Empirical Studies in Asset Management

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Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared below and specified in the text.

Chapter 1 "*The Hidden Costs of Networking: The Consequences on Mutual Fund Manager Incentives and Performance*" is a solo-authored paper. Chapter 2 "*Satisfied Employees, Satisfied Investors: How Employee Well-being Impacts Mutual Fund Returns*" is co-authored with my advisor Prof. Pedro Saffi. I am responsible for two-thirds of the work. Chapter three "*Outsourcing in the Mutual Fund Industry*" is co-authored with my supervisor Prof. David Chambers and Prof. Richard B. Evans from the University of Virginia. I am responsible for one-third of the work.

The thesis is not substantially the same as any work submitted for any degree or other qualification at the University of Cambridge or any other institution. This dissertation does not exceed the 80,000-word limit set by the Cambridge Judge Business School Degree Committee.

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Abstract

The dissertation presents three empirical studies in the field of asset management. The first essay investigates whether within-firm connections alter manager career concerns and if investment distinctiveness, employee risk-taking and fund performance are affected. I measure connectedness using a dataset of within-firm networks based on 13,357 mutual fund managers across 26 years. Well-connected managers within the fund family face lower performance-turnover and -promotion sensitivities. The advantageous treatment enjoyed by better-connected managers in these career altering decisions is associated with lower risk-taking and lower investment distinctiveness of the funds they manage. Funds of better-connected managers deviate less from their peers in systematic factor and sector exposures and exhibit lower risk-adjusted performance. Mutual fund investors are unaware of this phenomenon, illustrated by the lack of a flow differential.

The second essay uses proprietary data on self-reported employee reviews from Glassdoor.com to study the relationship between employee satisfaction and mutual fund performance and size. Using the staggered adoption of Anti-SLAPP (Strategic Lawsuits Against Public Participation) laws in the U.S. and variation from mergers between asset management companies to tackle endogeneity issues, we find that employee satisfaction is positively linked to fund performance and size but that only performance-critical employees' satisfaction matters. A one-point increase on the 5-point scale of employee satisfaction leads to a 36bps (36bps) higher annual 3-factor (4-factor) abnormal performance. Furthermore, a one-point increase of employee satisfaction is associated with a 0.2% larger mutual fund size. Finally, while there is a positive effect of employee satisfaction on risk-taking, we cannot establish a causal relationship.

The third essay investigates why fund families continue to outsource the portfolio management of their funds to unaffiliated investment advisors despite the well-documented underperformance of outsourced funds. Our empirical analysis shows that investment expertise, or the lack of it, drives the decision to enter an outsourcing relationship and impacts the way fee revenues are shared. Furthermore, market thickness, defined as the number of subadvisors the fund family could contract with, also impacts the fund family's decision to outsource and its relative bargaining power in the resulting relationship. We link the impact of market thickness on the relative power of both parties in the outsourcing relationship to the threat of dismissal of the subadvisor and show that outsourced funds operating in thick markets perform better. Finally, once we account for the initial decision to outsource a mutual fund, we find that outsourced funds do not underperform and are not smaller than in-house managed funds. The fund family lacking the relevant in-house expertise could not have achieved a better performance than the subadvisor and the subadvisor, because of its lack of distribution capabilities, could not have gathered more assets.

In memory of Bettina Ohneberg

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Chapter 1

Introduction

This dissertation presents three empirical studies on factors influencing the severity of the principal-agent problem inherent in delegated asset management. The main principal-agent problem in delegated asset management results from the separation of the investor (the principal) and the individual managing the investor's assets (the agent). The first essay explores the effect of within-firm connections amongst portfolio managers on the severity of the principal-agent problem in mutual funds, through an analysis of promotion and turnover decisions, mutual fund risk and investment distinctiveness, and ultimately mutual fund performance. The second essay shows how employee satisfaction can help align interests between the mutual fund managers and the principal through the norm gift exchange model (Akerlof, 1982). Furthermore, it highlights the importance of marketing and sales personnel on the ability of mutual funds to gather assets under management. The third essay highlights and analyses a second layer principal-agent problem in mutual fund sub-advising. The first layer principal-agent problem remains between the investor and the mutual fund. However, due to the mutual fund's decision to outsource the portfolio management to an unaffiliated company, it acts as a principal in a second layer principal-agent problem. This essay documents the underlying reasons behind a mutual fund's decision to engage in outsourcing and the alleviating effect of market thickness on the severity of this second layer principal-agent problem.

The mutual fund industry is large. According to the Investment Company Institute, in 2021 equity mutual funds in the U.S. alone managed approximately $12.5 trillion. Furthermore, the granularity and quality of mutual fund data provide a laboratory for investigating questions that are difficult or impossible to answer through other means.

In my first essay, I examine if workplace connections lead to preferential treatment in firing and promotion decisions and if the change in incentives alters interest alignments between the principals (investors) and agents (mutual fund managers). Moreover, I document the effect these altered incentives have on mutual fund investment distinctiveness, risk-taking, and ultimately fund performance. The mutual fund industry provides an ideal setting for investigating the effect of workplace connectedness on incentivisation provided by firing and promotion decisions, employee behaviour, and performance because mutual fund data allows me to track 13,357 mutual fund managers across 26 years of data. Furthermore, mutual fund performance constitutes a precise and readily available measure of a portfolio manager's on-the-job performance. For most jobs, it is challenging or outright impossible to define a good outcome measure for employee performance, for others, even if a measure can be defined, data is generally lacking. How would one quantify the performance of an engineer at a manufacturing company? By the number of patents resulting from their work? By measuring cost reductions through better production technologies or the development of a higher quality product?

Employing my mutual fund sample, I find that better-connected managers face lower performance- promotion and -firing sensitivities. Furthermore, workplace connectedness hampers the incentivisation effects usually provided by promotion and firing decisions – the carrot and the stick. I next show that better-connected mutual fund managers manage their funds less distinctly, as evidenced by lower factor and beta deviations of the funds they manage. Sector and beta deviations measure the magnitude by which the mutual fund's sector and factor allocations differ from those of its peers. Moreover, mutual funds managed by better-connected managers exhibit a lower risk-adjusted performance. Thus I find that connectedness harms interest alignment between the principal and the agent, exacerbating the principal agent problem typically observed in mutual fund management. Finally, I document no effect of within-firm connectedness on mutual fund size or flows. The lack of an observable effect on mutual fund size may explain the persistence of the negative effects of within-firm connectedness.

The second chapter investigates the effect of employee (agent) satisfaction as an interest alignment tool in a principal-agent framework by using data on one million employee job reviews posted on Glassdoor.com for 437 mutual fund companies managing 3,266 funds over ten years. The specific agency problem investigated views the mutual fund company as the principal and the individual employees as the agents. According to the norm gift exchange model by Akerlof (1982) we would expect that better treatment of employees by the firm can help align interests between the mutual fund company and the employees, reducing the agency problems that are typically present in employer employee relationships. There is some existing evidence in the financial literature on the effect of employee satisfaction on firm performance (e.g., Edmans, 2011; Green et al., 2019; Huang et al., 2015; Symitsi et al., 2018). In contrast to this prior literature, we study the effect of employee satisfaction on employee-level performance metrics through interest alignment by leveraging the granularity of data on and the setting of the mutual fund industry. Mutual fund firms employ portfolio managers to generate investment returns. Similarly, sales and marketing employees in mutual fund firms have the task of raising the firm's assets under management. This allows us to test the effect of employee satisfaction on on-the-job performance for two distinct employee groups. The performance of marketing and sales personnel is measured through mutual fund size, and the performance of the investment personnel is measured by mutual fund risk-adjusted performance.

We find that a 1-point increase on the 5-point scale of average employee satisfaction leads to a 36bps (36bps) higher annual 3-factor (4-factor) alpha in our regression correcting for selection bias. Similarly, a 1-point increase on the 5-point scale of marketing and sales employee satisfaction increases mutual fund assets by 0.2%. Moving from the lowest to the highest point on the job satisfaction scale increases mutual fund size by 0.80% or by $14.54 million for the average mutual fund in our sample and 3-factor (4-factor) alpha by 1.44% (1.44%). The effect of marketing and sales employee satisfaction on mutual fund size is not trivial and lends further support to the importance of marketing and distribution efforts in a fund's ability to gather assets under management. Previous research investigating the importance of marketing and distribution on mutual fund size predominantly uses 12b-1 expenses as a proxy for marketing and distribution efforts. We would argue that the happiness of marketing and sales employees provides a cleaner test for the effects of marketing and distribution on mutual fund size. We confirm this positive effect of employee satisfaction on performance in an empirical setting that exploits the exogenous assignment of employees to fund families in mutual fund mergers. Unfortunately, we cannot apply this difference in differences analysis to our investigation into mutual fund size because of our inability to track whether the marketing and sales personnel remains the same throughout the merger. If anything we would expect that it is usually the mutual funds and their management that is acquired rather than the marketing and distribution capabilities. We additionally find some limiting evidence that happier employees manage their funds less conservatively by taking investment approaches more different to their peer group than less satisfied managers. Finally, we also investigate the effect of employee satisfaction on risk-taking and find some support for a positive effect that is consistent with the Affect Infusion Model (Forgas, 1995).

My final chapter investigates the puzzle as to why the outsourcing of mutual fund management by fund families remains popular - 20.71% of funds outsource their portfolio management throughout our sample period from 2001 to 2017 - notwithstanding the underperformance of these sub-advised mutual funds documented in prior research (e.g., Chen et al., 2013; Chuprinin et al., 2015; Del Guercio et al., 2010; Moreno et al., 2018). The decision of the mutual fund company to outsource the portfolio management of one of its funds to an unaffiliated subadvisor adds another layer to the agency problem conventionally observed in mutual fund management. The main agency problem remains between the mutual fund investor and the mutual fund management team. This paper provides a rational as to why mutual funds expose their investors to this additional layer of agency and sheds light on the factors influencing the underperformance of sub-advised funds previously reported in the literature. Our analysis follows Debaere & Evans (2015) and shows that the drivers of the initial decision to enter an outsourcing relationship can explain the underperformance of sub-advised mutual funds documented in the prior literature. Mutual fund families that lack internal expertise in portfolio management hire unaffiliated subadvisors to manage their funds. Similarly, we find that predominantly institutional investment advisors that lack retail distribution capabilities agree to sub-advise a mutual fund for an unaffiliated mutual fund family. Thus, the lack of the mutual fund family's internal investment expertise in this particular style would prevent it from being able to achieve higher fund performance than the subadvisor. Similarly, the subadvisor would not have been able to achieve a higher fund size because of its lack of internal retail distribution capabilities.

In addition, this chapter also explores the effect of market thickness on the sub-advising relationship. Market thickness is defined as the ease with which a party can find a trade partner in the open market (McLaren, 2003). We find that market thickness impacts the initial decision to outsource, the split of fee revenue between the fund family and the subadvisor, and mutual fund performance. A mutual fund family is more likely to outsource a mutual fund if the subadvisor market thickness is greater. Put differently, the larger the number of potential trade partners the family could outsource to, the more likely it is to do so. Market thickness also impacts bargaining power, which we gauge by investigating how advisory fees are shared in the relationship. The higher the number of potential outside trade partners (fund families) the subadvisor can choose from, the larger its bargaining power. Finally, we link the effect of market thickness to fund performance. Outsourced mutual funds that operate in thicker markets perform better. Thus, the effect of market thickness can, at least partially, explain the underperformance of sub-advised funds.

The rest of this thesis is structured as follows. The following three chapters present my three empirical papers. The last chapter concludes.

Chapter 2

The Hidden Costs of Networking: The Consequences on Mutual Fund Manager Incentives and Performance

Elias L. Ohneberg

Abstract

This paper examines the impact of within-firm connections on promotion and turnover decisions, risk-taking, investment distinctiveness, and fund performance. I compute connectedness using a novel measure of within-firm networks based on 13,357 mutual fund managers across 26 years. Well-connected managers within the fund family face lower performance-turnover and -promotion sensitivities. Funds of better-connected managers deviate less from their peers in systematic factor and sector exposures and exhibit lower risk-adjusted performance. A one standard deviation increase in mutual fund manager connectedness is associated with a 27bps decrease in annual 4-factor alpha. Mutual fund investors are unaware of this phenomenon, illustrated by the lack of a flow differential.

2.1. Introduction

Previous work on networks in the mutual fund literature has mainly investigated connections across different firms in an attempt to document the effects of access to information and its dissemination (see for example Augustiani et al., 2015; Butler & Gurun, 2012; Y. Chen et al., 2022; Cohen et al., 2008; Kuhnen, 2009; Pool et al., 2015; Rossi et al., 2018). In contrast to these previous studies, I examine the impact of connections inside the firm. My empirical work investigates the impact of connectedness amongst agents in a principal-agent problem. More specifically, it documents the impact of workplace connections amongst agents on incentive alignment with the principal. In the setting investigated, the mutual fund company constitutes the principal and the mutual fund managers the agents. The mutual fund industry lends itself well to investigate workplace connections' effects on incentive alignments, employee risk-taking and, ultimately, performance.

It is highly human capital intensive and sizable, with about $12.5 trillion in assets under management.[1] Furthermore, the granularity of mutual fund data allows me to track 13,357 individual portfolio managers over 26 years. My central research question is whether better-connected managers are in an advantageous position within the firm, as evidenced by firing and promotion decisions. Moreover, I investigate if a change in manager turnover and promotion sensitivities leads to a shift in manager risk-taking, investment distinctiveness, and mutual fund performance. I explore these questions by analysing within-firm employee connections for the U.S. equity mutual fund industry from December 1995 to November 2021.

I employ graph theory to build tenure-weighted directional within-firm networks to measure individual portfolio managers' connectedness with other portfolio managers at the fund family. I define two managers as connected if they have previously co-managed a fund. Because not all relationships are created equal, I assume that a connection to a more senior portfolio manager, where seniority is defined by the length of tenure at the firm, is more valuable than a connection to a junior manager. To incorporate this notion of seniority, I weigh each connection in my directional graph by the percentile rank of the connected manager's tenure at the fund family. To quantify the connectedness of a portfolio manager within the fund family, I calculate a weighted version of in-degree centrality.

[1] Investment Company Institute Fact Book (2021)

I, first, document differential treatment of well-connected managers within fund families in firing and promotion decisions and, subsequently, examine how the resulting distortion of incentives manifests itself in manager risk-taking, investment distinctiveness, and fund performance. Throughout my empirical analysis, I control for the informational effects documented in prior research by including a measure for the managers' connectedness outside of the firm. My main hypothesis is that if two portfolio managers are similar in a multitude of fund and manager characteristics, the more connected manager within the firm is less likely to be fired for bad performance and more likely to be promoted despite of bad performance. More specifically, I examine the relationship between within-firm connectedness and decisions to fire and promote managers by analysing 11,151 turnover and 7,322 promotion events. I identify a turnover event if a mutual fund manager leaves the current firm and is left with fewer assets after they left. Portfolio managers are considered to have received a promotion if they are listed as a portfolio manager on an extra fund and they are still working for the same firm. To quantify the effect of connectedness on promotion and turnover probabilities, I employ a logistic regression framework that accounts for the manager's network outside of the firm, past fund performance and other fund-specific and manager-level controls, as well as time- and firm-fixed effects. I find that workplace connections are associated with an increase in the probability of being promoted and a decrease in the performance-promotion and performance-turnover sensitivities. This suggests that the incentive alignment effects typically provided by promotion and turnover decisions are weaker for better connected managers, potentially exacerbating the principal agent problem.

Previous research has shown that career concerns induced by the threat of firing can affect manager behaviour (e.g. Chevalier & Ellison, 1999). Both the threat of firing and the hope for promotion should incentivise employees to exert effort. Suppose better-connected managers experience a lower threat of being fired and an increased probability of receiving an (undeserved) promotion. In that case, it may hamper the incentivisation mechanisms of promotions and dismissals. Existing theoretical work on that extends the standard principal-agent problem of Holmstrom & Milgrom (1987) shows that the inclusion of non-performance considerations, such as simply liking or knowing somebody, in performance evaluations hampers incentivisation and leads to lower employee effort (Prendergast & Topel, 1993). Thus, I hypothesise that, if being well-connected favourably impacts the probability of a manager being promoted or fired, well connected managers exert less effort in managing their mutual funds and their funds thus experience poorer performance.

Furthermore, Augustiani et al. (2015) show that connected mutual funds invest more similarly. If mutual fund managers share their investment approaches and ideas with their connections, a better-connected manager will have access to a larger variety of investment ideas. If they combine more of these ideas into their investment approach, I expect their mutual fund's investment style to converge to the means of their peer group as their connectedness increases. Thus, I investigate if well-connected portfolio managers also manage their funds more similarly.

I employ two measures to capture the mutual fund's investment distinctiveness. First, I look at the sector allocation of a mutual fund compared to its Morningstar category. Second, I look at the magnitude of the factor deviations of a fund from its peers (Chevalier & Ellison, 1999; Arnold et al., 2021). The measure purposefully ignores any directionality in factor deviations and thus does not contain information on whether a fund takes more or less risk than its peers. It simply measures the uniqueness of a fund when compared to its peers with respect to factor exposures. I explore the effect of my connectedness measure on these two measures in a two-way fixed effect model that accounts for numerous fund- and manager-level control variables. I find that higher portfolio manager within-firm connectedness is associated with smaller sector and factor deviations.

Additionally, I investigate whether workplace connections also impact risk-taking. Existing evidence suggests that incentives can induce changes in risk-taking by mutual fund managers. Massa & Patgiri (2009) study the implicit incentives provided by the flow-performance relationship and find that they lead to an increase in risk-taking of mutual fund managers in the mutual funds they manage, measured by annual return volatility. Kempf et al. (2009) study incentive contracts instead. The authors define two distinct incentives: "employment incentives" that decrease risk-taking and "compensation incentives" that increase risk-taking. Well-connected managers face decreased incentives via the threat of firing (decrease in employment risk) and the increased probability of receiving a promotion (decrease in compensation incentives). Consequently, the effect of connectedness on risk-taking is ambiguous and ultimately an empirical question.

Using a two-way fixed effects regression specification, I find that better-connected mutual fund managers take less systematic and idiosyncratic risk, suggesting that being well connected has a stronger impact on compensation incentives than on employment incentives. This result is consistent with my finding that connectedness at the firm has a larger economic impact on the promotion decision than on the turnover decision.

After establishing that workplace connectedness alters manager investment behaviour, I investigate if there is an impact on fund performance in a two-way fixed effect regression. Fund performance varies inversely with a mutual fund manager's degree of within-fund family connectedness. A one standard deviation increase in connectedness leads to a 27-bps reduction in annualised 4-factor alpha. This finding is consistent with the theoretical predictions of Prendergast & Topel (1993). The diminished incentive alignment through turnover and promotion decisions face by well-connected managers increases agency issues as evidenced by poorer mutual fund performance.

Last, I investigate whether investors are aware of the negative effect of connections on mutual fund performance by looking at mutual fund net flows and assets under management through a two-way fixed effects regression. I find no effect of connectedness on mutual fund flow or size. This finding could help explain the persistence of the negative effects of within mutual fund family connectedness. I, furthermore, reconfirm all my previously drawn conclusions on a propensity score matched sample, where the sample is split into treatment and control groups on the median of my connectedness measure. Moreover in unreported results that are available upon request, I re-run all my analysis using mangers' degree centrality and a simple count of a manager's current connections as alternative measures for manager connectedness within the firm.

I contribute to three strands of literature. First, I add to studies on mutual fund manager turnover by showing that workplace connections impact turnover and promotion decisions and alter manager behaviour. Second, the finding that being well connected can distort incentivisation mechanisms highlights a negative and unintended effect of connectedness, hitherto unreported in the literature on networks and mutual funds. Lastly, I contribute more broadly to the economics literature of the effect of workplace connections n employee incentivisation by providing a large-scale study in a high-skill human capital-intensive industry, highlighting the impact of workplace connections on promotion and turnover decisions and, ultimately, employee behaviour.

The rest of the paper is structured as follows. First, I give an overview of the related literature. Second, I describe the data and how I measure connectedness at the firm. I then present my empirical evidence by looking at turnover, promotion, manager investment behaviour, and mutual fund performance. Next, I investigate investor responses by looking at mutual fund flows and size. Subsequently, I conclude.

2.2. Literature Review

This paper relates to three different strands of literature. First, it relates to the literature on mutual fund manager turnover and career concerns. This literature has focused on determining the impact of performance and flows on the firing decision (Chevalier & Ellison, 1999; Hu et al., 2000; Kostovetsky & Warner, 2015) and the incentives it provides (Chevalier & Ellison, 1999). Chevalier & Ellison (1999) show that the performance-turnover sensitivity is higher for younger managers. They further uncover that this age-induced difference in performance-firing sensitivities leads to differing incentives for young and old managers. These incentive effects lead younger managers to manage their investments more conservatively. Kostovetsky & Warner (2015) also investigate firing decisions but focus on the length of past performance considered in these decisions. They add to the literature by looking at subadvisor rather than portfolio manager departures from the fund. Portfolio manager departure data suffers from the fact that voluntary and involuntary departures cannot be distinguished. By looking at subadvisor departures instead, the authors argue that their sample leans more towards involuntary departure events. This stems from their conjecture that subadvisors are less likely to end an outsourcing relationship of their own accord. A portfolio manager may leave a mutual fund voluntarily to take a better job elsewhere or retire. A subadvisor firm does not need to end a concurrent outsourcing relationship to grow. It could simply add more clients (Kostovetsky & Warner, 2015).

A more recent paper investigates the effect of job security on effort-taking by mutual fund managers. Zhou (2020) exploits legal proceedings of subadvisor firms to examine the effect of increased job security of portfolio managers on effort-taking at the firm. An active legal dispute against an existing subadvisor negatively impacts the attractiveness of outsourcing (further) assets and, thus, increases the job security of internal portfolio managers. Exploiting this shock to job security, the author finds that an increase in job security leads to lower effort levels of in-house portfolio managers. This finding directly relates to the main research question of my paper. My contribution to this literature is to highlight that connectedness within the firm constitutes another factor that influences the decision to fire or promote a portfolio manager and to show that connectedness hampers the incentivisation effects of promotion and turnover decisions.

Second, my work relates to the literature on social/workplace connections and mutual fund managers. Most studies investigate the effect of relationships between portfolio managers and individuals outside the firm, such as CEOs and auditors (see for example Butler & Gurun, 2012; Chen et al., 2022; Cohen et al., 2008; Kuhnen, 2009). These papers generally find evidence for preferential treatment between two parties characterised by a pre-existing relationship.

Another related strand of literature sheds light on information sharing across connected individuals (Augustiani et al., 2015; Pool et al., 2015; Rossi et al., 2018). Pool et al. (2015) highlight that portfolio managers that live in the same neighbourhood share information. They uncover that a trading strategy that buys stocks bought by neighbouring portfolio managers and sells stocks sold by neighbouring portfolio managers produces alpha. Rossi et al. (2018) look at connected pension funds. They uncover that pension funds with the same fund sponsors or consultants generate higher risk-adjusted returns. Augustiani et al. (2015) perform a similar exercise on mutual funds and document that more interconnected funds invest more similarly. In contrast, my paper instead looks at mutual fund portfolio manager networks within the firm and investigates the effect of these connections on portfolio manager career outcomes, the resulting changes in incentives, risk-taking, investment distinctiveness, fund performance, and ultimatiely tries to answer the question whether workplace connections exacerbate agency issues.

Lastly, this paper adds to a broader literature on (personal) connections and performance appraisals, promotions, and incentives in the social sciences. Below I summarise the literature relating (personal) connections to performance appraisals and employee turnover and newer literature linking (personal) connections to incentives and effort exertion.

Studies employing survey data linking the effect of personal connections to performance appraisals by Tsui & Barry (1986), Cardy & Dobbins (1986), and Judge & Ferris (1993) all show that supervisors' affect toward their subordinates positively impacts performance ratings. Furthermore, another study by Breuer et al. (2013) shows that personal connections between employees and supervisors positively impact the performance evaluations of workers in a call centre. Therefore, previous literature suggests that (positive) personal ties impact performance appraisals.

The next logical question is concerned with the impact on promotion as well as demotion decisions. Kingstrom & Mainstone (1985) study the responses to a questionnaire sent to employees in the sales division of an international manufacturer of data processing equipment. To the best of my knowledge, the study is the first to establish that close acquaintances of supervisors are less likely to be fired and receive significantly more favourable performance ratings. A much more recent study by Zhu et al. (2021) finds that favouritism, measured by hometown ties between board members and CEOs in Chinese corporations, reduces the CEO's probability of being fired.

Finally, turning to the effect of (personal) connections on effort levels, Prendergast & Topel (1993) adapt the standard principal-agent model of Holmstrom & Milgrom (1987) and show that a personal bias by supervisors towards one of their subordinates may lead to inefficient resource allocation as well as weaker incentives for employees. The higher inefficiency stems from supervisors promoting the wrong (preferred) employees resulting in inefficient task allocation. The weaker incentivisation of promotion and demotion decisions follows from the fact that employee effort/performance is seen as no longer being the only factor impacting the promotion decision.

Bandiera et al. (2009) provide empirical evidence that social connections impacts firm performance. The authors study employees and managers of a UK soft fruit farm. When managers are paid a fixed wage, they favour connected employees. In contrast, when managers are paid variable wages dependent on the entire firm's performance, they target higher-ability workers. This finding leads the authors to conclude that favouring connected employees harms the firm.

Therefore, previous theoretical work supports the idea that (personal) connections between employees and supervisors impact employee appraisals, career outcomes, incentives, and effort levels. Limited prior empirical evidence is also consistent with these propositions but is missing a large-scale study that spans multiple years and industries and is less reliant on survey data. This empirical study addresses that gap in the empirical literature by investigating whether (personal) connections impacts employee career outcomes and effort levels in a high-skill and human capital intensive industry over a quarter of a century.

2.3. Hypothesis Development

As described in the previous section, employee-subadvisor relationships shape performance appraisals (Breuer et al., 2013; Cardy & Dobbins, 1986; Judge & Ferris, 1993; Kingstrom & Mainstone, 1985; Tsui & Barry, 1986; Wayne & Ferris, 1990) and ultimately firing as well as promotion decisions (Kingstrom & Mainstone, 1985; Zhu et al., 2021). While I cannot directly observe the full dimensionality and complexity of the relationships a portfolio manager has within a firm, I can look at how many people the portfolio manager knows at the firm and how senior, in terms of tenure, these connections are. I, therefore, first examine whether the connectedness of portfolio managers at their firm leads to differential treatment in promotion and firing decisions.

In light of the aforementioned existing evidence in the psychology and economics literature a portfolio manager with personal connections to (more) senior people could receive beneficial treatment over other portfolio managers regarding career-altering decisions. Thus, my first set of hypotheses investigates whether the connectedness of the portfolio manager leads to preferential treatment in firing and promotion decisions. The potential advantageous effect of workplace connections on firing and promotion decisions can appear through a level effect or a decrease in the performance-turnover (promotion) sensitivity.

Hypothesis 1a: *Higher connectedness within the mutual fund family leads to a lower probability of being fired from a fund.*

Hypothesis 1b: *Higher connectedness within the mutual fund family lowers the performance-firing sensitivity.*

Hypothesis 1c: *Higher connectedness within the mutual fund family leads to a higher probability of receiving a promotion in the form of more funds under management.*

Hypothesis 1d: *Higher connectedness within the mutual fund family lowers the performance-promotion sensitivity.*

Given previous evidence from Augustiani et al. (2015) that connectedness may lead to less distinct investment approaches I next investigate distinctiveness of a mutual fund by looking at two measures – deviations in sector allocations and deviations in factor loadings. The factor deviation measure is designed to measure whether the fund deviates from its peers' investment style and not to quantify whether a fund is taking more or less risk. Thus, the factor deviation measure is large for funds that take more systematic risk than their peers and those that take less risk. Similarly, this measure may also be large if the peer group has a small-cap value tilt while the fund follows a growth, large-cap strategy.

Hypothesis 2: *Funds of well-connected manager beings are less distinctive in their investment approach as captured by lower deviations in sector allocations and factor loadings relative to the peer group.*

Next, I turn to the implications of connectedness on employee risk-taking. In this context, risk-taking is restricted to the amount of financial risk a portfolio manager takes in the mutual fund and is generally measured by the fund's return volatility. Employing U.S. equity mutual fund data from 1980 to 2003, Kempf et al. (2009) show that incentives impact risk-taking by portfolio managers. The authors identify two types of incentives: *employment* incentives associated with the threat of job loss and *compensation* incentives associated with potential gains in compensation (promotion). These two incentives have opposing effects on portfolio manager risk-taking. First, employment incentives negatively impact risk-taking. If a portfolio manager takes (too) much risk, the probability of large losses is high. Because poor performance increases the potential for being fired, fund managers may choose to take less risk to minimise the likelihood of job loss. Second, compensation incentives have a positive effect on risk-taking. These incentives instil the desire in a portfolio manager to increase his pay/position at the firm and are documented to impact risk-taking positively. Managers may be tempted to increase fund risk in the hope of achieving high absolute returns and being rewarded through higher compensation. This compensation can come in multiple forms, namely, bonuses and, more relevantly, promotions in this study's context. Thus, while employment incentives decrease risk-taking, compensation incentives increase risk-taking.

The benefits enjoyed by better-connected managers in firing and promotion decisions decrease employment incentives through a reduction in the performance-turnover sensitivity and compensation incentives by increasing the probability of receiving a promotion. Because better-connected managers have a lower probability of being fired for poor performance, they can afford to take more risks than worse-connected managers. Moreover, because better-connected managers are more likely to receive a promotion than worse-connected managers, they face a lower incentive to increase risk in the hope of a high absolute returns. Therefore, given that connectedness decreases both compensation and employment incentives and that these two incentives have opposite effects on risk-taking by mutual fund managers, the directionality of the effect of connectedness on risk-taking is ambiguous.

Accordingly, I formulate two hypotheses for risk-taking. As previously described, employment and compensation incentives have the opposite effect on risk-taking. Therefore, the two hypotheses, 3a and 3b, aim to test whether the beneficial position of well-connected managers has a stronger impact on compensation incentives or employment incentives.

I examine these hypotheses by looking at mutual funds' total return volatility and idiosyncratic risk.

Hypothesis 3a: *The impact of connectedness on compensation incentives is stronger than on employment incentives. Thus, the better a portfolio manager is connected within the firm, the less risk he/she takes.*

Hypothesis 3b: *The impact of connectedness on employment incentives is stronger than on compensation incentives. Thus, the better a portfolio manager is connected at the firm, the more risk he/she takes.*

The advantageous standing of well-connected portfolio managers in firing and promotion decisions could impact their effort exertion. As previously discussed, there is some existing literature – mostly theoretical – asserting that non-performance considerations in promotion and firing decisions alter effort levels by employees (Bandiera et al., 2009; Prendergast & Topel, 1993).

Firing and promotion decisions are important incentivisation mechanisms at any firm. If portfolio managers do not exert enough effort, they will be fired. If portfolio managers perform well, they will probably be promoted by receiving more funds to manage. The preferential treatment enjoyed by better-connected managers alters both these incentivisation mechanisms by adding an extra factor that impacts firing and promotion decisions distinct from effort provision. Thus, a better-connected manager striving for a promotion needs to exert less effort. Similarly, better-connected managers can afford to exert less effort before they are fired. If well-connected mutual fund managers exert less effort I would expect their funds to exhibit poorer performance. Thus, I investigate whether mutual funds managed by well-connected managers perform worse.

Hypothesis 4: *Mutual funds managed by better-connected portfolio managers experience worse performance than those of worse-connected managers.*

Finally, I investigate the effect of connectedness on mutual fund size and flows. If better-connected mutual fund managers exert less effort and provide sub-par performance, rational investors should allocate fewer resources to these funds. Thus, one would expect better-connected managers to manage smaller funds with lower inflows.

Hypothesis 5: *Mutual funds managed by better-connected portfolio managers manage smaller funds and receive lower inflows*

2.4. Data

I obtain mutual fund data from Morningstar Direct from December 1995 to November 2021. This paper focuses on actively managed U.S. domestic equity mutual funds. I use an index fund flag provided by Morningstar as well as name searches for keywords such as "IDX", "index", "ETF", and "S&P" to remove all passive funds from my dataset. To avoid double-counting, I aggregate all observations from the share class to the fund level by calculating TNA-weighted fund averages for all share class level data points. I delete each fund's first 36 months of observations to account for incubation bias (Evans, 2010). The final sample consists of 6,880 unique equity mutual funds. I use gross returns in all my performance measures. Taking out the effect of differential fees should result in a better measure of manager skill and performance. I employ 1, 3, and 4-factor alphas for my risk-adjusted performance measures. I calculate these alphas by estimating factor loadings on the past 36 months of data. The estimated loadings are then used to calculate a concurrent expected return. This expected return is, in turn, employed to calculate alpha. Monthly net flows are measured as the percentage change in assets under management accounting for the increase in assets due to fund return (2.1).

$$NetFlow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times \left(1 + r_{i,t}\right)}{TNA_{i,t-1}} \tag{2.1}$$

A turnover event is identified when a mutual fund manager managing a fund for a fund family in month t is not listed as a manager on any of the other firm's funds in the following month t+1. The turnover events identified using this methodology may contain lateral moves. A manager may move to a different firm where they manage the same or a larger amount of assets. As this does not constitute a firing event, I only code these turnover events as a firing event if the manager is left with fewer assets after having left the fund family. When calculating the manager's assets under management, I sum the total net assets of the funds associated with the manager. I assume that assets are split evenly among team members for team-managed funds. Because a manager could be left with fewer assets under management even in a lateral move if some of his funds experienced outflows, I consider the growth/decline of the assets under management of the actively managed U.S. equity mutual fund market. Specifically, if a manager leaves a firm and is left with fewer assets after adjusting for the growth/decline in the overall U.S. equity mutual fund market, I code the manager to be fired.

A manager is considered to have received a promotion if the number of funds under his/her management increases the following month. For example, if a manager is currently managing three funds and manages four funds the next month, this manager is coded as receiving a promotion.

One concern about the current specification could be that promotions and firings are clustered around specific dates, such as financial year-end. The figures below depict the frequency of promotion and demotion events across calendar months.

[Figure 2.1 About Here]

Figure 2.1 shows while there is a slightly higher incidence of firing events from December to April, overall, the distribution of events seems well spread out across months. Furthermore, there does not seem to be a concentration of events in months at the start or at the end of a financial year (March, June, September, December).

I look at two measures to estimate how distinctively a mutual fund is managed. The first measure is called Sector Deviation. It measures how much the sector allocation of the fund deviates from its peers. I collect the sector allocation of mutual funds from Morningstar Direct and subsequently calculate peer group average allocations. Morningstar splits the allocation into the following 11 sectors: Basic Materials, Communication Services, Consumer Cyclical, Consumer

Defensive, Energy, Financial Services, Health Care, Industrials, Real Estate, Technology, and Utilities. A funds peer group consists of all other funds in the relevant Morningstar Category. Subsequently, I calculate the sum of squared deviations between the sector allocation of the fund in question and the average sector allocation of its peer group. This measure is then normalised by taking the square root and is as follows:

$$SectorDeviation_{i,t,c} = \sqrt{\sum_{s}^{S} \left(w_{s,i,t} - \bar{w}_{s,c,t}\right)^2} \tag{2.2}$$

where *f* stands for the factor, *i* for the fund, and *c* for the Morningstar Category. Some funds report their sector allocation quarterly. Thus, to prevent concurrency in timing between the Sector Deviation variable and my independent variables, I lead the Sector Deviation variable by three months throughout my empirical analysis.

