(0.83)	(−3.70)	(−2.99)	(−3.23)	(−2.77)	(−0.40)	(0.39)	(−0.09)	(−0.73)	(−1.89)	(3.27)
Log(TNA)	−0.0006***	−0.0006***	−0.0004***	−0.0002**	−0.0004***	−0.0003***	−0.0004***	−0.0002*	−0.0001*	−0.0003***	−0.0053***	−0.0052***	−0.0047***	−0.0032***	−0.0032***
	(−6.06)	(−6.90)	(−4.24)	(−2.06)	(−5.23)	(−3.63)	(−4.84)	(−1.93)	(−1.78)	(−4.06)	(−26.71)	(−26.41)	(−22.97)	(−18.62)	(−18.66)
Exp. Ratio	−0.3025***	−0.2849***	−0.2939***	−0.2516***	−0.0343	−0.2876***	−0.2782***	−0.2779***	−0.2518***	−0.0308	−0.2240***	−0.2167***	−0.2189***	−0.2697***	−0.0180
	(−14.90)	(−20.29)	(−13.41)	(−14.49)	(−0.80)	(−16.02)	(−20.13)	(−16.12)	(−15.71)	(−0.68)	(−12.43)	(−8.90)	(−12.24)	(−9.67)	(−0.37)
Turn. Ratio	−0.0005	−0.0005*	−0.0006**	−0.0006***	−0.0007***	−0.0005**	−0.0004*	−0.0008***	−0.0006***	−0.0006***	0.0004	0.0004	−0.0004	−0.0003	−0.0004
	(−1.65)	(−1.73)	(−2.03)	(−2.74)	(−3.42)	(−2.12)	(−1.77)	(−3.22)	(−2.86)	(−2.90)	(1.08)	(1.05)	(−1.30)	(−0.86)	(−1.18)
Flow	−0.0000**	0.0000	−0.0000**	−0.0000	−0.0000*	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000**	−0.0000	−0.0000**	0.0000
	(−2.45)	(0.09)	(−2.04)	(−0.15)	(−1.68)	(−1.16)	(−0.13)	(−1.21)	(−1.47)	(−0.46)	(0.27)	(2.17)	(−0.89)	(−2.11)	(0.25)
I(Team)	0.0001	0.0002	−0.0000	−0.0004	−0.0002	0.0001	0.0001	−0.0001	−0.0004	−0.0003	−0.0002	0.0002	−0.0004	−0.0003	−0.0006*
	(0.31)	(0.55)	(−0.11)	(−1.48)	(−0.81)	(0.28)	(0.47)	(−0.31)	(−1.62)	(−1.27)	(−0.48)	(0.52)	(−1.01)	(−0.77)	(−1.75)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,399	124,399	114,635	114,635	118,848	124,399	124,399	114,635	114,635	118,848	124,399	124,399	114,635	114,635	118,848
Adj. R^2	0.785	0.014	0.113	0.082	0.110	0.865	0.234	0.426	0.167	0.268	0.869	0.251	0.441	0.185	0.280

HvDZ (2012)

	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(6) Return	(7) SReturn	(8) Alpha1	(9) Alpha6	(10) DGTW	(11) Return	(12) SReturn	(13) Alpha1	(14) Alpha6	(15) DGTW
ICC	1.3982***	1.0384***	1.3457***	0.4581***	0.3893***	0.8791***	0.8380***	0.7186***	0.5783***	0.4673***	1.3443***	1.2327***	1.1755***	1.0208***	0.7308***
	(16.82)	(12.55)	(18.25)	(5.39)	(4.53)	(11.46)	(10.18)	(9.64)	(5.98)	(4.82)	(11.85)	(10.51)	(8.96)	(6.27)	(5.02)
Log(Age)	−0.0002	−0.0001	−0.0005**	−0.0004**	0.0001	−0.0008***	−0.0006***	−0.0006***	−0.0005***	−0.0001	0.0003	−0.0000	−0.0005	−0.0013*	0.0017***
	(−0.83)	(−0.57)	(−2.03)	(−2.26)	(0.72)	(−3.81)	(−3.08)	(−3.29)	(−2.81)	(−0.46)	(0.47)	(−0.02)	(−0.68)	(−1.83)	(3.32)
Log(TNA)	−0.0006***	−0.0006***	−0.0004***	−0.0001*	−0.0004***	−0.0003***	−0.0004***	−0.0001*	−0.0001	−0.0003***	−0.0054***	−0.0053***	−0.0047***	−0.0032***	−0.0032***
	(−5.76)	(−6.61)	(−3.80)	(−1.89)	(−5.10)	(−3.40)	(−4.60)	(−1.67)	(−1.55)	(−3.92)	(−27.13)	(−26.80)	(−23.25)	(−18.73)	(−19.20)
Exp. Ratio	−0.2969***	−0.2812***	−0.2913***	−0.2512***	−0.0337	−0.2835***	−0.2742***	−0.2773***	−0.2511***	−0.0294	−0.2152***	−0.2086***	−0.2126***	−0.2640***	−0.0143
	(−15.95)	(−20.63)	(−13.61)	(−14.35)	(−0.78)	(−17.46)	(−21.40)	(−16.04)	(−15.33)	(−0.65)	(−8.77)	(−6.57)	(−10.42)	(−7.87)	(−0.32)
Turn. Ratio	−0.0004	−0.0005	−0.0006*	−0.0006***	−0.0007***	−0.0006**	−0.0005*	−0.0009***	−0.0007***	−0.0006***	0.0003	0.0003	−0.0006*	−0.0004	−0.0004
	(−1.47)	(−1.60)	(−1.85)	(−2.78)	(−3.30)	(−2.14)	(−1.78)	(−3.25)	(−2.94)	(−2.84)	(0.72)	(0.74)	(−1.65)	(−1.23)	(−1.07)
Flow	−0.0000**	−0.0000	−0.0000**	−0.0000	−0.0000*	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000**	−0.0000	−0.0000*	0.0000
	(−2.55)	(−0.38)	(−2.21)	(−0.30)	(−1.77)	(−1.29)	(−0.32)	(−1.54)	(−1.59)	(−0.54)	(0.77)	(2.53)	(−0.51)	(−1.83)	(0.45)
I(Team)	0.0000	0.0001	−0.0001	−0.0004	−0.0002	0.0000	0.0001	−0.0001	−0.0004*	−0.0003	−0.0002	0.0002	−0.0004	−0.0003	−0.0006*
	(0.12)	(0.39)	(−0.20)	(−1.53)	(−0.86)	(0.11)	(0.31)	(−0.34)	(−1.65)	(−1.35)	(−0.61)	(0.41)	(−1.07)	(−0.84)	(−1.84)
Time FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Style FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Time×Style FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	124,396	124,396	114,635	114,635	118,842	124,396	124,396	114,635	114,635	118,842	124,396	124,396	114,635	114,635	118,842
Adj. R^2	0.784	0.012	0.111	0.082	0.111	0.865	0.232	0.426	0.167	0.270	0.868	0.250	0.440	0.184	0.281

rors are clustered at the fund level [Petersen (2009)]. The first five columns report results of regressions with time and style fixed effects to account for common time variant factors and commonalities within one style. In the next five columns, time and style fixed effects are interacted to control for commonality within time-style-combinations. The addition of fund fixed effects in the last five columns is meant to capture the impact of time-invariant unobserved heterogeneity between funds; this constitutes the main specification for the rest of the paper. Results are in line with the observations from the portfolio-sort analysis and uniform across different specifications of fixed effects. In general, ICCs are statistically significantly associated with future fund performance at the 1%-level. With respect to economic interpretation of coefficients, an increase in quarterly ICC by one percentage point, on average, was associated with an increase in future quarterly fund performance by one percentage point, irrespective of the specific performance measure. This corroborates the notion that the positive correlation between current ICCs and future fund performance does not seem to be attributable to effects specific to one time, style, or fund respectively characteristics at the fund-level.

With respect to the latter, Table 4.4 adds four additional variables shown to be associated with fund performance.[20] Besides active share (*ActShare*)[21] [Cremers and Petajisto (2009) and Cremers, Petajisto, and Zitzewitz (2013)], a measure for how much a fund deviates from its benchmark, it adds the industry concentration index (ICI) by Kacperczyk, Sialm, and Zheng (2005), a proxy for how concentrated a fund's holdings are within one industry relative to the market, and return gap (*RetGap*) [Kacperczyk, Sialm, and Zheng (2008)], aimed to quantify "unobserved actions" of mutual fund managers, calculated as the difference between actual gross fund returns and returns implied by the fund's latest portfolio disclosure. Finally, it adds the respective performance measure over the past quarter ($LaggedPerf$). In addition, I replace fund with fund-by-manager fixed effects. The intuition is that if high-ICC strategies were indeed able to translate into higher future fund perfor-

[20] Due to data limitations - the sample size drops by ⅘ - this specification is merely used as an additional analyses of whether the effect of ICCs is subsumed by different variables instead of being used as the main specification.

[21] Data on active share is obtained from `http://www.petajisto.net/data.html`.

Table 4.4: ICC and Mutual Fund Performance: Subsumption Test

This table presents results from pooled OLS regressions akin to Table 4.3, that relate future, quarterly fund performance with most recent fund-level ICC. The analysis is performed at the fund-quarter-level. The five analyzed performance measures are return (*Return*), style-adjusted return (*SReturn*), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha (*Alpha*1) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns (*DGTW*), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the quarterly level using compounding. The main independent variable is *ICC*; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2. In relation to Table 4.3, active share (*ActShare*) as per Cremers and Petajisto (2009) and Cremers, Petajisto, and Zitzewitz (2013), the industry concentration index (*ICI*) by Kacperczyk, Sialm, and Zheng (2005), the return gap (*RetGap*) in Kacperczyk, Sialm, and Zheng (2008), and the lagged, respective performance measure (*LaggedPerf*) are added as regressors. Controls are described in Table 4.1. Regressions are run with time-by-style and fund-by-manager fixed effects (FE), for each of the four earnings specifications used to obtain stock-level ICCs separately. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Analyst					EP (2014)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	2.6604***	2.5550***	2.0001***	1.3484***	1.5171***	1.5251***	1.4000***	1.4995***	1.9167***	0.8574***
	(8.44)	(8.09)	(5.98)	(4.12)	(4.85)	(5.38)	(4.77)	(5.00)	(6.40)	(3.36)
ActShare	0.0177***	0.0162***	0.0191***	0.0116**	0.0109**	0.0236***	0.0220***	0.0226***	0.0112**	0.0142***
	(3.78)	(3.46)	(4.05)	(2.43)	(2.56)	(4.94)	(4.61)	(4.70)	(2.28)	(3.24)
ICI	−0.0166***	−0.0196***	−0.0103*	−0.0054	−0.0091	−0.0214***	−0.0240***	−0.0138**	−0.0076	−0.0118**
	(−3.02)	(−3.33)	(−1.76)	(−0.90)	(−1.60)	(−3.71)	(−3.94)	(−2.28)	(−1.24)	(−2.02)
RetGap	0.0098	−0.0035	−0.0091	−0.0226	0.0392*	0.0166	0.0032	−0.0048	−0.0234	0.0390*
	(0.44)	(−0.16)	(−0.43)	(−0.82)	(1.79)	(0.75)	(0.14)	(−0.23)	(−0.85)	(1.79)
LaggedPerf	0.1605***	0.1901***	0.1525***	−0.0147	0.0790***	0.1495***	0.1800***	0.1454***	−0.0142	0.0741***
	(13.45)	(17.05)	(11.84)	(−0.94)	(5.64)	(12.80)	(16.25)	(11.31)	(−0.92)	(5.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund×Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,668	25,668	24,744	24,744	25,185	25,668	25,668	24,744	24,744	25,185
Adj. R^2	0.830	0.361	0.443	0.181	0.292	0.829	0.357	0.443	0.186	0.291
	RI (2014)					HvDZ (2012)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	1.8381***	1.7737***	1.3603***	1.5988***	0.8105***	1.4636***	1.4422***	1.2160***	1.3543***	0.5570**
	(6.72)	(6.57)	(4.96)	(5.11)	(3.22)	(5.88)	(5.94)	(4.90)	(5.36)	(2.43)
ActShare	0.0229***	0.0211***	0.0231***	0.0123**	0.0145***	0.0265***	0.0245***	0.0255***	0.0153***	0.0163***
	(4.74)	(4.39)	(4.79)	(2.50)	(3.31)	(5.54)	(5.15)	(5.28)	(3.08)	(3.73)
ICI	−0.0231***	−0.0258***	−0.0149**	−0.0089	−0.0128**	−0.0235***	−0.0263***	−0.0154**	−0.0094	−0.0130**
	(−3.99)	(−4.21)	(−2.47)	(−1.43)	(−2.19)	(−4.09)	(−4.29)	(−2.54)	(−1.52)	(−2.20)
RetGap	0.0149	0.0012	−0.0048	−0.0236	0.0402*	0.0163	0.0025	−0.0040	−0.0223	0.0403*
	(0.68)	(0.06)	(−0.23)	(−0.86)	(1.84)	(0.75)	(0.11)	(−0.19)	(−0.81)	(1.85)
LaggedPerf	0.1540***	0.1845***	0.1477***	−0.0109	0.0752***	0.1541***	0.1847***	0.1478***	−0.0115	0.0742***
	(13.20)	(16.73)	(11.45)	(−0.70)	(5.33)	(13.21)	(16.86)	(11.66)	(−0.74)	(5.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund×Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,661	25,661	24,738	24,738	25,179	25,661	25,661	24,738	24,738	25,179
Adj. R^2	0.830	0.358	0.441	0.183	0.290	0.830	0.357	0.441	0.182	0.290

mance, skilled managers might be more likely to choose them. Simultaneously, skilled managers, following an assortative matching rationale,[22] potentially are matched to specific funds with higher resources. Holding those matches constant, I aim to control for endogeneity at the time-invariant manager-skill- and manager-fund-match-level. Results indicate, that none of the considered aspects is able to explain the positive association of current ICCs with future fund performance, suggesting that a high-ICC strategy per se can help funds to achieve better performance.

Combining the positive association between future fund performance and current ICC on the one hand with its high autocorrelation and moderate turnover in portfolio sorts on the other suggests that correlation with performance might persist. That is, the association of ICCs with performance were not limited to next quarter's value, but to performance further afar. To test this hypothesis, I relate semi-annual, annual, and biennial future performance with current, correspondingly scaled ICC in regression (4.3). To avoid using overlapping observations and more closely resemble investment decisions of investors,[23] I consider ICCs as of December; semi-annual regressions allow to also use ICCs derived from holdings in June.

Table 4.5 documents results of corresponding regressions. While ICCs largely remain statistically significant for all maturities, consistent with strong, yet decreasing autocorrelation in Table 4.1, both economic significance, measured by the size of coefficients, and statistical significance decrease with increasing horizon. For example, the coefficients in regressions related to $Alpha6$ for HvDZ-based ICCs decrease from approximately 0.8, statistically significant at the 1%-level, to 0.2, statistically significant at the 10%-level. $Alpha6$ is also the measure with lowest signs of persistence; while significant in semi-annual and annual regressions, it is not significantly related to ICCs in biennial regressions for EP- and RI-based earnings forecasts. This is in line with factor loadings in Table 4.2, which seem to explain part of the return accruing to ICC-based strategies.

Results are consistent with the notion that ICCs as a persistence characteristic

[22] For studies on assignment models, confer Mayer (1960), Sattinger (1975, 1993), Rosen (1982), Gabaix and Landier (2008), and Terviö (2008).

[23] Several studies argue that investors primarily make their investment decisions based on calendar year returns, confer, e.g., Brown, Harlow, and Starks (1996), Sirri and Tufano (1998), and Chaudhuri, Ivković, and Trzcinka (2018).

