Three Essays on Hedge Funds

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Summary

This dissertation consists of three stand-alone research papers on hedge funds. The research papers are organized into three chapters. The first chapter focuses on the role of social ties among hedge fund managers in the managers' investment decisions. The second chapter utilizes biographical information on hedge fund managers to disentangle abnormal performance tied to the hedge fund and the individual hedge fund manager. The third chapter studies the realized performance of different types of hedge fund investors. The chapters' main research questions, applied methodologies, and key results are summarized below.

Birds of a Feather: Do Hedge Fund Managers Flock Together?

The first chapter presents a research paper co-authored with my doctoral advisor Jens Jackwerth from the University of Konstanz and Alberto Plazzi from the Università della Svizzera Italiana.

In this paper, we contribute to the understanding of hedge funds' investment behavior by looking at social connections that arise among managers sharing a common prior employment history. We contend that social ties that were developed at the prior industry or company employment are natural candidates for explaining differences in hedge fund returns.

Our study relies on data from mandatory filings that are compiled by management companies domiciled in the UK that run hedge funds. In combination with commercial hedge fund databases, this data avails us of a complete historical record of performance, fund charac-

teristics, and work trajectories of the UK hedge fund industry, which is the basis for our analysis.

The combined data set allows us to construct the following three measures of social connectedness among UK hedge fund management companies. A first variable, *Industry*, links two companies whose managers worked in the same industry at some point in time. For a second variable, *Firm*, a tighter link is established for managers who worked for the same past employer, but at potentially non-overlapping times. Finally, a third variable, *Overlap*, identifies network connections from managers overlapping for a significant time frame (in our setup, at least 24 months) while working for the same employer.

We utilize this information to ask whether social ties and work experience can explain similarities in hedge fund returns. We test for the impact of employment history separately along the three dimensions of hedge fund performance, namely abnormal performance (alpha), systemic risk factors (beta), and idiosyncratic shocks (residuals). To that end, we resort to the widely used Fung and Hsieh (2004) 7-factor model, which we estimate at the fund level. For each pair of funds, we then compute the average absolute distance in their factor exposures ($\Delta\beta$), the time-series average in the absolute difference in residuals ($\Delta\epsilon$), and the absolute difference in abnormal returns ($\Delta\alpha$). These three distances serve as dependent variables for our analysis.

We document that social connections, in particular prior *Industry* and *Firm* experience explain a significant fraction of cross-sectional differences across the three dimensions of returns. The corresponding coefficients are not only statistically but also economically large, as they imply that the distance in alpha for any fund pair is 0.25% per month closer for connected funds, or about 3% per year. For the distance in exposure to risk factors, connected funds have each factor exposure reduced by 0.27 on average. The idiosyncratic component, $\Delta\epsilon$, is even reduced by 0.62% on average, or more than 7% per year. The effect of overlapping times spent at a joint former employer (*Overlap*) does not affect $\Delta\alpha$ and $\Delta\beta$ but significantly impacts $\Delta\epsilon$. The idiosyncratic risk taking seems to depend more on social networks and personal interaction rather than industry and firm effects.

These results are robust to the inclusion of standard controls such as the distances in funds' size, age, compensation structures, and a style dummy. We show that our results are stronger for smaller funds and funds operating in styles where information sharing is likely to play a crucial role. To show that our results are not driven by manager characteristics we control for gender and age, as well as for physical proximity between the managers.

We control for manager skill by first resorting to a measure capturing the strength of the labor market in the year the manager entered the fund, *Hiring Climate*. We compute a manager's *Hiring Climate* as the number of people being newly employed minus people leaving the financial industry during the month when the manager was hired at the hedge fund. It proxies for average manager skill within a company. We use *Hiring Climate* either as an additional control or an instrumental variable. Alternatively, for ex-hedge fund managers, we compute their past alpha. Notwithstanding the inclusion of these variables, the economic and statistical significance of social ties from prior employment remains intact.

Finally, we gauge the economic significance of hedge funds' employment background for the performance of individual funds, rather than pairs. Namely, we ask whether sorting funds on managers' prior industry training is associated with significant dispersion in abnormal performance. We find that industry experience of a manager significantly influences future alpha with managers from pension funds and banks outperforming and managers from investment management underperforming. We also explore the economic gains from loading on connected funds through a bootstrap exercise. We document that the decile of most connected funds outperforms the decile of least connected funds by a significantly positive abnormal return of about 60 basis points per month. Overall, the results lend further support to the claim that managers' connections have ultimately beneficial effects on performance, consistent with Pool, Stoffman, and Yonker (2015).

Manager Alpha

The second chapter contains a single-authored research paper studying the difference between performance measures associated with the hedge fund and the individual hedge fund manager.