As a further measure of investment distinctiveness, I estimate the deviation of a given mutual fund's factor exposures from those of its peers, following Chevalier & Ellison (1999). More precisely, it is represented by the square root of the sum of the squared deviations of a fund's factor loadings from the average factor loadings of peer funds as defined by its Morningstar Category and is as follows:

$$BetaDeviation_{i,t,c} = \sqrt{\sum_{f=1}^{3} \left(\beta_{f,i,t} - \bar{\beta}_{f,c,t}\right)^2} \tag{2.3}$$

where *f* stands for the factor, *i* for the fund, and *c* for the Morningstar Category.

Turning to risk-taking measures, I define total risk as the standard deviation of a fund's returns over the trailing 12 months. Idiosyncratic risk is measured as the standard deviation of the residuals from a 4-factor regression over the trailing 12 months. I lead all estimated dependent variables by the number of months used in the estimation in the analysis that follows. This ensures no concurrent timing of my independent variables and the estimation window of the dependent variable. Therefore, using 12 months of data in the estimation of my risk and Beta Deviation measures requires me to lead my dependent variable by 12 months throughout my empirical analysis.

Manager variables such as gender and ethnicity are inferred from the names of the mutual fund manager by using the 2000 and 2010 U.S. censuses and the 2017 Florida Voter Registration data. A very similar approach is used by Evans et al. (2019).

Manager experience is defined as the number of months a manager has spent in the mutual fund industry and measured by the months elapsed since the first time the manager entered the dataset. Manager tenure is the number of months a manager has managed a particular fund. All continuous variables are winsorised at the 1% level to limit the impact of outliers.

2.4.1. Mutual fund Manager Connections

My key explanatory variable in this paper is the connectedness of the mutual fund manager within the fund family. I track mutual fund managers by their first and last names and the initials of any middle names. This allows me to follow a mutual fund manager throughout his/her time in the sample. I first build weighted directional networks (graphs) for each fund family and month to calculate this connectedness measure, covering 13,357 unique mutual fund managers. A node depicts each mutual fund manager in a family. Mathematically, this is done by representing the network in the form of a weighted adjacency matrix (hollow square matrix), where each column and row corresponds to an individual mutual fund manager (node) in the network. A connection (edge) is drawn between mutual fund managers if they have previously co-managed a fund at least once. I also capture instances where mutual fund managers may know each other from managing a fund together at a different firm. Each edge is then represented by a positive cardinal number corresponding to the weight of the connection in the cells corresponding to the two nodes in the matrix. Put differently, a connection between manager i and manager j will be represented by $w_{i,j}$ and $w_{j,i}$, where w stands for the weight of a connection. Employing a directional network allows for $w_{i,j}$ and $w_{j,i}$ to differ. This is important as the value of a connection between two managers may differ.

My prior is that the connection between a junior portfolio manager and a senior portfolio manager is more valuable for the junior manager than for the senior manager. I choose to proxy the value or importance of the connection between two employees by one portfolio manager's time with the firm relative to that of other managers at the firm. More precisely, I construct the weights by ranking all portfolio managers within a fund family each month by the time they have worked at the fund family. The weight of a connection is then defined as the percentile rank of the connection's tenure at the firm.

Below is an example of a network with three portfolio managers represented by a three-by-three weighted adjacency matrix. An edge between manager 2 (PM2) and manager 3 (PM3) would be represented by the cells $w_{PM2,PM3}$ and $w_{PM3,PM2}$. If PM2 has a percentile rank of one and PM3 a percentile rank of 0.5 in the mutual fund family, I assign $w_{PM2,PM3}$ a weight of 0.5 and $w_{PM3,PM2}$ a weight of 1, as depicted below:

(M)

	PM1	PM2	PM3
PM1	0	0	0
PM2	0	0	0.5
PM3	0	1	0

A visual representation of a simple, non-weighted graph for the network of portfolio managers working at Congress Asset Management in January 2015 is depicted in Figure 2.2. Each point on the graph corresponds to a node - a portfolio manager working for Congress Asset Management - and the lines between the nodes correspond to edges (connections).

[Figure 2.2 About Here]

A standard measure for the connectedness of nodes in a network is degree centrality (DC). This measure represents a count of the number of direct connections a manager has with other fund managers in the fund family. Mathematically the degree centrality for manager *i* is calculated as follows:

$$DC_i = \sum_{j}^{N} c_{i,j}\, , where\ c_{i,j} = \begin{cases} 1\ if\ w_{i,j} > 0 \\ 0\ if\ w_{i,j} = 0 \end{cases} \qquad (2.4)$$

In the example in matrix *M*, manager one would have a degree centrality of zero because the manager has no connections within the firm. Managers 2 and 3 both have a degree centrality of one because they know one person. Therefore, the higher the number of connections, the better connected a fund manager is. I use this simple degree measure to calculate the number of external connections a fund manager has. It represents a count of the number of managers a portfolio manager knows outside of his firm. I will employ this measure to control for the effect that a more expansive network can have more generally on a portfolio manager's information acquisition and outside employment opportunities. Knowing more people provides the potential to gain more insights and information on potential investment strategies. Because portfolio managers belonging to the same fund generally have access to the same research, resources, and sometimes even share analysts, connections to portfolio managers outside of one’s firm should allow for more novel and distinct information compared to internal connections. Furthermore, knowing people at competing firms may make it easier for portfolio managers to switch firms. Especially in promotion decisions, these outside opportunities could allow for more bargaining power in promotion negotiations. For these reasons, I deem it important to include the outside network as a control variable in all my regressions.

The degree centrality measure described above treats all connections as equally important. In contrast, the node strength (NS) measure captures the importance of weightings and is often considered to be an equivalent measure to the degree centrality in unweighted networks. It is defined as follows:

$$NS_i = \sum_{j}^{N} w_{i,j} \tag{2.5}$$

While it is common to employ node strength instead of degree centrality in weighted networks, Opsahl et al. (2010) argue that it is not a good measure of the total involvement of a node in a weighted network. Node strength is good at measuring the strength of connections but misses some information on the total number of connections a node has. Therefore, to preserve the importance of the size of each manager's network, I employ the measure of Opsahl et al. (2010), which is defined as follows:

$$OC_i^{w\alpha} = DC_i * \left(\frac{NS_i}{DC_i}\right)^{\alpha} = (DC_i)^{1-\alpha} * (NS_i)^{\alpha} \tag{2.6}$$

I will refer to this measure as the Opsahl Centrality (OC). The measure multiplies the number of connections of a node in the network (DC) with the average node strength of its connections $\left(\frac{NS_i}{DC_i}\right)$. α is a tuning parameter. If α is set to 1, the measure collapses to the node strength, and if it is equal to 0, it collapses to the degree centrality measure. I set alpha to the midpoint of 0.5, giving equal weight to both node strength and degree centrality. In the earlier example, this would result in a weighted directional centrality measure of 0, 0.71, and one for nodes 1, 2, and 3, respectively.

[Figure 2.3 About Here]

In my empirical analysis, I log normalise the raw OC measure. As can be seen from Figure 2.3, the raw within-firm tenure-weighted OC variable is highly skewed with a few very large observations. After log-normalising, the variable exhibits a more normal distribution.

In unreported results, I re-run all my regressions employing two alternative measures of connectedness. The two measures are the degree centrality (2.4) and a simple count of the number of current connections a manager has in the firm. The latter measure reduces the connectedness measure to the number of distinct co-managers of a mutual fund manager. My analysis is robust to using these two measures for a manger's connectedness.

[Table 2.1 About Here]

[Figure 2.4 About Here]

Summary statistics are reported in Table 2.1. My sample's average within-firm tenure-weighted Opsahl centrality amounts to 5.19, with a standard deviation of 7.72. Figure 2.4 plots the monthly average log Opsahl Centrality measure over time. At the beginning of my sample in January 1996 the measure averages 0.68 and at the end 1.53. The most significant increase in the measure from 1.02 to 1.39 occurs between 2003 and 2007. This rise coincides with an increase in the average team size of mutual funds throughout that period. From 2007 to the end of the sample, the measure stays quite level at a monthly average ranging from 1.39 to 1.55. Due to the fact that I define two managers as being connected when they have co-managed a fund in the past, one may be concerned that manager tenure and experience are highly correlated with my connectedness measure. While both manager tenure and experience are positively correlated, the (spearman) correlations are not problematic at 6.56% (11.36%) and 15.04% (24.42%) respectively. On average, managers in my sample have 19.39 connections outside their firm and manage 2.72 funds. During the sample period from Nov 1995 to November 2021, I identify 11,151 events where a portfolio manager left a fund and 7,322 promotion events.

2.5. Empirical Analysis

In this section, I examine each of my five hypotheses discussed in section 2.3. I will first focus on hypotheses 1a, 1b, 1c, and 1d by investigating whether well-connected managers are treated differently in promotion and firing decisions. Next, I analyse the effect of connectedness on the investment distinctiveness of the mutual funds investment approach as laid out in hypothesis two. Subsequently, I investigate risk-taking by analysing hypotheses 3a and 3b. Finally, I explore whether there are any performance impacts (hypothesis 4) and fund size and flow differentials between funds managed by better- and worse-connected managers (hypothesis 5).

I will perform all my analyses on the full sample described in Table 2.1 and a propensity score-matched sample. To construct the propensity score-matched sample, I first split my sample into a treatment and a control group. An observation is assigned to the treatment group if it ranks in the top half on the within-firm tenure-weighed Opsahl centrality measure. Otherwise, it is assigned to the control group. Next, I employ a logistic regression model to calculate propensity scores. The independent variables used in this logistic regression are 4-factor alpha, the natural logarithm of fund size, the natural logarithm of fund family size, monthly net flow, team size, turnover, the expense ratio, the natural logarithm of fund age, manager experience, manager tenure, and the manager's external connections. Finally, I match each treatment observation to one control observation by minimising the distance in propensity scores. To avoid bad matches between my control and treatment groups, I restrict the maximum distance between propensity scores to be no larger than 0.00001. Figure 2.5 plots a histogram of the propensity score distribution of the treatment and control groups before and after matching.

[Figure 2.5 About Here]

The resulting propensity score matched sample encompasses 1,272,587 observations. The means of all variables used in matching the treatment and control samples are reported in Table 2.2.

[Table 2.2 About Here]

2.5.1. Mutual Fund Manager Turnover

In this section, I examine the effect of being well-connected within the fund family on the turnover probability controlling for time and firm fixed effects and manager and fund characteristics. Fund managers are considered to have left the firm if they are not listed as a manager on any of the fund family's mutual funds in the next month, but the fund they managed stays in existence, and they are left with fewer assets. In unreported results, I alter the turnover event definition by requiring a manager to experience a drop in assets under management of at least one standard deviation. Results are qualitatively and quantitatively similar to the main specification and available upon request. I follow Kostovetsky & Warner (2015) by looking only at turnovers where the fund was not closed because the fund closure decision is inherently different to a turnover decision. In the regressions exploring the level effect of connectedness on the turnover probability, my main explanatory variable is the natural logarithm of the mutual fund manager within-firm tenure-weighted Opsahl Centrality. In the regressions exploring the interaction effects between connectedness and mutual fund performance, I measure connectedness by a dummy variable. The dummy variable (*Highly Connected*) is equal to one if a manager ranks in the top third with respect to the connectedness measure at the firm and zero otherwise. Thus, I run the following two logistic regressions:

$$\begin{aligned} \ln\left(\frac{p_{m,i,t+1}}{1-p_{m,i,t+1}}\right) &= \beta_0 + \beta_1 * LN\ Connectedness_{m,t} \\ &\quad + F'_{i,t}\gamma_1 + M'_{m,t}\gamma_2 + \alpha_i + \theta_t + \varepsilon_{m,i,t} \end{aligned} \tag{2.7}$$

$$
\begin{aligned}
\ln\left(\frac{p_{m,i,t+1}}{1-p_{m,i,t+1}}\right) = {} & \beta_0 + \beta_1 Highly\ Connected_{m,t} \\
& + \beta_2\ Past\ Perf_{i,t\ to\ t-12} \\
& + \beta_3\ Highly\ Connected_{m,t}\ \times Past\ Perf_{i,t\ to\ t-12} \\
& + \beta_4\ Past\ Perf_{i,t-13\ to\ t-24} \\
& + \beta_5\ Highly\ Connected_{m,t}\ \times Past\ Perf_{i,t-13\ to\ t-24} \\
& + \beta_6\ Past\ Perf_{i,t-25\ to\ t-36} \\
& + \beta_7\ Highly\ Connected_{m,t}\ \times Past\ Perf_{i,t-25\ to\ t-36} \\
& + F'_{i,t}\gamma_1 + M'_{m,t}\gamma_2 + \alpha_i + \theta_t + \varepsilon_{m,i,t}
\end{aligned} \tag{2.8}
$$

where *P* refers to the probability of being fired, *F* corresponds to my fund level controls, *M* to the manager level controls, *theta* to time fixed effects, and *alpha* represents firm fixed effects. Subscripts *i* refer to the fund, *t* to time, and *m* to the manager. Due to the inclusion of firm and time-fixed effects, my model may suffer from the incidental parameter bias problem. To correct this potential bias, I perform an asymptotic bias correction derived by Fernández-Val & Weidner (2016). Furthermore, I follow Arnold et al. (2021) and control for the last three years of performance. Kostovetsky & Warner (2015) show that only the past three years of performance matter for turnover regressions. I include the following control variables on top of the past three years of performance: the natural logarithm of fund size, yearly fund flows, the natural logarithm of family size, the natural logarithm of fund age in months, the natural logarithm of team size, turnover over the past year and net expense ratios, manager tenure at the fund in months, experience as measured by the number of months a fund manager has been active in the industry, the manager's ethnicity, and gender. I furthermore control for the natural logarithm of the manager's connections outside of the firm. All regressions include time and firm fixed effects. I follow Kostovetsky & Warner (2015) in only including observations in the regression where the manager's tenure is at least 2 years. Standard errors allow for clustering on the firm and date level. In unreported regressions I employ two alternate measures of a manger's connectedness. Namely, the manager's degree centrality and a count of a managers current connections at the firm – ignoring all past connections. My results are robust to these two alternate measures of connectedness. Results of these alternate specifications are available upon request.

Regression results are reported in Table 2.3. All variables are standardised to have a mean of zero and a standard deviation of one. Columns one and two report regressions that only include a level effect of connectedness. In these regressions, connectedness is measured by the natural logarithm of the within-firm tenure-weighed Opsahl centrality measure. Columns 3 and 4 include an interaction effect between the within-firm connectedness and past performance. In these regressions, connectedness is measured by the *Highly Connected* dummy variable. Columns 1 and 3 report results from the full sample analysis, and columns 2 and 4 from the propensity score matched sample.

[Table 2.3 About Here]

In my full sample tests, reported in columns 1 and 3 of Table 2.3, I find negative coefficients on my connectedness variables. This supports the idea that ceteris paribus better-connected mutual fund managers are less likely to be fired. The size of these coefficients suggests that a one standard deviation change in connectedness has a larger impact on the firing probability than past performance. The connectedness coefficient in column 1 (-0.188) translates to an average marginal effect of -1.75% in annual turnover probability. This result supports hypothesis 1a. The interaction effects between past performance and connectedness in column 3 are all positive but statistically insignificant.

While there is no significant level effect of connectedness on the turnover sensitivity directly in the propensity score matched sample, I find evidence that highly connected managers enjoy a lower sensitivity to past year's performance. The probability of being fired is half as sensitive to past year's performance for portfolio managers that are highly connected. Thus, a highly connected manager is half as likely to be fired for bad performance.

Given the results from the propensity score matched sample analyses, I conclude that there is no level effect of connectedness on the probability of being fired but that connected managers enjoy a lower performance-turnover sensitivity. Thus, I confirm hypothesis 1b and reject hypothesis 1a.

The number of outside connections seems to not significantly impact the probability of being fired. As expected, and in agreement with the previous literature, I find a negative relationship between performance, fund size, and flows and the likelihood of being fired.

Furthermore, in line with previous research, I find that team size, fund age, and being a female manager increases the turnover probability. Moreover, manager experience, measured by the number of months since first entering the sample, positively affects the turnover probability. This result may seem counter-intuitive but could stem from the fact that more experienced managers are more likely to retire. Additionally, I find that the number of other funds the manager manages decreases the probability of being fired.

2.5.2. Mutual Fund Manager Connections and Promotions

Having established that a mutual fund manager's within-firm connections impact the performance-turnover sensitivity, I next examine promotions. Manager are considered promoted if they manage at least one more fund next month. I run the same logistic regression models described in equations (2.7) and (2.8) by substituting the probability of being promoted. All control variables are the same as in the turnover regression in section 2.5.1. Furthermore, in unreported results I furthermore reconfirm my findings using the two alternative measures of connectedness described in section 2.4.1. Regression results of the main specification are reported in Table 2.4.

[Table 2.4 About Here]

If better-connected portfolio managers experience preferential treatment in promotion decisions, the level effect should be positive and significant, and the interaction effects should be negative. I find that throughout all model specifications from columns 1 through 4, connectedness is positively associated with the probability of being promoted. More specifically, a one standard deviation increase in the connectedness measure increases the likelihood of being promoted by 10.66% per year (Column 1). The average partial effect on the annual promotion probability in the propensity score matched sample (Column 3) is 7.74%. This effect is economically meaningful. Thus, I find clear support for hypothesis 1c.

None of my interaction effects in the full sample analysis are significant. Furthermore, only past year's performance statistically significantly influences the probability of receiving a promotion. A joint Chi-squared test that tests if the effect of past year's performance is equal to zero for highly connected managers cannot be rejected with a value of 1.50. Therefore, it seems that for highly connected individuals, even past year's performance does not impact the likelihood of receiving a promotion.

In the propensity score matched sample analysis reported in column 4, highly connected portfolio managers experience a lower sensitivity to performance. Note that in this regression, both past year's performance and the performance from two years ago are not statistically significant. Only the performance from three years ago has a significant positive effect on the probability of being promoted, and its interaction effect with the highly connected dummy variable is negative. A Chi-squared test that tests if the performance sensitivity of highly connected managers is equal to zero cannot be rejected with a value of 0.2623. None of the performance measures seem to impact the probability of receiving a promotion for highly connected managers. Thus, I find support for hypothesis 1d.

Unsurprising, I find some positive coefficients on past performance. Mutual fund managers that perform better are more likely to be promoted. I further find that team size and portfolio manager tenure decrease the probability of being promoted.

Having shown that being well-connected within the firm indeed seems to impact turnover and promotion decisions, I next investigate the consequences.

2.5.3. Manager Behaviour

Connections positively impacting promotions and negatively impacting firing decisions can alter manager risk-taking and mutual fund investment distinctiveness. As described in section 2.3 and summarised in hypotheses 3a and 3b, the effect of connectedness on risk-taking could be either positive or negative, depending on whether it has a stronger impact on compensation or employment incentives. Given my previous findings that connectedness has a larger impact on the promotion decision, I would expect that connectedness has a larger effect on compensation incentives than on employment incentives and thus expect to find a net negative effect on risk-taking.

Furthermore, as outlined in hypothesis two, mutual funds managed by well-connected managers could be less distinct in their investment approach than funds managed by worse connected managers.

2.5.3.1. Investment Distinctiveness

As outlined in the hypothesis section and formulated in hypothesis two, if well-connected managers implement a wider set of investment ideas gathered from their connections, their funds might be managed less distinctively with an investment approach more closely resembling the average fund in their category. I test this hypothesis using the Sector Deviation and Factor Deviation measures in this section.

Because sector allocation data is only reported quarterly for some funds, I lead my sector deviation measure to avoid concurrent timing between my left- and right-hand side variables. The factor loadings used to calculate the Factor Deviation measure are estimated using 12 months of data. To avoid concurrent timing, I lead the measure by 12 months. All independent variables are lagged by one month. My main independent variable is the natural logarithm of the mutual fund manager within-firm connectedness. I include the following fund control variables: 4-factor alpha, the natural logarithm of fund size, fund flows, the natural logarithm of family size, the natural logarithm of fund age in months, the natural logarithm of team size, turnover over the past year and net expense ratios. Furthermore, I control for manager characteristics such as tenure at the fund in months, experience measured by the number of months a fund manager has been active in the industry, and the manager's ethnicity and gender, as well as manager tenure. I furthermore control for the natural logarithm of the manager's connections outside the firm. All regressions include Morningstar Category, month, and fund fixed effects. Standard errors allow for clustering on the fund level. Regression results for analyses on both the full sample and the propensity score matched sample are reported in Table 2.5. In unreported results using the two alternative connectedness measures described in section 2.4.1 I recover the results of the main specification in table 2.5.

[Table 2.5 About Here]

The negative coefficients on the within-firm tenure-weighted Opsahl Centrality for all four regressions indicate that being well connected within the firm leads to lower factor and sector deviations. In other words, funds managed by well-connected managers are more similar in sector allocation and factor exposure to their peers, consistent with Hypothesis 2.

Up to this point, my evidence suggests that better-connected mutual fund managers are treated favourably in firing and promotion decisions and that their funds are less distinctive in their investment approach.

2.5.3.2. Mutual Fund Manager Connections and Risk-Taking

In this section, I investigate the effect of within-firm connectedness on risk-taking. I consider total risk, as measured by the standard deviation of returns and idiosyncratic risk, as defined by the standard deviation of residuals from a 4-factor regression. All risk measures are estimated using 12 months of data. To avoid overlap in the timing of my dependent variables and my regression, I lead all independent variables by 12 months and lag all independent variables by one month.

$$\begin{aligned} Y_{i,t+12} &= \beta_1 * LN\ Connectedness_{m,t-1} \\ &\quad + F'_{i,t-1}\gamma_1 + M'_{m,t-1}\gamma_2 + \alpha_i + \theta_t + Style_{i,t} + \varepsilon_{m,i,t} \end{aligned} \tag{2.9}$$

My main independent variable is the natural logarithm of the mutual fund manager within-firm Opsahl Centrality. I include the following standard fund control variables: the natural logarithm of fund size, fund flows, the natural logarithm of family size, the natural logarithm of fund age in months, turnover over the past year and net expense ratios. Furthermore, I control for manager characteristics such as tenure at the fund in months, experience measured by the number of months a fund manager has been active in the industry, and the manager's ethnicity and gender, as well as manager tenure. I furthermore control for the natural logarithm of the manager's connections outside the firm and the natural logarithm of team size. All regressions include Morningstar Category, month, and fund fixed effects. T-Statistics from robust standard errors that allow for clustering on the fund level are reported in parentheses. Regression results are reported in Table 2.6. Table 2.6 again reports results from the full and propensity score matched sample analyses. In unreported results using the two alternative connectedness measures described in section 2.4.1I recover the results of the main specification reported in table 2.6.

[Table 2.6 About Here]

Within-firm connections do seem to lead to decreased risk-taking. Total risk is unaffected, but idiosyncratic risk declines as within-firm connections increase. Given the negative effect observed, it seems that mutual fund manager within-firm connectedness indeed mostly impacts compensation incentives. This is in line with the fact that connections seem to have a larger impact on the promotion probability than on the firing decision. This finding thus simultaneously supports hypothesis 3a and rejects hypothesis 3b.

Outflows seem to be positively associated with a reduction in total risk and an increase in idiosyncratic risk. This suggests that portfolio managers who experience outflows try to recover by taking more idiosyncratic risk. In line with Massa & Patgiri (2009), I also find that larger turnover and a higher expense ratio are indicators of funds that take larger risks.

Overall, I conclude that connectedness leads to lower risk-taking by mutual fund managers.

2.5.4. Mutual Fund Manager Connections and Performance

This section investigates whether portfolio manager within-firm connectedness results in negative consequences for investors. Given the existing theoretical evidence of Prendergast & Topel (1993) that preferential treatment of employees in promotion and firing decisions lowers employee effort, I expect a negative impact of manager within-firm connectedness on risk-adjusted performance. I measure performance as the monthly alpha of the Single Index Model, the Fama French 3 Factor model, or the Carhart 4 Factor model (Carhart, 1997).

$$\begin{aligned} Y_{i,t} &= \beta_1 * LN\ Connectedness_{m,t-1} \\ &\quad + F'_{i,t-1}\gamma_1 + M'_{m-1,t}\gamma_2 + \alpha_i + \theta_t + Style_{i,t} + \varepsilon_{m,i,t} \end{aligned} \tag{2.10}$$

My main independent variable is the natural logarithm of the mutual fund manager within-firm tenure-weighted Opsahl Centrality. I employ the same standard control variables as in previous regressions and Morningstar Category, month, and fund fixed effects. Standard errors allow for clustering on the fund level. Regression results are reported in Table 2.7 for both the full sample results and the propensity score matched sample results. In unreported results using the two alternative connectedness measures described in section 2.4.1 I recover the results of the main specification in table 2.7.

[Table 2.7 About Here]

The coefficient on connectedness is negative across all three performance measures and statistically significant when performance is measured using the Carhart 4 Factor model in the full sample analysis. In the propensity score matched sample analysis, effect sizes are larger, and all connectedness coefficients are statistically significant. More specifically, a one standard deviation increase in my connectedness measure leads to a reduction in the annualised one (four) factor-alpha of 27bps (27bps) in the propensity score matched sample.

2.5.5. Mutual Fund Manager Connections and Fund Flows and Size

Well-connected managers occupy an advantageous position in the mutual fund industry when it comes to firing and promotion decisions. I do find that this impacts manager risk-taking, investment distinctiveness and, ultimately, mutual fund performance. Why does this behaviour persist? Mutual fund families ultimately should only care about company profits. Fund performance does not have a direct impact on revenue generation. Mutual fund flows and the resulting fund size does. Therefore, I next investigate whether better-connected managers attain lower in-flows and whether they manage smaller funds. I run a monthly mutual fund flow regression and a standard fund size regression for the full and propensity score matched samples. Regressions are reported in Table 2.8. In unreported results using the two alternative connectedness measures described in section 2.4.1 I recover the results of the main specification reported in table 2.8.

[Table 2.8 About Here]

Columns one and two of Table 2.8 report results from a standard mutual fund flow-performance regression complemented with my connectedness measure and manager-level controls. The regressions reported in columns 3 and 4 incorporate an interaction effect between performance and connectedness, thus allowing for a differential flow-performance effect varying across the level of connectedness. Columns 5 and 6 report estimates of the fund size regressions.

Looking at the first four columns of Table 2.8, I do not find that portfolio manager within-firm connectedness impacts fund flows. Thus, it seems that investors are not aware of the negative consequences of connectedness within the firm. Looking at the interaction effect between fund performance and connectedness in columns 3 and 4, I find that being well-connected decreases the flow-performance relationship. While I cannot directly test why this is the case, one possibility is that better-connected managers at the fund family have better access to marketing through their workplace ties. Thus, despite their lower performance, they enjoy better support from the marketing department, which reduces the flow-performance relationship.

Fund size also shows no sensitivity to portfolio manager connectedness. Therefore, I cannot find support for hypothesis five and conclude that portfolio manager within-firm connectedness is not associated with smaller funds or lower inflows. This might explain why mutual fund families do not deem it important to tackle the preferential treatment received by better connected managers and, ultimately, why this phenomenon persists in the mutual fund industry to this day.

2.6. Conclusion

I empirically study the effects of agents' connectedness on incentivisation and outcomes within a principal-agent framework in a large sample of mutual fund managers from November 1995 to November 2021. In contrast to the traditional principal-agent problem, characterised by a single principal and a single agent, my work explores the situation where multiple agents are interconnected within a network. I first explore the effect of workplace connections on turnover and promotions. Portfolio manager connections positively impact the probability of being promoted. Furthermore, I find evidence that connectedness decreases performance-turnover and performance-promotion sensitivities. Moreover, this preferential treatment received by well-connected employees seems to alter their behaviour. Well-connected managers manage their funds more similarly to their peer group and take fewer risks in their investment approach. Within-firm connectedness seems to negatively affect mutual fund investors through sub-par mutual fund performance. A one standard deviation increase in portfolio manager within-firm connectedness reduces annual 4-factor and 1-factor alpha by 27bps. Investors do not seem aware of this adverse effect on performance. This is evidenced by mutual fund flows and size not being impacted by the connectedness of mutual fund managers within their fund family. My findings suggest that introducing a network structure of interconnected agents in a principal-agent framework can worsen incentive alignments and exacerbate agency issues.

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2.8. Figures

Figure 2.1: Turnover and Promotion Frequency by Calendar Month

This figure plots a frequency histogram of turnover and promotion events across calendar months. A promotion is defined as a fund manager managing an extra fund next month. A turnover event is recorded if a manager stops managing a fund next month and is left with fewer assets under management accounting for the growth or decline in the U.S. equity mutual fund market.

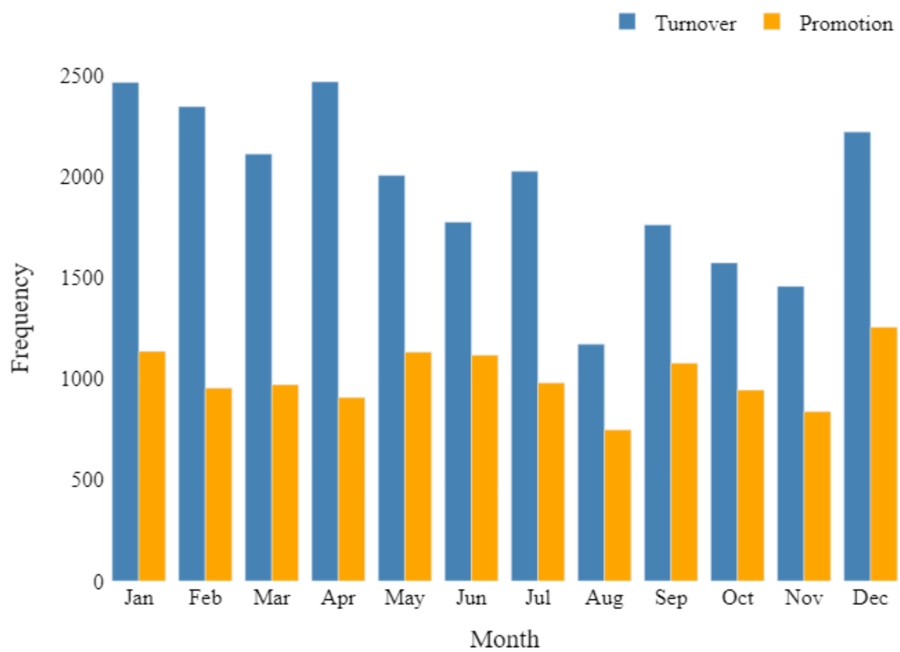


Figure 2.2: Within-Firm Network Congress Asset Management January 2015

This figure shows a network graph for Congress Asset Management in January 2015. Nodes are depicted by the blue dots where the size corresponds to the number of within-firm connections each portfolio manager has. Connections are drawn between nodes by grey lines.

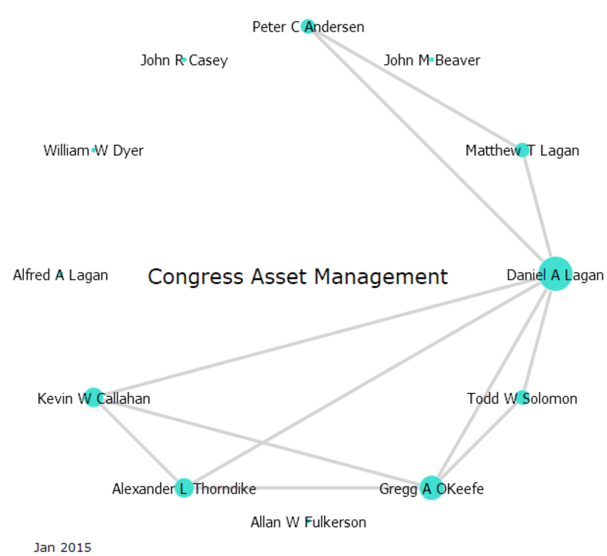


Figure 2.3: Within-Firm Tenure-Weighted Indegree Centrality Measure

This figure plots a frequency histogram of my within-firm tenure-weighted Opsahl centrality measure. The left histogram depicts the distribution of the raw measure. The right depicts the log-transformed variable.

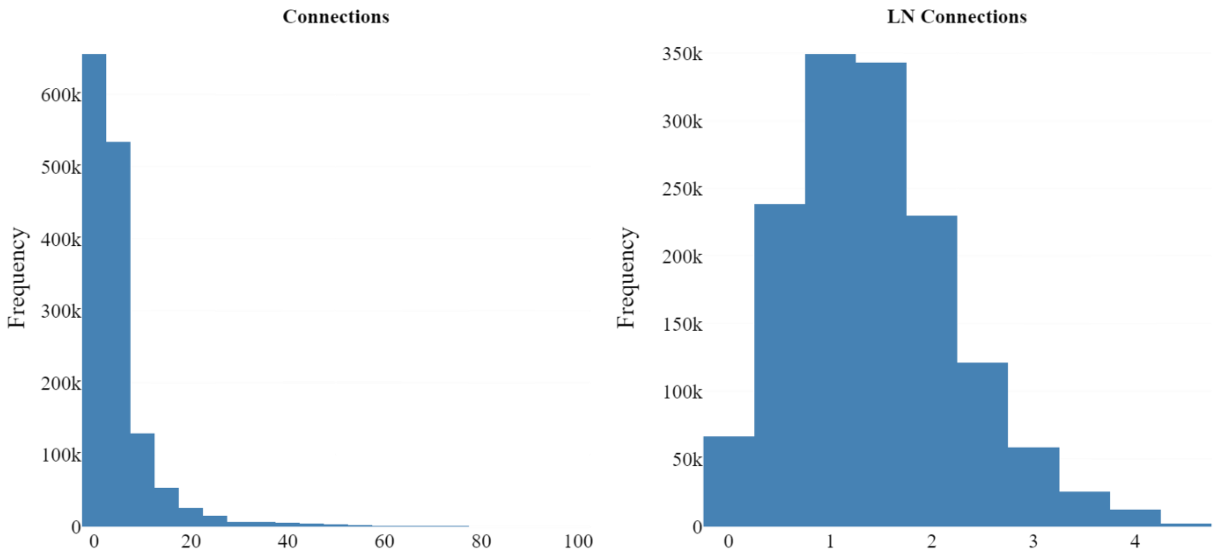


Figure 2.4: Monthly Average Log Opsahl Centrality Measure

This figure plots the monthly average Opsahl centrality measure used in the main analysis.