Table 4.5: ICC and Mutual Fund Performance: Persistence

This table presents results from pooled OLS regressions that relate future, quarterly fund-portfolio performance with most recent fund-level ICC. The analysis is performed at the fund-semi-annual-, fund-annual- and fund-biannual-level. The five analyzed performance measures are return (*Return*), style-adjusted return (*SReturn*), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha (*Alpha*1) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns (*DGTW*), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the respective time-level using compounding. In particular, for each performance measure, the first columns correspond to semi-annual, the second columns to annual, and the third columns to biannual values of the respective performance measures. The main independent variable is *ICC*; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2. ICCs are scaled to match the respective time horizon. Controls are described in Table 4.1. Regressions are run with time-by-style and fund fixed effects (FE), for each of the four earnings specifications used to obtain stock-level ICCs separately. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 4.5: ICC and Mutual Fund Performance: Persistence (Continued)

Analyst

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	1.4296***	1.3464***	1.4351***	1.2638***	1.0832***	1.2203***	1.4274***	0.8486***	1.1244***	0.9238***	0.3717***	0.5196***	0.7900***	0.7764***	0.7876***
	(5.80)	(5.51)	(7.96)	(5.49)	(5.26)	(8.47)	(10.63)	(4.92)	(8.02)	(5.90)	(2.86)	(3.82)	(6.46)	(6.24)	(6.37)
Log(Age)	−0.0005	0.0024	0.0052	−0.0010	0.0018	0.0099	−0.0085***	0.0001	−0.0015	−0.0077***	−0.0030	0.0009	0.0026**	0.0075***	0.0134**
	(−0.38)	(0.92)	(0.69)	(−0.83)	(0.75)	(1.50)	(−5.05)	(0.05)	(−0.22)	(−4.91)	(−1.04)	(0.14)	(2.33)	(3.53)	(2.20)
Log(TNA)	−0.0109***	−0.0230***	−0.0462***	−0.0105***	−0.0215***	−0.0431***	−0.0034***	−0.0185***	−0.0365***	−0.0023***	−0.0125***	−0.0277***	−0.0065***	−0.0135***	−0.0280***
	(−25.91)	(−23.84)	(−22.58)	(−25.99)	(−24.30)	(−23.68)	(−9.15)	(−22.37)	(−21.11)	(−6.66)	(−18.25)	(−16.62)	(−19.56)	(−19.68)	(−18.02)
Exp. Ratio	−0.4029***	−0.5965***	−0.8918***	−0.3959***	−0.5625***	−0.7957***	−0.3403***	−0.4704***	−0.7026***	−0.3494***	−0.6585***	−0.6834***	0.0699***	0.1109***	−1.5375***
	(−10.32)	(−8.13)	(−5.05)	(−10.69)	(−7.57)	(−4.14)	(−12.10)	(−6.37)	(−6.39)	(−9.66)	(−8.08)	(−5.59)	(2.89)	(3.55)	(−5.40)
Turn. Ratio	0.0016**	0.0022	0.0054**	0.0016*	0.0031	0.0049*	−0.0005	−0.0011	0.0003	−0.0007	−0.0008	−0.0012	−0.0015**	−0.0024*	−0.0062**
	(1.97)	(1.08)	(1.96)	(1.81)	(1.43)	(1.95)	(−0.85)	(−1.25)	(0.22)	(−1.23)	(−0.82)	(−0.72)	(−2.42)	(−1.82)	(−1.97)
Flow	0.0000***	−0.0000***	−0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.06)	(−3.55)	(−0.23)	(1.81)	(−4.37)	(1.20)	(1.47)	(−1.10)	(−0.73)	(4.24)	(−0.40)	(0.47)	(1.92)	(3.13)	(0.12)
I(Team)	−0.0003	−0.0012	−0.0068*	0.0005	−0.0000	−0.0052	−0.0013*	−0.0023	−0.0050	−0.0013*	−0.0012	−0.0034	−0.0011*	−0.0016	−0.0019
	(−0.47)	(−0.75)	(−1.88)	(0.71)	(−0.01)	(−1.61)	(−1.70)	(−1.48)	(−1.38)	(−1.82)	(−0.78)	(−1.04)	(−1.73)	(−1.23)	(−0.61)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,014	29,462	12,182	60,014	29,462	12,182	54,472	27,592	12,175	54,472	27,592	12,175	56,159	26,476	10,208
Adj. R^2	0.837	0.843	0.886	0.292	0.296	0.316	0.449	0.482	0.517	0.159	0.204	0.174	0.316	0.330	0.341

EP (2014)

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	0.9516***	0.9972***	0.7169***	0.9363***	0.9280***	0.7555***	0.9927***	0.5812***	0.1974	0.6691***	0.3605***	0.2174	0.6366***	0.7890***	0.4877***
	(7.88)	(5.82)	(4.22)	(7.87)	(6.30)	(5.81)	(7.62)	(3.94)	(1.58)	(4.97)	(2.80)	(1.62)	(5.99)	(6.12)	(5.05)
Log(Age)	−0.0001	0.0028	0.0053	−0.0007	0.0021	0.0097	−0.0081***	0.0002	−0.0006	−0.0075***	−0.0030	0.0009	0.0028**	0.0076***	0.0135**
	(−0.06)	(1.08)	(0.71)	(−0.56)	(0.86)	(1.48)	(−4.90)	(0.08)	(−0.09)	(−4.82)	(−1.07)	(0.15)	(2.45)	(3.53)	(2.23)
Log(TNA)	−0.0109***	−0.0227***	−0.0464***	−0.0104***	−0.0212***	−0.0429***	−0.0033***	−0.0184***	−0.0375***	−0.0022***	−0.0123***	−0.0278***	−0.0065***	−0.0132***	−0.0280***
	(−26.27)	(−23.85)	(−22.67)	(−26.19)	(−24.20)	(−23.55)	(−9.21)	(−22.74)	(−21.22)	(−6.82)	(−18.48)	(−16.85)	(−19.48)	(−19.40)	(−17.82)
Exp. Ratio	−0.4014***	−0.6349***	−0.8050***	−0.3768***	−0.5438***	−0.7602***	−0.3512***	−0.5136***	−0.6145***	−0.3807***	−0.6335***	−0.6343***	0.0063	0.1164***	−1.6381***
	(−15.15)	(−9.69)	(−5.94)	(−9.89)	(−9.75)	(−4.44)	(−17.46)	(−11.06)	(−6.69)	(−16.43)	(−9.72)	(−5.63)	(0.11)	(4.48)	(−6.09)
Turn. Ratio	0.0016**	0.0024	0.0045*	0.0016**	0.0032*	0.0043*	−0.0005	−0.0008	−0.0005	−0.0007	−0.0005	−0.0016	−0.0013**	−0.0023*	−0.0060*
	(2.41)	(1.35)	(1.80)	(2.16)	(1.67)	(1.89)	(−0.87)	(−0.95)	(−0.40)	(−1.22)	(−0.62)	(−0.97)	(−2.06)	(−1.74)	(−1.96)
Flow	0.0000***	−0.0000***	−0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.06)	(−3.28)	(−0.26)	(1.76)	(−4.17)	(1.23)	(1.35)	(−1.10)	(−0.89)	(4.17)	(−0.43)	(0.45)	(1.88)	(3.53)	(0.19)
I(Team)	−0.0005	−0.0016	−0.0084**	0.0004	−0.0002	−0.0064*	−0.0015*	−0.0026	−0.0068*	−0.0014**	−0.0012	−0.0040	−0.0012*	−0.0017	−0.0026
	(−0.64)	(−0.92)	(−2.20)	(0.57)	(−0.14)	(−1.90)	(−1.88)	(−1.59)	(−1.77)	(−1.96)	(−0.80)	(−1.20)	(−1.83)	(−1.25)	(−0.81)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,042	29,472	12,187	60,042	29,472	12,187	54,493	27,598	12,180	54,493	27,598	12,180	56,178	26,478	10,210
Adj. R^2	0.836	0.843	0.884	0.291	0.298	0.314	0.449	0.481	0.508	0.161	0.208	0.174	0.315	0.332	0.340

Table 4.5: ICC and Mutual Fund Performance: Persistence (Continued)

RI (2014)

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	1.3488***	1.2200***	1.0160***	1.2238***	1.0612***	0.9090***	1.1786***	0.7885***	0.4322***	0.7873***	0.3909***	0.0973	0.7438***	0.6485***	0.4366***
	(11.02)	(7.25)	(5.65)	(10.23)	(7.45)	(6.43)	(10.69)	(5.95)	(3.22)	(6.14)	(3.66)	(0.81)	(6.96)	(4.97)	(4.25)
Log(Age)	−0.0003	0.0027	0.0049	−0.0009	0.0020	0.0096	−0.0084***	−0.0001	−0.0010	−0.0076***	−0.0031	0.0013	0.0027**	0.0076***	0.0135**
	(−0.21)	(1.02)	(0.67)	(−0.69)	(0.83)	(1.46)	(−5.01)	(−0.03)	(−0.15)	(−4.87)	(−1.08)	(0.20)	(2.35)	(3.55)	(2.21)
Log(TNA)	−0.0108***	−0.0229***	−0.0464***	−0.0105***	−0.0214***	−0.0432***	−0.0033***	−0.0184***	−0.0372***	−0.0023***	−0.0124***	−0.0282***	−0.0065***	−0.0135***	−0.0285***
	(−26.15)	(−23.84)	(−22.89)	(−25.96)	(−24.20)	(−23.73)	(−9.07)	(−22.43)	(−21.23)	(−6.69)	(−18.27)	(−16.91)	(−19.38)	(−19.70)	(−18.04)
Exp. Ratio	−0.3879***	−0.6377***	−0.8261***	−0.3621***	−0.5434***	−0.7721***	−0.3357***	−0.5190***	−0.6299***	−0.3702***	−0.6322***	−0.6277***	0.0215	0.1291***	−1.6543***
	(−12.57)	(−9.11)	(−5.49)	(−8.47)	(−10.35)	(−4.23)	(−16.20)	(−10.12)	(−6.42)	(−18.82)	(−9.96)	(−5.44)	(0.43)	(4.16)	(−5.72)
Turn. Ratio	0.0015**	0.0020	0.0045*	0.0015**	0.0029	0.0043*	−0.0005	−0.0012	−0.0004	−0.0007	−0.0009	−0.0016	−0.0014**	−0.0022*	−0.0062**
	(2.19)	(1.18)	(1.66)	(1.97)	(1.54)	(1.78)	(−1.00)	(−1.46)	(−0.33)	(−1.33)	(−0.97)	(−0.97)	(−2.24)	(−1.72)	(−1.98)
Flow	0.0000***	−0.0000***	−0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.05)	(−3.04)	(−0.16)	(1.80)	(−3.86)	(1.25)	(1.40)	(−1.10)	(−0.80)	(4.20)	(−0.40)	(0.41)	(1.95)	(3.37)	(0.13)
I(Team)	−0.0004	−0.0014	−0.0079**	0.0005	−0.0001	−0.0061*	−0.0014*	−0.0025	−0.0064*	−0.0014*	−0.0012	−0.0041	−0.0012*	−0.0018	−0.0026
	(−0.47)	(−0.87)	(−2.11)	(0.71)	(−0.10)	(−1.83)	(−1.78)	(−1.54)	(−1.70)	(−1.87)	(−0.80)	(−1.25)	(−1.74)	(−1.33)	(−0.83)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,027	29,465	12,181	60,027	29,465	12,181	54,480	27,592	12,174	54,480	27,592	12,174	56,168	26,473	10,208
Adj. R^2	0.837	0.843	0.884	0.293	0.298	0.313	0.449	0.483	0.509	0.161	0.208	0.172	0.317	0.329	0.337

HvDZ (2012)

	Return			SReturn			Alpha1			Alpha6			DGTW		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ICC	1.0415***	1.1818***	1.1578***	0.9633***	1.0441***	0.9992***	1.1440***	0.7225***	0.5272***	0.7779***	0.2578*	0.1914*	0.5953***	0.6021***	0.4220***
	(5.51)	(5.77)	(7.41)	(5.00)	(5.99)	(7.87)	(10.87)	(4.13)	(4.52)	(6.07)	(1.79)	(1.72)	(5.54)	(5.70)	(4.28)
Log(Age)	−0.0002	0.0027	0.0058	−0.0008	0.0020	0.0104	−0.0083***	0.0000	−0.0007	−0.0076***	−0.0029	0.0013	0.0028**	0.0076***	0.0139**
	(−0.12)	(1.01)	(0.78)	(−0.61)	(0.80)	(1.58)	(−4.97)	(0.01)	(−0.10)	(−4.83)	(−1.03)	(0.19)	(2.45)	(3.57)	(2.27)
Log(TNA)	−0.0110***	−0.0229***	−0.0461***	−0.0106***	−0.0213***	−0.0430***	−0.0034***	−0.0184***	−0.0370***	−0.0023***	−0.0125***	−0.0280***	−0.0066***	−0.0135***	−0.0285***
	(−26.35)	(−24.18)	(−23.00)	(−26.00)	(−24.41)	(−23.89)	(−9.11)	(−22.68)	(−21.23)	(−6.68)	(−18.25)	(−16.87)	(−19.75)	(−19.98)	(−18.12)
Exp. Ratio	−0.3819***	−0.6305***	−0.8239***	−0.3568***	−0.5375***	−0.7683***	−0.3330***	−0.5119***	−0.6309***	−0.3686***	−0.6256***	−0.6318***	0.0207	0.1167***	−1.5969***
	(−10.48)	(−10.72)	(−5.75)	(−7.14)	(−8.98)	(−4.36)	(−15.73)	(−11.52)	(−6.56)	(−19.21)	(−9.01)	(−5.48)	(0.44)	(4.25)	(−5.48)
Turn. Ratio	0.0015**	0.0024	0.0042	0.0016**	0.0032*	0.0040*	−0.0006	−0.0009	−0.0005	−0.0008	−0.0006	−0.0016	−0.0013**	−0.0021*	−0.0060*
	(2.35)	(1.51)	(1.59)	(2.08)	(1.81)	(1.71)	(−1.01)	(−1.14)	(−0.42)	(−1.29)	(−0.73)	(−0.98)	(−2.05)	(−1.66)	(−1.92)
Flow	0.0000***	−0.0000***	0.0000	0.0000*	−0.0000***	0.0000	0.0000	−0.0000	−0.0000	0.0000***	−0.0000	0.0000	0.0000*	0.0000***	0.0000
	(3.10)	(−3.09)	(0.15)	(1.82)	(−3.93)	(1.47)	(1.47)	(−1.11)	(−0.64)	(4.27)	(−0.41)	(0.48)	(1.90)	(3.42)	(0.09)
I(Team)	−0.0004	−0.0014	−0.0077**	0.0005	−0.0001	−0.0059*	−0.0014*	−0.0024	−0.0063*	−0.0013*	−0.0012	−0.0040	−0.0012*	−0.0018	−0.0025
	(−0.55)	(−0.83)	(−2.03)	(0.64)	(−0.06)	(−1.78)	(−1.75)	(−1.52)	(−1.66)	(−1.85)	(−0.83)	(−1.21)	(−1.81)	(−1.34)	(−0.81)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,027	29,464	12,181	60,027	29,464	12,181	54,481	27,593	12,174	54,481	27,593	12,174	56,168	26,473	10,208
Adj. R^2	0.836	0.843	0.885	0.290	0.299	0.317	0.449	0.482	0.510	0.161	0.207	0.173	0.315	0.329	0.337

lend themselves as a measure for the long-term fate of a fund. This potentially accommodates investors, considering that determination of a fund's ICC arguably is not a straightforward endeavor, in particular for retail investors (as discussed in Section 4.5.2). Further, whereas investors' positive flow response to high past fund performance is still erroneous on average, for the subset of funds with both high past performance and high ICC, investors are more likely to see their expectation of high future performance fulfilled. Hence, albeit spuriously, for these investors investment decisions could lead to a positive feed-back loop, potentially adding to the explanation for why investors cater to past returns.