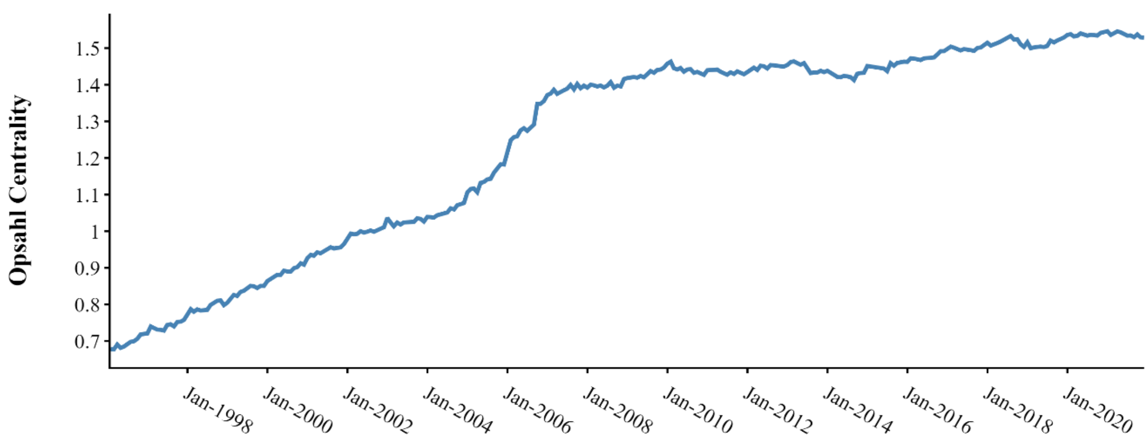
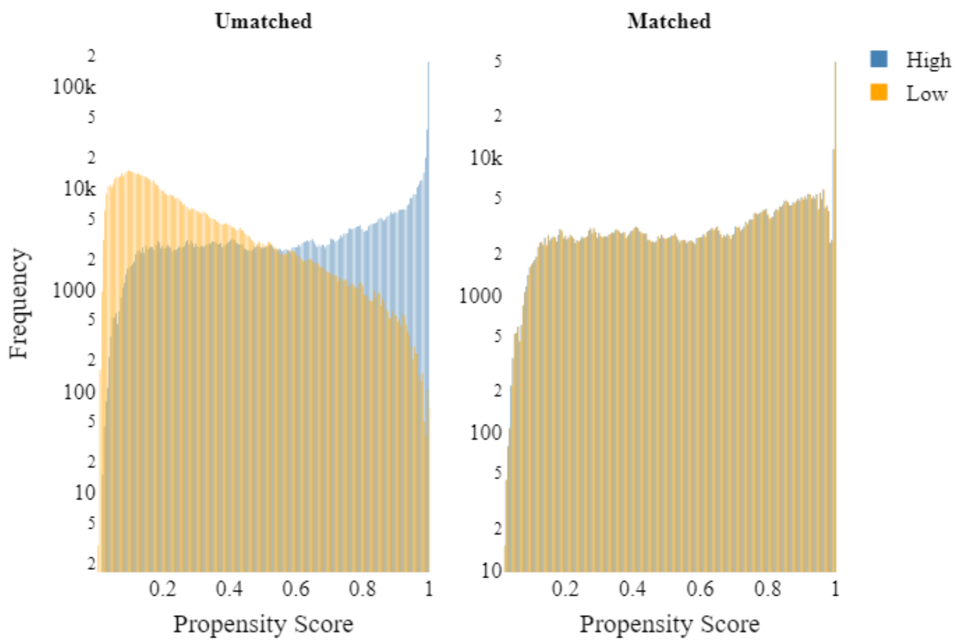


Figure 2.5: Propensity Score Matching Balance
This figure plots a frequency histogram of the propensity scores of the treatment and control groups before and after matching. The Y-axis is plotted on a log scale.



2.9. Tables

Table 2.1: Summary Statistics

	Mean	Std	Q25	Median	Q75
Managers (13,357)					
Connections (OC)	5.19	7.72	1.41	2.83	5.76
Connections (Outside)	19.39	35.66	1.00	6.00	22.00
Experience (Months)	92.58	68.50	37.00	77.00	136.00
Number of Funds	2.72	5.03	0.00	1.00	3.00
Funds (6,880)					
Monthly Gross Return (%)	0.86	5.32	-1.77	1.25	3.85
Monthly 1 Factor Alpha (%)	0.00	2.18	-1.07	-0.03	1.03
Monthly 3 Factor Alpha (%)	-0.03	1.87	-0.93	-0.03	0.85
Monthly 4 Factor Alpha (%)	-0.05	1.86	-0.94	-0.05	0.83
R2	0.91	0.11	0.90	0.95	0.98
Beta Deviation	9.21	23.34	0.21	0.38	0.92
Total Risk	0.05	0.02	0.03	0.04	0.06
Idiosyncratic Risk	0.01	0.01	0.01	0.01	0.01
Fund Size ($ Million)	2352.51	10225.72	84.89	339.51	1237.29
Family Size ($ Billion)	155.94	431.71	3.37	29.49	101.37
Monthly Net Flow	0.08	6.00	-1.46	-0.41	0.76
Turnover (%)	75.85	76.84	31.00	56.00	94.39
Expense Ratio (%)	1.18	0.46	0.91	1.13	1.41
Fund Age (Months)	133.24	77.54	68.00	121.00	191.00
Team Size	4.30	4.63	2.00	3.00	5.00
Tenure (Months)	64.15	56.15	22.00	48.00	90.00

Table 2.2: Propensity Score Matched Sample Means

This table shows the mean values for the covariates before and after propensity score matching. The treatment group is defined by having a within-firm tenure-weighted Opsahl centrality that ranks in the top half of the sample. Propensity scores are estimated with a logistic regression. I used the following predictors in the regression: 4-factor alpha, the natural logarithm of fund size, the natural logarithm of fund family size, monthly net flow, team size, turnover, expense ratio, the natural logarithm of fund age, manager experience, manager tenure, and the manager's external connections. Each treatment firm is matched to one control firm on propensity scores. To avoid bad matches, treatment firms that cannot be matched to a control firm with a propensity score difference below 0.0001 are discarded.

	Before Matching		After Matching	
	Treatment	Control	Treatment	Control
Propensity Score	0.727	0.268	0.631	0.631
4-Factor Alpha	-0.067	-0.053	-0.057	-0.085
LN Fund Size	20.261	19.386	20.028	19.926
LN Family Size	24.306	23.299	24.207	24.476
Monthly Net-flow	-0.150	-0.052	-0.076	-0.088
Number of Funds	6.422	3.005	6.104	7.050
Team Size	8.731	2.727	5.689	5.517
Turnover	71.931	75.070	71.447	70.964
Expense Ratio	1.070	1.214	1.110	1.099
LN Fund Age	4.823	4.812	4.805	4.785
Experience	111.312	101.444	109.724	111.294
Tenure	64.983	67.369	67.524	62.172
LN External Connections	2.896	1.549	2.593	2.755

Table 2.3: Portfolio Manager Connectedness and Manager Turnover

This table investigates the probability of a portfolio manager being fired from one of his/her funds. A portfolio manager is considered fired if he/she is not listed as a portfolio manager on any of the asset management firm's fund in the following year and his/her assets under management decrease. The main independent variable is the natural logarithm of the within-firm tenure-weighted Opsahl centrality measure of the portfolio manager. Control variables include past performance ranging from 1 to 5 years, the natural logarithm of fund size, past year's net flows, the natural logarithm of the family size, the size of the portfolio management team, the natural logarithm of fund age, the manager tenure in months, the experience in months, the portfolio managers gender inferred from his/her name, the number of other funds the portfolio manager manages, and the natural logarithm of the number connections the portfolio manager has outside of his/her own firm. I, furthermore, include time, firm and manager ethnicity fixed effects. I follow Kostowetsky and Warner (2015) in limiting the sample to only include managers who have been managing a fund for at least 2 years. T-Statistics are calculaed from standard errors that allow for clustering at the month and firm level and reported in parentheses. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Manager Left Firm & Fund Survived			
	(1)	(2)	(3)	(4)
	Full Sample	PSM	Full Sample	PSM
LN Connections/ High Conn.	-0.188***	0.067	-0.215***	0.089
	(-3.429)	*(1.533)*	*(-4.781)*	*(1.420)*
4F Alpha prior 12 months	-0.151***	-0.200***	-0.151***	-0.259***
	(-7.824)	*(-5.221)*	*(-6.656)*	*(-4.597)*
x High Connectedness			0.002	0.127**
			(0.070)	*(2.325)*
4F Alpha prior 24-13	-0.100***	-0.095***	-0.109***	-0.078
	(-4.821)	*(-2.618)*	*(-4.478)*	*(-1.614)*
x High Connectedness			0.026	-0.032
			(0.889)	*(-0.626)*
4F Alpha prior 36-25	-0.112***	-0.122***	-0.122***	-0.138***
	(-6.209)	*(-4.227)*	*(-4.478)*	*(-3.319)*
x High Connectedness			0.025	0.038
			(-0.717)	*(0.782)*
LN External Connections	-0.012	0.019	-0.018	0.029
	(-0.110)	*(0.146)*	*(-0.157)*	*(0.221)*
LN Fund Size	-0.343***	-0.308***	-0.340***	-0.308***
	(-10.728)	*(-6.014)*	*(-10.811)*	*(-6.045)*
Net-flow	-0.147***	-0.141**	-0.147***	-0.141**
	(-3.911)	*(-2.422)*	*(-3.901)*	*(-2.414)*
LN Family Size	0.069	0.008	0.052	0.002
	(0.477)	*(0.041)*	*(0.356)*	*(0.011)*
LN Team Size	1.050***	0.688***	0.992***	0.708***
	(13.266)	*(11.545)*	*(13.084)*	*(12.252)*
LN Fund Age	0.189***	0.086	0.189***	0.091
	(4.623)	*(1.133)*	*(4.737)*	*(1.228)*
Tenure	0.126***	0.145***	0.121***	0.144***
	(4.761)	*(3.604)*	*(4.626)*	*(3.679)*
Experience	0.051*	0.083*	0.049*	0.085*
	(1.802)	*(1.871)*	*(1.799)*	*(1.957)*
Gender: Male	-0.138**	-0.213*	-0.134**	-0.211*
	(-2.248)	*(-1.836)*	*(-1.836)*	*(-1.825)*
Number of Funds	-0.528	-0.948*	-0.530	-0.940*
	(-1.356)	*(-1.835)*	*(-1.345)*	*(-1.841)*
Fixed Effects:				
Firm & Date	Yes	Yes	Yes	Yes
Manager Ethnicity	Yes	Yes	Yes	Yes
Observations	1,214,927	806,689	1,214,927	806,689

Table 2.4: Portfolio Manager Connectedness and Manager Promotions

This table investigates the probability of a portfolio manager receiving a promotion in the form of getting an extra fund. The main independent variable is the natural logarithm of the within-firm tenure-weighted Opsahl centrality measure of the portfolio manager. Control variables include past performance ranging from 1 to 5 years, the natural logarithm of fund size, past year's net flows, the natural logarithm of the family size, the size of the portfolio management team, the natural logarithm of fund age, the number of months the fund manager has served as a portfolio manager on the fund (tenure), the number of months the portfolio manager has been managing funds in our sample (experience), the portfolio managers gender inferred from his/her name, the number of other funds the portfolio manager manages, and the natural logarithm of the number connections the portfolio manager has outside of his/her own firm. I, furthermore, include time, firm and manager ethnicity fixed effects. T-Statistics are calculated from standard errors that allow for clustering at the month and firm level and reported in parentheses. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Promotion			
	(1)	(2)	(3)	(4)
	Full Sample	PSM	Full Sample	PSM
LN Connections/ High Conn.	0.815***	0.546***	0.591***	0.491***
	(10.205)	*(5.630)*	*(6.584)*	*(2.809)*
4F Alpha prior 12 months	0.044*	0.049	0.043*	0.052
	(1.935)	*(1.412)*	*(1.750)*	*(1.467)*
x High Connectedness			-0.010	-0.018
			(-0.352)	*(-0.652)*
4F Alpha prior 24-13	0.024	0.049*	0.009	0.044
	(1.122)	*(1.681)*	*(0.247)*	*(0.873)*
x High Connectedness			0.017	-0.001
			(0.429)	*(-0.027)*
4F Alpha prior 36-25	0.027	0.048*	0.018	0.092**
	(1.326)	*(1.839)*	*(0.247)*	*(2.377)*
x High Connectedness			0.011	-0.079*
			(-0.314)	*(-1.958)*
LN External Connections	-0.196*	-0.300**	-0.090	-0.177
	(-1.781)	*(-2.104)*	*(-1.047)*	*(-1.286)*
LN Fund Size	-0.000	-0.001	-0.003	-0.007
	(-0.018)	*(-0.021)*	*(-0.129)*	*(-0.228)*
Net-flow	0.016	0.024	0.016	0.026
	(0.624)	*(0.917)*	*(0.588)*	*(0.972)*
LN Family Size	-0.106	-0.119	0.013	-0.064
	(-0.544)	*(-0.591)*	*(0.074)*	*(-0.337)*
LN Team Size	-0.387***	-0.214***	-0.152***	-0.125**
	(-6.139)	*(-3.432)*	*(-3.048)*	*(-2.312)*
LN Fund Age	0.004	0.010	0.014	0.031
	(0.140)	*(0.236)*	*(0.453)*	*(0.748)*
Tenure	-0.059*	-0.007	-0.063*	-0.019
	(-1.806)	*(-0.185)*	*(-1.815)*	*(-0.486)*
Experience	-0.131***	-0.157***	-0.092***	-0.126***
	(-5.098)	*(-4.272)*	*(-3.239)*	*(-3.156)*
Gender: Male	-0.110	-0.212	-0.099	-0.181
	(-1.113)	*(-1.413)*	*(-1.041)*	*(-1.387)*
Number of Funds	0.320***	0.420***	0.307***	0.415***
	(5.059)	*(6.036)*	*(4.199)*	*(5.681)*
Fixed Effects:				
Firm & Date	Yes	Yes	Yes	Yes
Manager Ethnicity	Yes	Yes	Yes	Yes
Observations	1,169,950	795,429	1,169,950	795,429

Table 2.5: Portfolio Manager Connectedness and Effort-Taking

This table reports results from fixed effect regressions investigation the impact of portfolio manager within-firm connections on the Sector Deviation measure as well as the Beta Deviation measure used in Arnold et al. (2021). The Beta Deviation measure is estimated using 12 months of data and led by 12 months to prevent concurrent timing in the data used in the estimation of the Beta Deviation and my independent variables. The main independent variable is the natural logarithm of the within-firm tenure-weighted Opsahl centrality measure of the portfolio manager lagged by one month. All control variables are also lagged by one month and include monthly performance measured by 4-factor alpha, the natural logarithm of fund size, monthly net flow, the natural logarithm of the family size, the size of the portfolio management team, the natural logarithm of fund age, the number of months the fund manager has served as a portfolio manager on the fund (tenure), the number of months the portfolio manager has been managing funds in our sample (experience), the portfolio managers gender inferred from his/her name, the number of other funds the portfolio manager manages, and the natural logarithm of the number connections the portfolio manager has outside of his/her own firm. I, furthermore, include time, manager ethnicity, Morningstar Category, and fund fixed effects. Standard errors are clustered at the fund level. T-statistics are reported in parentheses. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Sector Deviation		Beta Deviation	
	Full Sample	PSM Sample	Full Sample	PSM Sample
	(1)	(2)	(3)	(4)
LN Connections	-0.117*	-0.170**	-0.254**	-0.043
	(-1.846)	(-2.225)	(-2.256)	(-0.254)
LN External Connections	-0.002***	-0.002	-0.000	-0.001
	(-2.681)	(-1.509)	(-0.140)	(-0.247)
4 Factor Alpha	0.009*	0.008	0.007	0.007
	(1.882)	(0.823)	(0.473)	(0.233)
LN Fund Size	-0.010	-0.027	0.038	0.130
	(-0.150)	(-0.333)	(0.319)	(0.678)
LN Family Size	0.055	0.125	0.147	0.118
	(0.470)	(0.761)	(0.715)	(0.343)
Monthly Net-flow	-0.007***	-0.007**	0.012*	0.013
	(-3.037)	(-2.184)	(1.879)	(1.239)
Number of Funds	0.014***	0.008*	0.002	-0.008
	(3.086)	(1.945)	(0.199)	(-0.594)
LN Team Size	-0.514***	-0.399**	-0.606**	-0.168
	(-3.714)	(-2.334)	(-2.400)	(-0.402)
Turnover	-0.000	0.000	0.001	0.002
	(-0.584)	(0.213)	(1.017)	(0.931)
Expense Ratio	0.476*	0.383	0.991*	1.354
	(1.798)	(1.091)	(1.849)	(1.589)
LN Fund Age	-1.199***	-1.242***	-2.158***	-1.722*
	(-3.629)	(-2.918)	(-3.026)	(-1.662)
Experience	0.000	0.001	-0.000	0.001
	(0.947)	(1.228)	(-0.117)	(0.713)
Tenure	0.001	0.000	0.002**	0.001
	(1.426)	(0.538)	(2.242)	(0.938)
Gender: Female	-0.124***	-0.101**	0.017	-0.066
	(-2.742)	(-2.144)	(0.170)	(-0.484)
Fixed Effects:				
Date	Yes	Yes	Yes	Yes
Morningstar Category	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes
Manager Ethnicity	Yes	Yes	Yes	Yes
Cluster: Fund	Yes	Yes	Yes	Yes
Observations	1,605,746	1,118,210	1,594,619	1,099,436
R2	0.714	0.752	0.709	0.730

Table 2.6: Portfolio Manager Connectedness and Risk-Taking

This table reports results of fixed effect regressions investigation the impact of portfolio manager within-firm connections on risk-taking. Total Risk is measured by the standard deviation of monthly returns, and idiosyncratic risk refers to the residual standard deviation from a 4-factor regression. Total risk, idiosyncratic risk, and all beta loadings are estimated using 12 months of data and lead by 12 months. The main independent variable is the natural logarithm of the within-firm tenure-weighted Opsahl centrality measure of the portfolio manager lagged by one month. All control variables are also lagged by one month and include monthly performance measured by 4-factor alpha, the natural logarithm of fund size, monthly net flow, the natural logarithm of the family size, the size of the portfolio management team, the natural logarithm of fund age, the number of months the fund manager has served as a portfolio manager on the fund (tenure), the number of months the portfolio manager has been managing funds in our sample (experience), the portfolio managers gender inferred from his/her name, the number of other funds the portfolio manager manages, and the natural logarithm of the number connections the portfolio manager has outside of his/her own firm. I, furthermore, include time, manager ethnicity, Morningstar Category, and fund fixed effects. Standard errors are clustered at the fund level. T-statistics are reported in parentheses. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Total Risk		Idiosyncratic Risk	
	Full Sample	PSM Sample	Full Sample	PSM Sample
	(1)	(2)	(3)	(4)
LN Connections	-0.000	-0.000	-0.000***	-0.000***
	(-1.069)	(-1.584)	(-3.222)	(-2.922)
LN External Connections	0.000	-0.000	0.000	0.000
	(0.942)	(-0.697)	(1.592)	(1.258)
4 Factor Alpha	-0.000***	-0.000***	0.000	0.000
	(-7.871)	(-6.272)	(0.856)	(0.058)
LN Fund Size	0.001***	0.001***	0.000	-0.000
	(7.283)	(4.918)	(0.815)	(-0.822)
LN Family Size	0.000	0.001*	0.000	0.000
	(1.622)	(1.800)	(0.193)	(0.615)
Monthly Net-flow	-0.000***	-0.000***	0.000***	0.000***
	(-4.787)	(-2.633)	(4.086)	(4.223)
Number of Funds	-0.000	0.000	0.000*	0.000***
	(-0.829)	(0.866)	(1.925)	(2.967)
LN Team Size	-0.001***	-0.001*	-0.000**	-0.000
	(-2.746)	(-1.788)	(-2.120)	(-0.583)
Turnover	0.000***	0.000***	0.000***	0.000***
	(6.947)	(5.792)	(9.329)	(5.064)
Expense Ratio	0.002***	0.002***	0.001***	0.001**
	(3.235)	(3.084)	(3.790)	(2.570)
LN Fund Age	-0.002***	-0.002*	-0.000	-0.000
	(-3.297)	(-1.918)	(-0.802)	(-0.549)
Experience	0.000	0.000	0.000	-0.000
	(0.536)	(0.933)	(0.879)	(-0.214)
Tenure	0.000**	0.000**	-0.000	0.000
	(2.180)	(2.395)	(-0.051)	(0.979)
Gender: Female	-0.000*	-0.000	-0.000***	-0.000***
	(-1.888)	(-1.029)	(-3.158)	(-3.200)
Fixed Effects:				
Date	Yes	Yes	Yes	Yes
Morningstar Category	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes
Manager Ethnicity	Yes	Yes	Yes	Yes
Cluster: Fund	Yes	Yes	Yes	Yes
Observations	1,635,542	1,125,024	1,635,542	1,125,024
R2	0.823	0.843	0.738	0.736

Table 2.7: Portfolio Manager Connectedness and Fund Performance

This table reports results of fixed effect regressions investigation the impact of portfolio manager within-firm connections on fund performance as measured by 1-, 3-, and 4-factor alphas. Factor loadings are estimated using 36 months of prior data. The main independent variable is the natural logarithm of the within-firm tenure-weighted Opsahl centrality measure of the portfolio manager lagged by one month. All control variables are also lagged by one month and include the natural logarithm of fund size, monthly net flow, the natural logarithm of the family size, the size of the portfolio management team, the natural logarithm of fund age, the number of months the fund manager has served as a portfolio manager on the fund (tenure), the number of months the portfolio manager has been managing funds in our sample (experience), the portfolio managers gender inferred from his/her name, the number of other funds the portfolio manager manages, and the natural logarithm of the number connections the portfolio manager has outside of his/her own firm. I, furthermore, include time, manager ethnicity, Morningstar Category, and fund fixed effects. Standard errors are clustered at the fund level. T-statistics are reported in parentheses. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	1 Factor Alpha		3 Factor Alpha		4 Factor Alpha	
	Full Sample	PSM Sample	Full Sample	PSM Sample	Full Sample	PSM Sample
	(1)	(2)	(3)	(4)	(5)	(6)
LN Connections	-0.008	-0.033**	-0.008	-0.027**	-0.010*	-0.034***
	(-1.042)	(-2.528)	(-1.358)	(-2.369)	(-1.840)	(-2.898)
LN External Connections	-0.002	0.020***	0.002	0.016**	-0.000	0.014**
	(-0.387)	(2.649)	(0.593)	(2.217)	(-0.020)	(1.998)
LN Fund Size	-0.140***	-0.143***	-0.092***	-0.091***	-0.111***	-0.108***
	(-20.265)	(-11.423)	(-17.624)	(-8.871)	(-22.552)	(-11.468)
LN Family Size	0.004	0.008	0.033***	0.042***	0.020**	0.028*
	(0.322)	(0.418)	(3.609)	(2.664)	(2.426)	(1.890)
Monthly Net-flow	0.001	0.002	0.001**	0.002	0.001	0.001
	(1.617)	(1.108)	(2.189)	(1.589)	(0.992)	(0.978)
Number of Funds	-0.000	-0.002*	0.000	-0.002	-0.000	-0.002*
	(-0.953)	(-1.907)	(0.616)	(-1.399)	(-0.287)	(-1.853)
LN Team Size	-0.006	-0.055	-0.008	-0.060*	0.002	-0.045
	(-0.333)	(-1.581)	(-0.667)	(-1.935)	(0.149)	(-1.505)
Turnover	0.000	0.000	0.000**	0.000**	0.000	0.000
	(1.031)	(1.467)	(2.177)	(2.493)	(0.241)	(1.565)
Expense Ratio	-0.038	-0.176**	0.050**	-0.082	0.020	-0.111*
	(-1.353)	(-2.555)	(2.164)	(-1.342)	(0.892)	(-1.913)
LN Fund Age	-0.003	-0.008	-0.035	-0.025	-0.036	-0.057
	(-0.076)	(-0.137)	(-1.359)	(-0.543)	(-1.361)	(-1.160)
Experience	-0.000	-0.000**	-0.000	-0.000*	0.000	-0.000
	(-0.403)	(-2.066)	(-0.283)	(-1.883)	(0.476)	(-1.199)
Tenure	-0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(-1.056)	(-0.221)	(-0.723)	(0.155)	(-1.320)	(-0.029)
Gender: Female	-0.003	-0.009	-0.004	-0.018**	-0.007*	-0.020***
	(-0.665)	(-0.994)	(-0.911)	(-2.340)	(-1.766)	(-2.600)
Fixed Effects:						
Date	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Category	Yes	Yes	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes	Yes	Yes
Manager Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes
Cluster: Fund	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,763,537	1,266,534	1,763,537	1,266,534	1,763,537	1,266,534
R2	0.108	0.132	0.084	0.118	0.087	0.118

Table 2.8: Portfolio Manager Connections and Fund Size and Flows

This table reports regression results from percentage fund flow and fund size regressions. Percentage fund net flow is defined as in equation 2.1. The dependent variable for the fund size regression is the natural logarithm of a fund's assets under management. My main independent variable is the one-month lagged within-firm tenure-weighted Opsahl measure. Control variables are all lagged by one month and include the natural logarithm of fund size, the natural logarithm of fund family size, monthly net flow, the number of other funds a manager manages, the team size, fund turnover, expense ratio, the natural logarithm of fund age, the experience and the tenure of the manager measured in months, a female manager dummy, and the natural logarithm of the number of outside connections. I, furthermore, control for manager ethnicity, time, and fund fixed effects. For the fund flow regressions, I additionally control for past performance (4-factor alpha). T-statistics computed from fund clustered standard errors are reported in parentheses. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Monthly Net Flow				LN Fund Size	
	Full Sample	PSM Sample	Full Sample	PSM Sample	Full Sample	PSM Sample
	(1)	(2)	(3)	(4)	(5)	(6)
LN Connections	-0.008	0.032	-0.011	0.028	-0.000	-0.000
	(-0.330)	(0.742)	(-0.435)	(0.668)	(-0.353)	(-0.100)
4 Factor Alpha	0.151***	0.140***	0.209***	0.223***	0.002***	0.002***
	(19.771)	(11.516)	(16.565)	(8.395)	(11.408)	(6.272)
x LN Connections			-0.043***	-0.051***		
			(-5.600)	(-3.610)		
LN External Connections	-0.052***	-0.029	-0.052***	-0.029	-0.000	0.000
	(-2.731)	(-1.021)	(-2.743)	(-1.021)	(-0.626)	(0.476)
LN Fund Size	-0.601***	-0.631***	-0.600***	-0.631***	0.982***	0.983***
	(-17.528)	(-12.637)	(-17.516)	(-12.631)	(504.994)	(420.192)
LN Family Size	0.359***	0.386***	0.359***	0.385***	0.011***	0.011***
	(7.136)	(4.518)	(7.123)	(4.510)	(7.590)	(5.734)
Monthly Net-flow	0.181***	0.182***	0.181***	0.182***	0.001***	0.002***
	(16.384)	(14.820)	(16.355)	(14.794)	(7.879)	(7.266)
Number of Funds	0.007***	0.007***	0.007***	0.007***	0.000***	0.000
	(4.164)	(3.036)	(4.119)	(3.020)	(3.079)	(1.451)
LN Team Size	-0.100*	-0.112	-0.099	-0.113	0.001	0.000
	(-1.664)	(-1.021)	(-1.644)	(-1.033)	(0.946)	(0.136)
Turnover	0.000	0.000	0.000	0.000	-0.000*	-0.000
	(0.533)	(0.147)	(0.504)	(0.132)	(-1.867)	(-1.203)
Expense Ratio	0.012	-0.067	0.009	-0.069	-0.007**	-0.008***
	(0.109)	(-0.382)	(0.080)	(-0.392)	(-2.358)	(-2.860)
LN Fund Age	-2.604***	-2.130***	-2.606***	-2.130***	-0.032***	-0.028***
	(-17.307)	(-9.177)	(-17.310)	(-9.180)	(-11.962)	(-7.374)
Experience	-0.000	-0.000	-0.000	-0.000	-0.000**	-0.000***
	(-0.184)	(-1.382)	(-0.161)	(-1.382)	(-2.128)	(-2.880)
Tenure	0.000**	0.000	0.000**	0.000	0.000***	0.000***
	(2.201)	(1.037)	(2.197)	(1.049)	(4.261)	(3.428)
Gender: Female	-0.029*	0.005	-0.029*	0.005	-0.000	-0.000
	(-1.737)	(0.197)	(-1.732)	(0.212)	(-0.252)	(-0.903)
Fixed Effects:						
Date	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Category	Yes	Yes	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes	Yes	Yes
Manager Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes
Cluster: Fund	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,760,548	1,272,587	1,760,548	1,272,587	1,760,646	1,272,587
R2	0.116	0.138	0.116	0.138	0.995	0.996

Chapter 3

Satisfied Employees, Satisfied Investors: How Employee Well-being Impacts Mutual Fund Returns

Elias L. Ohneberg Pedro A.C. Saffi

Abstract

This paper uses proprietary data on self-reported employee reviews from Glassdoor.com to study the relationship between employee satisfaction and mutual funds' performance. Using the staggered adoption of Anti-SLAPP (Strategic Lawsuits Against Public Participation) laws in the U.S. and variation from mergers between asset management companies to control for endogeneity issues, we find that employee satisfaction is positively linked to fund performance and size but that only performance-critical employees' satisfaction matters. A one-point increase on the 5-point scale of employee satisfaction leads to a 36bps (36bps) higher annual 3-factor (4-factor) abnormal performance. Finally, while there is a positive effect of employee satisfaction on risk-taking, we cannot establish a causal relationship.

3.1. Introduction

It is safe to assume that human beings prefer being happy to sad. However, in 2022 more than 23% of people stated that they felt sad at work.[2] This is even more prevalent in the UK, with 36% of employees saying they are unhappy in their jobs (Waugh, 2022). For employers, it is important to know if happiness at work is associated with better outcomes (e.g., profits and stock prices). Edmans et al. (2014) point out one mechanism through which employee satisfaction can increase job performance. Namely, the norm gift exchange model in Akerlof (1982). The starting premise is that there is a social construct to reciprocate a gift, such that a gift received requires a gift in kind. If an employer treats their employees well and, thus, increases their happiness, employees may view it as a gift from their employer and increase their effort exertion as a gift from themselves to their employer. In a principal-agent framework better treatment of the agent (employee) by the principal (employer) could be viewed as a gift and the agent may reciprocate by expanding more effort in their job. Therefore, employee satisfaction may help align incentives between the principal and the agent.

The literature often resorts to examining the impact of job satisfaction on overall firm performance and stock returns (e.g., Edmans, 2011; Green et al., 2019; Huang et al., 2015; Symitsi et al., 2018). However, measuring performance due to an individual employee's effort is challenging. Performance is often dependent on a combination of factors, including an employee's knowledge, skill, and ability, as well as the specific demands of the job and her level of motivation and engagement. For example, an individual's performance may be influenced not only by their own effort but also by factors such as the support they receive from their colleagues and the organisation's overall effectiveness. As a result, it is difficult to isolate the specific contribution of an individual to organizational outcomes and to attribute those outcomes to their individual performance.

Our paper examines the role of employee satisfaction on performance in U.S. active mutual funds and highlights the potential incentive alignment mechanism offered by employee satisfaction in a principal-agent problem. The outcome of the decisions made by portfolio managers in asset management companies to construct portfolios can be measured by fund performance characteristics – such as fund returns and volatility – that are directly linked to a manager's effort and risk-taking. Similarly, the outcome of sales and marketing employees' efforts can be measured

[2] Gallup: State of the Global Work Place Report 2022.

via assets under management. Therefore, mutual funds provide a suitable setting to study the effect of job satisfaction on performance since there is a clear, measurable link between employee effort and performance.

Using proprietary data on more than one million employee job reviews posted on Glassdoor.com about 437 mutual fund companies managing 3,266 funds from 2009 to 2019, we study if mutual funds managed by companies with more satisfied employees perform better and change their total and idiosyncratic risk profiles. Mutual fund managers that work for companies with higher employee satisfaction perform better. More specifically, a 1-point increase on the 5-point scale of average employee satisfaction leads to a 36bps (36bps) higher annual 3-factor (4-factor) alpha in our regression correcting for selection bias. This is economically significant since a move from the lowest (1) to the highest (5) employee satisfaction implies an increase in 4-factor alpha of 1.44% per year. We also show that a one-point increase in the employee satisfaction score of marketing and sales employees increases fund size by 0.2%. This suggest that employee satisfaction can help alleviate agency problems. Furthermore, our finding that the job satisfaction of marketing and sales personnel positively impacts mutual fund size offers further support for the importance of marketing and distribution efforts as a driver of mutual fund size.

We start by defining three measures of job satisfaction based on self-reported reviews made on Glassdoor.com between 2009 and 2019. The first measure is based on the average score of all reviews made in the past 24 months for a particular mutual fund company. The second measure is based on reviews by employees with job titles relevant to mutual fund performance. Job titles that fall under this category are broadly related to research, trading, and fund management. We call the satisfaction score derived from these reviews "Asset Management". Finally, "Marketing & Sales" contains job titles related to marketing and sales, such as "sales representative", "marketing manager", and "relationship manager". We can match 70% of total assets under management of all active funds on the CRSP Mutual Fund database at the start of our sample in 2009 and over 90% by 2019. Our matched sample has an average of 2,003 funds per year managed by 437 companies.

Next, we estimate regressions with time and investment objective-fixed effects to compute the effect of employee satisfaction on funds' abnormal returns. Consistent with the hypothesis that happier employees exhibit superior performance, we find that an increase in the satisfaction of employees working in "Asset Management" jobs is associated with higher abnormal performance.

Estimating causal relationships in this context may be affected by several endogeneity issues. Employee review data may suffer from selection bias as inclusion in our sample is conditional on at least one employee of the company having reviewed their employer on Glassdoor.com. Without at least one employee review posted on Glassdoor.com in the past 24 months, we cannot quantify employee satisfaction at a mutual fund company level. If the companies reviewed on Glassdoor.com are inherently different from companies without any reviews, our analysis could be biased. To address this problem, we employ a Heckman-selection model. Our instrument in the first-stage selection equation is the staggered adoption of Anti-SLAPP (Strategic Lawsuits Against Public Participation) laws in the U.S. A SLAPP suit is a lawsuit that aims to censor criticism by burying the defendant in legal costs. Anti-SLAPP laws add extra layers of protection for the reviewer and decrease the probability of being targeted by a SLAPP suit. As a result, the passing of Anti-SLAPP legislation increases the number of reviews written on Glassdoor.com and lowers average satisfaction ratings (Chemmanur et al., 2019).

Controlling for this selection bias, we find that satisfaction of employees working on "Asset Management" jobs is still associated with higher abnormal performance, but not employee satisfaction for the company as a whole nor for "Marketing & Sales" jobs. Going from the lowest satisfaction score of "Asset Management" jobs (1) to the highest (5) implies an increase in annual 3-factor (4-factor) alpha by 1.44% (1.44%). Similarly, the size of assets under management is positively related to the satisfaction of "Marketing & Sales" jobs but unrelated to the satisfaction of "Asset Management" jobs and overall employee satisfaction. These results show that job satisfaction only affects outcomes when measured for employees that directly impact the outcome metric employed.

Another potential endogeneity issue is due to reverse causality. For instance, companies with better-performing mutual funds may simply have more resources to spend on increasing employee satisfaction. To alleviate these concerns, we exploit mergers between mutual fund companies. Because individual employees have no impact on whether their company is being acquired, we argue that mergers constitute an exogenous shock to employee satisfaction. More specifically, we examine differences between mutual funds that are part of a mutual fund company that has been acquired by another company with a higher employee satisfaction rating (i.e., our treatment group) relative to mutual funds of mutual fund companies that have gone through a merger but where the acquiring company has an equal or worse employee satisfaction score (i.e., our control group). We search the SDC database for asset management companies' mergers and hand-collect newspaper articles on any merger and acquisition activity using Factiva from 2008 to 2020. We can identify 139 (381) mergers (funds) in our matched sample. Further, we identify funds that kept the same portfolio management team by looking at the first last and middle names of portfolio managers as reported by the CRSP Survivorship Bias Free Mutual Fund Database. Overall, 108 funds, run by 85 distinct mutual fund companies, keep the same managers after a merger.

Using a difference-in-differences estimation setup, we find that mutual funds that merge into an acquiring asset management company with a higher employee satisfaction score have both higher 3-factor and 4-factor abnormal returns compared to funds that went through a merger, but the acquirer had a lower or equal employee satisfaction score. We find that funds acquired by a company with a higher employee satisfaction enjoy a 4.3% (5.37%) higher annual 3-factor (4-factor) alpha.

Finally, we study if mutual funds exhibit different levels of risk-taking depending on job satisfaction. We define a fund's total risk as the standard deviation of its returns over the past 12 months and its idiosyncratic risk as the standard deviation of residuals from a 4-factor regression. The psychology literature offers two competing theories on how happiness can influence risk-taking. The “mood maintenance hypothesis” (MMH) predicts a negative effect of happiness on risk-taking (Isen & Patrick, 1983). Instead, the “affect infusion model” (AIM) predicts a positive effect of happiness on risk-taking (Forgas, 1995). While we find support for the “affect infusion model”, with a positive correlation between employee satisfaction and risk-taking in the sample-selection corrected Heckman regressions, this effect is not causal. In our difference-in-differences setup, we do not find evidence of significant changes in risk measures. This result is consistent with the suggestion by Lane (2017) that the true effect of happiness on risk-taking is zero but that existing evidence reports both positive and negative effects due to publication bias against null results in the literature to date.

Overall, our results provide evidence that employee satisfaction leads to higher fund performance, but it does not affect fund risk measures. Our findings that mutual fund performance and fund size are linked to the job satisfaction the relevant employee groups is consistent with theoretical predictions of the norm gift exchange model (Akerlof, 1983) and the aiding effects of employee satisfaction in alleviation agency problems typically observed in employee employer relationships.

This paper adds to multiple strands of literature. First, it adds to the finance literature on employee satisfaction. Whether employee satisfaction matters to the firm's performance has been a topic of recent interest in the academic finance literature. Edmans (2011) investigates employee satisfaction and long-run returns in a non-causal analysis and uncovers a positive relation. Huang et al. (2015) employ Glassdoor data and show that employee satisfaction is higher for family-run firms than public or scion-run firms, and that employee satisfaction is positively related to firm performance. Symitsi et al. (2018) also employ Glassdoor Inc.'s data but focus on UK companies, finding that employee satisfaction positively impacts firm performance. Two other recent finance papers employ Glassdoor employee reviews, but instead of looking at employee satisfaction, they investigate the informational effects these public online reviews have on the financial market. Chemmanur et al. (2019) look at the firm's external financing and show that equity investors gain new valuable information from employee reviews. Green et al. (2019) report a positive relation between employee satisfaction scores and stock market performance and attribute the effect to the revelation of new information contained in these reviews to the market. As previously mentioned, we add to this literature by providing evidence of the effect of employee satisfaction on performance closer to the employee level. Furthermore, we provide a causal analysis which is lacking in the empirical finance literature to date.

Second, we contribute to the existing literature on job satisfaction and performance in the fields of psychology and economics. While there is ample evidence of a relationship between employee satisfaction and on-the-job performance, causal evidence is difficult to establish. Prior studies link job satisfaction to higher productivity (Bellet et al., 2022; Böckerman & Ilmakunnas, 2012; Bryson et al., 2017; Harter et al., 2002; Iaffaldano & Muchinsky, 1985; Judge et al., 2001; Krekel et al., 2019; Oswald et al., 2015). To date, only two papers claim some causality regarding the effect of employee satisfaction/happiness on productivity/performance - an experimental study by Oswald et al. (2015) and an empirical paper by Bellet et al. (2022). The latter uses the weather as an instrumental variable for happiness in a survey study of British Telecom employees. We add to this literature by providing a more comprehensive analysis that covers 437 mutual fund companies that manage 3,266 funds over ten years and seeks to test for causality.

Third, we provide further evidence that marketing and sales channels constitute an essential determinant of a mutual fund's ability to attract assets under management. Existing evidence of the effects of marketing and sales on fund size and flows has typically resorted to proxying marketing and sales efforts by 12b-1 fees at the mutual fund level or aggregate advertising expenditure at the mutual fund family level (Barber et al., 2005; Gallaher et al., 2015; Khorana & Servaes, 2012; Roussanov et al., 2021; Sirri & Tufano, 1998). While 12b-1 fees are earmarked for marketing expenses, they are a rather crude measure of sales and marketing efforts. According to an Investment Company Institute report from 2005 only about 5% of 12b-1 fees are actually sued for marketing and sales. Jiang & Xiaolan (2017) proxy for the marketing efforts of the mutual fund family through the share of employees in marketing and sales positions. The authors find that a higher share of marketing and sales employees at the mutual fund family level translates to a greater ability of gathering assets. We provide further non fee or expense based evidence on the importance of marketing and sales as drivers of a mutual fund's ability to gather assets by highlighting that marketing and sales employee's job satisfaction positively impact mutual fund size.

Finally, we add to the literature on employee satisfaction and risk-taking. There is existing empirical evidence for both the AIM (Kamstra et al., 2003; Kessler et al., 2022; Otto et al., 2016) and the MMH (Goudie et al., 2014; Guven & Hoxha, 2015; Kliger & Levy, 2003). Given the inconclusive evidence in the literature, our paper also adds additional evidence on how risk-taking is impacted by happiness by investigating the risk-taking of portfolio managers in managing their funds.

The rest of the paper is structured as follows. First, we provide an overview of the related literature. Second, we describe the data and how we measure employee satisfaction. We then present our empirical evidence by looking at performance and fund size. Subsequently, we analyse effort exertion as a potential channel for the effect of employee satisfaction on performance. We then explore the effect of employee satisfaction on risk-taking. Subsequently, we conclude.

3.2. Literature Review

Multiple studies have examined the relation between job satisfaction and financial variables in the past. For example, Huang et al. (2015) investigate job satisfaction differences between family-run, scion, and public firms, and find a positive impact of employee satisfaction on firm profitability. Symitsi et al. (2018) are the first to employ Glassdoor data for UK firms and find evidence of a positive correlation between employee satisfaction and corporate performance. Green et al. (2019) examine the link between Glassdoor reviews and corporate performance. The authors, nevertheless, focus on stock returns as a measure of firm performance, also uncovering a positive relationship. Unlike previous studies, they associate the positive returns with an information effect of online reviews. Online employee reviews bring novel company-specific information into the market, which slowly gets incorporated into stock prices, driving prices higher. Chemmanur et al. (2019) take a similar approach to Green et al. (2019) but investigate the impact of the information contained in employee reviews on a firm's access to external financing.

Three of these papers find a positive link between employee satisfaction, as measured by Glassdoor reviews, and corporate performance. Huang et al. (2015) claim causality, Symitsi et al. (2018) do not, and Green et al. (2019) attribute the increase in performance not to the underlying happiness of employees but rather to the dissemination of novel, company-specific information that is gradually incorporated into stock prices.

Our paper is closest to Huang et al. (2015) as we are both interested in the effect of employee satisfaction on performance. However, we examine performance not at the aggregate company level but closer to the employees themselves. We can do so by using mutual fund data, which allows us to measure the specific performance outcome of two groups of employees: portfolio managers, whose performance is measured by mutual fund risk-adjusted returns, and marketing & sales employees, whose performance is measured by fund size.

There is also evidence from the fields of psychology, behavioural finance, and economics on the impact of happiness on productivity and risk-taking. The first field that studied the effect of employee satisfaction/happiness on productivity was psychology. In this literature, happiness is often termed mood, with most of the evidence coming from meta-analyses. Early work uncovered little to no correlation between employee satisfaction and performance (Brayfield & Crockett, 1955; Iaffaldano & Muchinsky, 1985; Vroom, 1964) but suffer from small sample sizes. For example, Brayfield & Crockett (1955) include only nine studies in their meta-analysis. By the 1980s, the number of studies investigating the correlation between employee satisfaction and performance increased, with Iaffaldano & Muchinsky (1985) including 74 individual studies in their meta-analysis. They report a correlation of 0.17, reconfirming the earlier studies by Brayfield & Crockett (1955) and Vroom (1964). Judge et al. (2001) include 312 samples in their meta-analysis greatly increasing the power of their statistical procedures. They find a correlation coefficient of 0.3 between employee satisfaction and performance. Harter et al. (2002) employ data on 7,939 individual business units of 36 individual companies and report significant and positive correlations between employee happiness and business unit profitability and productivity. A similar result is found by Krekel et al. (2019), covering 339 individual studies on a total of 82,248 business units across 230 organisations.

Further evidence for the impact of employee satisfaction on employee performance comes from the human resource and economics literature. Böckerman & Ilmakunnas (2012) employ data from the European Community Household Panel and Finnish Longitudinal Employer-Employee Data and show a positive effect of employee satisfaction on productivity in Finish manufacturing plants. Bryson et al. (2017) find a positive effect in the UK using 2011 data from the Workplace Employment Survey. Bellet et al. (2022) use data from weekly surveys of call centre employees at British Telecom and report a positive effect of employee happiness on sales. The authors employ weather data as an instrument for employee happiness in their analysis, being the first purely empirical paper to claim causality.

However, apart from Bellet et al. (2022), most previous literature does not provide causal evidence of a relation between employee satisfaction and performance. In contrast to Bellet et al. (2022), who employ survey data from one UK company, our paper instead employs a much larger dataset on 437 individual mutual fund companies across a much wider period.

Additionally we add to the literature investigation the importance of marketing and sales efforts on the asset gather abilities of mutual funds. This research has predominantly proxied for marketing and sales efforts through the measurement of 12b-1 charges at the mutual fund level (Barber et al., 2005; Khorana & Servaes, 2012) or aggregate mutual fund marketing expenditures at the fund family level (Gallaher et al., 2015). 12b-1 fees are fees charged by the mutual fund family to the investor and earmarked for marketing expenses. A report by the Investment Company Institute from 2005, nevertheless, finds that only 5% of 12b-1 fees are actually used for marketing and sales expenditures. This would suggest that 12b-1 fees are a rather imprecise measure for marketing and sales efforts. These fee based studies have generally found a positive relationship between marketing and sales efforts and mutual fund size and flows. A study by Jiang & Xiaolan (2017) has also uncovered a positive effect of marketing and sales efforts on mutual fund size and flows by measuring marketing and sales effort of the mutual fund family through the share of personnel in marketing and sales roles. We add to this literature by providing some further evidence that marketing and sales plays an important part in a mutual fund's ability to gather assets through a new measure of a mutual fund companies marketing and sales efforts.

Finally, we discuss the existing literature on risk-taking. There are two competing theories on how happiness (mood) can influence risk-taking in the psychology literature. The "affect infusion model" (AIM) (Forgas, 1995) suggests that positive mood leads to more risk-taking, and the Mood-Maintenance Hypothesis (MMH) (Isen & Patrick, 1983) predicts the opposite. AIM postulates that mood affects the decision-making process through biases in cognitive processing and the selection of relevant information. High-mood (happy) individuals rely more heavily on positive signals during the decision-making process. Furthermore, these individuals are (positively) primed and thus more likely to rely on the positive aspects of the risky decision. This leads high-mood individuals to be more risk-taking than individuals in poor moods.

The MMH predicts that individuals want to maintain their good mood and increase it if they are in a bad mood. Thus, good-mood (happy) individuals will take fewer risks to minimize the probability of reducing their current mood and poor-mood (unhappy) individuals will take higher risks in the hope of a good outcome that increases their mood.

To this day, there is mixed evidence in the literature. Some studies find support for the MMH, others for the AIM.

Kliger & Levy (2003) study the relationship between risk-taking and happiness by estimating market-wide risk-aversion coefficients using S&P 500 options data. The authors proxy for mood with weather data - relying on ample existing evidence that weather is highly correlated to happiness. The authors find evidence for the MMH by showing that investors' risk-aversion coefficient is higher on good weather days. Kamstra et al. (2003) study the effect of Seasonal Affective Disorder (SAD) on risk-taking in equity markets and find evidence for the AIM. SAD is the phenomenon of a direct relationship between depression and the lack of sunlight caused by seasonality. In winter, when sunlight is not as abundant, and individuals are more depressed, individuals hold fewer risky assets. The lower demand for risky assets during winter results in lower returns. In spring, once days become longer again, the risk appetite of investors increases due to a lift in their mood which is reflected by higher returns.

Goudie et al. (2014) show that the results of the MMH can readily be replicated using expected utility theory. In an expected utility framework, happier people will be less attracted to risk because high-utility (happy) individuals have more to lose from taking risks. The authors test their theory through an empirical investigation into the decision to put on a seatbelt in the United States and find that happier individuals are more likely to wear a seatbelt.

Guven & Hoxha (2015) performs a similar study using weather data as a proxy for happiness. They show that happier people are more risk-averse and take more time in taking decisions, supporting the MMH. Otto et al. (2016) run an experiment on lottery gambling in New York City. The authors find that on days when the local sports team performed well or when a sunny day succeeded many cloudy days more people took part in the lottery. This finding is consistent with the AIM.

A more exhaustive literature review on the effect of happiness on risk-taking and economic behaviour is provided by Lane (2017). Regarding risk-taking, the author points out that while the sign of the effect of happiness on risk-taking varies across studies, the reported effect sizes are close to zero. This leads him to postulate that the actual effect may be zero and that publication bias may have resulted in null results being unreported in the literature thus far.

A later paper by Kessler et al. from 2022 employs an experimental setting and reports a coefficient in support of AIM, but the effect is statistically indistinguishable from zero. This study adds to the existing literature on happiness and risk-taking by performing a causal analysis of the effect of employee satisfaction on the investment risk mutual fund managers take in the funds they manage.

3.3. Hypothesis Development

This section describes our empirical hypotheses. Evidence of a positive correlation between employee happiness and productivity started emerging in the early 2000s in the field of psychology. Since then, numerous papers have shown a positive correlation between employee satisfaction/happiness and productivity (Bellet et al., 2022; Böckerman & Ilmakunnas, 2012; Bryson et al., 2017; Harter et al., 2002; Judge et al., 2001; Krekel et al., 2019). Two studies claim to have found a positive causal effect of employee happiness on productivity. Oswald et al. (2015) employ three different experiments to show a positive effect of happiness on productive. Bellet et al. (2022) employ survey data on a UK telecommunications company to show that employee happiness positively affects company sales. If happiness indeed increases productivity, we expect to see this reflected in better on-the-job performance.

Hypothesis 1a: *Higher employee satisfaction leads to better performance on the job. Higher employee satisfaction of mutual fund performance-critical employees achieve higher risk-adjusted returns, and higher employee satisfaction of marketing and sales personnel positively impacts mutual fund size.*

Our first hypothesis states that more satisfied employees perform better at their job. We test this hypothesis by investigating whether happier portfolio managers produce better risk-adjusted returns and whether happier marketing and sales personnel achieve higher assets under management. Portfolio managers are employed to achieve high mutual fund performance, and marketing and sales personnel are employed to ensure the company's funds are large.

The existing literature on employee satisfaction and productivity is silent on how employee satisfaction causes higher job productivity. One mechanism pointed out by Edmans et al. (2014) is through the norm gift exchange model by Akerlof (1982). The starting premise is that there is a norm to reciprocate a gift. A gift received requires a gift in kind. If an employer treats their employees well and, thus, increases their happiness, employees may view it as a gift from their employer. Therefore, employees increase their effort exertion as a gift from themselves to their employer. Thus, we next test whether happier employees exert more effort in managing their mutual funds.

Hypothesis 1b: *Higher employee satisfaction leads to higher effort exertion by employees as measured by Beta Deviation.*

We measure effort-taking by a Beta Deviation measure. This measure captures the extent to which a mutual fund differs from its peers in terms of factor/style exposures. The peer group is defined as the CRSP investment objective. We argue that it requires more effort from the mutual fund manager to come up with distinct investment ideas compared to simply following one's peers. Zhou (2020) employs a similar measure, which looks at how differently a mutual fund is managed compared to its peers in terms of sector allocations. The author argues that most of the effort exertion in managing a distinct fund comes from information acquisition and the formulation of a unique investment approach.

Next, we investigate the effect of employee satisfaction on risk-taking. Previous evidence finds significant but contradictory effects of satisfaction/happiness on risk-taking. The psychology literature offers two models that describe how satisfaction or happiness can impact risk-taking. The AIM predicts a positive relationship between satisfaction and risk-taking, while the MMA predicts a negative one. Lane (2017) postulates that the actual effect size could be zero due to publication bias. We formulate two hypotheses. The first is related to whether satisfaction influences risk-taking at all. The second investigates if there is support for the AIM or the MMH.

Hypothesis 2a: *Higher employee satisfaction influences risk-taking.*

Hypothesis 2b: *Higher employee satisfaction leads to increased risk-taking and thus supports AIM and not MMH.*

We examine these two hypotheses by looking at the investment risk-taken by portfolio managers in the fund they manage. More specifically, we look at both the total and idiosyncratic risk of mutual fund returns.

3.4. Data

For mutual fund data, we use the CRSP Survivorship Bias Free Mutual Fund Database and data from Morningstar Direct. We use a linking table provided by Pastor et al. (2020) to merge the two databases. We only include active equity mutual funds identified by the *CRSP Objective Code* and *Index Fund Flag* variables. Data from both vendors are reported at the share class level. To avoid double counting, we aggregate all share classes by weighting them by their total net assets (TNA). These two databases provide us with monthly fund characteristics such as the total assets under management, returns, the mutual fund company the fund belongs to, and the name of the fund managers.

We calculate gross returns by adding the fund's expense ratio to the monthly net returns. We employ gross returns in our investigation as it provides a stronger indicator of a mutual fund manager's performance that is not masked by fee differentials. For our risk-adjusted performance measures, we use the Fama French 3 Factor model and the Carhart (1997) 4-factor model. We calculate alphas by using 36 months of prior data to estimate factor loadings. These factor loadings are then employed to estimate an expected return for the current month. Alpha is then defined as the current month's return minus the expected return.

Monthly mutual fund net flows are measured as the percentage change of assets under management that is not due to fund return (3.1).

$$Net\ Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times \left(1 + r_{i,t}\right)}{TNA_{i,t-1}} \tag{3.1}$$

To gauge effort exertion by the mutual fund manager, we employ a Beta Deviation measure. This measure quantifies the deviation of a given mutual fund's factor exposures from that of its peers, following Chevalier & Ellison (1999). A measure focusing on *Sector Deviations* rather than factor deviations is used for the same purpose by Zhou (2020). It is generally thought that doing one's own research and coming up with a distinct investment approach requires more effort than simply following one's peer group. The *Beta Deviation* measure is represented by the square root of the sum of the squared deviations of a fund's factor loadings from the average factor loadings of peer funds as defined by its CRSP Objective Code and is calculated as follows:

$$Beta\ Deviation_{i,t,o} = \sqrt{\sum_{f=1}^{3} \left(\beta_{f,i,t} - \bar{\beta}_{f,o,t}\right)^2} \tag{3.2}$$

where *f* stands for the factor, *i* for the fund, and *o* for the CRSP Objective Code.

To measure risk-taking, we look at total as well as idiosyncratic risk. Total risk is the standard deviation of gross returns over the past 12 months. Idiosyncratic risk is defined as the standard deviation of the residuals from a 4-factor regression.

We complement this widely used mutual fund data with proprietary employee reviews provided by Glassdoor Inc. To match Glassdoor data to our mutual fund data, we match employer names from Glassdoor to the name of the mutual fund company. We employ a mix of fuzzy-string-matching and hand-matching to connect the mutual fund companies in CRSP with the companies in Glassdoor. This matches approximately one million reviews to 437 companies managing an average of 2,003 funds per year from 2009 to 2019.

Furthermore, we obtain more detailed data on the employer by matching the mutual fund data to form ADV. Form ADV is an annually updated registration of investment advisors operating in the US with the SEC. It contains data on, for example, the number of employees and total assets managed. This data is collected from Excel files provided by the SEC and matched to mutual fund company names as reported in Morningstar Direct. Like the Glassdoor Inc. data, ADV filings are matched to mutual fund company names through a mix of fuzzy string and hand matching.

To identify mergers and acquisitions between asset management companies, we search the SDC database and hand-search each asset management company for newspaper articles regarding any merger and acquisition activity using Factiva from 2008 to 2020. We can identify 139 (381) mergers (funds) in our sample of 437 companies that have Glassdoor data. Furthermore, we identify changes in the portfolio management team by looking at the first last and middle names of portfolio managers as reported by the CRSP Survivorship Bias Free Mutual Fund Database. Out of the 381 mutual funds that undergo a merger, 108 have experienced no change in their portfolio management team in the two years surrounding the merger – from one year before to one year after. These 108 mutual funds without a manager change are run by 85 distinct mutual fund companies.

All continuous variables are winsorised at the 1% level to mitigate the effect of outliers.

3.4.1. Glassdoor Employee Satisfaction

Glassdoor Inc. is a large international job site that allows current and former employees to review their employers. It was founded in 2008 and has accumulated over 7.7 million employee reviews between 2008 and 2020 on U.S. companies alone. The data includes information on the employee such as age, job title, current job, highest degree attained and answers to questions on job satisfaction. Each review contains an overall job satisfaction score that ranges from 1 (lowest) to 5 (highest), as well as sub-scores on “Culture and Values “, “Career Opportunities“, “Senior Management“, and “Work Life“.

Matching the Glassdoor data to the CRSP mutual fund data is done by employing the following matching technique. First, we sanitize all company names to include only alphanumeric characters and convert them to lowercase letters. Next, we try to match these two cleaned strings directly. To increase the number of matches, we subsequently use different string distance measures on the cleaned names to find the five closest matches between mutual fund company names in CRSP and employer names in Glassdoor. After narrowing down the potential matches, we go through each potential match and hand-check the validity.

For our different string distance measures, we employ the standard Levenshtein distance measure, the Jaro-Winkler distance measure, and a weighted Levenshtein distance measure. The Levenshtein distance measure is defined as the minimum number of substitutions, insertions, or deletions necessary to change one string to match another. The Jaro-Winkler distance is a version of string distance that places more importance on the beginning of the strings. Therefore, if two sets of strings of the same length have the same Levenshtein edit distance, but one of the strings has mismatches at the beginning, and the other has mismatches at the end, the set with mismatches at the beginning will be considered more dissimilar. This is useful because names of mutual fund companies usually have a distinct name as their first word followed by less specific words such as "advisor" or "management company". These distances can then be converted to similarity measures – the lower the edit distance, the more similar the two strings are. As a last measure, we use an approach that combines the Levenshtein similarity measure with the individual word frequency to build a similarity score. Here we first calculate the similarity between every single word in a company name with each word in the matching company name. Subsequently, we map a word in the comparison string to one word in the company name by choosing the matched word that has the lowest Levenshtein distance – highest similarity score. A company name consisting of three words will thus have three Levenshtein similarity scores. These scores are normalized to range from 0 to 1, where 1 is a perfect match, and zero is a complete mismatch. Next, we multiply each word's Levenshtein similarity by the inverse frequency of that word in all company names in CRSP. Therefore, distinct words will be assigned higher importance than relatively frequent words such as "advisor" or "company".

Finally, we sum them to get a single number depicting the similarity of the two company names. This technique results in a successful match of 437 mutual fund companies to employers in the Glassdoor data.

[Figure 3.1 About Here]

Figure 3.1 shows the matching rate between CRSP and our Glassdoor reviews throughout our sample period. Using the previously described matching technique, we matched about 40% of active U.S. equity mutual funds to Glassdoor employee reviews in 2009. At the end of the sample in 2019, we were able to match roughly 70% of the funds in CRSP. Our sample with Glassdoor data covers 70% of total assets under management in 2009 and 90% at the end of our sample period.

Our study's two most important data items are the job title and the overall job satisfaction score. We use the job title to determine whether the employee of the mutual fund company is in a role critical for performance. More specifically, we build three broad groups of employees. The first includes all employees at the company. The second contains employees whose job title has some relation to the field of asset management. This group is designed to include job positions that have an impact on mutual fund performance (e.g., “portfolio manager”, “research analyst”, “trading associate”, “equity valuation associate”, “asset manager”, etc.). The third group contains job titles related to marketing and sales, such as “sales representative”, ”marketing manager”, and ”relationship manager”. We aggregate all employee reviews that fall within the different groups by averaging over the past two years. Figure 3.2 reports the mean and standard deviation of employee satisfaction scores by the three different job title groupings and shows their distribution.

[Figure 3.2 about here]

A widespread problem with online review data is that it follows a bimodal distribution as a result of polarization bias. This is because often customers will only go through the effort of writing a review if they are either very content or very discontent with the product they are reviewing. This results in a bimodal distribution with two spikes - one at the bottom of the scale and one at the top. As can be observed from Figure 3.2, this is not the case with Glassdoor Inc. Employee Satisfaction scores.

3.4.2. Summary Statistics

[Table 3.1 About Here]

Table 3.1 shows average fund characteristics and performance for various levels of employee satisfaction. We split all funds into quintiles by our job satisfaction measure. These univariate sorts show that funds with the lowest employee satisfaction achieve higher gross returns and risk-adjusted-performance. Furthermore, funds run by companies with lower employee satisfaction scores are smaller, more expensive, younger, have more idiosyncratic and total risk, and are managed more passively. These simple univariate sorts suggest that funds with more satisfied employees perform worse than funds with dissatisfied employees on a return and fund size dimension. Furthermore, these simply univariate statistics seem to suggest that happy employees exert less effort in managing their funds by managing their funds more passively and deviating less from their peers. Table 3.1 also seems to support the "mood maintenance hypothesis" because mutual funds managed by companies with lower employee satisfaction scores have higher idiosyncratic and total risk.

3.5. Empirical Analysis

In this section, we examine the hypotheses laid out in section 3.3. First, we focus on hypothesis 1a, which states that happier employees should achieve better on-the-job performance. Second, we investigate whether we can link changes in performance to effort-taking as suggested by the gift-exchange model (Akerlof, 1982). Finally, we explore the effect of employee satisfaction on risk-taking as formulated in hypotheses 2a and 2b.

Throughout these investigations, we employ three different empirical approaches. We perform simple OLS regressions - as is customary in the mutual fund literature. Next, we control for selection bias in the data by employing a Heckman Correction model. Finally, we exploit a difference-in-differences design around mutual fund company mergers to alleviate endogeneity concerns.

3.5.1. Employee Satisfaction and Performance

We measure on-the-job performance using two measures. The first is concerned with the performance of the mutual fund. The second employee performance measure is the size of the mutual fund.

Our main independent variable of interest is the employee satisfaction score over the last 24 months. Because we are interested in whether the satisfaction of all employees or just the satisfaction of performance-critical employees matters, we construct three different satisfaction measures. The first satisfaction measure includes all reviews over the past 24 months. The second two measures only include satisfaction scores by employees who should impact our two performance measures – mutual fund return performance and fund size. To ensure that we measure employee satisfaction only for employees that can impact a fund's return performance, we focus on employee reviews with job titles that seem relevant for mutual fund performance. We call the employee satisfaction score derived from these reviews “asset management”. Job titles that fall under this category are generally related to research, trading, and fund management. While it is also in the interest of the investment team to ensure the fund is large, it can usually only impact fund size by providing above-par returns. The employees aiming to increase the assets under management belong to the marketing and sales teams. Thus, for our fund size outcome measure, we focus on satisfaction scores reported by marketing and sales employees.

We begin by testing whether job satisfaction impacts mutual fund performance by running the following OLS regressions:

$$Y_{i,t} = \beta_1 \, Satisfaction_{i,t-1} + X'_{i,t-1}\gamma + \alpha_o + \theta_t + \varepsilon_{i,t} \tag{3.3}$$

where the dependent variable is one of our performance measures, either 3- or 4-factor alpha or the natural logarithm of fund size. The independent variable of interest is one month lagged *Satisfaction*. This Satisfaction measure is defined as the average job satisfaction score reported by employees of the company over the past 24 months. The control variables are all lagged by one month and include the natural logarithm of fund size, the natural logarithm of fund family size, the expense ratio, turnover, the natural logarithm of fund age, as well as mutual fund net flow in percentages. We also control for past performance by including a 1-month lagged 4-factor alpha in our fund size regressions. We include time (θ) and investment objective (α) fixed effects and cluster standard errors by mutual fund companies.

We run these regressions using our three different measures of job satisfaction – all reviews, “asset management” reviews, and “marketing and sales” reviews.

While the “Marketing and Sales” employee satisfaction should only matter for fund size and not fund performance, we also run the performance regression using this measure as a sort of placebo test. We do the same for the “asset management” employee satisfaction and fund size.

[Table 3.2 About Here]

Table 3.2 reports the coefficients of our three job satisfaction measures for the 3-factor and 4-factor alpha regressions. Using this regression design, we find a positive and marginally statistically significant effect of employee satisfaction on mutual fund performance. This effect is only present for the employee satisfaction scores given by performance-relevant employees. The effect of the marketing and sales and the entire company's employee satisfaction has no bearing on mutual fund performance. Our control variables correspond to the prior literature. Contrary to the implications of our univariate sorts reported in Table 3.1, employee satisfaction does seem to positively impact mutual fund performance in a multivariate analysis, albeit the results are only significant at the 10% level. These findings lend some support to hypothesis 1a.

[Table 3.3 About Here]

Table 3.3 repeats the analysis with mutual fund size as the dependent variable. We find positive but not statistically significant effects of employee satisfaction on mutual fund size.

A problem that remains even in this multivariate regression framework is that our sample may suffer from sample selection bias. Our analysis only includes observations where at least one employee of the company decided to review their employer on Glassdoor. This selection into the sample could bias our results. Table 3.4 reports sample means across our independent and control variables for the entire CRSP sample and the sample where we observe at least one Glassdoor review. T-Statistics for the difference in mean tests are provided as well.

[Table 3.4 about here]

It is apparent from Table 3.4 that our sample is quite different from the overall CRSP active equity mutual fund universe. Mutual funds with at least one Glassdoor review exhibit higher return performance, are larger, older, more passively managed, and have lower idiosyncratic risk. We next employ a Heckman Sample Selection model to tackle this selection problem.

The first stage of our Heckman regression model accounts for this sample selection bias by modelling the probability of us observing an employee review for a fund. We use two instruments as independent variables in this first stage regression as follows:

$$\begin{aligned} Prob\left(SampleInclusion_{i,t} = 1\right) = \ &\Phi(\mu + \lambda_1 Number\ Employees_{i,t-1} \\ &+ \lambda_2 Anti\ SLAPP_{i,t} + X_{i,t}) \end{aligned} \tag{3.4}$$

where *SampleInclusion* is a dummy variable equal to one if we observe at least one review for the fund and zero otherwise, X refers to other control variables included in the outcome equation and $\Phi(\quad)$ represents the standard normal cumulative distribution function. The instruments used in this first stage probit model are the number of employees of the mutual fund company managing the fund in question and the passing of an Anti-SLAPP Law. Different states adopted Anti-SLAPP laws in the United States at different times. Some states still do not have any Anti-SLAPP laws to date. These laws decrease the threat of being sued by a company for publishing (truthful) reviews online. As a result, the passing of these laws increased the number of reviews written by employees and lowered average satisfaction ratings (Chemmanur et al., 2019). Our instruments are both highly significant, with minimum Z-Values of 14.33 and 73.25 reported in the first-stage regressions in Table 3.5. Our outcome regression follows the simple OLS regressions with the inclusion of the inverse Mills ratio retrieved from our first-stage selection regression.

$$\begin{aligned} Y_{i,t} = \alpha + \ & \beta_1 Satisfaction_{i,t-1} + X'_{i,t-1}\gamma \ + InvMill_{i,t} + InvObjective'\delta \\ & +\theta_y + \ \varepsilon_{i,t} \end{aligned} \tag{3.5}$$

Rather than performing this regression in two steps, we estimate both steps simultaneously using a maximum likelihood estimation procedure. Furthermore, due to the first stage probit model, we changed the time-fixed effects from the monthly (θ_t) to the yearly level (θ_y). Our standard errors still allow for clustering at the mutual fund company (firm) level.

[Table 3.5 about here]

Results of the Heckman selection model are reported in Table 3.5. In the top part of this table, we report the coefficient estimates from the first stage probit regression. We find that the number of employees at a mutual fund company and mutual fund family size both positively affect the probability of a Glassdoor review having been written. These both make sense, given that a larger pool of employees increases the chances of one of them having submitted a review on Glassdoor. Furthermore, we observe a positive coefficient on the Anti-SLAPP law dummy variable. This is also expected. As previously described, Anti-SLAPP laws reduce the probability of being sued by the reviewee company. Thus, in states where Anti-SLAPP laws exist, the potential cost of writing an online review is lower. This lower expected cost of writing a review should lead more employees to write a review - especially if it is negative.

Having accounted for selection bias, we again find a statistically significant and positive effect of employee satisfaction on mutual fund performance for the asset management regressions. We do not find a significant effect on either the marketing and sales employee satisfaction or the overall employee satisfaction at the company. Control variables again are in line with prior results. Economically the coefficient of the Heckman selection model suggests that an increase of one point on the 5-point scale of the employee satisfaction score for performance-sensitive employees increases mutual fund 3-factor (4-factor) alpha by 36 bps (36) per year. Moving from the lowest satisfaction score (1) to the highest (5) would thus imply an increase in annual 3-factor (4-factor) alpha by 1.44% (1.44%). This result again confirms hypothesis 1a.

Next, we turn to mutual fund size. We again perform a Heckman sample selection model to account for potential selection bias. The dependent variable is the natural logarithm of the mutual fund size, and our key independent variable is the employee satisfaction score. Control variables remain the same as in the prior fund size regression. We again include investment objective fixed effects as well as year fixed effects. Standard errors allow for clustering at the mutual fund company (firm) level. Regression results are reported in Table 3.6.

[Table 3.6 about here]

The first stage selection equation results are virtually the same as for the performance regression reported in Table 3.5 and available upon request. Turning to the outcome equation, we find that the employee satisfaction of “marketing and sales” employees positively affects the size of the fund. A one-point increase in employee satisfaction of marketing and sales employees is associated with an increase in fund size by 0.2%. Moving from the lowest to the highest employee satisfaction level would increase fund size by 0.8%. This is again in support of hypothesis 1a, that employee satisfaction impacts on-the-job performance. Both the overall satisfaction and the employee satisfaction of the “asset management” employees do not seem to impact the size of the fund. Furthermore, the positive effect of marketing and sales employees’ job satisfaction provides further support to the existing fee based evidence of the importance of marketing as a driver of mutual fund size documented in prior literature. The signs of control variables are in line with typical regressions investigating the impact on mutual fund size.