4.3.3 Fund Trades

After documenting evidence for a positive association between current ICC and future fund performance, this study turns towards a closer examination of trading mechanisms related to ICC. Retrospectively, given the time series of past returns and holdings, one can discern by how much contemporary fund performance was influenced by fund managers' trades. To investigate how trading decisions based on ICC altered a fund's performance, I determine the fraction of a manager's buys and sells "in the same direction" traded firms' ICCs changed. In particular, I compute the trade-weighted percentage of buys (sells) in firms whose ICC increased (decreased) over the same quarter, *%SameDir Buys* (*%SameDir Sells*).

Table 4.6 presents results for regression (4.3), augmented by the two trading variables. Statistically significant at the 1%-level, economically, the results imply that in case 100% of a fund's buys and sells have been in the same direction as the underlying firms' change in ICC, contemporary fund performance was higher by, respectively, approximately 2.5 percentage points. This corroborates the notion that explicitly tailoring a fund's strategy towards firms with higher ICC supports higher performance.

In summary, Section 4.3 provides evidence for a positive association between current ICC and future fund performance. This does not seem to be driven by time effects, differences in styles, or specific fund-manager-matches and appears to be distinct from associations with fund characteristics found in previous literature.

Table 4.6: Directional Trades and Fund Performance

This table presents results from pooled OLS regressions that relate quarterly fund performance with the percentage of buys and sells into the direction of the change in stock-level ICCs over the corresponding quarter. The analysis is performed at the fund-quarter-level. The five analyzed performance measures are return (*Return*), style-adjusted return (*SReturn*), calculated by subtracting from the raw return of a fund the mean raw return of funds with the same investment objective, Jensen-Alpha (*Alpha*1) and the Fama and French (2015) 5-factor alpha, augmented with the momentum factor (*Alpha*6), computed for a given fund each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns returns on the one respectively six risk factor(s), as well as characteristic-adjusted returns (*DGTW*), estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. These adjusted returns are then value-weighted at the fund-portfolio-level. Monthly measures are aggregated to the quarterly level using compounding. The main independent variables are *ICC*, *%SameDir Buys*, and *%SameDir Sells*. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, *ICC*, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2. *%SameDir Buys* (*%SameDir Sells*) denotes the trade-weighted fraction of total buys (sells) in stocks where the ICCs increased (decreased) from one quarter to the next. Controls are described in Table 4.1. Regressions are run with time-by-style and fund fixed effects (FE), for each of the four earnings specifications used to obtain stock-level ICCs separately. T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Analyst					EP (2014)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	1.2962***	1.1142***	0.9705***	0.6674***	0.3565***	1.4509***	1.2897***	1.4655***	1.2824***	0.5706***
	(8.49)	(7.64)	(6.73)	(4.42)	(2.63)	(10.49)	(9.92)	(9.16)	(8.35)	(4.22)
%SameDir Buys	0.0226***	0.0206***	0.0205***	0.0147***	0.0165***	0.0297***	0.0271***	0.0264***	0.0199***	0.0202***
	(20.10)	(18.68)	(19.34)	(15.36)	(16.22)	(25.76)	(23.84)	(24.40)	(20.78)	(19.11)
%SameDir Sells	0.0239***	0.0215***	0.0216***	0.0134***	0.0267***	0.0355***	0.0328***	0.0319***	0.0212***	0.0397***
	(23.80)	(21.28)	(23.79)	(15.57)	(27.55)	(32.65)	(30.50)	(31.85)	(22.63)	(37.97)
Log(Fund Age)	0.0005	0.0002	−0.0004	−0.0014	0.0020***	0.0007	0.0002	−0.0002	−0.0010	0.0021***
	(0.63)	(0.25)	(−0.45)	(−1.54)	(3.00)	(0.95)	(0.31)	(−0.19)	(−1.13)	(3.19)
Log(AUM)	−0.0057***	−0.0057***	−0.0050***	−0.0035***	−0.0032***	−0.0055***	−0.0054***	−0.0046***	−0.0031***	−0.0030***
	(−24.84)	(−25.30)	(−21.28)	(−16.59)	(−17.03)	(−24.73)	(−24.59)	(−21.20)	(−15.38)	(−16.21)
Exp. Ratio	−0.0877**	−0.0948**	−0.0690***	−0.1383***	0.0478***	−0.1498***	−0.1560***	−0.0970***	−0.1907***	0.0097
	(−2.42)	(−2.53)	(−3.66)	(−5.41)	(3.02)	(−3.71)	(−3.87)	(−2.85)	(−6.09)	(0.50)
Turn. Ratio	0.0001	−0.0004	−0.0003	0.0002	−0.0004	−0.0001	−0.0005	−0.0004	−0.0001	−0.0005
	(0.28)	(−0.91)	(−0.89)	(0.84)	(−1.33)	(−0.19)	(−1.35)	(−1.29)	(−0.17)	(−1.62)
Flow	0.0000	0.0000	−0.0000	−0.0000	0.0000	0.0000	0.0000	−0.0000	−0.0000	0.0000
	(0.06)	(1.48)	(−0.49)	(−1.35)	(0.38)	(0.37)	(1.39)	(−0.08)	(−0.95)	(0.55)
I(Team)	−0.0001	0.0003	−0.0002	−0.0006	−0.0005	−0.0001	0.0003	−0.0003	−0.0004	−0.0005
	(−0.29)	(0.79)	(−0.57)	(−1.36)	(−1.20)	(−0.33)	(0.61)	(−0.67)	(−0.87)	(−1.41)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,453	105,453	97,964	97,964	102,881	104,200	104,200	96,708	96,708	101,644
Adj. R^2	0.851	0.257	0.425	0.190	0.293	0.852	0.277	0.446	0.200	0.316

Table 4.6: Directional Trades and Fund Performance (Continued)

	RI (2014)					HvDZ (2012)				
	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW	(1) Return	(2) SReturn	(3) Alpha1	(4) Alpha6	(5) DGTW
ICC	1.7562^{***}	1.5651^{***}	1.1841^{***}	0.9860^{***}	0.6093^{***}	1.2241^{***}	1.1124^{***}	1.0276^{***}	0.8140^{***}	0.3834^{***}
	(13.57)	(12.09)	(10.41)	(8.67)	(5.15)	(10.48)	(9.24)	(9.11)	(7.17)	(3.58)
%SameDir Buys	0.0260^{***}	0.0236^{***}	0.0233^{***}	0.0167^{***}	0.0179^{***}	0.0231^{***}	0.0207^{***}	0.0218^{***}	0.0160^{***}	0.0163^{***}
	(23.53)	(21.86)	(22.15)	(17.89)	(17.95)	(20.49)	(18.66)	(20.72)	(16.82)	(16.29)
%SameDir Sells	0.0328^{***}	0.0304^{***}	0.0297^{***}	0.0208^{***}	0.0380^{***}	0.0289^{***}	0.0270^{***}	0.0274^{***}	0.0197^{***}	0.0343^{***}
	(31.02)	(29.06)	(30.42)	(23.15)	(37.27)	(28.56)	(26.84)	(29.06)	(22.60)	(35.28)
Log(Fund Age)	0.0006	0.0001	−0.0001	−0.0011	0.0020^{***}	0.0007	0.0002	0.0001	−0.0007	0.0021^{***}
	(0.79)	(0.14)	(−0.09)	(−1.17)	(3.11)	(0.95)	(0.30)	(0.09)	(−0.78)	(3.25)
Log(AUM)	-0.0054^{***}	-0.0053^{***}	-0.0046^{***}	-0.0032^{***}	-0.0029^{***}	-0.0054^{***}	-0.0054^{***}	-0.0047^{***}	-0.0032^{***}	-0.0030^{***}
	(−24.49)	(−24.74)	(−21.24)	(−15.83)	(−16.05)	(−25.17)	(−25.41)	(−21.14)	(−16.13)	(−16.49)
Exp. Ratio	-0.1409^{***}	-0.1524^{***}	-0.0937^{***}	-0.1849^{***}	0.0406^{**}	-0.1261^{***}	-0.1343^{***}	-0.0853^{***}	-0.1635^{***}	0.0549^{**}
	(−3.91)	(−3.88)	(−3.04)	(−5.50)	(2.38)	(−5.00)	(−5.12)	(−3.51)	(−8.99)	(2.08)
Turn. Ratio	−0.0002	-0.0007^{*}	-0.0008^{**}	−0.0003	-0.0007^{**}	−0.0001	−0.0005	−0.0003	0.0001	−0.0003
	(−0.66)	(−1.84)	(−2.46)	(−1.16)	(−2.45)	(−0.29)	(−1.37)	(−1.10)	(0.18)	(−1.11)
Flow	0.0000	0.0000^{**}	0.0000	−0.0000	0.0000	0.0000	0.0000	−0.0000	−0.0000	0.0000
	(0.78)	(1.98)	(0.29)	(−0.71)	(0.67)	(0.36)	(1.36)	(−0.08)	(−0.84)	(0.27)
I(Team)	−0.0002	0.0002	−0.0004	−0.0007	−0.0006	−0.0001	0.0003	−0.0004	−0.0006	−0.0005
	(−0.41)	(0.57)	(−1.04)	(−1.55)	(−1.59)	(−0.30)	(0.67)	(−0.94)	(−1.53)	(−1.41)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103,745	103,745	96,331	96,331	101,198	103,565	103,565	96,241	96,241	101,040
Adj. R^2	0.855	0.276	0.446	0.202	0.316	0.855	0.269	0.443	0.199	0.313

4.4 Determinants of ICC Strategies

Having documented possible performance implications of a strategy based on ICCs, this section seeks to uncover potential determinants of how likely managers are to employ such a strategy. For this, I examine cross-sectional heterogeneity to study correlations of ICCs with fund family and manager characteristics. Section 4.4.1 analyses the relation between trading efficiency as a measure for trading costs and ICCs, whereas Section 4.4.2 investigates correlations with fund managers' SAT scores as a proxy for skill.

4.4.1 Trading Efficiency and ICC

Evidence of this study points towards a fund-investment strategy based on ICC yielding actual profits, contrasting literature on ICC at the individual stock- and stock-portfolio-level, where transaction costs appear to predominate returns. One possible part of the explanation for why mutual funds seem to be able to seize the performance potential inherent to a strategy based on ICC could be, that mutual funds, as institutional investors, face particularly favorable trading conditions. This in turn could imply that the height of trading costs mutual funds face were negatively correlated with the probability that they employ high-ICC strategies.

Yet, funds' trading costs are not directly observable. However, Cici, Dahm, and Kempf (2018) derive a proxy for the efficiency of their families' trading desk. The higher the trading desk's efficiency, the lower trading costs arguably are. Hence, I test for the correlation between contemporaneous ICC and trading desk efficiency.

I follow Cici, Dahm, and Kempf (2018) to estimate trading desk efficiency at the family-level. In particular, it obtains as the difference between the gross return of the family's SP500 index fund,[24] incorporating trading costs, and the return of the underlying index, inherently net of costs, within a week before and after index reconstitutions. This difference is averaged for each index fund across all non-overlapping index adjustment periods in a specific quarter to obtain the variable

[24]In cases of multiple SP500 index funds, Cici, Dahm, and Kempf (2018) choose the index fund with the longest track record.

Table 4.7: Trading Efficiency and ICC

This table presents results from pooled OLS regressions which relate quarterly fund-level ICC with family-level trading efficiency. The analysis is performed at the fund-quarter-level. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, ICC, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2 and serves as the dependent variable. The main independent variable is $TradingEfficiency$, a contemporaneous measure for trading-efficiency at the family-level, following Cici, Dahm, and Kempf (2018), described in Section 4.4.1. Controls are described in Table 4.1. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
TradingEfficiency	0.1343**	0.1435**	0.2284***	0.2262***
	(2.26)	(2.33)	(4.10)	(3.97)
Log(Age)	0.0003**	0.0000	0.0001	0.0002
	(2.29)	(0.13)	(0.65)	(1.17)
Log(TNA)	−0.0002***	−0.0003***	−0.0003***	−0.0003***
	(−5.88)	(−4.68)	(−6.17)	(−6.09)
Exp. Ratio	−0.0081	0.0484**	−0.0023	0.0003
	(−0.48)	(2.30)	(−0.12)	(0.01)
Turn. Ratio	−0.0000	0.0000	0.0000	0.0000
	(−0.20)	(0.10)	(1.04)	(0.53)
Flow	0.0000	0.0000***	0.0000***	−0.0000
	(0.95)	(3.72)	(3.31)	(−0.95)
I(Team)	−0.0001	0.0001	−0.0000	−0.0001
	(−0.66)	(0.45)	(−0.12)	(−0.99)
Time×Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	20,432	20,458	20,443	20,436
Adj. R^2	0.705	0.674	0.824	0.836

$TradingEffiency$. It reflects the family's decisions, e.g., in terms of when to trade, which trading venues and/or brokers to use to what extent, and how to place and split which types of orders.

I use Morningstar Direct to obtain data on which funds identify as SP500 index funds (benchmark "SP 500 TR USD"). Because funds outsourced to an external asset management company presumably do not profit from the family's trading desk, Cici, Dahm, and Kempf (2018) exclude them from the analysis. To determine outsourced funds, I retrieve semi-annual and annual NSAR-A and -B filings from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system maintained by the SEC. Item #8. informs about a fund's advisors, the employers of the asset managers conducting the day-to-day-business. I manually match NSAR-information by fund share class name and date and construct a time series of which family is affiliated with which advisor.

Table 4.7 presents results from a regression akin to model (4.3), where I correlate contemporaneous ICC as the dependent variable to trading efficiency, which is the same for all funds in the same family in quarter t. Statistically significant at the 5%-level, results indicate that funds in families with higher trading efficiency are more likely to employ a high-ICC strategy. This is consistent with the notion that a favorable transaction cost environment helps funds monetizing the previously documented potential of ICC-based investments to generate outperformance.[25]

4.4.2 Fund Manager Skill and ICC

The positive association between ICC and fund performance is consistent with successfully employing investment strategies based on firms' ICCs reflecting skill, which some managers are equipped with and which others lack. Hence, measures for a manager's skill might positively correlate with her funds' ICC.

As a proxy for managerial skill I follow literature [e.g., Greenwood and Nagel (2009) and Fang, Kempf, and Trapp (2014)] and use the average matriculates' SAT score of the institution where a manager obtained her bachelor's degree. To collect information on which universities managers obtained their degree from, I use the following data sources. Besides Morningstar Direct and Morningstar Principia CDs from 1996 to 2005, I search through fund filings with the SEC (e.g., forms 485APOS/485BPOS, 497, and accompanying statements of additional information), Marquis Who's Who, newspaper articles, LinkedIn, Bloomberg, the websites of fund companies, as well as university sources such as yearbooks, alumni, and donation pages. Average SAT scores of these institutions are obtained from the College Score-

[25] Adding $TradingEfficency$ as a regressor to ICC in the analysis in Table 4.4 does not alter results, reinforcing ICCs themselves being the actual driver behind performance. In an aim to examine whether returns to ICC reflect an illiquidity premium, I consider alphas with respect to the model in Pástor and Stambaugh (2003), who add a liquidity factor. Results (not reported) are even stronger than for the six-factor alpha.