Despite correcting for selection bias, these results could still suffer from endogeneity. Huang et al. (2015) try to tackle this endogeneity by using an instrumental variable approach. Reviews can be written by current and ex-employees on Glassdoor. The authors use the percentage of reviews given by current employees and the industry average of that variable for their instruments in the first stage regression. We, nevertheless, refrain from using this approach because the instruments themselves are a proxy for job satisfaction, given that happy employees are more likely to be current employees. Furthermore, the percentage of current employees effectively proxies for employee turnover, which in our view, leads to a violation of the exclusion restriction in our performance regressions. In an unreported regression, we follow Huang et al. (2015) and find that at least one of our instrumental variables violates the exclusion restriction. Furthermore, our estimation suffers from a weak instrument. For these reasons, we decided to instead try to tackle the endogeneity problem by looking at mutual fund company mergers.

We postulate that mergers of asset management companies provide a shock to the way employees are treated at the company, independent of the performance of the individual fund and the self-selection of mutual fund managers into companies. Generally, we are concerned with good employees endogenously choosing good companies to work for. When an asset management company is acquired by another company, the acquired asset manager’s culture, human resources, and the way employees are treated change. Therefore, we look at an exogenous shock to how the company is managed and how happy employees are at the company. More specifically, we run a two-way fixed effects regression where we define an event if the company a mutual fund belongs to is acquired, and the portfolio management team remains the same for at least one year before to one year after the acquisition. We then look at interactions between this treatment dummy with a dummy variable that takes the value of one if the acquirer has a higher employee satisfaction score than the acquired company and zero otherwise. The regression specification with the dependent variable, Y, taken as 3-factor and 4-factor alpha, is as follows:

$$
\begin{aligned}
Y_{i,t} = {} & \beta_1\, Post\ Merger \times Same\ Manager \times Higher\ Satisfaction \\
& + \beta_2\, Post\ Merger \times Higher\ Satisfaction \\
& + \beta_3\, Post\ Merger \times Same\ Manage \\
& + \beta_4\, Post\ Merger + X'_{i,t-1}\gamma + \alpha_i + \theta_t
\end{aligned}
\tag{3.6}
$$

where α_i captures fund fixed effects and θ_t captures time-fixed effects. The coefficient of interest in the equation is β_1. In this design, a unit is defined to be treated if another company has acquired the company that owns the mutual fund, the fund's management team does not change around the merger, and the acquirer has a higher employee satisfaction score. The control group that this effect is compared to consists of funds managed by mutual fund companies that were acquired by another company, and the managers stayed the same. All regressions allow for the clustering of standard errors on the mutual fund company (firm) level. The regression results are reported in Table 3.7.

[Table 3.7 about here]

Looking at our coefficient of interest, we see that a mutual fund that has gone through a merger, where the managers stayed the same, and where the acquiring company has a higher employee satisfaction score has both a higher 3-factor and 4-factor alpha compared to a company that went through a merger and had no manager change but the acquirer had a lower or equal employee satisfaction score. This effect is not only highly statistically significant but also economically large. We find that funds that are acquired by a company with a higher employee satisfaction enjoy a 4.3% (5.37%) higher annual 3-factor (4-factor) alpha. All control variables have the expected coefficients. The regression suggests that general merger events do not significantly impact mutual fund performance, given that our post-dummy variable shows no statistical significance. If the managers stay the same, we do nonetheless find a negative impact on mutual fund performance.

We also perform an event study that is equivalent in design to the difference-in-differences style regression described earlier. Figure 3.3 plots the coefficient of the interaction of being acquired by a better company with time to merger dummy variables. Panel A shows these event plots for the regression specification where all Glassdoor reviews are considered. Here we find that the parallel trend assumption does not seem to hold only for the 3-factor regression. In panel

B, we show the event plot for the "Asset Management" reviews and find that our conditional parallel trends assumption seems to hold.

We refrain from performing this exercise for our fund size regression because we cannot observe whether the marketing and sales personnel that marketed and distributed the mutual fund changed during the merger.

Using standard OLS regressions, regressions controlling for sample selection bias, and a difference-in-differences setup, we conclude that employee satisfaction positively impacts job performance, thus confirming hypothesis 1a. Furthermore, we find that only performance-critical employees' job satisfaction matters.

3.5.1.1. Employee satisfaction and effort provision

Given that we have now established that employee satisfaction positively impacts job performance, we want to explore one potential channel through which this may happen. Thus, we explore whether more satisfied employees exert higher effort, as described in hypothesis 1b.

We proxy for effort exertion by a measure previously employed by Arnold et al. (2021) and Chevalier & Ellison (1999). It captures whether a mutual fund manager deviates more from his/her peers in the form of factor exposure. Deviating more from one's peers should require more effort than simply following the crowd. Zhou (2020) employs a similar measure for the same purpose. Instead of looking at factor deviations (style deviations), she employs sector deviations. The author argues that most of the extra effort exerted from managing a fund differently from one's peers comes from information acquisition and processing.

We employ the same methodology in this section as in the previous performance investigation. First, we perform a simple OLS regression. Next, we control for sample selection bias through a Heckman correction and finally exploit our difference-in-differences set up using merger events.

The OLS regression follows the same design defined in equation (3.3) except that we lead the independent variable by 12 months to avoid concurrency in timing. On top of the control variables used in the performance regression, we also control for past performance by adding the past month's 4-factor alpha. Standard errors allow for clustering on the mutual fund company (firm) level, and we control for time and investment objective fixed effects. Regression results are reported in Table 3.8.

[Table 3.8 about here]

Looking at the asset management employee satisfaction coefficient in Table 3.8, we find that more satisfied employees deviate more from their peers in terms of style exposure. This suggests that happier employees exert more effort. Our control variables suggest that better performance in the form of higher 4-factor alpha is associated with higher factor deviations from one's peers. The coefficient on expense ratios shows that more expensive funds deviate more from their peers in the form of factor exposure.

Knowing from Table 3.4 that our results could suffer from selection bias, we now turn to a Heckman Selection model. This model was previously defined in equations (3.4) and (3.5). We again employ the same control variables as in the previous regression. Regression coefficients are reported in Table 3.9.

[Table 3.9 about here]

The first-stage regression results align with our previous first-stage regressions reported in Table 3.5 and are available upon request. Turning to the outcome regressions, we can see that while the employee satisfaction coefficient is still positive for the Beta Deviation measure, it is not statistically significant.

[Table 3.10 about here]

Finally, we employ our merger set up in our final investigation into the effect of employee satisfaction on effort-taking. This regression corresponds to equation (3.6) and is reported in Table 3.10. The interaction effect between having undergone a merger, the managers staying unchanged, and the acquiring company having a higher employee satisfaction score is statistically indistinguishable from zero.

Overall, while some evidence in the simple OLS regression suggests that employee satisfaction leads to higher effort exertion, more robust regression models yield insignificant results. Thus, while we refrain from concluding that employee satisfaction does not impact effort exertion, we acknowledge that more work needs to be done. The task of pinning down a mechanism that may underly the positive effect of employee satisfaction on on-the-job performance may be aided by more theoretical work in the field of psychology.

3.5.2. Risk-Taking

In this section, we explore hypotheses 2a and 2b by investigating whether mutual funds managed by happier employees have different total and idiosyncratic risk than those managed by unhappy employees. Total risk is measured by the standard deviation of returns over the past 12 months, and the standard deviation of residuals from a 4-factor regression measures idiosyncratic volatility. We employ a Heckman correction model as well as our mutual fund company merger design.

All regression designs are the same as in the effort-taking regression in section 3.5.1.1. The regression estimates of the outcome equation of the Heckman Selection model are reported in Table 3.11.

[Table 3.11 about here]

All our first-stage regression estimates correspond to the first-stage regressions previously reported in Table 3.5 and are available upon request. Like our mutual fund performance regression, we would expect to only find significant coefficients for the employee satisfaction of investment-related jobs. Looking at the coefficient of the “asset management” employee satisfaction score, we find that both coefficients on total risk and idiosyncratic risk are positive. Only the coefficient on idiosyncratic risk is statistically significant. This finding is in line with hypotheses 2a and 2b. Namely, employee satisfaction has an impact on risk and the effect is positive in line with the "affect infusion model" (Forgas, 1995).

[Table 3.12 about here]

Finally, we turn to our merger difference-in-differences design. The model specifications are the same as in our previous effort regressions, and estimates are reported in Table 3.12. Parallel trend graphs on the interaction effect between a time-to-merger dummy where the managers stay unchanged and an indicator variable that is equal to one when the acquirer has a higher employee satisfaction score are plotted in Figure 3.5.

Looking at the effect of working for a company with a higher employee satisfaction score in table 3.12, we find no statistically significant effect. This result suggests no causal effect of employee satisfaction on risk-taking. Given our previous findings of positive coefficients in both the OLS and Heckman regression specifications, we conclude that there may be a positive correlation between employee satisfaction and risk-taking but that this effect is likely not of causal nature.

3.6. Conclusion

While prior studies have found that employee job satisfaction is positively correlated with future stock returns (for example Edmans, 2011 and Green et al., 2019), the setting does not allow for a direct test of whether job satisfaction leads to better employee performance as opposed to firm-level performance. Furthermore, previous papers that investigate the effect of employee satisfaction/happiness and productivity/performance fail to establish a causal relationship. In this paper, we examine whether employees' job satisfaction causally impacts their job performance. Mutual fund data allows us to precisely measure the exact performance metric that is important for employees, namely mutual fund performance for employees related to investment functions and mutual fund size for marketing & sales employees. Furthermore, the granularity of employee review data provided by Glassdoor allows us to group employees according to their job titles and determine whose job satisfaction matters most.

Accounting for selection bias as well as endogeneity concerns, we find that employee satisfaction of performance-critical employees, such as portfolio managers, materially increases mutual fund performance. More specifically, a 1-point increase on the 5-point scale of average employee satisfaction leads to a 36bps (36bps) higher annual 3-factor (4-factor) alpha in our regression correcting for selection bias. We also find that a one-point increase in the employee satisfaction of marketing and sales employees increases mutual fund size by 0.2%., providing further non fee based evidence of the importance of marketing and sales efforts on mutual fund size.

In addition, we explore whether employee satisfaction has an impact on risk-taking. The existing literature documents mixed evidence on the effect of employee satisfaction/happiness on risk-taking behaviour. In simple OLS and Heckman selection models, we find that employee satisfaction positively impacts the idiosyncratic risk of the mutual fund returns, suggesting support for the "affect infusion model" by Forgas (1995). In our difference-in-differences design, we fail to find a significant effect. This is in line with the conjecture by Lane (2017) that the actual causal effect of happiness on risk-taking is zero. However, publication bias has resulted in the existing literature reporting statistically significant positive and negative effects of employee satisfaction/happiness on risk-taking.

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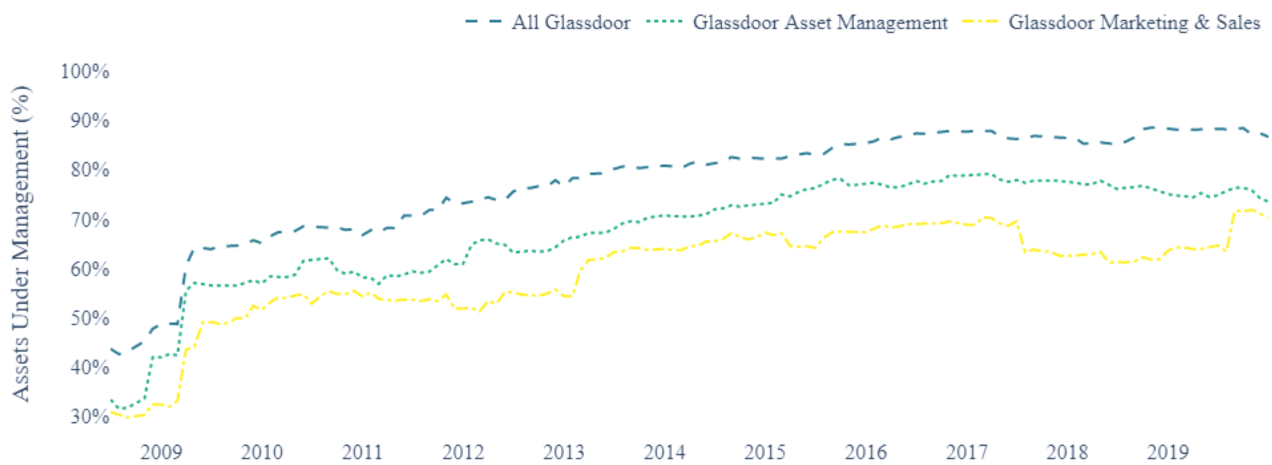
3.8. Figures

Figure 3.1: Matching between the CRSP Mutual Fund Database and Glassdoor

This figure shows the matching rate of the Glassdoor review data to our mutual fund database over time. Reviews are matched by the company name reported in Glassdoor to the name of the mutual fund company reported in the CRSP Survivorship Bias Free Mutual Fund Database. Matching is performed by a mix of string distance measures as well as by hand. "All Glassdoor" shows the per cent of all assets (Panel A) and the number of funds (Panel B) in our mutual fund database that could be matched to reviews. "Glassdoor Asset Management" restricts the reviews to falling within job positions related to Asset Management. "Glassdoor Marketing & Sales" refers to reviews by marketing & sales employees.

A: Percent of Assets under Management



B: Number of Funds

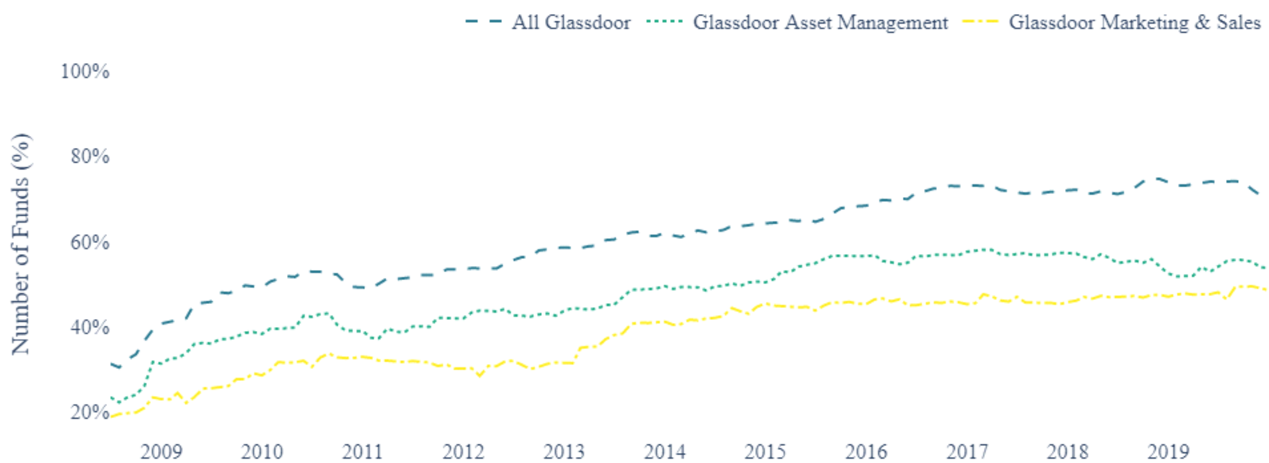
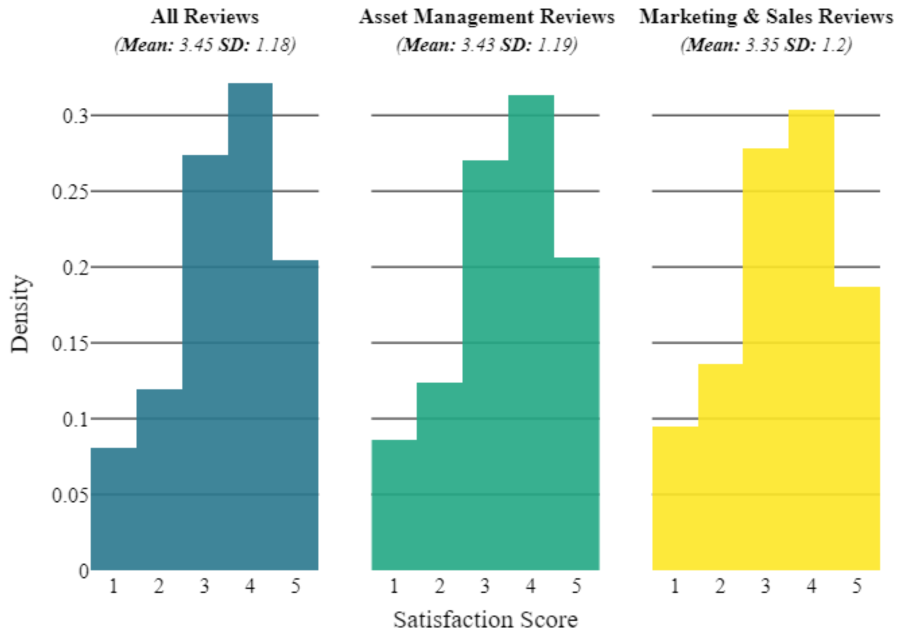


Figure 3.2: Glassdoor Employee Job Satisfaction Distribution

This figure Plots the distribution of Glassdoor reviews. Panel A plots the raw employee satisfaction score data. Panel B plots the distribution of the employee score measure averaged over the past 24 months. I report the mean and standard deviation of the overall Glassdoor job satisfaction score above each distribution. The Glassdoor job satisfaction score ranges from 1 (lowest) to 5 (highest). "All" includes reviews by all employee job titles. "Asset management" only contains reviews with a job title related to a research/financial job within the company that should be relevant to a fund's performance. "Marketing & Sales" refers to reviews from employees with a job title that falls into the marketing and sales department of the company.

A: Raw Review Data



B: Company Average over 24 Months

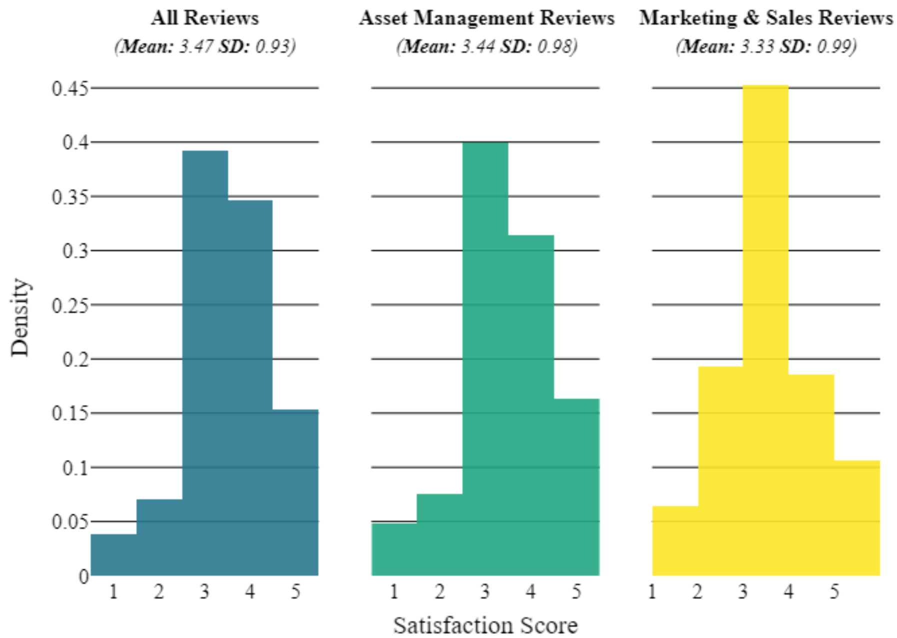
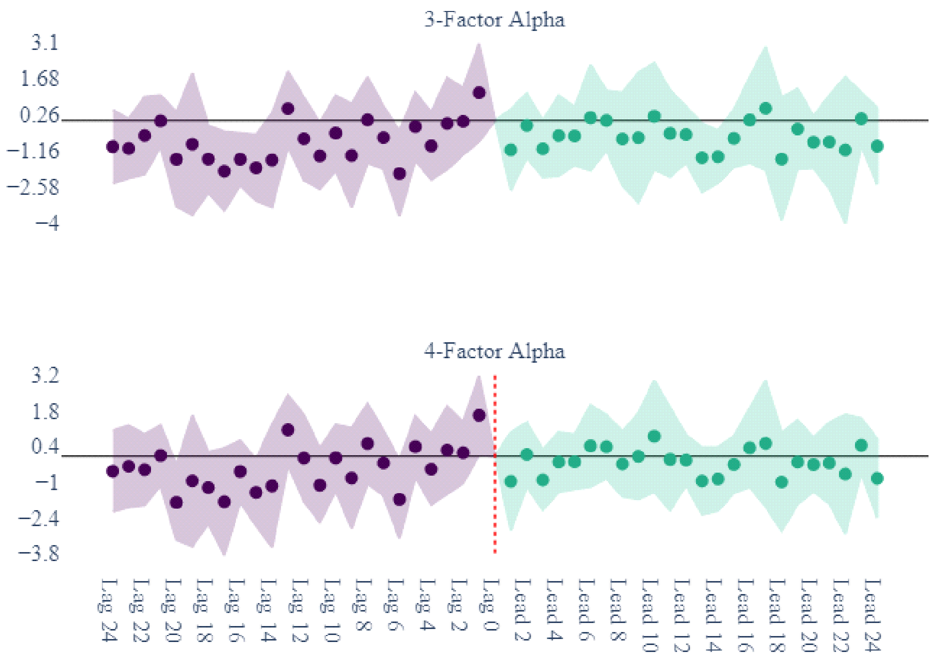


Figure 3.3: Parallel Trends for the Return Regressions

This figure depicts the conditional parallel trend graphs for the performance difference-in-differences regressions. The base month in the regression is the month of treatment. The points indicate the coefficient estimates of the interaction effect between moving to a higher employee satisfaction company and event dummy variables of a merger happening and the managers staying the same. I employ the same control variables and fixed effects as in the difference-in-differences regression reported in Table 3.8. Standard errors allow for clustering on mutual fund companies. The shaded errors depict the 95% confidence intervals.

A: All Reviews



B: Asset Management Reviews

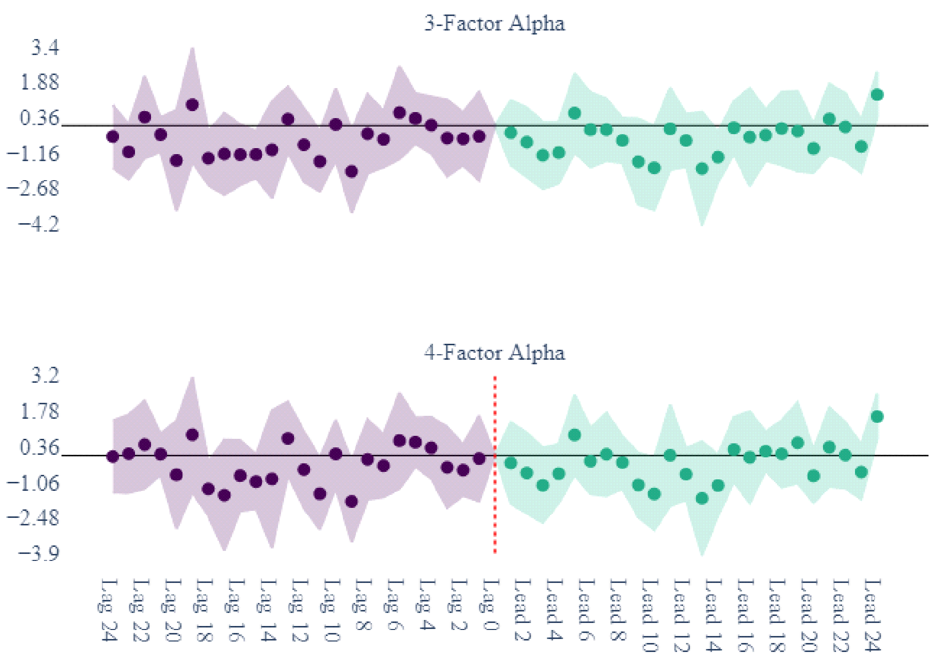
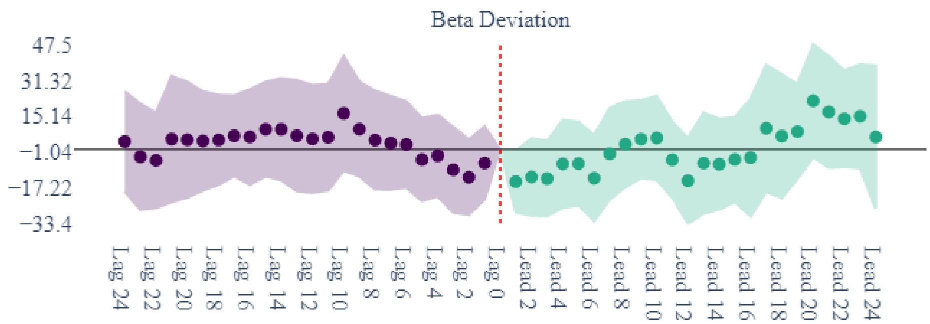


Figure 3.4: Parallel Trends for the Manager Effort Exertion Regressions

This figure depicts the conditional parallel trend graphs for the mutual fund effort-taking difference-in-differences regressions. The regression setup is analogue to Figure 3.3, and I employ the same control variables and fixed effects as in the difference-in-differences mutual fund effort-taking regressions reported in Table 3.10. Standard errors allow for clustering on mutual fund companies. The shaded errors depict the 95% confidence intervals.

A: All Reviews



B: Asset Management Reviews

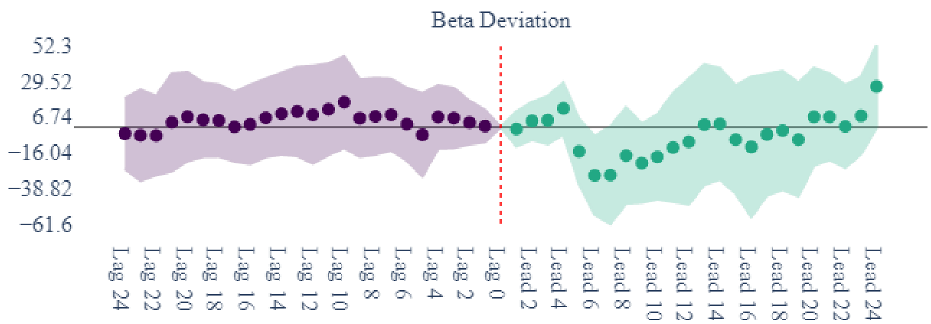
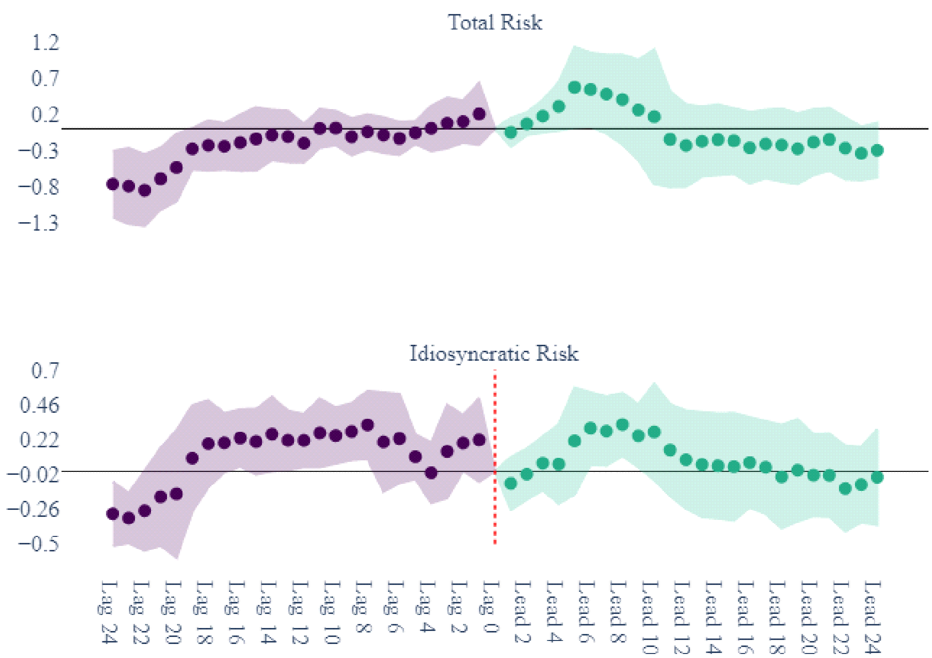


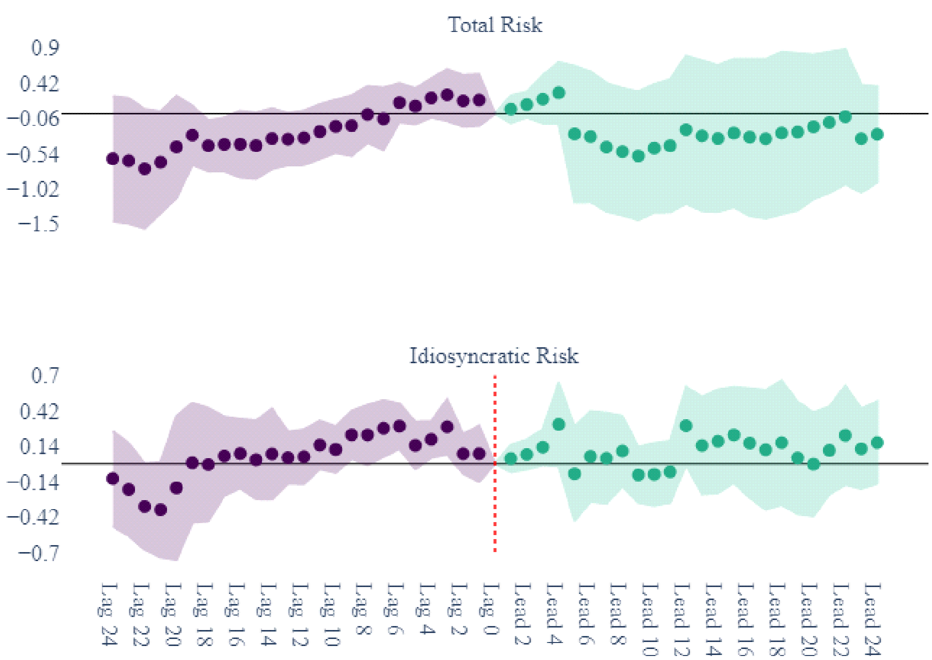
Figure 3.5: Parallel Trends for the Mutual Fund Risk Regressions

This figure depicts the conditional parallel trend graphs for the mutual fund risk difference-in-differences regressions. The regression set-up is analogue to Figure 3.3, and I employ the same control variables and fixed effects as in the difference-in-differences mutual fund risk regression reported in Table 3.12. Standard errors allow for clustering on mutual fund companies. The shaded errors depict the 95% confidence intervals.

A: All Reviews



B: Asset Management Reviews



3.9. Tables

Table 3.1: Fund Summary Statistics by Employee Job Satisfaction

This table shows the arithmetic mean of fund characteristics in our sample by job satisfaction quintiles. Job satisfaction is the overall job satisfaction rating of all employees from Glassdoor and ranges from 1 (least satisfied) to 5 (most satisfied). Fund size is reported in millions and fund family size is in billions. Our factor-adjusted returns are all calculated using gross returns and factor loadings are estimated based on the previous 36 months of data. T-statistics of a difference in mean test between the lowest and highest quintile are provided in the last column.

Quintile	1 (lowest)	2	3	4	5 (highest)	T-Stat (1-5)
Observations	24,251	30,978	27,689	27,644	27,652	
Job Satisfaction	2.41	3.12	3.39	3.65	4.18	-413.94
Gross Return	0.92%	0.96%	0.74%	0.68%	0.74%	4.52
1-Factor Alpha	0.13%	0.17%	0.11%	0.14%	0.09%	2.03
3-Factor Alpha	0.13%	0.18%	0.12%	0.13%	0.08%	2.69
4-Factor Alpha	0.09%	0.12%	0.09%	0.11%	0.04%	2.11
Size ($M)	1,187.34	1,525.93	2,103.16	2,924.73	1,786.36	-21.20
Family Size ($B)	68.75	212.17	210.20	437.99	233.06	-52.97
Expense Ratio	1.19%	1.13%	1.10%	1.05%	1.13%	17.96
Turnover	68.73%	81.60%	80.54%	62.20%	69.08%	-0.58
Age	17.37	18.02	18.92	20.10	17.96	-5.32
Number of Employees	571.79	601.61	892.96	950.47	340.47	34.68
Beta Deviation	0.49	0.51	0.50	0.51	0.56	-22.54
Idiosyncratic Risk	1.52%	1.62%	1.51%	1.45%	1.46%	3.87
Total Risk	4.79%	5.10%	4.31%	3.84%	3.87%	53.46
Net Flow	-0.23%	-0.24%	-0.14%	-0.27%	-0.31%	1.83

Table 3.2: Employee Satisfaction and Mutual Fund Performance

This table gives the regression estimates of the effect of employee satisfaction, proxied by the average overall Glassdoor review score over the past two years, on annual fund performance (3-factor alphas and 4-factor alphas) for OLS regressions. Controls include the following lagged fund observations. The natural logarithm of family size, the natural logarithm of fund size, the expense ratio, turnover, fund age, as well as past month's mutual fund net flows. The factor loadings for the risk-adjusted returns are estimated based on the previous 36 months. Sample refers to the subset of Glassdoor employee reviews considered. "All" makes use of all Glassdoor reviews. "Asset Management" only considers reviews with a financial/research job within the company that should be relevant for the performance of the funds. "Marketing and Sales" refers to reviews by job titles that fall within the marketing and sales department of the mutual fund company. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

		3-Factor Alpha			4-Factor Alpha		
		(1)	(2)	(3)	(4)	(5)	(6)
Satisfaction	All	0.0029			0.0000		
		(0.2846)			*(-0.0043)*		
	Asset Management		0.0166*			0.0170*	
			(2.173)			*(2.317)*	
	Marketing & Sales			-0.0029			0.0025
				(-0.3408)			*(0.312)*
	LN Fund Size	-0.0157***	-0.0180***	-0.0228***	-0.0141***	-0.0162***	-0.0206***
		(-3.733)	*(-3.923)*	*(-4.992)*	*(-3.629)*	*(-3.896)*	*(-4.986)*
	LN Family Size	0.0140***	0.0147***	0.0214***	0.0135***	0.0148***	0.0208***
		(4.417)	*(4.318)*	*(5.710)*	*(3.957)*	*(4.095)*	*(5.468)*
	Net Flow	0.0708	0.0840	-0.0718	0.1110	0.1318	-0.0708
		(0.5328)	*(0.4993)*	*(-0.4461)*	*(0.7819)*	*(0.7321)*	*(-0.4030)*
	Expense Ratio	1.272	-0.2533	1.277	1.370	-0.3516	1.612
		(0.6566)	*(-0.1365)*	*(0.5757)*	*(0.7340)*	*(-0.1921)*	*(0.7544)*
	Turnover	-0.0200*	-0.0136	-0.0196*	-0.0205**	-0.0107	-0.0163
		(-2.492)	*(-1.645)*	*(-2.018)*	*(-2.677)*	*(-1.379)*	*(-1.910)*
	LN Age	0.0494***	0.0568***	0.0693***	0.0506***	0.0565***	0.0657***
		(5.312)	*(5.666)*	*(6.653)*	*(5.897)*	*(5.998)*	*(6.549)*
	Fixed Effects:						
	Date	Yes	Yes	Yes	Yes	Yes	Yes
	Objective	Yes	Yes	Yes	Yes	Yes	Yes
	Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm
	R2	0.11811	0.11779	0.11452	0.11607	0.11592	0.11296
	Observations	181,280	141,685	115,536	181,280	141,685	115,536

Table 3.3: Employee Satisfaction and Mutual Fund Size

This table gives the regression estimates of the effect of employee satisfaction, proxied by the average overall Glassdoor review score over the past two years, on the natural logarithm of fund size. Controls include the following lagged fund observations. The natural logarithm of family size, the natural logarithm of fund size, monthly 4-factor alpha, the expense ratio, turnover, fund age, as well as past month's mutual fund net flows. Sample refers to the subset of Glassdoor employee reviews considered. “All“ makes use of all Glassdoor reviews. “Asset Management” only considers reviews with a financial/research job within the company that should be relevant for the performance of the funds. “Marketing & Sales” refers to reviews by job titles that fall within the marketing and sales department of the mutual fund company. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

		LN Fund Size		
		(1)	(2)	(3)
Satisfaction	All	-0.0001		
		(-0.1884)		
	Asset Management		0.0006	
			(1.099)	
	Marketing & Sales			0.0010
				(1.263)
	4-Factor Alpha	0.1860***	0.2096***	0.1947**
		(4.474)	*(3.968)*	*(3.114)*
	LN Fund Size	0.9988***	0.9989***	0.9984***
		(2,760.9)	*(2,217.1)*	*(1,870.6)*
	LN Family Size	0.0012***	0.0012***	0.0017***
		(4.788)	*(4.279)*	*(4.663)*
	Net Flow	0.1238	0.0763	0.0653
		(1.874)	*(1.018)*	*(0.7780)*
	Expense Ratio	-0.2497	-0.3604	-0.2241
		(-1.481)	*(-1.760)*	*(-0.9805)*
	Turnover	-0.0008	-0.0002	3.21e-5
		(-1.565)	*(-0.3678)*	*(0.0400)*
	LN Age	-0.0037***	-0.0043***	-0.0045***
		(-3.882)	*(-3.914)*	*(-3.542)*
	Fixed Effects:			
	Date	Yes	Yes	Yes
	Objective	Yes	Yes	Yes
	Clustered SE	Firm	Firm	Firm
	R2	99.7%	99.7%	99.6%
	Observations	180,386	140,991	115,012

Table 3.4: Mean Fund Characteristics by Sample Inclusion

This table shows fund characteristics by sample inclusion conditional on having at least one Glassdoor review.

	In Sample	Total CRSP	T-Stat
Observations	183,611	281,664	
Gross Return	0.99%	1.02%	2.33
1-Factor Alpha	0.11%	0.12%	2.13
3-Factor Alpha	0.11%	0.13%	3.43
4-Factor Alpha	0.07%	0.09%	1.62
Size ($M)	1,817.71	1,464.84	-31.03
Family Size ($B)	231.00	162.20	-58.39
Expense Ratio	1.05%	1.11%	50.73
Turnover	70.68%	71.29%	2.42
Age	17.53	16.54	-26.46
Number of Employees	679.67	485.67	-66.93
Beta Deviation	0.50	0.53	26.43
Idiosyncratic Risk	1.36%	1.41%	16.61
Total Risk	4.21%	4.35%	22.21
Net Flow	-0.22%	-0.23%	-0.89

Table 3.5: Employee Satisfaction and Performance controlling for Selection Bias

This table gives the regression estimates of the effect of employee satisfaction on annual fund performance (gross returns, 1-factor alpha, 3-factor alphas and 4-factor alphas) for regression controlling for selection bias. Controls include the following lagged fund observations. The natural logarithm of family size, the natural logarithm of fund size, the expense ratio, turnover, fund ag, as well as past month's mutual fund net flows. The factor loadings for the risk-adjusted returns are estimated over the prior 36 months. Selection is modelled by the lagged number of employees of the mutual fund company retrieved from form ADV filings. Employee reviews are split by job title as defined in Table 3.2. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Selection - Has Review=1	(1)	(2)	(3)	(4)	(5)	(6)
	Intercept	-3.952***	-4.866***	-5.853***	-3.952***	-4.866***	-5.853***
		(-166.27)	*(-192.18)*	*(-207.49)*	*(-166.27)*	*(-192.18)*	*(-207.49)*
	LN Number of Employees	0.212***	0.230***	0.175***	0.212***	0.230***	0.175***
		(90.27)	*(98.09)*	*(73.26)*	*(90.25)*	*(98.08)*	*(73.25)*
	LN Family Size	0.325***	0.364***	0.435***	0.325***	0.364***	0.435***
		(181.17)	*(192.47)*	*(205.96)*	*(181.17)*	*(192.47)*	*(205.95)*
	Has SLAPP (lag 24m)	0.210***	0.112***	0.240***	0.210***	0.112***	0.241***
		(28.19)	*(14.33)*	*(28.14)*	*(28.19)*	*(14.34)*	*(28.16)*
	LN Fund Size	-0.116***	-0.081***	-0.088***	-0.116***	-0.081***	-0.088***
		(-52.63)	*(-37.68)*	*(-40.30)*	*(-52.64)*	*(-37.69)*	*(-40.30)*
	Net Flow	0.140**	0.218***	0.242***	0.140**	0.218***	0.242***
		(2.35)	*(3.72)*	*(3.99)*	*(2.35)*	*(3.71)*	*(3.99)*
	Expense Ratio	19.067***	16.189***	12.539***	19.067***	16.181***	12.535***
		(23.52)	*(20.15)*	*(15.20)*	*(23.52)*	*(20.14)*	*(15.19)*
	Turnover	0.050***	0.055***	0.074***	0.050***	0.055***	0.074***
		(14.23)	*(15.43)*	*(20.24)*	*(14.23)*	*(15.43)*	*(20.24)*
	LN Age	0.177***	0.110***	0.157***	0.177***	0.110***	0.157***
		(30.96)	*(19.27)*	*(26.55)*	*(30.96)*	*(19.28)*	*(26.55)*
	Outcome	**3-Factor Alpha**			**4-Factor Alpha**		
		(1)	(2)	(3)	(4)	(5)	(6)
Satisfaction	All	0.013			0.01		
		(0.32)			*(0.26)*		
	Asset management		0.030***			0.030***	
			(2.98)			*(3.09)*	
	Marketing & Sales			0.002			0.013
				(0.23)			*(1.10)*
	LN Fund Size	-0.018	-0.018***	-0.022***	-0.015	-0.014***	-0.018***
		(-0.30)	*(-2.96)*	*(-3.60)*	*(-0.26)*	*(-2.86)*	*(-3.29)*
	LN Family Size	0.019	-0.000	-0.001	0.021	0.005	0.002
		(0.54)	*(-0.00)*	*(-0.04)*	*(0.62)*	*(0.47)*	*(0.11)*
	Net Flow	0.259*	0.253	0.055	0.369***	0.365*	0.129
		(1.83)	*(1.42)*	*(0.37)*	*(2.61)*	*(1.88)*	*(0.79)*
	Expense Ratio	-7.177***	-8.985***	-6.625**	-6.635***	-8.385***	-6.280**
		(-362.41)	*(-4.07)*	*(-2.24)*	*(-335.08)*	*(-4.04)*	*(-2.28)*
	Turnover	-0.018	-0.016*	-0.022**	-0.016	-0.01	-0.018*
		(-0.09)	*(-1.83)*	*(-2.09)*	*(-0.09)*	*(-1.15)*	*(-1.73)*
	LN Age	0.055	0.057***	0.068***	0.055	0.054***	0.061***
		(0.01)	*(4.64)*	*(4.79)*	*(0.01)*	*(4.85)*	*(4.54)*
	Intercept	0.352	0.671***	0.735**	-0.051	0.209	0.242
		(1.10)	*(3.44)*	*(2.17)*	*(-0.16)*	*(1.15)*	*(0.77)*
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Objective FE	Yes	Yes	Yes	Yes	Yes	Yes
	Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm
	Observations	240,361	240,361	240,361	240,361	240,361	240,361

Table 3.6: Employee Satisfaction and Fund Size controlling for Selection Bias

This table gives the regression estimates of the effect of employee satisfaction on the natural logarithm of mutual fund size for regression controlling for selection bias. The control variables are the same as in Table 3.3. Selection is modelled in the same way as in Table 3.5. Due to its similarity with the selection model reported in Table 3.5, the selection equation is omitted from this table. The first stage estimates of this model are available upon request. Employee satisfaction is split into the same three groups as in Table 3.2. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

		LN Fund Size		
		(1)	(2)	(3)
Satisfaction	All	-0.0002		
		(-0.01)		
	Asset management		0.001	
			(1.04)	
	Marketing & Sales			0.002**
				(2.36)
	4-Factor Alpha	0.174***	0.203***	0.189***
		(2.90)	*(3.44)*	*(2.70)*
	LN Fund Size	0.998***	0.998***	0.998***
		(28.60)	*(1973.86)*	*(1750.96)*
	LN Family Size	0.002	0.002***	0.002***
		(0.01)	*(4.28)*	*(2.88)*
	Net Flow	0.11	0.059	0.045
		(0.47)	*(0.72)*	*(0.48)*
	Expense Ratio	-0.231***	-0.38	-0.277
		(-11.58)	*(-1.57)*	*(-0.96)*
	Turnover	-0.001	-0.000	0.000
		(-0.00)	*(-0.01)*	*(0.32)*
	LN Age	-0.003	-0.004***	-0.004**
		(-0.00)	*(-2.98)*	*(-2.49)*
	Intercept	0.020	0.024**	0.017
		(0.06)	*(2.30)*	*(1.28)*
	Fixed Effects			
	Year	Yes	Yes	Yes
	Objective	Yes	Yes	Yes
	Clustered SE	Firm	Firm	Firm
	Observations	238,049	238,049	238,049

Table 3.7: Employee Satisfaction and Performance in a DID Setting

This table gives the regression estimates of the effect of employee satisfaction, proxied by the average overall Glassdoor review score over the past two years, on annual fund performance (3-factor alphas and 4-factor alphas) for a two-way fixed effects difference-in-differences regression. Post is equal to one if the company that manages the fund was acquired by another company. "Same Manager" is equal to one if the mutual fund managers stay unchanged in the two years surrounding the merger event. Higher Satisfaction is equal to one if the acquirer has a higher employee satisfaction score than the target company. Controls include the following lagged fund observations. The natural logarithm of family size, the natural logarithm of fund size, the expense ratio, turnover, fund age, as well as past month's mutual fund net flows. The factor loadings for the risk-adjusted returns are estimated over the prior 36 months. Sample refers to the subset of Glassdoor employee reviews considered. All makes use of all Glassdoor reviews. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	3-Factor Alpha		4-Factor Alpha	
	(1)	(2)	(3)	(4)
Higher Satisfaction x Post x Same Manager				
All	0.0016		0.0017	
	(0.87)		*(0.94)*	
Asset Management		0.0035***		0.0044***
		(2.80)		*(3.30)*
Higher Satisfaction x Post				
All	-0.0001		-0.0005	
	(-0.11)		*(-0.66)*	
Asset Management		-0.0007		-0.0012
		(-0.88)		*(-1.43)*
Post x Same Manager	-0.0012	-0.0022**	-0.0023*	-0.004***
	(-1.21)	*(-2.12)*	*(-1.92)*	*(-3.67)*
Post	-0.0007	-0.0006	0.0002	0.0005
	(-1.58)	*(-0.90)*	*(0.39)*	*(0.72)*
LN Fund Size	-0.0022***	-0.0024***	-0.0021***	-0.0022***
	(-9.81)	*(-8.54)*	*(-9.55)*	*(-7.87)*
LN Family Size	0.0002	0.0001	0.0002	0.0001
	(1.36)	*(0.66)*	*(1.22)*	*(0.39)*
Net Flow	-0.0025*	-0.0022	-0.0021	-0.0015
	(-1.89)	*(-1.25)*	*(-1.41)*	*(-0.76)*
Expense Ratio	-0.1535***	-0.1109**	-0.172***	-0.1171*
	(-2.85)	*(-2.02)*	*(-2.57)*	*(-1.76)*
Turnover	-0.0002	-0.0002	-0.0002	-0.0002
	(-1.08)	*(-0.95)*	*(-1.36)*	*(-1.05)*
LN Age	0.0032***	0.0029***	0.0027***	0.0025***
	(5.71)	*(4.63)*	*(4.50)*	*(3.62)*
Fixed Effects				
Fund	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Objective	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
R2	0.14	0.142	0.142	0.143
Observations	185,547	143,943	185,547	143,943

Table 3.8: Employee Satisfaction and Effort

This table gives the regression estimates of the effect of employee satisfaction on effort-taking by mutual fund managers. Effort-taking is proxied by the Beta Deviation measure. It is estimated using the past 12 months of gross returns. Controls include the following lagged fund observations. The natural logarithm of family size, the natural logarithm of fund size, monthly 4 Factor alpha, the expense ratio, turnover, fund age, as well as past month's mutual fund net flows. Employee reviews are split by job titles. "All" makes use of all Glassdoor reviews. "Asset Management" only considers reviews with a financial/research job within the company. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

		Beta Deviation	
		(1)	(2)
Satisfaction	All	0.0144	
		(1.762)	
	Asset Management		0.0180*
			(2.479)
	4 Factor Alpha	0.1440*	0.1342
		(2.442)	*(1.935)*
	LN Fund Size	-0.0029	-0.0058
		(-0.7541)	*(-1.449)*
	LN Family Size	-0.0058	-0.0006
		(-1.708)	*(-0.1719)*
	Expense Ratio	15.2300***	14.6200***
		(6.207)	*(5.570)*
	Turnover	0.0085	-0.0009
		(0.8831)	*(-0.1178)*
	LN Age	0.0138	0.0219*
		(1.532)	*(2.356)*
	Net Flow	0.0253	0.0553
		(0.7497)	*(1.584)*
	Fixed Effects:		
	Date	Yes	Yes
	Objective	Yes	Yes
	Clustered SE	Firm	Firm
	R2	0.16355	0.16422
	Observations	154,877	122,086

Table 3.9: Employee Satisfaction and Effort controlling for Selection Bias

This table gives the regression estimates of the effect of employee satisfaction on effort-taking by the mutual fund managers for regression controlling for selection bias. Effort-taking is proxied by the same variable as in Table 3.8 and the selection model is described in Table 3.5. Due to its similarity with the selection model reported in Table 3.5, the selection equation is omitted from this table. The first stage estimates of this model are available upon request. Employee reviews are split by job titles. “All” makes use of all Glassdoor reviews. “Asset Management” only considers reviews with a financial/research job within the firm. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

		Beta Deviation	
		(1)	(2)
Satisfaction	All	0.006	
		(0.16)	
	Asset management		0.007
			(1.37)
	4-Factor Alpha	0.008	0.006
		(0.29)	*(0.08)*
	LN Fund Size	-0.022	-0.022***
		(-1.21)	*(-4.20)*
	LN Family Size	0.078	0.109***
		(1.40)	*(10.73)*
	Net Flow	-0.007	0.050
		(-0.04)	*(0.79)*
	Expense Ratio	16.954***	15.990***
		(1088.91)	*(5.27)*
	Turnover	0.021	0.018
		(0.12)	*(0.98)*
	LN Age	0.048	0.048***
		(0.01)	*(3.29)*
	Intercept	-0.737***	-1.169***
		(-3.16)	*(-7.58)*
	Fixed Effects		
	Year	Yes	Yes
	Objective	Yes	Yes
	Clustered SE	Firm	Firm
	Observations	219,201	219,201

Table 3.10: Employee Satisfaction and Effort in a DID Setting

This table gives the regression estimates of the effect of employee satisfaction, proxied by the average overall Glassdoor review score over the past two years, on mutual manager effort-taking (Beta Deviation) for a two-way fixed effects difference-in-differences regression. Post is equal to one if the company that manages the fund was acquired by another company. "Same Manager" is equal to one if the mutual fund managers stay unchanged in the two years surrounding the merger event. Higher Satisfaction is equal to one if the acquirer has a higher employee satisfaction score than the target company. The Beta Deviation measure IS estimated in the same way as described in Table 3.9. Controls include the following lagged fund observations. The monthly 4 Factor alpha, the natural logarithm of family size, the natural logarithm of fund size, the expense ratio, turnover, fund age, as well as past month's mutual fund net flows. The factor loadings for the risk-adjusted returns are estimated over the prior 36 months. Sample refers to the subset of Glassdoor employee reviews considered. "All" makes use of all Glassdoor reviews. "Asset Management" only considers reviews with a financial/research job within the company. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Beta Deviation	
	(1)	(2)
Higher Satisfaction x Post x Same Manager		
All	-0.0782	
	(-1.29)	
Asset Management		-0.1492
		(-1.25)
Higher Satisfaction x Post		
All	0.0009	
	(0.02)	
Asset Management		-0.0877*
		(-1.70)
Post x Same Manager	0.0690	0.1457
	(1.19)	*(1.45)*
Post	-0.0036	0.0632
	(-0.09)	*(1.51)*
4 Factor Alpha	0.1752***	0.1379***
	(3.48)	*(2.58)*
LN Fund Size	0.0010	0.0051
	(0.20)	*(0.89)*
LN Family Size	-0.0041	-0.0007
	(-0.62)	*(-0.09)*
Net Flow	-0.0047	-0.0099
	(-0.21)	*(-0.41)*
Expense Ratio	-1.3994	-2.9322
	(-0.77)	*(-1.63)*
Turnover	0.0043	0.0018
	(0.76)	*(0.31)*
LN Age	-0.0707***	-0.0329
	(-3.05)	*(-1.43)*
Fixed Effects		
Fund	Yes	Yes
Date	Yes	Yes
Objective	Yes	Yes
Cluster	Firm	Firm
R2	0.506	0.518
Observations	153,200	119,586

Table 3.11: Employee Satisfaction and Risk controlling for Selection Bias

This table gives the regression estimates of the effect of employee satisfaction on risk-taking by the mutual fund managers for regression controlling for selection bias. The total risk as well as the idiosyncratic risk measures are estimated using the past 12 months of gross returns. All other variables and regression specifications are the same as in Table 3.9. Due to its similarity with the selection model reported in Table 3.5, the selection equation is omitted from this table. The first stage estimates of this model are available upon request. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

		Total Risk		Idiosyncratic Risk	
		(1)	(2)	(3)	(4)
Satisfaction	All	-0.0003		0.0001	
		(-0.01)		*(0.00)*	
	Asset management		0.0003		0.0002**
			(1.52)		*(2.07)*
	4-Factor Alpha	0.0010	0.0010	-0.0080	-0.0080***
		(0.02)	*(0.39)*	*(-0.19)*	*(-4.81)*
	LN Fund Size	0.0001	0.0001	-0.0004	-0.0004***
		(0.00)	*(1.27)*	*(-0.01)*	*(-3.91)*
	LN Family Size	0.0004	0.0005	0.0010	0.0010***
		(0.00)	*(1.01)*	*(0.01)*	*(4.86)*
	Net Flow	0.0001	0.0010	0.0010	0.0020**
		(0.00)	*(0.67)*	*(0.00)*	*(2.26)*
	Expense Ratio	0.2900***	0.3190***	0.2000***	0.1990***
		(13.93)	*(5.87)*	*(10.30)*	*(3.84)*
	Turnover	0.0010	0.0010***	0.0004	0.0004
		(0.00)	*(2.63)*	*(0.00)*	*(1.35)*
	LN Age	0.0020	0.0020***	0.0010	0.0010***
		(0.00)	*(5.79)*	*(0.00)*	*(4.84)*
	Intercept	0.0500	0.0450***	0.0060	0.0010
		(0.15)	*(6.64)*	*(0.02)*	*(0.31)*
	Fixed Effects				
	Year	Yes	Yes	Yes	Yes
	Objective	Yes	Yes	Yes	Yes
	SE Cluster	Firm	Firm	Firm	Firm
	Observations	224,425	224,425	219,201	219,201

Table 3.12: Employee Satisfaction and Risk in a DID Setting

This table gives the regression estimates of the effect of employee satisfaction on mutual fund risk for a two-way fixed effects difference-in-differences regression. Post is equal to one if the company that manages the fund was acquired by another company. "Same Manager" is equal to one if the mutual fund managers stay unchanged in the two years surrounding the merger event. Higher Satisfaction is equal to one if the acquirer has a higher employee satisfaction score than the target company. Total risk and idiosyncratic risk are both estimated in the same way as described in Table 3.11. Controls include the following lagged fund observations. The monthly 4 Factor alpha, the natural logarithm of family size, the natural logarithm of fund size, the expense ratio, turnover, fund age, as well as past month's mutual fund net flows. The factor loadings for the risk-adjusted returns are estimated over the prior 36 months. Sample refers to the subset of Glassdoor employee reviews considered. All makes use of all Glassdoor reviews. Asset Management only considers reviews with a financial/research job within the company that should be relevant to the performance of the funds. T-statistics calculated from standard errors that allow for clustering on the mutual fund company (firm) level are reported in brackets. Significance Levels: p<0.1 *, p<0.05 **, p<0.01 ***

	Total Return		**Idiosyncratic Risk**	
	(1)	(2)	(3)	(4)
Higher Satisfaction x Post x Same Manager				
All	0.0023		-0.0006	
	(1.10)		*(-0.49)*	
Asset Management		-0.0020		0.0008
		(-0.71)		*(0.41)*
Higher Satisfaction x Post				
All	-0.0003		-0.0005	
	(-0.16)		*(-0.53)*	
Asset Management		0.0007		-0.0018**
		(0.25)		*(-2.09)*
Post x Same Manager	-0.0018	-0.0007	-0.0019	-0.0022
	(-0.97)	*(-0.26)*	*(-1.50)*	*(-1.24)*
Post	0.0015	0.0015	0.0016*	0.0025***
	(0.92)	*(0.56)*	*(1.73)*	*(2.98)*
4 Factor Alpha	0.0111***	0.0111***	-0.0043***	-0.004***
	(6.60)	*(5.38)*	*(-4.33)*	*(-3.30)*
LN Fund Size	0.0011***	0.0013***	-0.0005***	-0.0006***
	(4.65)	*(4.60)*	*(-4.75)*	*(-4.29)*
LN Family Size	-0.0001	-0.0000	-0.0001	-0.0001
	(-0.35)	*(-0.02)*	*(-0.75)*	*(-0.46)*
Net Flow	-0.002***	-0.0023***	0.0002	0.0001
	(-3.42)	*(-3.85)*	*(0.46)*	*(0.25)*
Expense Ratio	-0.0636	-0.1136	-0.0376	-0.0281
	(-0.53)	*(-0.82)*	*(-0.83)*	*(-0.58)*
Turnover	0.0001	0.0001	0.0002	0.0002
	(0.34)	*(0.23)*	*(1.52)*	*(1.44)*
LN Age	-0.0068***	-0.0069***	0.0012**	0.0019***
	(-8.31)	*(-8.48)*	*(2.07)*	*(2.86)*
Fixed Effects				
Fund	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Objective	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
R2	0.874	0.875	0.759	0.777
Observations	156,510	122,111	153,200	119,586

Chapter 4

Outsourcing in the Mutual Fund Industry

David Chambers Richard B. Evans Elias L. Ohneberg

Abstract

We investigate why fund families continue to outsource the portfolio management of their funds to unaffiliated investment advisors despite the well-documented underperformance of outsourced funds. Our empirical analysis shows that investment expertise, or the lack of it, drives the decision to enter an outsourcing relationship and impacts the way fee revenues are shared. Furthermore, market thickness, defined as the number of subadvisors the fund family could contract with, also impacts the fund family's decision to outsource and its relative bargaining power in the resulting relationship. We link the impact of market thickness on the relative power of both parties in the outsourcing relationship to the threat of dismissal of the subadvisor and show that outsourced funds operating in thick markets perform better. Finally, once we account for the initial decision to outsource a mutual fund, we find that outsourced funds do not underperform and are not smaller than in-house managed funds. The fund family lacking the relevant in-house expertise could not have achieved a better performance than the subadvisor and the subadvisor, because of its lack of distribution capabilities, could not have gathered more assets.

4.1. Introduction

Typically mutual fund investors subject themselves to only one layer of agency. The investors provide the capital and the mutual fund company takes the investment decision on their behalf. In the case of mutual fund outsourcing another layer of agency is added. This second layer of agency is between the mutual fund company and the unaffiliated sub-advisor hired to take the fund's investment decisions. Previous research has shown that sub-advised mutual funds underperform their in-house managed peers (see for example Chen et al. (2013), Del Guercio et al. (2010), Chuprinin et al. (2015), Moreno et al. (2018), Ma et al. (2019)), and typically attributed this underperformance to agency issues. This paper revisits this previously uncovered underperformance and addresses the puzzling question as to why asset management companies, which are typically thought of as sophisticated investors, would enter into these seemingly value-destroying relationships.

Outsourcing in the mutual fund industry is common. One in five funds outsource their portfolio management throughout our sample period from 2001 to 2017, when form NSAR was discontinued. Given that the mutual fund industry in the U.S. alone currently manages $24 trillion,[3] we estimate that approximately $5 trillion is managed by subadvisors in the U.S. alone as of 2021.

Individual funds share distribution capabilities, a brand name, and marketing resources more broadly through fund families. Often, although not always, investment resources are also shared among funds from the same fund family. Investment resources, or more specifically, the portfolio management of individual funds, can either be sourced internally or outsourced to an unaffiliated company (e.g. (J. Chen et al., 2013; Chuprinin et al., 2015; Del Guercio et al., 2010; Kuhnen, 2009). For example, the Nationwide Small Company Growth Fund is distributed by Nationwide and marketed as a Nationwide fund, but the fund's portfolio management is outsourced to Brown Capital Management LLC. The subadvisor is hired directly by the advisor of the fund and its compensation is taken out of the advisory fee paid by the fund to the advisor. The advisor, Nationwide Fund Advisors, was paid an advisory fee of $2,471,895 (or 0.84% of the average monthly assets under management) in 2021. Brown Capital Management LLC received $1,617,994 (about 0.55% of the average monthly assets under management (AUM)) or 65% of this advisory fee. In our sample, the median share of the advisory fee paid to the subadvisor is 45.82%.

[3] Investment Company Institute, 2021

Prior literature on outsourcing has documented a systematic underperformance of sub-advised mutual funds compared to in-house managed funds (e.g., Chen et al., 2013; Chuprinin et al., 2015; Del Guercio et al., 2010) and proposed various agency problems as potential underlying causes. In contrast to these previous studies, we, similar to Debaere & Evans (2015), explore the initial decision to outsource and propose the decision's underlying drives as the root cause of the underperformance of outsourced funds. Once we account for the initial decision to outsource sub-advised funds, we recover the result of Debaere & Evans (2015) that outsourced funds do not underperform and are not smaller than in-house managed funds. Fund families decide to outsource the portfolio management of their funds because they lack in-house investment expertise. Figure 4.1 shows that outsourcing is more prevalent in Morningstar categories new to the fund family. Because of the fund family's lack of in-house expertise, it would not have been able to achieve better performance than the subadvisor. Subadvisors lack in-house distribution facilities. We show that it is primarily institutional investment advisors that are missing expertise in marketing their funds to retail clients that decide to sub-advise a fund for an unaffiliated fund family. Thus, these investment advisors agree to sub-advise a fund to access the fund family's existing (retail) distribution channels. Put differently a subadvisor exerts only as much as effort as necessary to keep the mutual fund company indifferent between staying in the outsourcing relationship and taking the management of the mutual fund in-house. The lower the mutual fund family's expertise in managing the fund's assets the more a subadvisor can shirk before the fund family will deem it necessary to take the fund management in-house. Thus, the mutual fund family's investment expertise determines the maximum potential severity of the agency problem from outsourcing.

Furthermore, we explore the effects of market thickness on the initial decision to enter an outsourcing relationship, its effect on the relative power of the two parties in the relationship, and ultimately on the outcome of the outsourcing relationship – fund performance. Market thickness is defined as the ease with which one party can find a trade partner in the open market (McLaren, 2003). It is usually quantified through the number of market participants. We measure market thickness on the Morningstar category and year level by aggregating propensities from logistic regressions that model the fund family and subadvisor decisions to outsource. Consistent with prior theoretical work (Gan & Li, 2004; McLaren, 2000), we would expect to find that the probability of entering an outsourcing relationship increases with market thickness. The larger the number of potential subadvisors, the easier it is to find a suitable subadvisor. Furthermore, the higher the market thickness, the more attractive outsourcing becomes through a decrease in the severity of potential hold-up problems (McLaren, 2000). We show in Figure 4.2 that market thickness impacts the prevalence of outsourcing in the mutual fund market. Employing a logistic regression framework, we explore the effect of market thickness on the initial decision to outsource. As expected, we find that subadvisor market thickness increases the likelihood of a new fund being outsourced.

We next show that relative market thickness alters the power of fund families and subadvisors in the outsourcing relationship by analysing how fee revenue is split. Higher fund family (subadvisor) market thickness decreases (increases) the power of the fund family in the relationship, evidenced by a higher portion of the advisory fee being paid to the subadvisor.

Subsequently, we explore subadvisor turnover as a channel through which market thickness can impact (bargaining) power. It is easier to find a trade partner in thick markets because of lower search costs (McLaren, 2000; Ramey & Watson, 2001). The decrease in search costs increases the ease with which a current subadvisor can be replaced. As it becomes easier to find a replacement for a current subadvisor, the threat of dismissal increases. Using a logistic regression framework, we show that subadvisor market thickness increases the likelihood of the subadvisor being fired.

Finally, we look at the effects of market thickness on the performance of sub-advised mutual funds. Existing theoretical evidence suggests that the effect of market thickness on returns is positive. A positive effect is consistent with matching theory, where higher market thickness leads to better matches (Gan & Li, 2004). It is also consistent with the model of Ramey & Watson (2001), where higher market thickness decreases search costs in the market for alternate trade partners and increases the threat of firing. In line with our prior and existing theory, we find that a higher market thickness improves fund performance.

Overall our findings suggest that the mutual fund family's lack of in-house expertise determines the upper bound of agency costs incurred from outsourcing, while market thickness helps align incentives and drives agency costs towards zero. While we cannot fully measure the exact cost of subjecting investors to this second layer of agency, our results are consistent with harm to investors being relatively minor. Mutual fund companies demand mutual fund return performance from their subadvisors, which is demanded by mutual fund investors from the mutual fund company itself. Thus, both principals in the two layers of agency agree on the desired output of the subadvisor. Furthermore, our findings that outsourced mutual funds do not perform worse after accounting for the fund family's lack of internal investment expertise suggests that investors do not suffer direct performance implications form the fund family's decision to outsource the management of the fund to an unaffiliated subadvisor.

Our study contributes to the literature on mutual fund outsourcing and the literature on market thickness and outsourcing more generally. Early studies in the mutual fund literature have focused on documenting the underperformance of sub-advised funds compared to in-house managed funds and have usually attributed the underperformance to agency problems. Del Guercio et al. (2010) find that the decision to outsource depends on the type of investor the specific mutual fund caters to. The authors split the mutual fund clientele into two broad groups. One group consists of investors that value other services, such as general financial advice on top of simple return generation. The other group refers to performance-sensitive investors. Funds with a performance-sensitive investor clientele internalise their investors' preferences and spend more on portfolio management. These funds are also more likely to buy expertise in the open market by hiring a subadvisor. A mutual fund with a performance-insensitive investor clientele that values additional services beyond investment performance spends less on portfolio management and directs part of its resources towards providing holistic wealth management solutions. The latter funds predominantly manage their assets in-house. They find that funds that outsource their portfolio management to a third party underperform. This is puzzling because funds with performance-sensitive clientele are more likely to outsource the management of their funds.

Chen et al. (2013) confirm the underperformance of outsourced funds in their data. Sub-advised funds in their sample underperform by 52 basis points annually compared to internally run mutual funds. This underperformance is attributed to agency problems arising from contractual externalities. Their finding that outsourced funds rely more heavily on higher-powered incentives in the form of fund closures corroborates their story.

Chuprinin et al. (2015) also report the underperformance of outsourced funds and attribute it to agency problems. Contrary to prior literature, the authors investigate the role of the subadvisor in explaining the underperformance of outsourced funds. Subadvisors give preferential treatment in IPO allocations, cross trading, and more general trading opportunities to their in-house distributed funds rather than the funds they sub-advised. We show that expertise and market thickness can explain which outsourcing relationships are more likely to suffer from agency problems and how market thickness effects can help align interests.

Subsequent literature has shifted attention towards finding solutions to these agency problems. Moreno et al. (2018) focus on contractual agreements such as co-branding, multi-advising, and performance-based compensation. While these measures seem to help align interests between the fund family and the subadvisor, funds only implement these measures when the fund's investor base is performance sensitive. This finding is in line with Del Guercio et al. (2010). Ma et al. (2019) find further evidence for performance-based remuneration and add that these measures will only be employed if agency costs are severe.

The underperformance of sub-advised funds is nonetheless still puzzling. It is difficult to comprehend why a fund family outsources to a subadvisor that only provides sub-par performance. One might expect that fund families learn about the inefficiencies of outsourcing and cease this practice – especially because outsourcing is most prevalent in funds with performance-sensitive investors (Del Guercio et al., 2010).

We further add to this literature by showing that the lack of internal resources and capabilities can explain the underperformance of sub-advised mutual funds. In so doing, we highlight the importance of market thickness in the decision to outsource, its impact on the power dynamics in the outsourcing relationship, and its explanatory power in the performance of outsourced funds.

The literature on market thickness is mainly theoretical. The few existing empirical studies on vertical integration and outsourcing have either been conducted using data on sector or firm-level data in an international trade setting where there is a lack of product-level information or in specific industry settings (for example Hubbard (2008)) for which generalizability may be limited. We believe that the outsourcing setting within the mutual fund industry provides a better empirical test of market thickness and how relative bargaining power influences bilateral trade outcomes.

The rest of the paper is structured as follows. First, we describe the data employed in our analysis. Next, we explore the drivers behind the decision to outsource. Then, we show how expertise and market thickness impact the relative bargaining power in the outsourcing relationship by analysing how free revenue is split amongst both parties. Furthermore, we link the effect of market thickness on (bargaining) power to subadvisor turnover. Subsequently, we document that market thickness impacts the performance of outsourced funds. Finally, we find that prior findings of underperformance and the smaller size of outsourced funds disappear once we account for the decision to outsource in the first place.