Table 4.8: Fund Manager SAT Score and ICC

This table presents results from pooled OLS regressions which relate quarterly fund-level ICC with fund managers' SAT score. The analysis is performed at the fund-quarter-level. For every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, ICC, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2 and serves as the dependent variable. The main independent variable is SAT, a contemporaneous measure for the SAT score of a fund's managers, which obtains as the mean of a fund's corresponding managers' associated SAT score. Controls are described in Table 4.1. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. Throughout this table, ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
SAT	0.0007***	0.0009***	0.0008***	0.0010***
	(3.47)	(3.04)	(2.86)	(3.18)
Log(Age)	0.0001*	0.0001	0.0002*	0.0001
	(1.70)	(1.07)	(1.80)	(1.44)
Log(TNA)	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(−8.57)	(−8.80)	(−5.98)	(−6.12)
Exp. Ratio	−0.0115***	0.0428***	0.0280***	0.0087***
	(−3.93)	(11.83)	(8.90)	(4.47)
Turn. Ratio	0.0000	0.0000	0.0000**	0.0000
	(1.25)	(1.16)	(2.06)	(0.86)
Flow	−0.0000	0.0000	−0.0000	−0.0000
	(−0.73)	(0.32)	(−0.15)	(−0.92)
I(Team)	−0.0001***	−0.0001*	−0.0001***	−0.0002***
	(−2.61)	(−1.67)	(−2.74)	(−2.97)
Time×Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	83,843	83,870	83,863	83,856
Adj. R^2	0.805	0.825	0.877	0.872

card provided by the U.S. Department of Education.[26] To arrive at a value for SAT at the fund-level, SAT, I compute the mean over the SAT scores of all managers managing a fund at a specific point in time, requiring non-missing values for all the fund's managers. In order to ease interpretation of coefficients, SAT scores are divided by 1,000.

Table 4.8 documents results from a regression of contemporaneous fund-level ICC on SAT. Statistically significant at the 1%-level for each of the four ICC specifications, economically results imply that managers associated with the highest SAT

[26] Confer `https://collegescorecard.ed.gov/`.

scores, on average, had quarterly ICCs which were approximately 10 basis points larger than ICCs of managers from universities at the other end of the spectrum, which amounts to roughly 15% of the interquartile range of quarterly ICCs. This provides evidence for skillful managers being more likely to tailor their investments towards high ICCs, consistent with that one particular manifestation of innate ability in the mutual fund industry consists of applying a high-ICC strategy.

4.5 Implications of ICCs' Correlation with Fund Performance

This final section examines, what responses the positive association between current ICCs and future fund performance might evoke, considering two of the central parties involved in mutual fund markets. Section 4.5.1 analyses if incentives of managers themselves are altered, whereas Section 4.5.2 turns towards an examination of whether investors into mutual funds are influenced in their investment decisions.

4.5.1 ICCs' Impact on Managerial Tournament Incentives

Given funds posses the means to capitalize on ICC strategies, they should try to seize them. This knowledge in turn potentially affects a manager's incentives. In particular, she may rely on high ICCs to pay off in the future. This might induce her to react differently from a manager who does not count on such a strategy.

Past research documents how a manager's incentives influence risk-taking. In particular, managers which lie behind their peers in the middle of the year tend to engage into "risk shifting", i.e., to increase risk, in an aim to catch up. Incentives for this behavior are rooted in the pay-off structure managers in the mutual fund industry face, which resembles a "tournament", where winners obtain a price whilst losers come away empty handed. This is due to the industry's remuneration structure. Managers' compensation comprises claims on variable, asymmetric boni [Ma, Tang, and Gómez (2019)] "simply" expiring worthless, given a certain threshold is not met. Simultaneously, another part of managerial pay is based on assets under management [Hu, Hall, and Harvey (2000) and Elton, Gruber, and Blake (2003)]. In this regard, it are investors who incentivize managers via their asymmetric response to past performance; whereas high past performance is eminently rewarded with large inflows, funds with low past performance loose comparably low amounts of assets [e.g., Sirri and Tufano (1998) and Ferreira, Keswani, Miguel, and Ramos (2012)]. Taken together, managers' pay-off resembles that of an option - whose value, ceteris paribus, increases with increasing "risk".

Hence, managers have incentives to "shift" their risk to higher levels given they trail their peers in order to increase their chances to catch up. If a manager, however, in addition or instead relies on other parts of her investment strategy, e.g., high ICC, to pay off, her incentives to increase risk might be muted respectively shut off.

To test for whether managers with high ICC temper their risk shifting, which were lending support to the notion that managers are aware of the benefits of high-ICC strategies and indeed utilize them, I relate mid-year, i.e., end-of-June, ICCs with mid-year performance of managers. To capture how much fund managers intend to change their risk in the second half of the year relative to the first, I construct the risk adjustment ratio as in Kempf, Ruenzi, and Thiele (2009),

$$RAR_{f,t} = \frac{\sigma_{f,t}^{(2),int}}{\sigma_{f,t}^{(1)}}, \tag{4.4}$$

where $\sigma_{f,t}^{(1)}$ denotes realized portfolio risk of fund f in the first half of the year (January to June), calculated using actual portfolio holdings and volatility of corresponding daily portfolio returns in the first half of the year; $\sigma_{f,t}^{(2),int}$ represents intended portfolio risk for the second part of the year (July to December), which is computed using actual portfolio holdings in the second half of the year and a forecast of volatility of corresponding returns, obtained as realized volatility of that portfolio had it been held in the first half of the year. The regression model to test for the impact of high-ICC strategies on tournament behavior is given by

$$\begin{aligned} RAR_{f,t} = \; & \delta_1 \cdot Rank_{f,t} + \delta_2 \cdot HighICC_{f,t} + \delta_3 \cdot Rank_{f,t} \cdot HighICC_{f,t} \\ & + \vec{\boldsymbol{\gamma}} \cdot \vec{\boldsymbol{c}}_{f,t} + \vec{\boldsymbol{\iota}} \cdot \vec{\boldsymbol{\varphi}} + \epsilon_{f,t}, \end{aligned} \tag{4.5}$$

Table 4.9: ICC and Tournament Behavior

This table presents results from pooled OLS regressions which relate mid-year risk-shifting to mid-year performance-ranks and fund-level ICC. The analysis is performed at the fund-year-level. The dependent variable is the risk-adjustment ratio, *RAR*, as defined in Section 4.5.1, equation (4.4). The main independent variables are *Rank*, *HighICC*, and their interaction. *Rank* is calculated for each investment category and year separately. It is normalized to be equally distributed between zero and one, with the best fund manager in its respective investment category being assigned rank one. To obtain *HighICC*, first, for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, *ICC*, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2. Second, this ICC is transformed into an indicator variable, *HighICC*, which takes the value of one, if the respective fund's ICC is larger than the median ICC in that year in the investment category the fund belongs to, and zero else. Controls are described in Table 4.1. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. Throughout this table, ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
Rank	−0.0171***	−0.0189***	−0.0178***	−0.0171***
	(−5.63)	(−6.55)	(−5.74)	(−5.45)
HighICC	−0.0069**	−0.0043	0.0040	0.0031
	(−2.43)	(−1.57)	(1.41)	(1.06)
Rank · HighICC	0.0117***	0.0158***	0.0135***	0.0125***
	(2.78)	(3.76)	(3.20)	(2.98)
Log(Age)	0.0047*	0.0046	0.0046*	0.0045
	(1.67)	(1.64)	(1.65)	(1.63)
Log(TNA)	−0.0011	−0.0010	−0.0009	−0.0009
	(−1.56)	(−1.41)	(−1.24)	(−1.27)
Exp. Ratio	−0.2092***	−0.2143***	−0.2129***	−0.2133***
	(−11.65)	(−11.76)	(−11.87)	(−11.83)
Turn. Ratio	−0.0002	−0.0002	−0.0002	−0.0002
	(−0.18)	(−0.16)	(−0.18)	(−0.14)
Flow	−0.0000***	−0.0000***	−0.0000***	−0.0000***
	(−6.34)	(−7.01)	(−5.32)	(−5.70)
I(Team)	−0.0008	−0.0008	−0.0008	−0.0007
	(−0.53)	(−0.54)	(−0.51)	(−0.48)
Time×Style FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	22,415	22,441	22,442	22,436
Adj. R^2	0.164	0.164	0.166	0.166

where $\epsilon_{f,t}$ denotes the error term. $Rank_{f,t}$, based on fund performance over the first six months each year, is calculated for each investment category separately. It is normalized to be equally distributed between zero and one, with the best fund in its respective investment category being assigned rank one. As $Rank_{f,t}$ is interacted with a fund's ICC, I transform it into indicator variable $HighICC_{f,t}$, equal to one for all funds whose ICC is larger than the median ICC in the same investment category in June of the respective year and zero else. A negative δ_1 were consistent with the tournament literature, suggesting that the lower a manager's rank, the larger her risk shifting. The main variable of interest is δ_3; a positive value lent support to the notion that managers with the same low mid-year rank, albeit high ICC, increase risk less relative to managers with low ICC.

Table 4.9 documents results from regression (4.5). The negative coefficient of $Rank$, statistically significant at the 1%-level, provides evidence for the existence of tournament-like behavior in the sample. In comparison, the coefficient of the interaction with $HighICC$ is statistically significant positive at the same level. Furthermore, associated coefficients, δ_1 and δ_3, are approximately on par in absolute values, with $|\delta_3|$ amounting to roughly 75% of $|\delta_1|$, on average, consistent with managers strongly tempering risk-shifting in case they have a high-ICC strategy at command. This might serve as evidence for managers being both aware of the merits of such a strategy and indeed relying on it.

4.5.2 Investors' Response to Funds' ICCs

Finally, this study aims to investigate investors' awareness of the association between ICCs and fund performance. For this purpose, it considers the relation between current ICC and future fund flows. Rational investors probably would react to the signal ICCs allegedly pose and direct investments into funds with high expected performance. This signal, however, comes at a cost, which presumably is not constant throughout a fund's investor base. In terms of data necessary to determine a fund's ICC, a fund only provides its holdings. Data at the stock-level, e.g., market and book values of equity, dividends, and earnings together with predictions thereof, which are either based on analysts or obtained via statistical models, have to be accessible for and gathered by investors themselves. Consecutively, ICCs need to be actually computed, necessitating the knowledge of the various models and respective resources required for calculation. Furthermore, the association between ICC and fund performance is not advertised either, such that investors have to uncover it themselves.

Table 4.10: ICC and Mutual Fund Flows

This table presents results from pooled OLS regressions, that relate quarterly flows with fund-level ICC. The analysis is performed at the fund-share-class-quarter-level. The dependent variable is *Flow*, the percentage quarterly growth in fund's new money in %, net of the effect of returns. The analysis is split between retail share classes in Panel A and institutional share classes in Panel B. The main independent variable is *ICC*; for every fund every quarter, a value-weighted ICC of the funds' portfolios' constituents, based on four different proxies for expected earnings, is constructed as described in Section 4.2.2. Controls are described in Table 4.1. Regressions are run with time-by-style and fund fixed effects (FE). T-statistics, based on standard errors clustered at the fund level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Panel A: Retail share classes				Panel B: Institutional share classes			
	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)	(1) Analyst	(2) EP (2014)	(3) RI (2014)	(4) HvDZ (2012)
ICC	−0.0543	0.0884	−0.0679	0.2443	1.5890***	1.1785**	1.5882***	2.4125***
	(−0.20)	(0.51)	(−0.28)	(0.87)	(2.69)	(2.00)	(3.07)	(4.20)
Log(Age)	−0.0301***	−0.0301***	−0.0300***	−0.0300***	−0.0315***	−0.0315***	−0.0316***	−0.0318***
	(−19.25)	(−19.27)	(−19.40)	(−19.39)	(−12.70)	(−12.70)	(−12.73)	(−12.81)
Log(TNA)	−0.0094***	−0.0094***	−0.0094***	−0.0094***	−0.0240***	−0.0239***	−0.0239***	−0.0239***
	(−15.08)	(−15.10)	(−15.18)	(−15.18)	(−24.03)	(−24.02)	(−24.01)	(−24.03)
Exp. Ratio	−0.1422**	−0.1404**	−0.1354**	−0.1351**	−6.0129***	−6.0082***	−5.9959***	−6.0227***
	(−2.03)	(−2.05)	(−2.03)	(−2.02)	(−10.85)	(−10.85)	(−10.83)	(−10.88)
Turn. Ratio	0.0033**	0.0032**	0.0030**	0.0030**	−0.0056**	−0.0054**	−0.0056**	−0.0056**
	(2.41)	(2.45)	(2.38)	(2.38)	(−2.10)	(−2.02)	(−2.07)	(−2.09)
Flow	0.1987***	0.1986***	0.2000***	0.2000***	0.1558***	0.1553***	0.1555***	0.1555***
	(12.84)	(12.84)	(13.17)	(13.17)	(21.86)	(21.84)	(21.87)	(21.88)
I(Team)	−0.0015	−0.0015	−0.0014	−0.0014	0.0009	0.0005	0.0006	0.0008
	(−0.78)	(−0.79)	(−0.74)	(−0.74)	(0.22)	(0.13)	(0.14)	(0.19)
Past Return	0.3320***	0.3337***	0.3326***	0.3333***	0.3392***	0.3399***	0.3405***	0.3435***
	(15.43)	(15.71)	(15.66)	(15.66)	(12.17)	(12.29)	(12.27)	(12.38)
Time×Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	274,757	275,068	274,973	274,882	109,094	109,134	109,155	109,149
Adj. R^2	0.181	0.181	0.181	0.181	0.130	0.130	0.130	0.130

I hypothesize that a moderating factor for the subjective costs of the signal and hence investors' reaction can be derived from their classification into retail and institutional. While the "representative agent" for the former might be the average U.S.-household with presumably limited "resources" (confer the references in the introduction), institutional investors might have the means mentioned above at command. This suggests that retail investors would not react to current ICC, while institutional did.

Table 4.10 tests for this hypothesis, employing a fund's future flow as the dependent variable in regression (4.3) and past fund return (*Past Return*) as an additional control variable.[27] The analysis is stratified by retail (Panel A) and institutional share classes (Panel B). While there is no association between current ICC and future flow in the retail stratum, it is positive and significant at the 5%-level for EP-based ICCs and at the 1%-level for the remaining ICCs in the panel of institutional share classes. Concerning economic significance, a 1-percentage-point increase in ICCs is associated with a 1.5 percentage point increase in quarterly flows, on average. This is consistent with limited attention of retail investors respectively allegedly more sophisticated institutional investors' awareness of ICCs' positive association with future fund performance.

4.6 Conclusion

What kind of trading strategies do skillful mutual fund managers employ and how can investors identify them? Although research documents that portfolio selection based on firms' ICCs in general founders on necessary transaction costs, mutual fund managers seem to be able to bring to bearing corresponding return potentials.

Computing holdings' implied ICC of mutual funds, this study provides evidence for a viable correlation between a fund's current ICC and its future performance. This association is present both in portfolio sorts, which result into actual, risk- respectively style-adjusted performance after costs, and panel regressions, which allow to control for confounding factors at the time-, style-, and fund-level. Consistent

[27] Inferences remain the same, when return is replaced by either of the other four performance measures.

with mutual funds being particularly well equipped to actually implement ICC-based investment decisions due to their preferential trading opportunities, funds with access to trading desks with a high degree of efficiency are more prone to employ a high-ICC strategy. Likewise, based on the average matriculates' SAT score of the institutions managers received their bachelor's degree from, managers with supposed higher innate ability employ such a strategy more often. In general, managers themselves appear to be both aware of and confident with respect to ICC-based investment strategies, as they are less likely to engage into risk-shifting should they lie behind their peers in the middle of the year but have a high-ICC strategy at their command. With regard to investors' awareness, however, only more sophisticated institutional investors seem to recognize and trade based on the positive association between current ICCs and future performance as opposed to retail investors.

In summary, with regard to the questions raised in the introduction that are tackled by research - whether mutual fund managers have skill picking stocks and how information advantages are developed and exploited by market participants -, a fraction of funds seems to demonstrate skill by exploiting information and trading cost advantages with respect to an investment strategy based on ICC. Hence, part of the explanation for the "puzzling" prosperity of the mutual fund industry might be, that some funds with reliable proficiencies indeed exist.

Appendix to Chapter 2

NCCs in the Investment Industry

Since human capital is one of the most important means of production for mutual fund families [e.g., Berk, van Binsbergen, and Liu (2017)], the main rationale for utilizing NCCs by mutual fund management companies is to retain talent. In addition, by restricting employee mobility, fund families hinder dissemination of their organization knowledge to competitors and also keep their portfolio managers from taking the firms' clients with them when they join a competitor or start their own firm.