4.2. Hypotheses Development

Outsourcing is common in the mutual fund industry. 20.7% of mutual funds in our sample employ a subadvisor to manage the fund's investments. When a fund family opens a mutual fund, it can either source the investment expertise necessary to manage the fund in-house or through the open market by employing an unaffiliated investment advisor - the subadvisor. The marketing and distribution of the fund, even if the fund's portfolio management is outsourced to a third party, is performed in-house by the fund family. Thus, in an outsourcing relationship, the subadvisor is responsible for the mutual fund's performance and the fund family for growing the fund's assets under management (AUM). The subadvisor is paid for its service through a share of the advisory fee paid by the fund to the fund family.

In this paper, we conduct an empirical investigation into three broad sets of hypotheses. The first set concerns the initial decision to enter an outsourcing relationship. The second set investigates the power dynamics of the two parties in the relationship. The third set of hypotheses explores the effects of the initial decision to outsource and the relative power of both parties in the relationship on mutual fund performance and fund size.

The subadvisor and the fund family must jointly agree on an outsourcing relationship. Internal distribution capabilities are required to attract assets from investors, and investment expertise is required to generate investment returns. If any of these two resources are lacking in-house, an investment advisor may consider it worthwhile to acquire them in the open market. An investment advisor may find it appealing to manage the fund of an unaffiliated mutual fund family if it lacks the necessary distribution capabilities.

Similarly, a mutual fund family may engage in outsourcing if it lacks investment expertise internally. Thus, our first hypothesis 1a states that mutual fund families are more likely to outsource mutual funds when they lack in-house investment expertise, and investment companies are more likely to sub-advise a fund if they lack internal distribution capabilities.

Hypothesis 1a: *Fund families and investment advisors are more likely to enter an outsourcing relationship if they lack internal capabilities.*

Furthermore, mutual fund families will find it difficult to outsource the investment management of one of its funds if there are no suitable investment advisors interested in acquiring its distribution capabilities. From Gan & Li (2004) we know that if market thickness – the overall size of the market – increases, matching becomes more efficient. It is simply easier to find a suitable partner if there are more potential partners to choose from. Moreover, McLaren (2000) has shown that if market thickness increases, it generally becomes more efficient for firms to engage in outsourcing rather than vertical integration. Thus, our next hypothesis states that mutual fund families are more likely to outsource a fund in Morningstar categories with more potential trade partners – higher subadvisor market thickness.

Hypothesis 1b: *Mutual fund families are more likely to outsource the portfolio management of their fund if subadvisor market thickness is high.*

Our next set of hypotheses investigates the power dynamics of the fund family and the subadvisor in the outsourcing relationship. We gauge the relative power of both parties through an investigation into the way that fee revenue is shared. If a firm has more bargaining power, it should be able to extract higher rents. In our case, this would translate to a larger part of the advisory fee. The income to be shared by both parties is generated from advisory fees paid by mutual fund investors to the fund family. This advisory fee is then shared between the mutual fund family and the subadvisor. According to theories about the boundaries of the firm (Grossman & Hart, 1986), the gains from trade – fee revenue - should go to the party whose marginal investment in the relationship is more productive. Because both the fund family and the subadvisor bring their respective expertise – distribution capability and investment skill respectively - to the relationship, we would expect that the amount and quality of expertise impact how the fees are shared. Our next hypothesis states that the advisory fee is split according to the degree of expertise each party brings to the relationship.

Hypothesis 2a: *The advisory fee is split according to the degree of expertise each party brings to the relationship.*

Next, we are interested in gauging how the availability of potential alternative trade partners impacts the relative bargaining power of the fund family and the subadvisor. A larger pool of potential subadvisors decreases the cost of replacing a current subadvisor for the fund family. This ease of replacement gives the fund family more power in the relationship. The same argument holds the other way around. Thus, our next hypothesis states that an increase in potential trade partners leads to an increase in the share of fees a party receives.

Hypothesis 2b: *If fund family (subadvisor) thickness increases, the subadvisor receives a larger (smaller) share of the fee.*

To further test our earlier proposition that an increase in the number of potential trade partners decreases the cost of replacement, we investigate whether the subadvisor market's size impacts the probability of subadvisor dismissals. Thus, our next hypothesis states that the probability of subadvisor turnover is higher when the subadvisor market thickness is relatively large compared to the fund family market thickness. This hypothesis is also consistent with the theoretical predictions of the effect of market thickness on the breakdown of long-run relationships (Ramey & Watson, 2001). In the theoretical model of Ramey & Watson (2001), long-run relationships are sustained through high search costs incurred in finding a replacement for the current trade partner. An increase in market thickness decreases these search costs, thus lowering the costs of replacing a current trade partner. This reduction in search costs results in the breakdown of long-run relationships.

Hypothesis 2c: *The greater the thickness of the subadvisor market, the greater is the probability of dismissal of a subadvisor.*

Finally, we investigate the effect of the initial outsourcing decision and the power dynamics in the outsourcing relationship to mutual fund performance and fund size. First, we would expect that an increase in market thickness should influence the performance of outsourced funds. A higher threat of dismissal of the subadvisor in thicker markets should help align incentives with the mutual fund family. This is consistent with theoretical evidence from McLaren (2000), where an increase in market thickness through its effect on the ease of replacing a current trade partner leads to a reduction in hold-up problems. Thus we would expect that an increase in subadvisor market thickness reduces the agency problems documented in the prior literature (e.g. Chen et al., 2013; Chuprinin et al., 2015). Thus, we would expect that amongst outsourced funds, subadvisor market thickness positively affects performance.

Hypothesis 3a: *Outsourced funds that operate in thicker subadvisor markets perform better.*

Finally, we explain the underperformance and smaller fund size of outsourced mutual funds compared to in-house managed funds. Here we postulate that the initial decision to outsource a mutual fund is essential. A fund family will only engage in an outsourcing relationship if it lacks the necessary investment expertise to manage the fund. Similarly, the subadvisor will only manage a mutual fund for another firm if it lacks distribution capabilities. In equilibrium, the subadvisor will only exert as much effort as is necessary to maintain the outsourcing relationship. Thus, the fund will only perform as well as if the mutual fund family had managed the money in-house. Similarly, the fund family will only exert as much effort into the distribution of the fund as necessary, and thus the fund size should be as large as if the subadvisor had handled the distribution of the mutual fund in-house.

Hypothesis 3b: *Once we control for the initial decision to outsource, outsourced mutual funds are no smaller and do not perform any worse than if they were managed in-house.*

4.3. Data

We use the Morningstar database of open-ended mutual funds for general fund characteristics, returns, and fee information. Subadvisors and advisors are identified through N-SAR filings, while general investment advisor characteristics are retrieved from ADV filings. Our sample period starts in 2001 and ends in 2017, when NSAR filings were discontinued.

4.3.1. Morningstar Data

Morningstar data is widely used in mutual fund research. It records observations at the share class level and includes information on returns, total net assets (TNA), portfolio turnover, inception dates, fund families, portfolio managers, investment categories, expense ratios, and subadvisor and advisor fees.

To avoid double counting and because subadvisor fees are reported at the fund rather than the share class level, we aggregate all individual share classes to the fund level by weighting each share class observation by its total net assets. We remove index funds through an indicator variable supplied by Morningstar as well as through fund names. We further eliminate mutual funds which fall into the "Target Date" category. Moreover, we exclude Morningstar categories that do not fall within either equity, fixed income, or a mix of equity and income, such as currency, real estate, and natural resource funds.

We measure the expertise of a fund family in each Morningstar category by following Debaere & Evans (2015) in using data on a fund's regional asset allocation as provided by Morningstar. The measure of a fund family's regional expertise in managing a particular type of mutual fund is constructed in the following way. We first find the regional asset allocation of the fund family by value-weighting the regional allocation across all *in-house* managed funds. The regional asset allocation retrieved from the Morningstar database splits the fund's underlying securities into ten regions.[4] Next, we compare this asset allocation with the regional allocation of an entire Morningstar category. The overall regional allocation for a given Morningstar category is calculated by value-weighting the regional allocation of all funds within the Morningstar category. Subsequently, we sum the square of all deviations between the regional weights of the fund family and the Morningstar category as follows:

$$Regional\ Expertise_{Family,Category,t} = \sum_{r=1}^{10}\left(w_{Family,r,t} - w_{Category,r,t}\right)^2 \qquad (4.1)$$

The larger the value of this measure, the fewer of the fund family's in-house managed assets regionally overlap with the assets in the Morningstar category. If, for example, the Morningstar category has an 80% allocation to Europe developed and a 20% allocation to Asia emerging while the fund family's assets are all in the U.S., the measure is (100-0)^2 + (0-80)^2 + (0-20)^2 + 0 + 0 + 0 + 0 + 0 + 0 + 0 = 16800. If the Morningstar category is entirely invested in the U.S. (100%) and the fund family's assets are allocated solely to the U.S., the measure takes the value of 0. Therefore, a higher value of our regional expertise measure indicates lower expertise in managing a mutual fund in a specific Morningstar category. We also use an alternative measure

[4] The ten regions are: Africa/Middle East, Asia Developed, Asia Emerging, Australia, Europe Developed, Europe Emerging, Japan, Latin America, North America, and United Kingdom.

for the fund family's expertise in managing the assets of one of their funds. This variable measures the percentage of the fund family's assets managed outside of the fund's Morningstar category. A larger value of these expertise measures corresponds to lower fund family investment expertise.

We report fund performance using gross returns, Fama French 3-factor alphas and Carhart (1997)'s 4-factor alphas. Factor returns are taken from Ken French's website. Alphas are estimated with 36 months of data. Additionally, we employ an investment objective alpha in our final return regressions. The investment objective alpha is calculated by subtracting the value-weighted net return of all other funds in the Morningstar category from the fund's net return.

4.3.2. N-SAR and ADV Data

While Morningstar records subadvisor fees, it does not keep a separate historical record of the subadvisors of a fund. Thus, even though a fund might be sub-advised, we are not able to classify the fund as such if Morningstar does not have the relevant sub-advisor fee information. Therefore, we collect advisor and subadvisor information from N-SAR filings retrieved from EDGAR. The Investment Company Act of 1940 requires all mutual funds to file N-SAR filings with the SEC. We are especially interested in item 8. This item contains the name, the firm's SEC identification number, and a flag indicating whether the entity serves as a fund's advisor or sub-advisor. Unfortunately, the SEC discontinued the use of N-SAR filings in 2018. Thus, similarly to Broman et al. (2022), our sample ends in 2017.

While we can now identify the funds that employ a subadvisor, in some cases, the portfolio management is "outsourced" to a manager affiliated with the fund family (advisor). Therefore, an extra step is required to check whether the subadvisor is affiliated with the fund's advisor.

We use ADV filings - the annual registration filing of an investment advisor with the SEC – for this purpose. We retrieve these filings in the form of excel sheets from the SEC website. This data is available from 2001. The unique SEC identification number found in item 8 in the NSAR filings also serves as the key identifier in the ADV filing. This allows us to link our ADV and NSAR data. Item 7. A of form ADV records all affiliated legal entities of the filing entity. Furthermore, item 10. B lists the ultimate parent of the reporting investment advisor if it has not already been mentioned in Item 7. A. We use the information provided in both sections to determine whether the advisor and subadvisor are affiliated. Funds where the subadvisor is affiliated with the advisor are recorded as not outsourced in our data set. This procedure leads us to re-classify approximately 435 funds in an average sample year. 42.7% of funds that list a subadvisor in file N-SAR are sub-advised by an affiliated firm.

The ADV filings also provide us with further information on the investment advisor, such as the firm's discretionary assets under management, the number of clients, accounts, and employees, the number of employees in investment roles and whether the investment advisor offers a wrap fee program. Furthermore, we retrieve the percentage of clients split into the following categories: individual investors, mutual funds, financial institutions, hedge funds and other pooled investment vehicles, pension funds, charities, governmental organisations, and an "other" category. After merging with the N-SAR database, our sample consists of 4,472 unique funds across 52 Morningstar categories.

4.3.3. Summary Statistics

Table 4.1 contains summary statistics of our mutual fund sample partitioned into In-house managed and Sub-advised funds. These univariate statistics show that sub-advised funds are smaller, have higher expense ratios, lower gross returns and alpha, are less likely to be broker-sold, as indicated by front- or rear-end loads, and belong to smaller fund families.

[Table 4.1 About Here]

4.4. Empirical Analysis

In this section, we test our hypotheses described in section 4.3. We first analyse the initial outsourcing decision. We then explore how fees are shared between the fund family and the subadvisor. In the subsequent section, we examine the impact of market thickness on subadvisor turnover. After, we show that higher subadvisor market thickness positively links to fund performance. Finally, we test hypothesis 3b through a Heckman-based treatment effect model that accounts for the initial decision to outsource.

4.4.1. The Decision to Enter an Outsourcing Relationship

In this section, we investigate the decision of the subadvisor and the fund family to enter an outsourcing relationship. We first focus on the subadvisor's decision, followed by the fund family's decision.

For the subadvisor's decision to sub-advise a fund for an unaffiliated fund family, we follow Evans and Debaere (2015)'s empirical design. We consider all investment advisors advising or sub-advising a mutual fund in a given year. We are specifically interested in whether an investment advisor only acts as a subadvisor. Therefore, we code the dummy variable as one if the investment advisor only sub-advises a mutual fund and zero if the investment advisor manages a fund in-house. Our independent variables are a dummy variable indicating whether the investment advisor is based in the U.S., the natural logarithm of the average account size, the natural logarithm of the total discretionary assets under management, the percentage of employees with investment roles, the percentage of assets under management over which the investment advisor has investment discretion, as well as the percentage mix of assets by client type ("other" category is omitted). Regression estimates are reported in Table 4.2.

[Table 4.2 About Here]

We find that investment advisors located outside of the U.S., with a smaller amount of discretionary assets, more employees in investment roles, and more institutional clients are more likely to outsource. These effects suggest that it is predominantly institutional investment advisors that sub-advise. A one standard deviation increase in the percentage of retail (mutual fund) clients decreases the likelihood of an investment company to sub-advise by 5.55% (36.26%). We would suggest that this is strong evidence that the lack of access to retail clients is an important driver of the investment advisor's decision to sub-advise a fund for an unaffiliated fund family. This finding agrees with our first hypothesis, 1a.

We now turn to an exploration of the drivers of the fund family's outsourcing decision. Before presenting estimates from our formal regression analysis, we present visual evidence on the prevalence of outsourcing across new and already served Morningstar categories and thick and thin markets.

[Figure 4.1 About Here]

Figure 4.1A shows the percentage of aggregate assets that are outsourced by funds operating in Morningstar categories in which the fund family has not previously managed any assets. Specifically, we sort funds into the new Morningstar category if the fund belongs to a Morningstar category where the fund family has not managed any money before 2001. Figure 4.1B shows the percentage of the number of funds. Both figures clearly show that outsourcing is most prevalent in funds that operate in Morningstar categories new to a fund family. Thus, these figures indicate that expertise may play a role in the outsourcing decision.

[Figure 4.2 About Here]

Similarly, we want to investigate the effect of subadvisor market thickness on the fund family's outsourcing decision. Subadvisor thickness captures the size of the subadvisor market. The larger the number of investment companies willing to engage in an outsourcing relationship, the easier it should be for a fund family to find a suitable subadvisor. We measure subadvisor thickness by extracting predicted probabilities from a logit model investigating the subadvisor's decision to sub-advise. The logit regression is reported in Table 4.2.[5] Next, all individual predicted probabilities are aggregated by year and Morningstar category. This measure captures the number of investment advisors willing to sub-advise an unaffiliated mutual fund. Figure 4.3 graphs this subadvisor market thickness measure over time.

[Figure 4.3 About Here]

Subadvisor market thickness generally increases throughout our sample period but experiences a sharp fall from 2008 to 2011. While we do not know the precise reason for this drop, the number of investment advisors that only sub-advise in our data also sharply falls over this same period. We employ this measure because a simple count of active subadvisors would miss investment advisors that would like to sub-advise but cannot find a fund family to contract with. Figure 4.2 indicates that subadvisor market thickness may also influence a fund family's decision to outsource their fund's portfolio management. The higher the number of investment advisors that want to sub-advise for a fund family, the easier it becomes for that fund family to find a suitable

[5] The precise regression is slightly different. First to attain variation not only across time but also across Morningstar categories we re-code our sub-advising variable to be equal to one if an investment advisor sub-advises in each year and Morningstar category. Additionally, we include objective fixed effects in this regression.

subadvisor. While outsourcing is most prevalent in *thick markets* throughout our sample, we observe an increase in outsourcing for *thin markets*. This is likely because subadvisor market thickness increased faster for *thin markets* than *thick markets*. More specifically, over our sample period, the average subadvisor thickness of *thin markets* increased by 37.66% more than for *thick markets*. The impact of expertise on the part of the fund family - hypothesis 1a - and the impact of market thickness - hypothesis 1b-are next investigated in a regression framework.

We investigate the decision of a mutual fund family to outsource the portfolio management of a newly opened fund. We build a dataset that indicates whether a mutual fund family opened a fund in a given Morningstar category and year and whether the management of this new fund is outsourced. In constructing the dataset, we account for all possible combinations of fund families and Morningstar categories each year. If the mutual fund family opened multiple funds in the same year and Morningstar category, each newly opened fund is recorded separately. Because we only observe the decision to outsource for funds that the mutual fund family initially decided to open, we run a Heckman selection model. The first stage of the selection model accounts for the fund family's decision to open a fund in a given Morningstar category and year as follows:

$$Prob\left(Open_{i,f,o,t} = 1\right) = \Phi\left(\alpha + X'_{i,f,o,t-1}\beta\right) \tag{4.2}$$

The subscript *i* refers to the fund, *f* to the fund family and *o* to the Morningstar category. We follow Khorana & Servaes (1999) and Evans and Debaere (2015) in the lagged independent variables (*X*) used in this first-stage regression. We include the natural logarithm of the Morningstar category size, the natural logarithm of fund family size, the natural logarithm of the fund family's assets under management in the Morningstar category, the Morningstar category's net flows, the fund family's net flows, the fund family's net flows in the Morningstar category, the return of the Morningstar category, the percentage of the fund family's assets that are broker-sold, and the number of new funds launched by the fund family. The second stage regression is a logit model that characterises the decision to outsource a fund, as follows:

$$
\log\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \alpha + \beta_1 ThickSub_{o,t} + \beta_2 Expertise_{f,o,t} + \beta_3 ObjectiveHHI_{f,t} + \beta_4 TNAOutsourced_{f,t-1} + \beta_5 InvMill_{i,t} + \varepsilon_{i,t} \tag{4.3}
$$

where $p_{i,t}$ denotes the probability of a fund family deciding to outsource fund *i* at time *t*.

The independent variables of interest in this regression are our two expertise measures – the regional expertise and the percentage of the fund family's assets outside of the Morningstar category -, a Herfindahl Hirschman Index measuring the fund family's product offering concentration and the percentage of assets the fund family outsourced the previous year, as well as our measure for the thickness of the subadvisor market. The HHI measure quantifies the extent to which a fund family specialises in offering a particular type of mutual fund. A less specialised mutual fund family that offers funds in many different Morningstar categories may focus more on distribution than investment expertise. Unlike Evans and Debaere (2015), we include our subadvisor market thickness measure as a key explanatory variable. Regression results are reported in Table 4.3.

[Table 4.3 About Here]

As expected, our expertise measures and our market thickness measure have a positive coefficient. Fund families that lack expertise are more likely to outsource, and outsourcing is more prevalent in Morningstar categories with higher subadvisor market thickness. Furthermore, a fund family with a more diversified investment product offering is also more likely to outsource. A more diverse investment product offering suggests that the fund family is more focused on mutual fund distribution than investment expertise. Lastly, fund families that have more prior experience with outsourcing are more likely to outsource again. Thus, we find support for both hypotheses, 1a and 1b.

4.4.2. Bargaining Power and Division of the Gains from Trade

The previous sections have shown that the expertise or the lack thereof impacts the decision to outsource and sub-advise. Now we investigate our second set of hypotheses – 2a and 2b - on how the relative expertise that the two parties bring to the relationship and the size of the outsourcing market can influence their relative bargaining power. To measure relative bargaining power, we examine how fee revenue is split. More specifically, we define our dependent variable as the share of the advisory fee paid to the subadvisor. We divide the subadvisor fee by the advisory fee and multiply the resulting ratio by 100. 2.79% of the observations in our sample report a subadvisor fee substantially larger than the advisor fee, which except for minor rounding errors is not possible. We exclude such observations. Furthermore, we follow Del Guercio et al. (2010) in only investigating outsourcing relationships with a single subadvisor for the same reason - we do not observe the size of the assets each subadvisor is managing, making it impossible for us to calculate the division of the gains of trade for mutual funds that have multiple subadvisors. This reduces our sample size by 14.35%.

Our measure of subadvisor market thickness is calculated as before by aggregating the predicted probabilities of the investment advisor deciding to sub-advise a fund.

For the fund family thickness, the number of fund families interested in entering an outsourcing relationship in a given year and Morningstar category, we use the predicted probabilities from the regression in Table 4.3, excluding the subadvisor market thickness variable to not contaminate our thickness measure. We then aggregate these predicted probabilities by year and Morningstar category to attain a measure for the number of potential trade partners.

Regression results for our fixed-effects models that analyse the fee split between the fund family and the subadvisor are reported in Table 4.4. We are specifically interested in the effects of our expertise and market thickness measures. Results relating to subadvisor variables, fund family variables, and market thickness variables are reported in panels A, B, and C, respectively.

[Table 4.4 About Here]

Looking at panel A of Table 4.4, we find that larger subadvisors receive more fee revenue. Moreover, subadvisor with larger average account sizes - a characteristic of institutional asset managers - also attain a larger share of the fees. A one standard deviation increase in the natural logarithm of the average account size translates into 6.19% more of the fee revenue going to the subadvisor. We further find that subadvisors with a larger share of retail clients receive a smaller share of the advisory fee. Furthermore, subadvisors with fewer client assets from hedge funds and other pooled investment vehicles but more clients from governmental organisations receive a higher share of the fees. Although not statistically significant, we also observe that subadvisors with more employees with investment responsibilities, more investment discretion, and that do not offer a wrap fee programme obtain a higher share of the advisory fees. These findings suggest that larger subadvisors that are managing more money in separately managed accounts as opposed to comingled investment vehicles receive a higher share of the fees.

Turning to the effect of family characteristics on the fee split in panel B, we can see that the fund family can extract a higher share of the fee revenue if it has fewer employees in investment roles. A higher number of employees outside of investment roles translates to more employees in other roles, such as marketing and distribution. A one standard deviation increase in the percentage of employees in investment roles decreases the share of fees that the fund family can retain by 2.27%. A smaller share of assets over which the fund family exerts investment discretion also increases its fee revenue share. This can be interpreted in the following way. A fund family that manages fewer assets by itself is likely to focus more on distribution. In line with this, we also find that a higher percentage of broker-sold assets and a more comprehensive product offering (Family Category HHI) allow the fund family to retain a larger share of the fees. A one standard deviation increase in the percentage of a fund family's assets that are broker-sold allows it to retain 2.79% more of the fee revenue. Furthermore, the lower the expertise of the fund family in managing such a fund in-house the fewer fees it can retain. We interpret this finding the following way. Lower expertise means that the fund family relies more on an outside party to manage the fund, leading to a shift in bargaining power to the subadvisor. Put differently, a fund family with expertise in managing a particular fund is less likely to outsource to retain all the fee revenue. The less expertise the fund family has in managing the fund's portfolio, the more willing it is to give up some of these fees to find a suitable subadvisor. The evidence presented in panel B largely conforms with our hypothesis 2a.

In panel C of Table 4.4, we observe a negative effect of the subadvisor market thickness measure and a positive effect of the family market thickness measure on the fee split. More specifically, a one standard deviation increase in the subadvisor (fund family) market thickness translates into the fund family retaining 7.11% (giving up 3.92%) more of the advisory fee. This finding confirms hypothesis 2b. The higher the number of potential alternative trade partners with which the fund family can contract, the higher its bargaining power in any fee negotiation. Similarly, an increase in fund family market thickness increases the fees paid to the subadvisor.

4.4.2.1. Market Thickness and Subadvisor Turnover

While the previous section has shown that market thickness impacts the division of fee revenue, we want to explore one channel through which market thickness could increase the power of the fund family in the outsourcing relationship.

Ramey & Watson (2001) show theoretically that an increase in market thickness can result in the breakdown of long-run relationships. In their model, long-run relationships are sustained because it is challenging to find alternate trade partners. Once market thickness increases, it becomes easier for either party to find a replacement for their current partner. This can be readily interpreted as a decrease in search costs. This decrease in search costs lowers the costs of ending an ongoing relationship.

In this section, we investigate how market thickness impacts subadvisor turnover of outsourced funds. We code a subadvisor as being fired if it is no longer listed as an advisor or subadvisor of the fund in the next year in filing N-SAR. Furthermore, we only look at funds that continue to exist after the subadvisors' departure. We follow the literature on subadvisor turnover, specifically Kostovetsky & Warner (2015), in our regression design. We employ a logit model where our dependent variable is coded as one if the subadvisor is fired (does not sub-advise the fund next year) and the fund continues to operate and 0 otherwise. Our main independent variables are our two market thickness measures. We control for the past three years of performance (4-factor alpha), the lag of the natural logarithm of the fund size, family size, the number of subadvisors, the age of the fund as well as the number of subadvisors. The regression equation can be written as follows:

$$\begin{aligned} \ln\left(\frac{p_{s,i,t+1}}{1-p_{s,i,t+1}}\right) = {} & \alpha + \beta_1\, Subadvisor\ Market\ Thickness_{s,i,t} \\ & + \beta_2\, Fund\ Family\ Market\ Thickness_{i,t} + F'_{i,t}\gamma \\ & + \varepsilon_{s,i,t} \end{aligned} \tag{4.4}$$

where p refers to the probability of being fired, and F corresponds to our fund-level control variables. Subscripts i refer to the fund, s to the subadvisor, and t to year. We cluster standard errors by year and weight each observation inversely by the number of subadvisors. This is to ensure that all our funds have equal weights. The results of our logit model are tabulated in Table 4.5.

[Table 4.5 About Here]

Throughout all three regressions, we find that a higher subadvisor market thickness positively influences subadvisor turnover. The average marginal effect of a one standard deviation increase in market thickness increases the turnover probability by 2.6% to 2.4%, depending on the length of past performance we control for. If we control for the past three years of performance, a one standard deviation increase in past year's performance reduces the turnover probability by 2.7%. We would therefore argue that the effect of market thickness on the subadvisor turnover decision is economically meaningful. This finding supports hypothesis 2c. We view this as one of the main drivers of how market thickness impacts the relative power of the fund family and the subadvisor in the outsourcing relationship. The more numerous the fund family's outside options, the more relative bargaining power it has.

In addition, we find that the probability of a subadvisor being fired is inversely related to fund performance and fund size. Furthermore, a subadvisor is more likely to be fired from managing a fund that has other subadvisors co-managing the fund. We also find that tenure decreases the probability of a subadvisor being fired.

4.4.3. Performance and Size of Outsourced Funds

Next, we investigate how market thickness impacts the performance of outsourced funds, as described in hypothesis 3a. We employ a standard fund performance regression and include our two market thickness measures. The regression equation can be written as follows:

$$
\begin{aligned}
Fund\ Performance_{i,t} = {} & \beta_1\ Subadvisor\ Market\ Thickness_{o,t} \\
& + \beta_2\ Fund\ Family\ Market\ Thickness_{o,t} + F'_{i,t}\gamma \qquad (4.5) \\
& + \alpha_o + \varepsilon_{i,t}
\end{aligned}
$$

where *F* refers to the fund control variables and *alpha* to Morningstar category fixed effects. Subscript *o* represents the Morningstar category. The dependent variable is fund performance, measured by 3- and 4-factor alphas. All control variables are lagged by one year and include the natural logarithm of fund size, the natural logarithm of the fund family size, whether the fund is broker-sold, the past yearly flows into the fund, fund age, turnover and expense ratio, and Morningstar category fixed effects. The output of this regression is reported in Table 4.6.

[Table 4.6 About Here]

We find that keeping the number of fund families looking for a subadvisor constant, subadvisor thickness has a positive effect on fund performance. A one standard deviation increase in our subadvisor thickness measure increases mutual fund 3-factor (4-factor) alpha by 1.06% (0.63%) per annum. We conjecture that the increased replaceability of the subadvisor shifts the balance of power towards the fund family. This shift in power allows the fund family to put more pressure on the subadvisor to exert effort and perform better. Therefore, consistent with hypothesis 3a, outsourced funds that operate in thicker markets perform better. Control variables have the expected signs, despite not being statistically significant.

We now turn to the underperformance of sub-advised funds compared to in-house managed funds, as reported in prior literature. We follow previous studies (such as Del Guercio et al. (2010), Chen et al. (2013), and Evans & Debaere (2015)) and first run a simple OLS regression with gross returns, 3-factor alphas, 4-factor alphas, and an investment objective alpha as the dependent variables. These regressions are reported in Table 4.7 and include the following controls: the natural logarithm of mutual fund size, the natural logarithm of fund family size, mutual fund net flow, age, the expense ratio, turnover, and a variable indicating if a fund is broker-sold.

[Table 4.7 About Here]

Our key variable of interest, the outsourced dummy variable, is significantly negative for all four performance measures. We find that outsourced funds underperform in-house managed funds by 1.01% in investment objective alpha and by 15.3bps 4-factor alpha per annum. This underperformance is slightly smaller than in previous papers that investigated shorter time horizons, such as Chen et al. (2013). It, nevertheless, confirms the underperformance of sub-advised funds documented in the prior literature.

Like Debaere & Evans (2015), we want to explore whether the lack of expertise of the fund family that underlies its decision to outsource can help to explain the average underperformance of outsourced funds. Different from them, we employ a Heckman-based treatment effect model. This model accounts for the fact that the fund family and the subadvisor decided to enter an outsourcing relationship. We estimate this model via maximum likelihood but will explain the 2-step procedure below. The first stage models the decision to enter an outsourcing relationship as follows:

$$Prob\left(Outsourced_{i,t} = 1\right) = \Phi\left(\alpha + K'_{i,t}\beta\right) \tag{4.6}$$

where $\Phi(.)$ is the cumulative normal distribution function. The dependent variable *Outsourced* is equal to one if the fund is outsourced and zero otherwise. Independent variables in this first stage probit regression correspond to selected variables from our earlier regressions investigating the decisions to outsource. Namely, the regional expertise measure, the fund family's Morningstar category HHI, the percentage of fund family assets outsourced, the percentage of the family's assets outside of the Morningstar category, the natural logarithm of the investment advisor's discretionary assets and the investment advisor's clientele mix. We then extract predicted probabilities from the first stage regression ($z_{i,t}$) and calculate $\lambda^*_{i,t}$ according to equation 4.7, where $\lambda(.)$ represents the inverse Mill's ratio and $\phi(.)$ and $\Phi(.)$ the standard normal density and cumulative normal density functions respectively as follows:

$$\lambda^*_{i,t} = \begin{cases} \lambda(z_{i,t}), & if\ Outsourced_{i,t} = 1 \\ -\lambda(-z_{i,t}), & if\ Outsourced_{i,t} = 0 \end{cases}, where\ \lambda(.) = \left(\frac{\phi(.)}{\Phi(.)}\right) \tag{4.7}$$

In the second stage, $\lambda^*_{i,t}$ is included in the following outcome equation:

$$Return_{i,t} = \beta_1 Outsourced_{i,t} + X'_{i,t-1}\gamma + \lambda^*_{i,t} + \varepsilon_{i,t} \tag{4.8}$$

The main independent variable of interest is our outsourced dummy variable. We include the same control variables as in our previous OLS regression. Panel A of Table 4.8 reports the coefficient estimates of our first-stage regression and Panel B the coefficients of our outcome regression.

[Table 4.8 About Here]

After accounting for the underlying lack of expertise of the fund family that drove its decision to outsource the portfolio management, we observe a negative but insignificant coefficient on our outsourcing dummy variable across all performance measures. This result conforms with hypothesis 3b and implies that if the fund family had managed the mutual fund in-house, it would not have achieved better performance.

Next, we examine the prediction of hypothesis 3b for mutual fund size. We first perform a simple OLS regression of fund size on the outsourcing dummy and other conventional control variables. Regression results are reported in Column 1 of Table 4.9.

[Table 4.9 About Here]

The coefficient of our outsourced dummy variable is significantly negative. This implies that outsourced mutual funds are smaller in size than in-house funds. Coefficients on all control variables are as expected.

However, as before, we need to control for the initial decision of both parties to enter the outsourcing relationship. Therefore, we run the same Heckman-based treatment effect model as in our mutual fund performance investigation. Coefficient estimates of the second stage outcome equation are reported in Column 2 of Table 4.9. The first stage regression specification is identical to the one presented in Table 8 (results are available upon request).

Accounting for the lack of expertise that drove the decision to enter this outsourcing relationship, we find that sub-advised funds are no smaller than in-house distributed funds. Our outsourcing dummy variable is insignificant, and all our control variables are as expected. Given the lack of in-house retail distribution capabilities, the subadvisor could not have gathered more assets than the fund family achieves in the outsourcing relationship.

4.5. Conclusion

The prior literature has shown that in-house managed funds outperform sub-advised funds. Why do fund families continue to outsource, given the sub-par performance of such arrangements? We answer this question by looking at the initial decision to engage in an outsourcing relationship. We find that fund families that lack investment expertise internally will acquire it in the open market through a subadvisor. Equivalently, investment advisors may decide to sub-advise a fund for an unaffiliated fund family to access the fund family's distribution channels. We find that subadvisors are more likely to be institutional asset managers who typically lack retail distribution capabilities.

Once we account for the decision of the subadvisor and the fund family to enter an outsourcing relationship, we find that outsourced funds have an indistinguishable fund size and performance from in-house managed funds. The mutual fund family could not have achieved better performance than the subadvisor, given its lack of investment expertise. The subadvisor could not have gathered more assets through its internal distribution capabilities.

We show that market thickness impacts bargaining power by analysing how the fee revenue is shared. A higher subadvisor market thickness gives more power to the fund family, and a higher fund family market thickness increases the power of the subadvisor. We further explore the impact of market thickness on bargaining power in the relationship and the heightened threat of dismissal of the subadvisor in thicker markets. The likelihood of subadvisor terminations is heightened in markets where subadvisor thickness is relatively large compared to fund family thickness. Finally, market thickness can also explain some return variation across sub-advised mutual funds. Through its effect on bargaining power in the outsourcing relationship and the heightened threat of subadvisor termination, subadvisor market thickness increases the performance of sub-advised funds.

Overall our findings are consistent with the (lack of) investment expertise of the mutual fund family determining the upper bound of agency costs, while market thickness can drive agency costs away from this maximum level towards zero.

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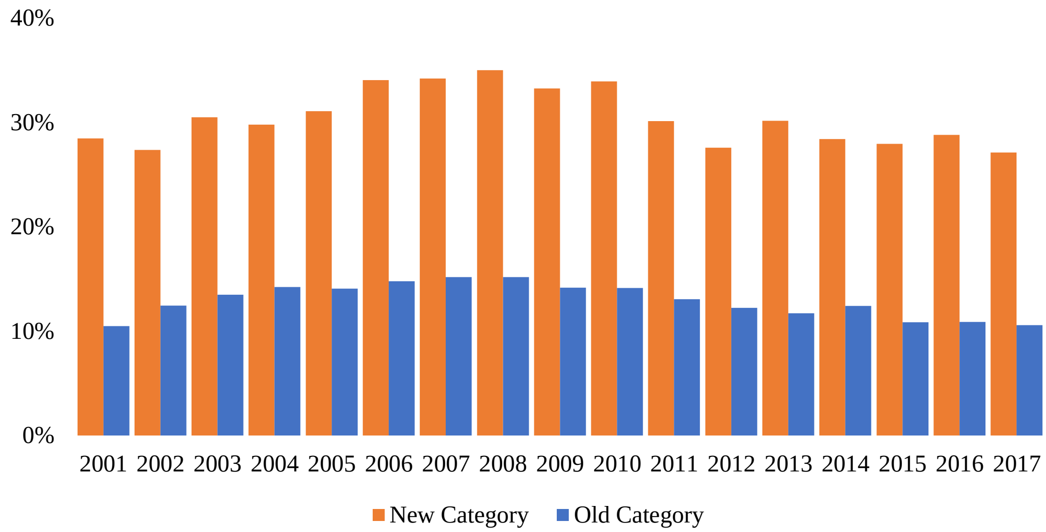
4.7. Figures

Figure 4.1 Outsourcing into New and Old Morningstar Categories

This figure depicts the percentage of assets (Panel A) and funds (Panel B) that are sub-advised, split into new and old Morningstar categories for the fund family. For each fund family, we identify the Morningstar categories in which it has managed assets before 2001. We then split the sample into funds in a new Morningstar category and funds in old Morningstar categories. Subsequently, we calculate the number of funds and assets that are outsourced over time for both subsets.

Panel A – Percent of Funds Outsourced



Panel B – Percent of Assets Outsourced

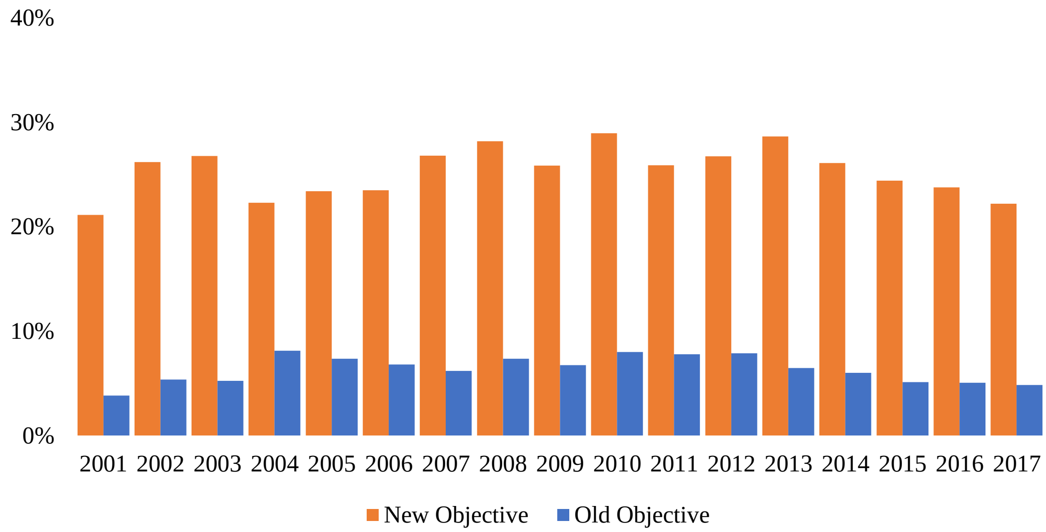


Figure 4.2 Outsourcing in Thick and Thin Markets

This figure depicts the percentage of sub-advised funds for Morningstar categories where the subadvisor market is thick compared to when it is thin. We calculate the subadvisor market thickness by aggregating predicted probabilities from our logistic regression, investigating the decision of an investment advisor to sub-advise. We run a slightly altered version of the regression in Table 4.2. First, we recode the independent variable to equal one if the investment advisor sub-advises a fund in a Morningstar category and year. Second, we add Morningstar category fixed effects. Next, we extract fitted probabilities for each year, investment advisor, and Morningstar category and aggregate them within each year and Morningstar category. This measure proxies for the number of subadvisors willing to manage assets for an unaffiliated fund family in a given year and Morningstar category. A Morningstar category is coded as thick in a year where it has a subadvisor thickness measure that is larger than the median subadvisor thickness of all other Morningstar categories that year and thin otherwise.

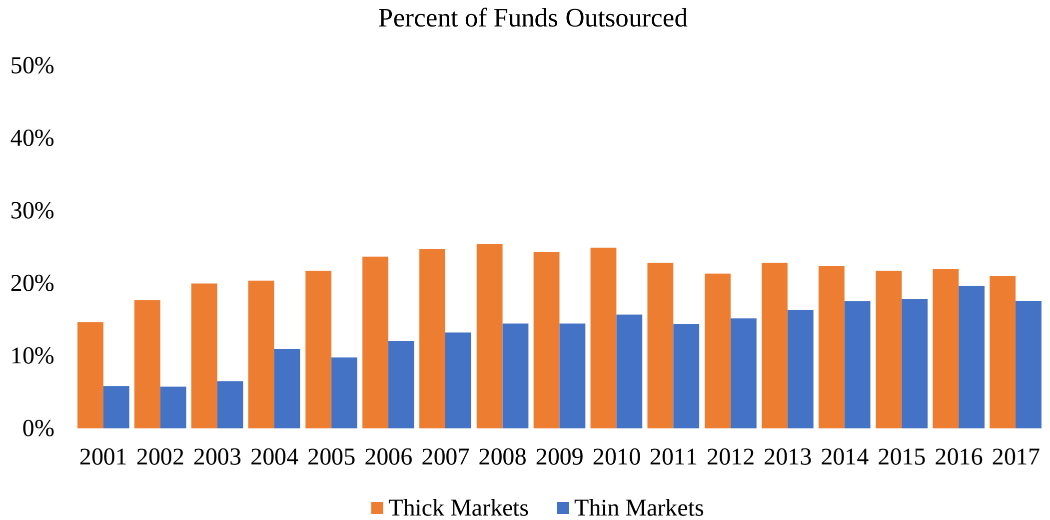
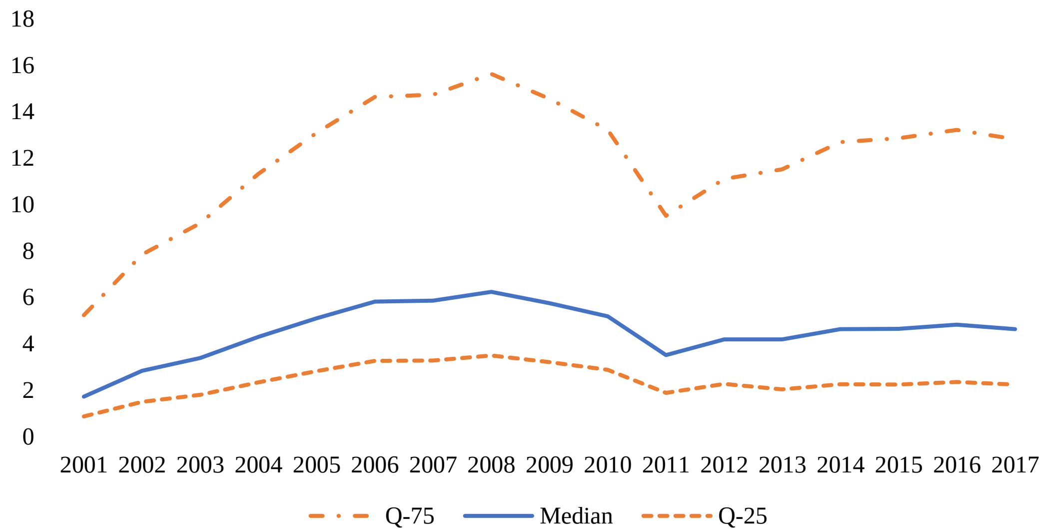


Figure 4.3 Subadvisor Market Thickness

This figure depicts the distribution of our subadvisor market thickness measure over time. The construction of this measure is described in Figure 4.2. We plot the median and the 25 and 75 percentiles of our subadvisor market thickness measure each year.



4.8. Tables

Table 4.1: Sample Statistics

This table shows descriptive statistics (mean, median, and standard deviation) for our mutual fund sample. The sample consists of all funds in Morningstar that could be matched to N-SAR filings and covers data from 2001 to 2017. We divided the sample into advised (in-house managed) and sub-advised funds. In total, we have 36,120 fund-year observations, of which 7,546 correspond to sub-advised and 28,574 to advised funds. In an average year in our sample, 20.7% of all funds are sub-advised. We report the following fund characteristics. Fund size in $ millions, the size of the fund family in $ billions, the expense ratio, turnover, age, and the percentage of funds that are broker sold as indicated by whether the fund charges a front or back load. Furthermore, we report annualised performance statistics. All performance statistics are calculated from gross returns except for the objective alpha. The objective alpha is calculated by subtracting the value-weighted average net return of all other funds in the same Morningstar category from the firm's net return. Alphas are estimated using 36 months of data and factors are taken from Kenneth French's website.

	Advised Funds (28,574 Fund-Year Obs.)			**Sub-Advised Funds** (7,546 Fund-Year Obs.)		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Fund Size ($ Millions)	1785	294	6889	792	255	1998
Family Size ($ Billions)	168	31	362	58	24	87
Expense Ratio	1.27%	1.27%	0.49%	1.31%	1.23%	0.52%
Turnover	103%	60%	277%	103%	68%	162%
Age	14.12	11	12.36	9.84	8	8.22
Broker Sold ==1	55%	-	-	46%	-	-
Gross Return	8.88%	9.07%	20.33%	8.14%	8.50%	19.54%
Objective Alpha	6.96%	7.32%	23.54%	5.86%	6.96%	22.40%
3 Factor Alpha	0.17%	0.00%	7.96%	-0.01%	-0.06%	5.79%
4 Factor Alpha	-0.03%	-0.09%	7.71%	-0.17%	-0.15%	5.67%

Table 4.2: Investment Company Decision to Subadvise

This table shows the regression estimates of a logit model of the determinants of an investment advisor's decision to sub-advise a mutual fund of an unaffiliated fund family. The dependent variable takes a value of one if the subadvisor only sub-advises in a given year and zero otherwise. The sample is constructed by taking all investment advisors that act either as subadvisor, advisors, or both to at least one mutual fund in our sample each year. The independent variables are all taken from form ADV and include a dummy variable indicating whether an investment advisor is based in the U.S., the log of the total discretionary asset under management, the log of the average account size, the per cent of assets over which the investment advisor has investment discretion, and the per cent of employees with investment responsibilities. Moreover, we include the percentage of the investment advisors' clients who are individual investors, mutual funds, financial institutions, hedge funds and other pooled investment vehicles, pension funds, charities, and governmental organisations. The "other" category is omitted. We include year-fixed effects and standard errors are clustered by investment advisor. T-statistics are reported in parentheses.

		Only Sub-advises = 1
	US Based ==1	-0.403***
		(-3.39)
	Log Discretionary Assets	-0.073***
		(-5.09)
	Log Average Account Size	0.009
		(0.51)
	% Investment Discretion	0.418*
		(1.68)
	% Employee in Investment Role	0.160***
		(3.04)
% Assets By Clientele	Retail	-0.005***
		(-3.64)
	Mutual Fund	-0.013***
		(-9.51)
	Financial Institution	-0.004
		(-1.02)
	Hedge Funds and Other Pooled	0.008***
		(4.34)
	Pension	0.005**
		(2.54)
	Charity	0.001
		(0.35)
	Governmental Organisations	0.016***
		(4.60)
	Adj. Pseudo R2	12.37%
	Observations	13,102
	Log-Likelihood	-7,369.50

Table 4.3: Fund Family Decision to Outsource Portfolio Management

This table reports the regression estimates from a Heckman selection model on a fund family's decision to outsource. The first stage selection model investigates the decision of the fund family to open a fund in a given Morningstar category and year. The independent variables in this selection equation are all lagged and include the natural logarithm of the size of the Morningstar category, the natural logarithm of the fund family's size, the natural logarithm of the number of assets the fund family manages in the Morningstar category, the annual net flows into the Morningstar category, the annual net fund flows into the family, the annual net fund flows into the assets of the fund family in the Morningstar category, investment objective returns, the per cent of assets of the fund family that are broker-sold, and the number of funds the fund family opened. The independent variables for the outcome model include the subadvisor market thickness, defined in Figure 4.2, the fund families Morningstar category Herfindahl, the per cent of assets the fund family outsourced the previous year, and two expertise measures. Regional expertise measures the difference in the family's regional asset allocation and the regional asset allocation of all funds in the Morningstar category. The other expertise measure gives the percentage of the fund family's assets that do not fall in the Morningstar category of the newly created fund. Standard errors are clustered by fund family and T-statistics are reported in parentheses.

	(1)	(2)
Selection Equation (Open New Fund ==1)		
Constant	-3.700***	-3.700***
	(-24.01)	(-23.95)
Log Objective Size	0.071***	0.071***
	(12.00)	(12.00)
Log Family Size	-0.060***	-0.061***
	(-27.40)	(-27.50)
Log Family Objective Size	0.088***	0.088***
	(68.08)	(67.97)
Category Net Flow	0.087***	0.087***
	(10.97)	(10.97)
Family Net Flow	-0.000	-0.000
	(-0.91)	(-0.90)
Family Objective Net Flow	0.024***	0.024***
	(18.50)	(18.48)
Objective Return	-0.006***	-0.006***
	(-11.11)	(-11.10)
% TNA Broker Sold	0.001***	0.001***
	(3.33)	(3.33)
Number of New Funds	0.045***	0.046***
	(24.89)	(25.02)
Outcome (Outsourced ==1)		
Constant	-0.945***	-1.779***
	(-8.22)	(-6.02)
Market Thickness (Subadvisor)	0.007***	0.007***
	(2.73)	(2.78)
Expertise (Regional)	0.000***	
	(3.39)	
Expertise (% TNA Outside Objective)		0.009***
		(3.35)
Family Objective HHI	-0.000***	-0.000***
	(-8.79)	(-6.42)
% TNA Outsourced	0.013***	0.013***
	(13.94)	(13.94)
Observations	319,604	319,604
Log-Likelihood	-11185.96	-11184.54

Table 4.4: Expertise and Market Thickness on Feesplits

This table gives the regression estimates of two fixed effects regressions investigating the percentage of the advisory fees paid to the subadvisor. The dependent variable is calculated by dividing the fee paid to the subadvisor by the advisory fee and multiplying the result by 100. Fund Family Thickness measures fund families' willingness to outsource in a given year and Morningstar category. It is calculated by first retrieving predicted probabilities from the logit model in Table 4.3 that excludes the subadvisor market thickness measure as an independent variable. Next, the predicted probabilities are aggregated by Morningstar category and year to attain a measure for the number of fund families willing to engage in an outsourcing relationship. The subadvisor market thickness measure is described in Figure 4.2. The number of clients, as well as the number of employees, are both retrieved from filing ADV. All other subadvisor variables are defined in Table 4.2. The remaining advisor/fund family measures of expertise are defined in Table 4.3. Standard errors are clustered at the subadvisor and fund family levels. T-Statistics are reported in parentheses. The use of year and Morningstar category fixed effects is indicated at the bottom of the table in Panel C. Panel A lists all coefficients of subadvisor variables, panel B all fund family variables, and panel C our both market thickness variables.

Panel A - Subadvisor Variables

		(1)	(2)
	Number of Clients	2.544***	2.706***
		(3.38)	*(3.47)*
	Number of Employees	2.128*	1.799
		(1.96)	*(1.42)*
	Log Discretionary Assets	-4.699***	-4.666***
		(-3.64)	*(-3.36)*
	Log Average Account Size	2.996**	3.118**
		(2.47)	*(2.52)*
	% Investment Discretion	13.357	14.119
		(1.41)	*(1.48)*
	% Employee in Investment Role	2.466	2.527
		(1.17)	*(1.13)*
	Offers Wrap Fee	-0.577	-0.372
		(-0.14)	*(-0.09)*
% Assets By Clientele	Retail	-0.085**	-0.088**
		(-2.31)	*(-2.41)*
	Mutual Fund	-0.088	-0.093
		(-1.17)	*(-1.24)*
	Financial Institution	-0.043	0.005
		(-0.55)	*(0.05)*
	Hedge Funds and Other Pooled	-0.124**	-0.123*
		(-1.99)	*(-1.95)*
	Pension	-0.119	-0.120
		(-1.40)	*(-1.43)*
	Charity	0.095	0.085
		(0.58)	*(0.51)*
	Governmental Organisations	0.162*	0.172*
		(1.69)	*(1.81)*

Panel B - Fund Family Variables

	(1)	(2)
Number of Clients	0.925*	1.002**
	(1.85)	*(2.02)*
Number of Employees	1.758***	1.785***
	(3.36)	*(3.22)*
Log Discretionary Assets	-1.189	-1.237
	(-1.51)	*(-1.51)*
Log Average Account Size	0.817	0.948
	(1.20)	*(1.37)*
% Investment Discretion	64.956*	62.128*
	(1.89)	*(1.80)*
% Employee in Investment Role	7.748**	8.055***
	(2.58)	*(2.62)*
Expertise (% TNA Outside Objective)	-0.043	-0.041
	(-0.42)	*(-0.40)*
% TNA Broker Sold	-0.071***	-0.072***
	(-2.92)	*(-2.96)*
Family Objective HHI	-0.002**	-0.002**
	(-2.33)	*(-2.32)*
Expertise (Regional)	0.001*	0.001*
	(1.85)	*(1.88)*

Panel C - Market Thickness Variables

	(1)	(2)
Market Thickness (Fund Family)	0.429*	0.441*
	(1.95)	*(1.95)*
Market Thickness (Subadvisor)	-0.513**	-0.270
	(-2.43)	*(-0.51)*
Adj. R2	23.88%	23.72%
Objective FE	Yes	Yes
Year FE	No	Yes
Observations	1,368	1,368

Table 4.5: Subadvisor Turnover

This table investigates the probability of a subadvisor being fired. A subadvisor is considered fired if it is not listed as either an advisor or a subadvisor in the following year in the fund's N-SAR filing. Our independent variables include our two market thickness measures. The subadvisor market thickness measure is defined in Figure 4.2 and the fund family market thickness measure is defined in Table 4.4. Other independent variables are lagged and include performance measured by a 4-factor alpha, the log of the fund size, the annual net flow of assets into the fund, the number of other subadvisors, and the tenure of the subadvisor. Observations are inversely weighted by the number of subadvisors to ensure all funds have an equal impact. Standard errors are clustered by year. T-Statistics are reported in parentheses.

	Subadvisor Left = 1		
	(1)	(2)	(3)
Constant	2.199***	2.480***	2.476***
	(5.69)	(5.45)	(4.19)
Market Thickness (Investment Company)	0.020***	0.019**	0.020*
	(3.16)	(2.28)	(1.65)
Market Thickness (Family)	-0.018	-0.013	-0.020
	(-1.20)	(-0.82)	(-0.99)
4 Factor Alpha 12m	-0.048***	-0.067***	-0.059***
	(-3.45)	(-5.72)	(-5.00)
4 Factor Alpha 24-13		0.013	0.015
		(0.98)	(1.08)
4 Factor Alpha 36-25			-0.021*
			(-1.88)
Log Fund Size	-0.205***	-0.196***	-0.211***
	(-4.77)	(-4.51)	(-4.29)
Net Flow	-0.002	-0.009	-0.022
	(-0.20)	(-0.63)	(-1.17)
Log Family Size	-0.043	-0.064	-0.046
	(-0.76)	(-1.18)	(-0.87)
Number of Subadvisors	0.269***	0.269***	0.281***
	(5.40)	(4.97)	(5.33)
Tenure	-0.063**	-0.071**	-0.074**
	(-1.97)	(-2.32)	(-2.16)
Adj. Pseudo R2	42.55%	44.20%	44.39%
Observations	7274	6480	5773
Log-Likelihood	-701.9	-605.3	-534.5

Table 4.6: Fund Performance of Outsourced Funds and Market Thickness

This table reports the results of fixed effect regressions investigating the impact of market thickness on fund performance as measured by 3- and 4-factor alphas. 3- and 4-factor loadings are estimated using 36 months of prior data. Our independent variables include our two market thickness measures. The subadvisor market thickness measure is defined in Figure 4.2 and the fund family market thickness measure is defined in Table 4.4. All other fund characteristics are lagged one year and include the natural logarithm of the family size, the natural logarithm of fund size, the annual net flow into the fund, the expense ratio, age and turnover of the fund. We also include an indicator variable of whether the fund is broker-sold, as indicated by either a front or rear load. We include Morningstar category fixed effects and standard errors are clustered at the Fund level. T-statistics are reported in parentheses.

	3-Factor Alpha	4-Factor Alpha
	(1)	(2)
Market Thickness (Subadvisor)	0.078***	0.047**
	(3.22)	(1.99)
Market Thickness (Fund Family)	-0.010	0.018
	(-0.44)	(0.86)
Log Family Size	0.061	0.026
	(1.26)	(0.51)
Log Fund Size	-0.010	-0.096
	(-0.15)	(-1.36)
Fund Net Flow	0.020	0.010
	(1.01)	(0.49)
Age	-0.002	0.017*
	(-0.27)	(1.72)
Expense Ratio	0.142	0.002
	(0.60)	(0.01)
Turnover	-0.000	-0.000
	(-0.48)	(-1.11)
Broker Sold ==1	0.027	-0.022
	(0.15)	(-0.11)
Objective FE	Yes	Yes
Adj. R2	5.70%	6.39%
Observations	9,649	9,649

Table 4.7: Return Regression

This table reports the estimates of an OLS regression of annual fund performance on a fund's outsourcing status. Performance measures include gross returns, 3-factor, and 4-factor alphas, as well as investment objective alphas. All return measures are based on gross returns except for the investment objective alpha. The factor loadings are calculated using 36 months of prior data. The investment objective alpha is measured by subtracting the value-weighted fund performance of all other funds in the Morningstar category from the fund's return. The lagged independent variables include the natural logarithm of the family size, the natural logarithm of fund size, the annual net flow into the fund, the expense ratio, age, and turnover. We also include an indicator variable of whether the fund is broker-sold, as indicated by either a front or rear load. T-statistics are reported in parentheses.

	Gross Return	3-Factor Alpha	4-Factor Alpha	Objective Alpha
	(1)	(2)	(3)	(4)
Constant	19.063***	0.103	2.128***	18.899***
	(14.12)	(0.19)	(4.09)	(12.27)
Outsourced Dummy	-0.804***	-0.252***	-0.153**	-1.013***
	(-3.62)	(-3.32)	(-2.09)	(-4.04)
Log Family Size	0.390***	0.195***	0.144***	0.519***
	(8.67)	(9.91)	(7.62)	(9.82)
Log Fund Size	-1.111***	-0.242***	-0.293***	-1.261***
	(-16.81)	(-9.39)	(-11.84)	(-16.35)
Fund Net Flow	-0.155***	-0.002	-0.005	-0.182***
	(-8.77)	(-0.32)	(-0.76)	(-8.99)
Age	0.116***	-0.004	0.008**	0.123***
	(13.73)	(-1.32)	(2.43)	(13.00)
Expense Ratio	2.324***	0.443***	0.217*	1.190***
	(9.94)	(3.42)	(1.66)	(4.37)
Turnover	-0.001***	-0.000	-0.000**	-0.002***
	(-3.27)	(-0.96)	(-2.03)	(-3.56)
Broker Sold ==1	-2.447***	-0.488***	-0.292***	-3.062***
	(-11.29)	(-4.75)	(-2.92)	(-12.18)
Adj. R2	1.40%	0.42%	0.37%	1.38%
Observations	48,489	44,801	44,801	48,627

Table 4.8: Performance Regression Treatment Effect Model

This table reports the estimates of a Heckman-based Treatment Effects Model of annual fund performance on lagged fund characteristics and an indicator variable on the outsourcing status of a fund. The selection equation models the decision of the fund family and subadvisor to enter the outsourcing relationship. The independent variables used in this selection equation are key independent variables from our outsourcing regressions in Table 4.2 and Table 4.3. The dependent variables in our outcome model include gross returns, 3-factor, and 4-factor alphas, and investment objective alphas. All return measures are based on gross returns except for the investment objective alpha. The investment objective alpha is measured by subtracting the value-weighted fund performance of all other funds in the Morningstar category from the fund's return. The lagged independent variables include the natural logarithm of the family size, the natural logarithm of fund size, the annual net flow into the fund, the expense ratio, age, and turnover. We also include an indicator variable of whether the fund is broker-sold, as indicated by either a front or rear load. T-statistics are reported in parentheses.

Panel A - Selection Equation

		Outsourced ==1			
		(1)	(2)	(3)	(4)
		Gross Return	3 Factor Alpha	4 Factor Alpha	Objective Alpha
	Constant	-1.812***	-1.993***	-1.992***	-1.824***
		(-12.34)	*(-12.60)*	*(-12.60)*	*(-12.42)*
	Expertise (Regional)	0.000***	0.000***	0.000***	0.000***
		(11.12)	*(11.83)*	*(11.78)*	*(11.33)*
	Family Objective HHI	-0.000***	-0.000***	-0.000***	-0.000***
		(-5.31)	*(-4.35)*	*(-4.36)*	*(-5.42)*
	% TNA Outsourced	0.034***	0.034***	0.034***	0.034***
		(112.64)	*(107.53)*	*(107.52)*	*(112.86)*
	Expertise (% TNA Outside Objective)	0.004***	0.004***	0.004***	0.004***
		(4.96)	*(4.19)*	*(4.19)*	*(4.73)*
	Log Discretionary Assets	-0.014***	-0.008	-0.008	-0.013***
		(-2.97)	*(-1.47)*	*(-1.47)*	*(-2.67)*
% Assets By Clientele	Retail	0.001***	0.001***	0.001***	0.001***
		(3.12)	*(3.24)*	*(3.24)*	*(2.93)*
	Mutual Fund	-0.006***	-0.006***	-0.006***	-0.006***
		(-12.19)	*(-11.25)*	*(-11.25)*	*(-12.17)*
	Financial Institution	-0.004***	-0.005***	-0.005***	-0.005***
		(-2.72)	*(-2.73)*	*(-2.73)*	*(-2.88)*
	Hedge Funds and Other Pooled	0.004***	0.003***	0.003***	0.004***
		(6.92)	*(5.54)*	*(5.55)*	*(7.02)*
	Pension	-0.001	-0.001	-0.001	-0.001
		(-1.50)	*(-0.95)*	*(-0.95)*	*(-1.46)*
	Charity	0.010***	0.010***	0.010***	0.011***
		(6.48)	*(5.77)*	*(5.77)*	*(6.79)*
	Governmental Organisations	0.013***	0.013***	0.013***	0.013***
		(10.00)	*(9.47)*	*(9.47)*	*(9.93)*

Panel B - Outcome Equation

	Gross Return	3-Factor Alpha	4-Factor Alpha	Objective Alpha
	(1)	(2)	(3)	(4)
Constant	17.50***	0.11	2.00***	17.55***
	(11.74)	*(0.18)*	*(3.37)*	*(10.34)*
Outsourced Dummy	-0.48	-0.18	-0.13	-0.44
	(-1.40)	*(-1.15)*	*(-0.86)*	*(-1.14)*
Log Family Size	0.38***	0.18***	0.13***	0.50***
	(8.11)	*(9.35)*	*(7.32)*	*(9.36)*
Log Fund Size	-1.05***	-0.23***	-0.28***	-1.19***
	(-15.08)	*(-7.92)*	*(-10.05)*	*(-15.07)*
Fund Net Flow	-0.15***	-0.00	-0.01	-0.18***
	(-9.40)	*(-0.34)*	*(-0.73)*	*(-9.67)*
Age	0.12***	-0.00	0.01**	0.12***
	(12.62)	*(-1.08)*	*(2.09)*	*(11.63)*
Expense Ratio	2.90***	0.48***	0.22**	1.69***
	(10.97)	*(4.39)*	*(2.10)*	*(5.60)*
Turnover	-0.00**	-0.00	-0.00	-0.00***
	(-2.43)	*(-0.70)*	*(-1.56)*	*(-3.34)*
Broker Sold ==1	-2.71***	-0.47***	-0.27***	-3.26***
	(-11.71)	*(-4.96)*	*(-2.98)*	*(-12.38)*
Observations	44,211	40,916	40,916	44,294
Log-Likelihood	-206431	-152017	-150187	-212622

Table 4.9: Fund Size Regression

This table reports estimates from regressions of the natural logarithm of fund size on lagged fund characteristics and an indicator variable of whether a fund is outsourced. The lagged independent variables include the natural logarithm of family size, the natural logarithm of fund size, the annual net flow into the fund, the expense ratio, age, and turnover of the fund. We also include an indicator variable of whether the fund is broker-sold, as indicated by either a front or rear load and the annual lagged annual investment objective alpha. Column 1 reports the coefficient estimates of an OLS regression. Column 2 reports the estimates of a Heckman-based Treatment Effects Model. Both the selection and outcome models are estimated simultaneously via maximum likelihood. The selection equation models the decision of the fund family and subadvisor to enter the outsourcing relationship. The first stage regression is modelled the same way as in Table 4.8 and is not reported here. The first stage regression can be made available upon request. T-statistics are reported in parentheses.

	LN Fund Size	
	(1)	(2)
	OLS	Treatment
Constant	0.605***	0.625***
	(7.85)	(16.88)
Outsourced Dummy	-0.019**	-0.012
	(-1.98)	(-1.47)
Log Family Size	0.023***	0.022***
	(10.90)	(19.37)
Log Fund Size	0.946***	0.945***
	(200.28)	(545.92)
Category Return Alpha	0.001***	0.001***
	(4.09)	(6.56)
Fund Net Flow	0.011***	0.011***
	(9.52)	(27.98)
Age	0.000	0.000
	(0.14)	(1.03)
Expense Ratio	-0.023*	-0.022***
	(-1.84)	(-3.31)
Turnover	0.000***	0.000***
	(-5.12)	(-8.30)
Broker Sold ==1	-0.036***	-0.033***
	(-3.80)	(-5.81)
Adj. R2	91.90%	
Log-Likelihood		-43,550
Observations	48,653	44,317

Chapter 5

Conclusion

This dissertation examines three topics in mutual funds. First, it analyses the impact of workplace connections on firing and promotion decisions, portfolio manager risk-taking, investment distinctiveness, and mutual fund performance. Second, this dissertation studies the effect of employee satisfaction on on-the-job performance through its effect on mutual fund performance and size. Lastly, it explains the puzzle of continued outsourcing in the mutual fund industry despite the ample evidence of underperformance of sub-advised funds documented in prior studies.

The first essay contributes to the literature on mutual fund turnover, networks in mutual funds, and personal connections and performance appraisals and productivity. I add to previous studies on mutual fund manager turnover by documenting that workplace connections impact firing and promotion decisions and investment distinctiveness, risk-taking, and ultimately fund performance. Furthermore, the first essay adds to the literature on mutual fund networks by complementing the existing analysis of network effects in the mutual fund industry with an analysis of within-firm connections and highlighting some negative effects of connectedness. Moreover, there is a relatively large literature on (personal) connections and performance appraisals in the fields of economics and psychology. I am the first to provide a large-scale study on the effects of connections in a high-skill human capital-intensive industry on firing and promotion decisions and employee behaviour.

The second essay contributes to four strands of literature. First, it adds to the finance literature on employee satisfaction (e.g., Chemmanur et al., 2019; Edmans, 2011; Green et al., 2019; Huang et al., 2015; Symitsi et al., 2018). Previous papers have largely refrained from causal inference and merely reported correlations. Thus, our paper adds to this literature by providing some causal evidence on the effect of employee satisfaction on performance. The paper closest to ours that tries to establish a causal link between employee satisfaction and performance is Huang et al. (2015). Their paper, in contrast to ours, investigates the effect of employee satisfaction on aggregate firm performance. We investigate the effect of employee satisfaction on performance much closer to the employee level and show that it is not firm-level employee satisfaction that matters but rather the satisfaction of employees that directly impacts the outcome measure. Second, it provides further non fee based evidence on the importance of marketing and sales efforts on a mutual fund's ability to gather assets. Previous studies mainly employed 12b-1 fees or aggregate marketing expenditure at the fund family level to proxy for marketing and sales efforts. Third, it contributes to the literature on employee satisfaction and performance in the economics and psychology literature. Previous studies in these fields have found it difficult to establish causal evidence. One recent paper by Bellet et al. (2022) claims causality but employs data from only one company. Thus, we add to this literature by providing causal evidence on a much wider sample of 3,266 mutual funds managed by 437 companies. Fourth, we add to the literature on employee satisfaction and risk-taking. The existing literature to date documents conflicting evidence on the effect of employee satisfaction on risk-taking. Some studies report a positive and some a negative effect. Thus, we add to this literature by providing further evidence on the directionality and causality of the effect of employee satisfaction on risk-taking.

The third chapter contributes to the literature on mutual fund sub-advising, the literature on market thickness, and outsourcing more generally. To date, the literature on mutual fund sub-advising has focused on documenting the underperformance of sub-advised mutual funds. This literature has largely attributed this underperformance to agency problems. More recent studies have focused on finding mechanisms that help in alleviating some of these agency problems through incentive alignments. We take a different but complementary take to these latter studies by showing that the lack of investment and distribution expertise drives the fund family and the investment advisor respectively to engage in outsourcing. We further find that market thickness is also a driver of the initial decision to outsource and affects the power of each party in the resulting outsourcing relationship. Furthermore, we document that an increase in market thickness can improve the performance of outsourced mutual funds. Once we account for the initial decision to outsource, the underperformance puzzle documented in the prior literature disappears. Sub-advised mutual funds are neither smaller nor perform worse than if they had been managed in-house. This essay also contributes to the literature on market thickness. The literature on market thickness to date is mainly theoretical with few empirical studies. Existing empirical studies on market thickness and outsourcing have been conducted on firm or sector-level data with limited generalizability. Through our analysis of the effect of market thickness on outsourcing in the mutual fund industry, we contribute to the existing literature by employing product-level data on a large industry spanning 17 years.

Finally, I list some avenues for further research. The first chapter could be extended with an analysis of manager replacements. It would be interesting to see whether worse-connected managers replace well-connected managers. Given my finding that well-connected managers are less likely to be fired for bad performance and more likely to be promoted despite of it, I think this happens infrequently. The next step would be to run an event study on the replacement of well-connected managers with worse-connected managers on fund performance, manager effort, and risk-taking. In line with prior findings, I expect improvements to fund performance and effort-taking when a worse-connected manager replaces a well-connected manager and vice versa. Furthermore, the analysis could be strengthened by looking at changes in mutual fund manager connectedness resulting from events outside the portfolio manager's control, such as a connected manager leaving the firm. The second chapter could benefit from an investigation into whether the effects of employee satisfaction differ between solo and team-managed funds. It may be easier to solo-manage a fund at a firm with very low satisfaction scores. The final chapter could be extended by investigating whether mutual fund families learn from their subadvisors. Fund families may outsource the first couple of funds in an area where they lack internal investment expertise and manage later funds in-house after some of the subadvisor's investment expertise has been internalised.

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