There are no requirements for investment firms such as mutual fund families and affiliated entities to report information related to their use of NCCs, thus detailed data on which of their employees are subject to NCCs and under what terms is unavailable. Nonetheless, given the human capital- and knowledge-intensive nature of the mutual fund industry, there are a number of indications that NCCs are commonly used in this industry. There is some indirect evidence that comes from the survey of Starr, Prescott, and Bishara (2019). Although the survey does not single out mutual fund managers, these individuals fit the income and industry profile of employees that the survey shows to be typically subjected to such restrictions. For example, Starr, Prescott, and Bishara (2019) document that employees in the highest income bracket ($150K+) have the highest incidence rate, as high as about 60%, of being subjected to NCCs. Moreover, the broader industry in which they work, i.e., financial services, is close to the top 20% of industries with the highest incidence rate of NCCs.

There is also some direct, albeit rather limited, evidence in the public domain, which is primarily available through business press coverage of career moves of well-known fund managers. This evidence suggests that NCCs have been used in the mutual fund industry for a long time. Below we provide a list of examples to illustrate the type of coverage that NCCs have received in the press. One of the earliest examples was the case of Jack Bogle, former CEO of Vanguard Group and a highly influential figure in the mutual fund industry. He was subject to a NCC with the Wellington Management Company after leaving in 1974 to found the Vanguard Group. The outstanding NCC restricted Bogle from entering the active fund management business, but it did not apply to passive management, which allowed Bogle to introduce the first index fund [Regan (2016)]. In a much later example we are told that Ryan Caldwell, a portfolio manager for Waddell & Reed, "resigned from Waddell & Reed in June 2014, and as soon as his non-compete agreement elapsed, he launched the Chiron Capital Allocation Fund" [Dornbrook (2017)]. Among all the NCC examples covered by the press, one stood out as the most restrictive. It involved Michael Price, a well-known fund manager. When he left Franklin Mutual Fund Advisors in 2001, it was disclosed that a NCC forbade him from working in the mutual fund business for another 10 years [Wiser (2001)].

Upon review of such articles, we identified a number of investment companies that at one point had a pending NCC with at least one departing fund manager.[1] These NCCs typically ranged from one to three years and in some cases were accompanied by non-solicitation agreements barring fund managers from doing business with their former firms' clients. In the process of reviewing these articles, we also came across additional evidence on the use of NCCs from coverage of lawsuits filed by investment firms against their former fund managers for breach of their NCCs. Asset management companies that brought lawsuits against their former fund managers that we were able to identify from the business press include Wellington Capital Management, Boston Partners Asset Management, Pilgrim, Baxter & Associates, State Street, Bridgewater Associates, and Citadel Investment Group.[2]

Finally, besides information on NCCs revealed in the business press, textual analysis of SEC filings by mutual fund companies (e.g., Prospectus or Statement of Additional Information) identified a couple of mutual funds self-reporting that

[1]The list includes AIM Fund Management, Boston Company, Boston Partners Asset Management, Bridgewater Associates, Citadel Investment Group, Fidelity Management & Research, Goldman Sachs Asset Management, Pilgrim, Baxter & Associates, Putnam Investments, State Street, Waddell & Reed, Wedge Capital Management, and Wellington Management Company.

[2]Lawsuits by these companies are respectively mentioned by Sakelaris (1998), Healy (2001), Franecki (1999), Capon (2012), Goldstein and Stevenson (2016), and Herbst-Bayliss (2009). It is likely that some other unreported disputes were settled earlier on out of court and never became public knowledge.

their portfolio managers were restricted by NCCs. For example, a 2014 filing by Natixis Funds states that "[t]he non-competition and non-solicitation undertakings will expire the later of one year from the termination of employment, or one year after the period during which severance payments are made pursuant to the agreement."[3] However, the information from these filings was very scant.

[3]See Natixis filing `https://www.sec.gov/Archives/edgar/data/1406305/000119312514271200/d755211d485apos.htm`.

Appendix to Chapter 4

Implied Cost of Capital Models

This appendix provides a brief description of the models underlying the implied cost of capital used throughout the analysis. For each firm, an average of eight commonly used metrics, ICC_{LNS13}, ICC_{GG97}, ICC_{GLS01}, ICC_{CT01}, ICC_{OJ05}, ICC_{MPEG}, ICC_{PEG}, and ICC_{PE}, is calculated.

If not obtained differently by means explicit to one model, proxies for expected earnings of firm i one, two, three, four, and five years ahead, conditional on the information set at time t, Ψ_t, $\mathbb{E}(E_{i,t+\tau}|\Psi_t) := \mathbb{E}_t(E_{i,t+\tau}) \; \forall \, \tau \in \{1, ..., 5\}$, are obtained following Li, Ng, and Swaminathan (2013). The approach necessitates an estimate for long-term earnings growth, $\overline{g}_{i,t}$. For expected earnings proxies based on analysts, this value is potentially reported; if not and for mechanical earnings forecasts, it is computed as the ratio of the farthest consecutive non-negative earnings forecasts, $\widehat{E}_{i,t+\tau}$, minus one, i.e., $\overline{g}_{i,t} = \widehat{E}_{i,t+5}/\widehat{E}_{i,t+4} - 1|\widehat{E}_{i,t+5} \wedge \widehat{E}_{i,t+4} > 0, \; \ldots, \; \widehat{E}_{i,t+2}/\widehat{E}_{i,t+1} - 1|\widehat{E}_{i,t+2} \wedge \widehat{E}_{i,t+1} > 0$.

If the respective one-year-ahead earnings forecast is not smaller zero, $\mathbb{E}_t(E_{i,t+1})$ is set equal to this value. Else, if past earnings, $E_{i,t}$, are positive and the estimate for earnings two years ahead is larger zero, $\mathbb{E}_t(E_{i,t+1})$ obtains assuming geometric growth, i.e., $\mathbb{E}_t(E_{i,t+1}) = E_{i,t} \cdot \sqrt{\widehat{E}_{i,t+2}/E_{i,t}}$. Finally, given only two-year-ahead forecasts being non-negative, they are scaled down by long-term growth, such that $\mathbb{E}_t(E_{i,t+1}) = \widehat{E}_{i,t+2}/(1 + \overline{g}_{i,t})$.

A proxy for expected earnings in two years, $\mathbb{E}_t(E_{i,t+2})$, obtains in a similar manner. Provided a non-negative two-year-ahead earnings forecast, $\mathbb{E}_t(E_{i,t+2})$ is set equal to this value. Else, in cases of both positive past earnings and forecast of earnings one year ahead, the latter is assumed to grow by the rate implied through growth from past earnings to next year's forecast, i.e., $\mathbb{E}_t(E_{i,t+2}) = \widehat{E}_{i,t+1} \cdot (\widehat{E}_{i,t+1}/E_{i,t})$. Finally, if only the earnings forecast one year ahead is positive, it is assumed to grow by the long-term growth rate, such that $\mathbb{E}_t(E_{i,t+2}) = \widehat{E}_{i,t+1} \cdot (1 + \overline{g}_{i,t})$.

Proxies for expected earnings three, four, and five years ahead obtain as the respective forecasts in cases they are positive and alternatively by assuming growth of last period's expected earnings proxy by the long-term growth rate.

A proxy for expected plowback rates of earnings, $\mathbb{E}_t(b_{i,t+1})$, if not stated otherwise, following literature, is obtained as one minus the ratio of most recent dividends, $D_{i,t}$, over earnings, $\mathbb{E}_t(b_{i,t+1}) = 1 - D_{i,t}/E_{i,t}$, if past year's earnings were larger zero. Else, a surrogate obtains using the ratio of past year's dividends over 6% of total assets, which proxies for normal earnings levels based on the long-run return on total assets in the U.S., $\mathbb{E}_t(b_{i,t+1}) = 1 - D_{i,t}/(0.06 \cdot AT_{i,t})$. $\mathbb{E}_t(b_{i,t+1})$ is winsorized to lie between zero and one.

The first two ICC-models belong to the realm of dividend discount models (DDMs). To begin with, ICCs according the model used by Pástor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Li, Ng, and Swaminathan (2013), ICC_{LNS13},

$$P_{i,t} = \sum_{\tau=1}^{15} \frac{\mathbb{E}_t[E_{i,t+\tau} \cdot (1 - b_{i,t+\tau})]}{(1 + r_{i,t})^{\tau}} + \frac{\mathbb{E}_t(E_{i,t+16})}{r_{i,t} \cdot (1 + r_{i,t})^{15}}, \tag{A4.1}$$

where $P_{i,t}$ denotes the market value of equity of firm i at time t and $r_{i,t}$ the implied cost of equity, are calculated. The model is partitioned into three phases; in phase one, for the first two expected earnings, the authors consider the respective explicit model forecasts, which imply a certain growth rate, $g_{i,t+2} = \mathbb{E}_t(E_{i,t+2})/\mathbb{E}_t(E_{i,t+1}) - 1$.[1] Thereafter, in phase two, earnings are expected to grow at rate $g_{i,t+\tau}$. For all firms, this rate is assumed to exponentially converge towards a long-term growth rate, $\overline{g}_t$, dictated by the historical mean growth rate of nominal GDP.[2] This in turn governs the plowback rate in the terminal value phase, $\overline{b}_{i,t}$ (since sustainable growth in general obtains as the product of return on equity and plowback rate), such that $\overline{b}_{i,t} = \overline{g}_{GDP,t}/r_{i,t}$; the initial plowback rate is assumed to linearly converge to this

[1] Li, Ng, and Swaminathan (2013) winsorize $g_{i,t+2}$ to lie between 2% and 100%.

[2] Data on GDP is obtained from the Bureau of Economic Analysis, `https://www.bea.gov/data/gdp/gross-domestic-product`.

long-term value in phase three. Taken together, the respective quantities obtain by

$$\begin{aligned}
\mathbb{E}_t(E_{i,t+\tau}) &= \mathbb{E}_t[E_{i,t+\tau-1} \cdot (1 + g_{i,t+\tau})] && \mid \ \tau \in \{3, ..., 16\}, && \text{(A4.2)} \\
\mathbb{E}_t(g_{i,t+\tau}) &= \mathbb{E}_t \left\{ g_{i,t+\tau-1} \cdot exp \left[log \left(\frac{\overline{g}_{GDP,t}}{g_{i,t+2}} \right) \right] \right\} && \mid \ \tau \in \{3, ..., 16\}, && \text{(A4.3)} \\
\mathbb{E}_t(b_{i,t+\tau}) &= \mathbb{E}_t \left(b_{i,t+\tau-1} - \frac{b_{i,1} - \overline{b}_{i,t}}{T} \right) && \mid \ \tau \in \{2, ..., 16\}. && \text{(A4.4)}
\end{aligned}$$

The second DDM is the finite horizon growth model by Gordon and Gordon (1997). The name alludes to the fact that the authors consider the first five estimates for expected earnings explicitly, allowing for growth. Thereafter, earnings are assumed to be fully distributed (such that necessarily no growth is possible, leaving the growth phase being finite). Formally, assuming constant $\mathbb{E}_t(b_{i,t+\tau}) = \mathbb{E}_t(b_{i,t+1}) \ \forall \ \tau$, ICC_{GG97} solves

$$P_{i,t} = \sum_{\tau=1}^{4} \frac{\mathbb{E}_t[E_{i,t+\tau} \cdot (1 - b_{i,t+\tau})]}{(1 + r_{i,t})^{\tau}} + \frac{\mathbb{E}_t(E_{i,t+5})}{r_{i,t} \cdot (1 + r_{i,t})^4}. \qquad \text{(A4.5)}$$

Next, two models based on the residual income model (RIM) are considered.[3] All models rely on the clean surplus relation (CSR) to hold, according to which all profits and expenses are recognized in the income statement, such that future book value of equity, $B_{i,t+1}$, obtains as current book value plus retained earnings, $B_{i,t} + E_{i,t+1} \cdot b_{i,t+1}$. Residual income is defined as income above capital requirements of equity holders, i.e., just earnings superseding ICC in monetary units, $E_{i,t} - r_{i,t} \cdot B_{i,t-1}$, which can be rephrased, using $roe_{i,t} := E_{i,t}/B_{i,t-1}$, as $(roe_{i,t} - r_{i,t}) \cdot B_{i,t-1}$.

The first RIM is based on the three-phase model by Gebhardt, Lee, and Swaminathan (2001). For the first three periods, they use explicit earnings forecasts. During the second phase, lasting until the twelfth year, return on equity is assumed to linearly converge to historical median return on equity in industry j[4] firm i be-

[3]Occasionally, the model is referred to as the Edwards-Bell-Ohlson valuation equation, confer Gebhardt, Lee, and Swaminathan (2001) and references therein, in particular Preinreich (1938), Edwards and Bell (1961), Peasnell (1982), and Ohlson (1995) for theoretical treatments, Feltham and Ohlson (1995, 1996) for implementations of this formula, and Lee (1999) for a survey of the literature on accounting-based valuation with focus on the RIM.

[4]Following Gebhardt, Lee, and Swaminathan (2001), I use the same 48 industry classification as in Fama and French (1997).

longs to, $\overline{roe}_{j,t}$, calculated based on a rolling window of ten years. Finally, for the terminal value phase, return on equity is assumed to stay constant at this rate. Hence, ICC_{GLS01} obtains as $r_{i,t}$ in following equation,

$$P_{i,t} = B_{i,t} + \sum_{\tau=1}^{11} \frac{\mathbb{E}_t[(roe_{i,t+\tau} - r_{i,t}) \cdot B_{i,t+\tau-1}]}{(1+r_{i,t})^{\tau}} + \frac{\mathbb{E}_t[(\overline{roe}_{j,t} - r_{i,t}) \cdot B_{i,t+11}]}{r_{i,t} \cdot (1+r_{i,t})^{11}}. \quad \text{(A4.6)}$$

The two-phase model by Claus and Thomas (2001) takes an even more "aggressive" stand on the terminal value phase; the authors do not only assume residual income to stay constant, but to even grow at an estimate for the inflation rate, $g_{CT01,t}$, calculated as the maximum of the difference between the current yield of ten-year government bonds[5] and 3% and zero. Such, ICC_{CT01} equates

$$\begin{aligned} P_{i,t} = B_{i,t} &+ \sum_{\tau=1}^{5} \frac{\mathbb{E}_t[(roe_{i,t+\tau} - r_{i,t}) \cdot B_{i,t+\tau-1}]}{(1+r_{i,t})^{\tau}} \\ &+ \frac{\mathbb{E}_t[(roe_{i,t+5} - r_{i,t}) \cdot B_{i,t+11} \cdot (1+g_{CT01,t})]}{(r_{i,t} - g_{CT01,t}) \cdot (1+r_{i,t})^{5}}. \end{aligned} \quad \text{(A4.7)}$$

The last four models can (but do not necessarily have to) be subsumed under the umbrella of abnormal earnings growth models (AEGMs).[6] Ohlson and Juettner-Nauroth (2005) model the dynamics of abnormal growth in earnings, i.e., growth in earnings above compounded retained earnings, $E_{i,t+1} - E_{i,t} - r_{i,t} \cdot (E_{i,t} - D_{i,t})$. In particular, they assume that short-term growth of abnormal growth in earnings asymptotically converges towards a long-term value, denoted as $(\gamma - 1)$, resulting into following valuation equation,

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+1})}{r_{i,t}} + \frac{\mathbb{E}_t[E_{i,t+2} - E_{i,t+1} - r_{i,t} \cdot (E_{i,t+1} - D_{i,t+1})]}{r_{i,t} \cdot [r_{i,t} - (\gamma - 1)]}, \quad \text{(A4.8)}$$

such that ICC_{OJ05} obtains as

$$r_{i,t} = A_i + \sqrt{A_i^2 + \mathbb{E}_t\{(E_{i,t+1}/P_{i,t}) \cdot [g_{i,t+2} - (\gamma - 1)]\}}, \quad \text{(A4.9)}$$

[5] Data on the term structure of interest rate is obtained from Federal Reserve Bank of St. Louis, `https://www.federalreserve.gov/`.

[6] Confer Easton (2004) for a detailed discussion.

where

$$A_i = 0.5 \cdot [(\gamma - 1) + \mathbb{E}_t(D_{i,t+1}/P_{i,t})], \tag{A4.10}$$

$$\mathbb{E}_t(g_{i,t+2}) = \mathbb{E}_t[(E_{i,t+2} - E_{i,t+1})/E_{i,t+1}]. \tag{A4.11}$$

Ohlson and Juettner-Nauroth (2005) set $(\gamma - 1)$ equal to the maximum of the difference between the current yield of a ten-year government bond and 3% and zero, analogously to the empirical implementation of long-term growth of residual income by Claus and Thomas (2001).

As illustrated by Easton (2004), assuming zero long-term growth, i.e., $(\gamma - 1) = 0$, leads to the modified price earnings growth (MPEG) model,

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+2} - E_{i,t+1} + r_{i,t} \cdot D_{i,t+1})}{r_{i,t}^2}, \tag{A4.12}$$

such that ICC_{MPEG} obtains as

$$r_{i,t} = \mathbb{E}_t(D_{i,t+1})/(2 \cdot P_{i,t}) + \sqrt{[\mathbb{E}_t(D_{i,t+1})/2 \cdot P_{i,t}]^2 + \mathbb{E}_t(E_{i,t+2} - E_{i,t+1})/P_{i,t}}. \tag{A4.13}$$

Imposing further zero expected dividends in $t+1$ yields the familiar price earnings growth (PEG) model,

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+2} - E_{i,t+1})}{r_{i,t}^2}, \tag{A4.14}$$

which ICC_{PEG} solves as

$$r_{i,t} = \sqrt{\mathbb{E}_t(E_{i,t+2} - E_{i,t+1})/P_{i,t}}. \tag{A4.15}$$

Finally, assuming zero (abnormal) growth in earnings whatsoever results into

$$P_{i,t} = \frac{\mathbb{E}_t(E_{i,t+1})}{r_{i,t}}, \tag{A4.16}$$

such that ICC_{PE} obtains solely from the inverse forwarded price earnings (PE) ratio,

$$r_{i,t} = \mathbb{E}_t(E_{i,t+1})/P_{i,t}. \tag{A4.17}$$

Following literature, ICCs smaller zero are set missing; further, ICCs are winsorized at the 1st and 99th percentile.

Mechanical Earnings Forecast Models

The first model is the earnings persistence (EP) model by Li and Mohanram (2014), specified as

$$E_{i,t+\tau} = \alpha_0 + \alpha_1 \cdot E_{i,t} + \alpha_2 \cdot NegE_{i,t} + \alpha_3 \cdot E_{i,t} \cdot NegE_{i,t} + \eta_{i,t+\tau}. \tag{A4.18}$$

$E_{i,t}$ denotes earnings of firm i in period t. $NegE_{i,t}$ is an indicator variable equal to one, if earnings of firm i in period t are negative, and zero else.[7]

As a second model, I employ the residual income model (abbreviated RI to allow for distinction towards ICC-models, abbreviated RIM), which takes the following form,

$$\begin{aligned} E_{i,t+\tau} = \lambda_0 + \lambda_1 \cdot B_{i,t} + \lambda_2 \cdot E_{i,t} + \lambda_3 \cdot NegE_{i,t} + \lambda_4 \cdot E_{i,t} \cdot NegE_{i,t} \\ + \lambda_5 \cdot TACC_{i,t} + \omega_{i,t+\tau}. \end{aligned} \tag{A4.19}$$

$B_{i,t}$ denotes book value of equity and $TACC_{i,t}$ total accruals following Richardson, Sloan, Soliman, and Tuna (2005), defined as the sum of the change in non-cash working capital, net non-current operating assets, and net financial assets.[8]

The third, most comprehensive model was introduced by Hou, van Dijk, and Zhang (2012) (HvDZ),

$$\begin{aligned} E_{i,t+\tau} = \kappa_0 + \kappa_1 \cdot A_{i,t} + \kappa_2 \cdot D_{i,t} + \kappa_3 \cdot DD_{i,t} + \kappa_4 \cdot E_{i,t} + \kappa_5 \cdot NegE_{i,t} \\ + \kappa_6 \cdot AC_{i,t} + \varrho_{i,t+\tau}. \end{aligned} \tag{A4.20}$$

The authors add dividend payments, $D_{i,t}$, and a related indicator variable, $DD_{i,t}$,

[7] Hence, the EP model resembles an autoregressive model, allowing for differences in persistence depending on whether a firm accrued losses in the τ periods lagged fiscal year, based on economic reasoning and empirical evidence for losses being less persistent, confer, e.g., Elliott and Shaw (1988), Elgers and Lo (1994), and Fama and French (2000).

[8] The inclusion of accruals owes to evidence for lower persistence in the accrual part of earnings as opposed to the fraction related to cash flow, confer, e.g., Sloan (1996) and Fama and French (2006).

equal to one, if firm i paid a dividend in t, and zero else.[9] Accruals, $AC_{i,t}$, are calculated using the balance-sheet method prior to 1988, as the change in non-cash current assets less the change in current liabilities, excluding the change in short-term debt and the change in taxes payable, minus depreciation and amortization expenses, and using the cash flow statement method, as the difference between earnings and cash flows from operations, thereafter.

$\eta_{i,t+\tau}$, $\omega_{i,t+\tau}$, and $\varrho_{i,t+\tau}$ are the respective error terms. For each point in time t, explicit earnings forecasts for up to five periods ahead are calculated, i.e., $\tau \in \{1, ..., 5\}$. Following literature, level variables are winsorized at the 1st and 99th percentile.

[9] Firms paying dividends have been documented to be more profitable and striving for persistence and smoothness in dividend payments, confer, e.g., Fama and French (2001). Further, Fama and French (2000) argue that dividends contain information about expected earnings because of firms targeting dividends to the permanent component of earnings [Miller and Modigliani (1961)].

Bibliography

Addison, John T., Liwen Chen, and Orgul D. Ozturk (2018), Occupational Match Quality and Gender over Two Cohorts, *Industrial and Labor Relations Review (forthcoming).*

Agarwal, Vikas, Gerald D. Gay, and Leng Ling (2014), Window Dressing in Mutual Funds, *The Review of Financial Studies*, 27(11), 3133–3170.

Agarwal, Vikas, Kevin A. Mullally, Yuehua Tang, and Baozhong Yang (2015), Mandatory Portfolio Disclosure, Stock Liquidity, and Mutual Fund Performance, *The Journal of Finance*, 70(6), 2733–2776.

Agarwal, Vikas, Rahul Vashishtha, and Mohan Venkatachalam (2018), Mutual Fund Transparency and Corporate Myopia, *The Review of Financial Studies*, 31(5), 1966–2003.

Ali, Ashiq, Ningzhong Li, and Weining Zhang (2019), Restrictions on Managers' Outside Employment Opportunities and Asymmetric Disclosure of Bad versus Good News, *The Accounting Review*, 94(5), 1–25.

Amir, On and Orly Lobel (2013), Driving Performance: A Growth Theory of Noncompete Law, *Stanford Technology Law Review*, 16(3), 833–874.

Anand, Smriti, Iftekhar Hasan, Priyanka Sharma, and Haizhi Wang (2018), State enforceability of noncompete agreements: Regulations that stifle productivity!, *Human Resource Management*, 57(1), 341–354.

Andersson, Fredrik (2002), Career Concerns, Contracts, and Effort Distortions, *Journal of Labor Economics*, 20(1), 42–58.

Andreu, Laura and Alexander Puetz (2017), Choosing two business degrees versus choosing one: What does it tell about mutual fund managers' investment behavior?, *Journal of Business Research*, 75, 138–146.

Angrist, Joshua David and Jörn-Steffen Pischke (2009), *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press: Princeton, New Jersey.

Antonovics, Kate and Limor Golan (2012), Experimentation and Job Choice, *Journal of Labor Economics*, 30(2), 333–366.

Aobdia, Daniel (2018), Employee mobility, noncompete agreements, product-market competition, and company disclosure, *Review of Accounting Studies*, 23(1), 296–346.

Asthana, Sharad, Steven Balsam, and Srinivasan Sankaraguruswamy (2004), Differential Response of Small versus Large Investors to 10-K Filings on EDGAR, *The Accounting Review*, 79(3), 571–589.

Atkinson, Stanley M., Samantha Boyce Baird, and Melissa B. Frye (2003), Do Female Mutual Fund Managers Manage Differently?, *Journal of Financial Research*, 26(1), 1–18.

Avery, Christopher N. and Judith A. Chevalier (1999), Herding over the career, *Economics Letters*, 63(3), 327–333.

Bai, John, Linlin Ma, Kevin A. Mullally, and David H. Solomon (2019), What a difference a (birth) month makes: The relative age effect and fund manager performance, *Journal of Financial Economics*, 132(1), 200–221.

Balasubramanian, Natarajan, Jin Woo Chang, Mariko Sakakibara, and Evan P. Starr (2020), Locked in? The Enforceability of Covenants Not to Compete and the Careers of High-Tech Workers, *Journal of Human Resources (forthcoming)*.

Ball, Ray and Philip Brown (1968), An Empirical Evaluation of Accounting Income Numbers, *Journal of Accounting Research*, 6(2), 159–178.

Balsam, Steven, Eli Bartov, and Carol Marquardt (2002), Accruals Management, Investor Sophistication, and Equity Valuation: Evidence from 10-Q Filings, *Journal of Accounting Research*, 40(4), 987–1012.

Bär, M., A. Kempf, and S. Ruenzi (2011), Is a Team Different from the Sum of its Parts? Evidence from Mutual Fund Managers, *Review of Finance*, 15(2), 359–396.

Barber, Brad M., Xing Huang, and Terrance Odean (2016), Which Factors Matter to Investors? Evidence from Mutual Fund Flows, *The Review of Financial Studies*, 29(10), 2600–2642.

Barber, Brad M., Anna Scherbina, and Bernd Schlusche (2018), Performance Isn't Everything: Personal Characteristics and Career Outcomes of Mutual Fund Managers, *SSRN Electronic Journal*.

Barillas, Francisco and J. A.Y. Shanken (2018), Comparing Asset Pricing Models, *The Journal of Finance*, 73(2), 715–754.

Barnett, Jonathan and Ted M. Sichelman (2016), Revisiting Labor Mobility in Innovation Markets, *SSRN Electronic Journal*.

Barras, Laurent, Olivier Scaillet, and Russ Wermers (2010), False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas, *The Journal of Finance*, 65(1), 179–216.

Beckmann, Daniela and Lukas Menkhoff (2008), Will Women Be Women? Analyzing the Gender Difference among Financial Experts, *Kyklos*, 61(3), 364–384.

Berk, Jonathan B. and Jules H. van Binsbergen (2015), Measuring skill in the mutual fund industry, *Journal of Financial Economics*, 118(1), 1–20.

— (2016), Assessing asset pricing models using revealed preference, *Journal of Financial Economics*, 119(1), 1–23.

Berk, Jonathan B., Jules H. van Binsbergen, and Binying Liu (2017), Matching Capital and Labor, *The Journal of Finance*, 72(6), 2467–2504.

Bertrand, Marianne and Sendhil Mullainathan (2003), Enjoying the Quiet Life? Corporate Governance and Managerial Preferences, *Journal of Political Economy*, 111(5), 1043–1075.

Bielstein, Patrick and Matthias X. Hanauer (2019), Mean-variance optimization using forward-looking return estimates, *Review of Quantitative Finance and Accounting*, 52(3), 815–840.

Bishara, Norman D. (2011), Fifty Ways to Leave Your Employer: Relative Enforcement of Covenants Not to Compete, Trends, and Implications for Employee Mobility Policy, *University of Pennsylvania Journal of Business Law*, 13(3), 751–795.

Bishara, Norman D., Kenneth J. Martin, and Randall S. Thomas (2015), An Empirical Analysis of Noncompetition Clauses and Other Restrictive Postemployment Covenants, *Vanderbilt Law Review*, 68(1), 1–51.

Bishara, Norman D. and David Orozco (2012), Using the Resource-Based Theory to Determine Covenant Not to Compete Legitimacy, *Indiana Law Journal*, 87(3), 979–1031.

Bishara, Norman D. and Evan Starr (2016), The Incomplete Noncompete Picture, *Lewis & Clark Law Review*, 20(2), 497–546.

Bonner, Sarah E., Beverly R. Walther, and Susan M. Young (2003), Sophistication-Related Differences in Investors' Models of the Relative Accuracy of Analysts' Forecast Revisions, *The Accounting Review*, 78(3), 679–706.

Botosan, Christine A. and Marlene A. Plumlee (2005), Assessing Alternative Proxies for the Expected Risk Premium, *The Accounting Review*, 80(1), 21–53.

Botosan, Christine A., Marlene A. Plumlee, and H. E. Wen (2011), The Relation between Expected Returns, Realized Returns, and Firm Risk Characteristics, *Contemporary Accounting Research*, 28(4), 1085–1122.

Bradshaw, Mark T., Michael S. Drake, James N. Myers, and Linda A. Myers (2012), A re-examination of analysts' superiority over time-series forecasts of annual earnings, *Review of Accounting Studies*, 17(4), 944–968.

Brown, Keith C., W. V. Harlow, and Laura T. Starks (1996), Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry, *The Journal of Finance*, 51(1), 85–110.

Brown, Lawrence D., Gordon D. Richardson, and Steven J. Schwager (1987), An Information Interpretation of Financial Analyst Superiority in Forecasting Earnings, *Journal of Accounting Research*, 25(1), 49–67.

Brown, Stephen J., Juan Sotes-Paladino, Jiaguo Wang, and Yaqiong Yao (2017), Starting on the wrong foot: Seasonality in mutual fund performance, *Journal of Banking & Finance*, 82, 133–150.

Capon, Andrew (2012), The cost of constraint, *Institutional Investor Magazine*.

Carhart, Mark M. (1997), On Persistence in Mutual Fund Performance, *The Journal of Finance*, 52(1), 57–82.

Chaudhuri, Ranadeb, Zoran Ivković, and Charles Trzcinka (2018), Cross-Subsidization in Institutional Asset Management Firms, *The Review of Financial Studies*, 31(2), 638–677.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers (2000), The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers, *The Journal of Financial and Quantitative Analysis*, 35(3), 343–368.

Chen, Tai-Yuan, Guochang Zhang, and Yi Zhou (2018), Enforceability of non-compete covenants, discretionary investments, and financial reporting practices: Evidence from a natural experiment, *Journal of Accounting and Economics*, 65(1), 41–60.

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

Chevalier, Judith and Glenn Ellison (1999a), Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance, *The Journal of Finance*, 54(3), 875–899.

— (1999b), Career Concerns of Mutual Fund Managers, *The Quarterly Journal of Economics*, 114(2), 389–432.

Choi, James and Kevin Zhao (2020), Did Mutual Fund Return Persistence Persist?, *NBER Working Paper Series*.

Chopra, Navin, Josef Lakonishok, and Jay R. Ritter (1992), Measuring abnormal performance, *Journal of Financial Economics*, 31(2), 235–268.

Chuprinin, Oleg and Denis Sosyura (2018), Family Descent as a Signal of Managerial Quality: Evidence from Mutual Funds, *The Review of Financial Studies*, 31(10), 3756–3820.

Cici, Gjergji, Laura K. Dahm, and Alexander Kempf (2018), Trading efficiency of fund families: Impact on fund performance and investment behavior, *Journal of Banking & Finance*, 88, 1–14.

Cici, Gjergji, Monika Gehde-Trapp, Marc-André Göricke, and Alexander Kempf (2018), The Investment Value of Fund Managers' Experience outside the Financial Sector, *The Review of Financial Studies*, 31(10), 3821–3853.

Cici, Gjergji, Mario Hendriock, and Alexander Kempf (2020a), Finding your calling: Skill matching in the mutual fund industry, *Working Paper*.

— (2020b), The Impact of Labor Mobility Restrictions on Managerial Actions: Evidence from the Mutual Fund Industry, *SSRN Electronic Journal*.

Claus, James and Jacob Thomas (2001), Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets, *The Journal of Finance*, 56(5), 1629–1666.

Conti, Raffaele (2014), Do non-competition agreements lead firms to pursue risky R&D projects?, *Strategic Management Journal*, 35(8), 1230–1248.

Costa, Bruce A. and Gary E. Porter (2003), Mutual fund managers: Does longevity imply expertise?, *Journal of Economics and Finance*, 27(2), 224–235.

Cox, D. R. (1972), Regression Models and Life-Tables, *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2), 187–220.

Cremers, K. J. Martijn and Antti Petajisto (2009), How Active Is Your Fund Manager? A New Measure That Predicts Performance, *The Review of Financial Studies*, 22(9), 3329–3365.

Cremers, Martijn, Antti Petajisto, and Eric Zitzewitz (2013), Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation, *Critical Finance Review*, 2(1), 1–48.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers (1997), Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *The Journal of Finance*, 52(3), 1035–1058.

Daniel, Kent and Sheridan Titman (1997), Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, *The Journal of Finance*, 52(1), 1–33.

Dechow, Patricia M., A. P.M.Y. Hutton, and Richard G. Sloan (2000), The Relation between Analysts' Forecasts of Long-Term Earnings Growth and Stock Price Performance Following Equity Offerings*, *Contemporary Accounting Research*, 17(1), 1–32.

Diamond, Peter A. (1981), Mobility Costs, Frictional Unemployment, and Efficiency, *Journal of Political Economy*, 89(4), 798–812.

Doellman, Thomas, Fariz Huseynov, Tareque Nasser, and Sabuhi Sardarli (2020), Corporate tax avoidance and mutual fund ownership, *Accounting and Business Research*, 1, 1–28.

Dornbrook, James (2017), Leawood money manager takes just 18 months to top $1B in AUM, *Kansas City Business Journal*.

Dougherty, Conor (2017), How Noncompete Clauses Keep Workers Locked In, *New York Times*.

Easton, Peter D. (2004), PE Ratios, PEG Ratios, and Estimating the Implied Expected Rate of Return on Equity Capital, *The Accounting Review*, 79(1), 73–95.

— (2007), Estimating the Cost of Capital Implied by Market Prices and Accounting Data, *Foundations and Trends® in Accounting*, 2(4), 241–364.

Easton, Peter D., Martin Kapons, Peter Kelly, and Andreas Neuhierl (2020), Inferences About Properties of Earnings With Disappearing Data, *SSRN Electronic Journal*.

Ecker, Jacob (2015), At the Breaking Point: Adapting Louisiana Employment Noncompete Law to the Information Age, *Louisiana Law Review*, 75(4), 1317–1362.

Edwards, Edgar Owen and Philip Wilkes Bell (1961), *The theory and measurement of business income*. University of California Press: Berkeley, California.

Elgers, Pieter T. and May H. Lo (1994), Reductions in Analysts' Annual Earnings Forecast Errors Using Information in Prior Earnings and Security Returns, *Journal of Accounting Research*, 32(2), 290–303.

Elliott, John A. and Wayne H. Shaw (1988), Write-Offs As Accounting Procedures to Manage Perceptions, *Journal of Accounting Research*, 26, 91–119.

Elton, Edwin J. and Martin J. Gruber (2011), Mutual Funds, *SSRN Electronic Journal*.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake (2003), Incentive Fees and Mutual Funds, *The Journal of Finance*, 58(2), 779–804.

Eriksson, Tor and Jaime Ortega (2006), The Adoption of Job Rotation: Testing the Theories, *ILR Review*, 59(4), 653–666.

Esterer, Florian and David Schröder (2014), Implied Cost of Capital Based Investment Strategies - Evidence from International Stock Markets, *Annals of Finance*, 10(2), 171–195.

Evans, Richard B. and Yang Sun (2018), Models or Stars: The Role of Asset Pricing Models and Heuristics in Investor Risk Adjustment, *SSRN Electronic Journal*.

Evans, Richard Burtis, Melissa Porras Prado, and Rafael Zambrana (2020), Competition and cooperation in mutual fund families, *Journal of Financial Economics*, 136(1), 168–188.

Ewens, Michael and Matt Marx (2018), Founder Replacement and Startup Performance, *The Review of Financial Studies*, 31(4), 1532–1565.

Fallick, Bruce, Charles A. Fleischman, and James B. Rebitzer (2006), Job-Hopping in Silicon Valley: Some Evidence Concerning the Microfoundations of a High-Technology Cluster, *Review of Economics and Statistics*, 88(3), 472–481.

Fama, Eugene F. (1980), Agency Problems and the Theory of the Firm, *Journal of Political Economy*, 88(2), 288–307.

Fama, Eugene F. and Kenneth R. French (1997), Industry costs of equity, *Journal of Financial Economics*, 43(2), 153–193.

— (2000), Forecasting Profitability and Earnings, *The Journal of Business*, 73(2), 161–175.

— (2001), Disappearing dividends: changing firm characteristics or lower propensity to pay?, *Journal of Financial Economics*, 60(1), 3–43.

— (2006), Profitability, investment and average returns, *Journal of Financial Economics*, 82(3), 491–518.

— (2010), Luck versus Skill in the Cross-Section of Mutual Fund Returns, *The Journal of Finance*, 65(5), 1915–1947.

— (2015), A five-factor asset pricing model, *Journal of Financial Economics*, 116(1), 1–22.

— (2018), Choosing factors, *Journal of Financial Economics*, 128(2), 234–252.

Fang, Jieyan, Alexander Kempf, and Monika Trapp (2014), Fund Manager Allocation, *Journal of Financial Economics*, 111(3), 661–674.

Feltham, Gerald A. and James A. Ohlson (1995), Valuation and Clean Surplus Accounting for Operating and Financial Activities, *Contemporary Accounting Research*, 11(2), 689–731.

— (1996), Uncertainty Resolution and the Theory of Depreciation Measurement, *Journal of Accounting Research*, 34(2), 209–234.

Ferreira, Miguel A., Aneel Keswani, Antonio F. Miguel, and Sofia B. Ramos (2012), The flow-performance relationship around the world, *Journal of Banking & Finance*, 36(6), 1759–1780.

Ferson, Wayne E. and Rudi W. Schadt (1996), Measuring Fund Strategy and Performance in Changing Economic Conditions, *The Journal of Finance*, 51(2), 425–461.

Flinn, Christopher J. (1986), Wages and Job Mobility of Young Workers, *Journal of Political Economy*, 94(3), 88–110.

Franco, Gus de, Hai Lu, and Florin P. Vasvari (2007), Wealth Transfer Effects of Analysts' Misleading Behavior, *Journal of Accounting Research*, 45(1), 71–110.

Franecki, David (1999), Pilgrim Baxter is off the block – again, *Wall Street Journal*.

Frazzini, Andrea, Ronen Israel, and Tobias J. Moskowitz (2018), Trading Costs, *SSRN Electronic Journal*.

Gabaix, Xavier and Augustin Landier (2008), Why Has CEO Pay Increased So Much?, *The Quarterly Journal of Economics*, 123(1), 49–100.

Garmaise, M. J. (2011), Ties that Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment, *Journal of Law, Economics, and Organization*, 27(2), 376–425.

Gaspar, José-Miguel, Massimo Massa, and Pedro Matos (2006), Favoritism in Mutual Fund Families? Evidence on Strategic Cross-Fund Subsidization, *The Journal of Finance*, 61(1), 73–104.

Gebhardt, William R., Charles M. C. Lee, and Bhaskaran Swaminathan (2001), Toward an Implied Cost of Capital, *Journal of Accounting Research*, 39(1), 135–176.

Gerakos, Joseph J. and Robert B. Gramacy (2012), Regression-Based Earnings Forecasts, *SSRN Electronic Journal*.

Gilson, Roland J. (1999), The Legal Infrastructure of High Technology Industrial Districts: Silicon Valley, Route 128, and Covenants Not to Compete, *New York University Law Review*, 74(3), 575–629.

Goldstein, Matthew and Alexandra Stevenson (2016), Labor Board Challenges Secrecy in Wall Street Contracts, *New York Times*.

Golec, Joseph H. (1996), The effects of mutual fund managers' characteristics on their portfolio performance, risk and fees, *Financial Services Review*, 5(2), 133–147.

Gordon, Joseph R. and Myron J. Gordon (1997), The Finite Horizon Expected Return Model, *Financial Analysts Journal*, 53(3), 52–61.

Gottesman, Aron A. and Matthew R. Morey (2006), Manager education and mutual fund performance, *Journal of Empirical Finance*, 13(2), 145–182.

— (2019), Mutual Fund Manager Education Background and Activeness, *The Journal of Investing*, 28(6), 128–139.

Greenwood, Robin and Stefan Nagel (2009), Inexperienced investors and bubbles, *Journal of Financial Economics*, 93(2), 239–258.

Grinblatt, Mark and Sheridan Titman (1989), Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings, *The Journal of Business*, 62(3), 393–416.

— (1992), The Persistence of Mutual Fund Performance, *The Journal of Finance*, 47(5), 1977–1984.

— (1993), Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns, *The Journal of Business*, 66(1), 47–68.

Groes, F., P. Kircher, and I. Manovskii (2015), The U-Shapes of Occupational Mobility, *The Review of Economic Studies*, 82(2), 659–692.

Gruber, Martin J. (1996), Another Puzzle: The Growth in Actively Managed Mutual Funds, *The Journal of Finance*, 51(3), 783–810.

Guercio, Diane Del and Paula A. Tkac (2008), Star Power: The Effect of Morningstar Ratings on Mutual Fund Flow, *The Journal of Financial and Quantitative Analysis*, 43(4), 907–936.

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

Hand, John R. M. (1990), A Test of the Extended Functional Fixation Hypothesis, *The Accounting Review*, 65(4), 740–763.

Hartzmark, Samuel M. and Abigail B. Sussman (2019), Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows, *The Journal of Finance*, 74(6), 2789–2837.

He, Zhaozhao (2018), Money held for moving stars: Talent competition and corporate cash holdings, *Journal of Corporate Finance*, 51, 210–234.

He, Zhaozhao and Modupe Babajide Wintoki (2018), Non-Competes and Profit Generation by Corporate Employees, *SSRN Electronic Journal*.

Healy, Beth (2001), 'Golden handcuffs' keep Boston investment executives unemployed longer, *KRTBN Knight Ridder Tribune Business News*.

Heinrichs, Nicolas, Dieter Hess, Carsten Homburg, Michael Lorenz, and Soenke Sievers (2013), Extended Dividend, Cash Flow, and Residual Income Valuation Models: Accounting for Deviations from Ideal Conditions, *Contemporary Accounting Research*, 30(1), 42–79.

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser (1993), Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance, 1974-1988, *The Journal of Finance*, 48(1), 93–130.

Hendriock, Mario (2020), Implied Cost of Capital and Mutual Fund Performance, *SSRN Electronic Journal*.

Herbst-Bayliss, Svea (2009), Citadel sues former employees who set up Teza Tech, *Reuters*.

Hess, Dieter, Martin Meuter, and Ashok Kaul (2019), The Performance of Mechanical Earnings Forecasts, *SSRN Electronic Journal*.

Hirshleifer, David (2015), Behavioral Finance, *Annual Review of Financial Economics*, 7(1), 133–159.

Hirshleifer, David A., James N. Myers, Linda A. Myers, and Siew Hong Teoh (2008), Do Individual Investors Cause Post-Earnings Announcement Drift? Direct Evidence from Personal Trades, *The Accounting Review*, 83(6), 1521–1550.

Holmstrom, Bengt (1982), Managerial incentives - a dynamic perspective, *Essays in honor of Lars Wahlbeck*.

Holmstrom, Bengt (1999), Managerial Incentive Problems: A Dynamic Perspective, *The Review of Economic Studies*, 66(1), 169–182.

Hong, Harrison, Terence Lim, and Jeremy C. Stein (2000), Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *The Journal of Finance*, 55(1), 265–295.

Hou, Kewei, Mathijs A. van Dijk, and Yinglei Zhang (2012), The implied cost of capital: A new approach, *Journal of Accounting and Economics*, 53(3), 504–526.

Howell, Michael J. (2001), Fund Age and Performance, *The Journal of Alternative Investments*, 4(2), 57–60.

Hu, Fan, Alastair R. Hall, and Campbell Harvey (2000), Promotion or Demotion? An Empirical Investigation of the Determinants of Top Mutual Fund Manager Change, *Working Paper*.

Huang, Nellie (2014), 10 Best Funds for Aggressive Investors, *Kiplinger*.

Ibert, Markus, Ron Kaniel, Stijn van Nieuwerburgh, and Roine Vestman (2018), Are Mutual Fund Managers Paid for Investment Skill?, *The Review of Financial Studies*, 31(2), 715–772.

Investment Company Institute (2019), *2019 Investment Company Factbook*. Vol. 59. Investment Company Institute: Washington, DC.

Ippolito, Richard A. (1989), Efficiency With Costly Information: A Study of Mutual Fund Performance, 1965-1984, *The Quarterly Journal of Economics*, 104(1), 1–23.

— (1992), Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry, *The Journal of Law & Economics*, 35(1), 45–70.

Jeffers, Jessica (2019), The Impact of Restricting Labor Mobility on Corporate Investment and Entrepreneurship, *SSRN Electronic Journal*.

Jensen, Michael C. (1968), The Performance Of Mutual Funds In The Period 1945-1964, *The Journal of Finance*, 23(2), 389–416.

Jiang, H. A.O. and Michela Verardo (2018), Does Herding Behavior Reveal Skill? An Analysis of Mutual Fund Performance, *The Journal of Finance*, 73(5), 2229–2269.

Jones, Robert C. and Russ Wermers (2011), Active Management in Mostly Efficient Markets, *Financial Analysts Journal*, 67(6), 29–45.

Jovanovic, Boyan (1979), Job Matching and the Theory of Turnover, *Journal of Political Economy*, 87(5), 972–990.

— (1984), Matching, Turnover, and Unemployment, *Journal of Political Economy*, 92(1), 108–122.

Jovanovic, Boyan and Robert Moffitt (1990), An Estimate of a Sectoral Model of Labor Mobility, *Journal of Political Economy*, 98(4), 827–852.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng (2005), On the Industry Concentration of Actively Managed Equity Mutual Funds, *The Journal of Finance*, 60(4), 1983–2011.

— (2008), Unobserved Actions of Mutual Funds, *The Review of Financial Studies*, 21(6), 2379–2416.

Kambourov, Gueorgui and Iourii Manovskii (2008), Rising Occupational And Industry Mobility In The United States: 1968-97, *International Economic Review*, 49(1), 41–79.

— (2009a), Occupational Mobility and Wage Inequality, *Review of Economic Studies*, 76(2), 731–759.

— (2009b), Occupational Specifity of Human Capital, *International Economic Review*, 50(1), 63–115.

Kaniel, Ron, Shuming Liu, Gideon Saar, and Sheridan Titman (2012), Individual Investor Trading and Return Patterns around Earnings Announcements, *The Journal of Finance*, 67(2), 639–680.

Kempf, Alexander and Stefan Ruenzi (2008), Tournaments in Mutual-Fund Families, *The Review of Financial Studies*, 21(2), 1013–1036.

Kempf, Alexander, Stefan Ruenzi, and Tanja Thiele (2009), Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry, *Journal of Financial Economics*, 92(1), 92–108.

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

Khorana, Ajay, Peter Tufano, and Lei Wedge (2007), Board structure, mergers, and shareholder wealth: A study of the mutual fund industry, *Journal of Financial Economics*, 85(2), 571–598.

Kini, Omesh, Ryan Williams, and Sirui Yin (2019), CEO Non-Compete Agreements, Job Risk, and Compensation, *SSRN Electronic Journal*.

Konstantinidi, Theodosia and Peter F. Pope (2016), Forecasting Risk in Earnings, *Contemporary Accounting Research*, 33(2), 487–525.

Kothari, S. P. and Jerold B. Warner (2001), Evaluating Mutual Fund Performance, *The Journal of Finance*, 56(5), 1985–2010.

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

Lakonishok, Josef, Andrei Shleifer, Richard Thaler, and Robert Vishny (1991), Window Dressing by Pension Fund Managers, *American Economic Review*, 81(2), 227–231.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny (1992), The impact of institutional trading on stock prices, *Journal of Financial Economics*, 32(1), 23–43.

Larocque, Stephannie A. (2013), Analysts' Earnings Forecast Errors and Cost of Equity Capital Estimates, *Review of Accounting Studies*, 18(1), 135–166.

Lee, Charles, David Ng, and Bhaskaran Swaminathan (2009), Testing International Asset Pricing Models Using Implied Costs of Capital, *Journal of Financial and Quantitative Analysis*, 44(2), 307–335.

Lee, Charles M. C. (1999), Accounting–Based Valuation: Impact on Business Practices and Research, *Accounting Horizons*, 13(4), 413–425.

Lee, Charles M. C., Andrei Shleifer, and Richard H. Thaler (1991), Investor Sentiment and the Closed-End Fund Puzzle, *The Journal of Finance*, 46(1), 75–109.

Lehmann, Bruce N. and David M. Modest (1987), Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons, *The Journal of Finance*, 42(2), 233–265.

Li, Kevin K. and Partha Mohanram (2014), Evaluating cross-sectional forecasting models for implied cost of capital, *Review of Accounting Studies*, 19(3), 1152–1185.

Li, Yan, David T. Ng, and Bhaskaran Swaminathan (2013), Predicting market returns using aggregate implied cost of capital, *Journal of Financial Economics*, 110(2), 419–436.

Lim, Terence (2001), Rationality and Analysts' Forecast Bias, *The Journal of Finance*, 56(1), 369–385.

Lin, Hsiou-wei and Maureen F. McNichols (1998), Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics*, 25(1), 101–127.

Lobo, Gerald J. (1992), Analysis and comparison of financial analysts', time series, and combined forecasts of annual earnings, *Journal of Business Research*, 24(3), 269–280.

Lou, Yun, Rencheng Wang, and Yi Zhou (2017), Non-Competes, Career Concerns, and Debt Covenants, *SSRN Electronic Journal*.

Ma, Linlin, Yuehua Tang, and Juan-Pedro Gómez (2019), Portfolio Manager Compensation in the U.S. Mutual Fund Industry, *The Journal of Finance*, 74(2), 587–638.

Malkiel, Burton G. (1995), Returns from Investing in Equity Mutual Funds 1971 to 1991, *The Journal of Finance*, 50(2), 549–572.

Malsberger, Brian 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, *SSRN Electronic Journal*.

Marx, Matt, Jasjit Singh, and Lee Fleming (2015), Regional disadvantage? Employee non-compete agreements and brain drain, *Research Policy*, 44(2), 394–404.

Marx, Matt, Deborah Strumsky, and Lee Fleming (2009), Mobility, Skills, and the Michigan Non-Compete Experiment, *Management Science*, 55(6), 875–889.

Massa, Massimo (2003), How do family strategies affect fund performance? When performance-maximization is not the only game in town, *Journal of Financial Economics*, 67(2), 249–304.

Mayer, Thomas (1960), The Distribution of Ability and Earnings, *The Review of Economics and Statistics*, 2(2), 189–195.

McCall, Brian P. (1990), Occupational Matching: A Test of Sorts, *Journal of Political Economy*, 98(1), 45–69.

McNichols, Maureen and Patricia C. O'Brien (1997), Self-Selection and Analyst Coverage, *Journal of Accounting Research*, 35, 167–199.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis (2007), When Security Analysts Talk, Who Listens?, *The Accounting Review*, 82(5), 1227–1253.

Miller, Merton H. and Franco Modigliani (1961), Dividend Policy, Growth, and the Valuation of Shares, *The Journal of Business*, 34(4), 411–433.

Miller, Robert A. (1984), Job Matching and Occupational Choice, *Journal of Political Economy*, 92(6), 1086–1120.

Mohanram, Partha and Dan Gode (2013), Removing predictable analyst forecast errors to improve implied cost of equity estimates, *Review of Accounting Studies*, 18(2), 443–478.

Mortensen, Dale T. (1978), Specific Capital and Labor Turnover, *The Bell Journal of Economics*, 9(2), 572–586.

— (1986), Job search and labor market analysis, *Handbook of labor economics*. Ed. by Orley Ashenfelter and Peter R. G. Layard. Vol. 2. Handbooks in economics. Elsevier: Amsterdam, 849–919.

Mukherjee, Arijit and Luis Vasconcelos (2011), Optimal job design in the presence of implicit contracts, *The RAND Journal of Economics*, 42(1), 44–69.

Nagypál, Éva (2007), Learning by Doing vs. Learning about Match Quality: Can We Tell Them Apart?, *The Review of Economic Studies*, 74(2), 537–566.

Nalebuff, Barry J. and Joseph E. Stiglitz (1983), Prizes and Incentives: Towards a General Theory of Compensation and Competition, *The Bell Journal of Economics*, 14(1), 21–43.

Newey, Whitney K. and Kenneth D. West (1987), A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 55(3), 703–708.

Niessen-Ruenzi, Alexandra and Stefan Ruenzi (2019), Sex Matters: Gender Bias in the Mutual Fund Industry, *Management Science*, 65(7), 3001–3025.

O'Brien, Patricia C. (1988), Analysts' forecasts as earnings expectations, *Journal of Accounting and Economics*, 10(1), 53–83.

Ohlson, James A. (1995), Earnings, Book Values, and Dividends in Equity Valuation, *Contemporary Accounting Research*, 11(2), 661–687.

Ohlson, James A. and Beate E. Juettner-Nauroth (2005), Expected EPS and EPS Growth as Determinantsof Value, *Review of Accounting Studies*, 10(2), 349–365.

Ortega, Jaime (2001), Job Rotation as a Learning Mechanism, *Management Science*, 47(10), 1361–1370.

Papageorgiou, Theodore (2014), Learning Your Comparative Advantages, *The Review of Economic Studies*, 81(3), 1263–1295.

— (2018), Large firms and within firm occupational reallocation, *Journal of Economic Theory*, 174, 184–223.

Pástor, Ľuboš, Meenakshi Sinha, and Bhaskaran Swaminathan (2008), Estimating the Intertemporal Risk-Return Tradeoff Using the Implied Cost of Capital, *The Journal of Finance*, 63(6), 2859–2897.

Pástor, Ľuboš and Robert F. Stambaugh (2003), Liquidity Risk and Expected Stock Returns, *Journal of Political Economy*, 111(3), 642–685.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor (2015), Scale and skill in active management, *Journal of Financial Economics*, 116(1), 23–45.

Patel, Saurin and Sergei Sarkissian (2017), To Group or Not to Group? Evidence from Mutual Fund Databases, *Journal of Financial and Quantitative Analysis*, 52(5), 1989–2021.

Peasnell, K. V. (1982), Some Formal Connections Between Economic Values and Yields and Accounting Numbers, *Journal of Business Finance & Accounting*, 9(3), 361–381.

Petajisto, Antti (2013), Active Share and Mutual Fund Performance, *Financial Analysts Journal*, 69(4), 73–93.

Petersen, Mitchell A. (2009), Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *The Review of Financial Studies*, 22(1), 435–480.

Pinnuck, Matt (2003), An Examination of the Performance of the Trades and Stock Holdings of Fund Managers: Further Evidence, *The Journal of Financial and Quantitative Analysis*, 38(4), 811–828.

Preinreich, Gabriel A. D. (1938), Annual Survey of Economic Theory: The Theory of Depreciation, *Econometrica*, 6(3), 219–241.

Prescott, J. J., Norma D. Bishara, and Evan Starr (2016), Understanding Noncompetition Agreements: The 2014 Noncompete Survey Project, *Michigan State Law Review*, 2016(2), 369–469.

Rakowski, David and Xiaoxin Wang (2009), The dynamics of short-term mutual fund flows and returns: A time-series and cross-sectional investigation, *Journal of Banking & Finance*, 33(11), 2102–2109.

Regan, Michael (2016), Q&A With Jack Bogle: 'We're in the Middle of a Revolution', *Bloomberg*.

Richardson, Scott, İrem Tuna, and Peter Wysocki (2010), Accounting anomalies and fundamental analysis: A review of recent research advances, *Journal of Accounting and Economics*, 50(2-3), 410–454.

Richardson, Scott A., Richard G. Sloan, Mark T. Soliman, and İrem Tuna (2005), Accrual reliability, earnings persistence and stock prices, *Journal of Accounting and Economics*, 39(3), 437–485.

Rosen, Sherwin (1982), Authority, Control, and the Distribution of Earnings, *The Bell Journal of Economics*, 13(2), 311–323.

— (1986), Prizes and Incentives in Elimination Tournaments, *American Economic Review*, 76(4), 701–715.

Russell, Kinnel (2010), How Expense Ratios and Star Ratings Predict Success, *Morningstar Advisor*.

Sakelaris, Linda (1998), And the battle continues ... Russell, Utah sue Wellington over noncompete clause, *Pensions & Investments*.

Samila, Sampsa and Olav Sorenson (2011), Noncompete Covenants: Incentives to Innovate or Impediments to Growth, *Management Science*, 57(3), 425–438.

Sattinger, Michael (1975), Comparative Advantage and the Distributions of Earnings and Abilities, *Econometrica*, 43(3), 455–468.

— (1993), Assignment Models of the Distribution of Earnings, *Journal of Economic Literature*, 31(2), 831–880.

Scharfstein, David S. and Jeremy C. Stein (1990), Herd Behavior and Investment, *American Economic Review*, 80(3), 465–479.

Schröder, David (2018), The Role of Market Efficiency on Implied Cost of Capital Estimates - an International Perspective, *SSRN Electronic Journal*.

Sias, Richard W. and Laura T. Starks (1997), Return autocorrelation and institutional investors, *Journal of Financial Economics*, 46(1), 103–131.

Sirri, Erik R. and Peter Tufano (1998), Costly Search and Mutual Fund Flows, *The Journal of Finance*, 53(5), 1589–1622.

Sloan, Richard G. (1996), Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?, *The Accounting Review*, 71(3), 289–315.

Solomon, David H., Eugene Soltes, and Denis Sosyura (2014), Winners in the spotlight: Media coverage of fund holdings as a driver of flows, *Journal of Financial Economics*, 113(1), 53–72.

Starr, Evan (2019), Consider This: Training, Wages, and the Enforceability of Covenants Not to Compete, *ILR Review*, 72(4), 783–817.

Starr, Evan, Natarajan Balasubramanian, and Mariko Sakakibara (2017), Screening Spinouts? How Noncompete Enforceability Affects the Creation, Growth, and Survival of New Firms, *Management Science*, 64(2), 552–572.

Starr, Evan, J. J. Prescott, and Norman D. Bishara (2019), Noncompetes in the U.S. Labor Force, *SSRN Electronic Journal*.

Starr, Evan P., Martin Ganco, and Benjamin A. Campbell (2018), Strategic Human Capital Management in the Context of Cross-Industry and Within-Industry Mobility Frictions, *Strategic Management Journal*, 39(8), 2226–2254.

Stuart, Toby E. and Olav Sorenson (2003a), Liquidity Events and the Geographic Distribution of Entrepreneurial Activity, *Administrative Science Quarterly*, 48(2), 175–201.

— (2003b), The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms, *Research Policy*, 32(2), 229–253.

Taylor, Chris (2011), Analysis: Why some fund managers don't invest in their own funds, *Reuters*.

Terrell, Daniel S. (2004), The Louisiana Legislature's Response to SWAT 24 Shreveport Bossier, Inc. v. Bond:' The Noncompete Pendulum Swings Toward Debt Peonage. Will the Judiciary's Answer Achieve the Fragile Employer-Employee Balance?, *Lousiana Law Review*, 64(3), 609–734.

Terviö, Marko (2008), The Difference That CEOs Make: An Assignment Model Approach, *American Economic Review*, 98(3), 642–668.

Timmermann, Allan, Clive William John Granger, and Graham Elliott (2006), *Handbook of economic forecasting.* 1st ed. Vol. 24. Handbooks in economics. Elsevier North-Holland: Amsterdam and Boston.

U.S. Department of the Treasury (2016), Non-compete Contracts: Economic Effects and Policy Implications, *U.S. Treasury.*

van Binsbergen, Jules H., Jeong Ho Kim, and Soohun Kim (2019), Capital Allocation and the Market for Mutual Funds: Inspecting the Mechanism, *SSRN Electronic Journal.*

van Nieuwerburgh, Stijn and Laura Veldkamp (2009), Information Immobility and the Home Bias Puzzle, *The Journal of Finance*, 64(3), 1187–1215.

Veronesi, Pietro (1999), Stock Market Overreactions to Bad News in Good Times: A Rational Expectations Equilibrium Model, *The Review of Financial Studies*, 12(5), 975–1007.

Walther, Beverly R. (1997), Investor Sophistication and Market Earnings Expectations, *Journal of Accounting Research*, 35(2), 157–179.

Wermers, Russ (1999), Mutual Fund Herding and the Impact on Stock Prices, *The Journal of Finance*, 54(2), 581–622.

— (2000), Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses, *The Journal of Finance*, 55(4), 1655–1695.

— (2020), Active Investing and the Efficiency of Security Markets, *The Journal of Investment Management (forthcoming).*

Westphal, James D. and Michael B. Clement (2008), Sociopolitical Dynamics In Relations Between Top Managers and Security Analysts: Favor Rendering, Reciprocity, and Analyst Stock Recommendations, *Academy of Management Journal*, 51(5), 873–897.

Whaley, Robert E. (2002), Return and Risk of CBOE Buy Write Monthly Index, *The Journal of Derivatives*, 10(2), 35–42.

White House (2016), Non-Compete Agreements: Analysis of the Usage, Potential Issues, and State Responses, *White House.*

Wiser, Justin (2001), Michael Price to leave Mutual Series, *MarketWatch.*

Yin, Desheng, Iftekhar Hasan, Nada Kobeissi, and Haizhi Wang (2017), Enforceability of noncompetition agreements and firm innovation: does state regulation matter?, *Innovation*, 19(2), 270–286.

Zambrana, Rafael and Fernando Zapatero (2017), A Tale of Two Types: Generalists vs. Specialists in Mutual Funds Asset Management, *SSRN Electronic Journal*.

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Eidesstattliche Erklärung

Hiermit versichere ich an Eides Statt, dass ich die vorgelegte Dissertation selbstständig und ohne die Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Aussagen, Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Bei der Auswahl und Auswertung folgenden Materials haben mir die nachstehend aufgeführten Personen in der jeweils beschriebenen Weise entgeltlich/unentgeltlich geholfen:

Prof. Dr. Gjergji Cici und Prof. Dr. Alexander Kempf (gemeinsame Projektarbeit für die Inhalte in Kapitel 2 und Kapitel 3).

Weitere Personen, neben den in der Einleitung der Dissertation aufgeführten Koautorinnen und Koautoren, waren an der inhaltlich-materiellen Erstellung der vorliegenden Dissertation nicht beteiligt. Insbesondere habe ich hierfür nicht die entgeltliche Hilfe von Vermittlungs- bzw. Beratungsdiensten in Anspruch genommen. Niemand hat von mir unmittelbar oder mittelbar geldwerte Leistungen für Arbeiten erhalten, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen. Die Dissertation wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt. Ich versichere, dass ich nach bestem Wissen die reine Wahrheit gesagt und nichts verschwiegen habe.

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