Acknowledging that many hedge funds are managed by multiple managers over the course of their lifetime, or single managers manage multiple funds at the same time, this paper takes a complimentary stance on this issue and focuses on the human capital represented by the hedge fund manager. First, I ask whether alpha is a property of the hedge fund or the hedge fund *manager*. Acknowledging, that alpha is a property of both, the hedge fund, and the hedge fund manager, I investigate the effect of a turnover in management on the hedge fund's performance and fund flows. Finally, I study the drivers behind the probability of a turnover event.

Using a novel data set, which allows me to observe key employees of hedge funds domiciled in the UK, I am able to identify the exact periods at which a hedge fund is managed by a specific manager. This allows for the identification of managerial fixed effects. By showing that these fixed effects are highly significant in performance regressions, I provide first evidence for the importance of the individual hedge fund manager for producing alpha.

Next, I show that at the change of management there is a structural break in the intercept of the Fung and Hsieh (2004) seven factor model. I construct a panel model relating a fund's excess returns to a fund fixed effect and the seven factors proposed by Fung and Hsieh (2004). The factor exposure is allowed to vary across the funds and I account for a potential trend in the average abnormal returns using time fixed effects and control for a linear trend in average returns over a fund's lifetime, as well as potentially diminishing returns to scale. Dummy variables capture the effects of different periods on alpha. One dummy represents the period during which we can identify the manager and a second dummy represents the period after the manager has left. If the coefficients on these dummies are not equal to zero, there is evidence in favor of a structural break in alpha. According to an F-test, these dummy variables are significantly different from zero. Estimating a cross-sectional average effect for

the two sets of dummy variables, I document a negative effect between -2.71% and -3.04% on annualized alpha whenever a manager leaves a fund. Conditioning on relative past performance reveals that this negative effect is driven by outperforming managers leaving. The departure of an outperforming manager (as defined by performing above the cross-sectional median of average returns before replacement) decreases annual alpha by -4.57%. Next, I study the implications of a change of management on fund flows. Consistent with existing evidence for mutual funds, I document an inverse relationship between past performance and future fund flows around a replacement event. I find that if an underperforming manager leaves, subsequent fund flows increase by 3.8%. If an outperforming manager is replaced, fund flows decrease by -1.9% on a monthly basis.

Finally, I focus on the determinants of a replacement event. Using a Probit model, I estimate probabilities of replacement conditional on the fund's age, assets under management, past performance, and past fund flows. I find that the probability of replacement increases with the age of the fund and is a decreasing, concave function of the fund's past absolute performance.

Hedge Fund Investors

The third chapter presents a single-authored research paper on the realized performance and investment objectives of different classes of hedge fund investors, as well as potential influences the investors exert on the fund managers' strategies.

There is an enormous body of literature focusing on the question whether hedge funds are worth their fees and are able to deliver abnormal performance. However, few studies take the presence of different groups of investors into account. This paper demonstrates that the universe of potential hedge fund investors is heterogeneous. Existing evidence on investment returns in the hedge fund industry do not necessarily translate to every group of investors. Hedge fund investments by different classes of investors differ in their realized performance. Besides, I present evidence compatible with hedge fund investors exerting influence on the

hedge fund managers to align the managers' strategies with the investors' objectives.

Using a sample of Form ADV filings and data on hedge fund performance and characteristics, I estimate the performance which different classes of investors realize. I differentiate between the following classes of investors: Individuals (other than high net worth individuals); High net worth individuals; Banking and thrift institutions; Investment companies; Business development companies; Pension and profit sharing plans (but not the plan participants); Charitable organizations; Corporations or other businesses not listed above; State or municipal government entities; Other investment advisers; Insurance companies.

In the first part of this study, I employ cross-sectional and panel regressions in order to estimate the raw, abnormal, and risk-adjusted performance the groups of investors realize. I find that Corporations or other businesses tend to earn larger raw returns than other investment companies. However, this outperformance can be attributed to systematic risk factors and fund-level characteristics. The hedge fund investments by Banking or thrift institutions perform poorly in terms of raw returns, as well as in terms of abnormal returns. This result is robust to the inclusion of fund-level control variables. An increase in the holding of Banking or thrift institutions by 10% decreases annual abnormal returns by -0.83%. To account for differences in the attitudes towards risk among the investors, I study risk-adjusted performance measures. Hedge fund investments by Banking or thrift institutions underperform on a risk-adjusted basis. An increase by 10% in the holding of Banking or thrift institutions decreases the annualized Sharpe Ratio by -0.12. State or municipal government entities realize a larger risk-adjusted performance, corresponding to an increase by 0.19 in the annual Sharpe Ratio for an increase by 10% in the holding of State or municipal government entities.

In the second part of this study, I estimate the revealed investment objectives of the classes of investors. By regressing the relative size of the investors' allocations to different funds on fund characteristics, I document heterogeneity in the preferences across the groups of investors. Charities and High net worth individuals prefer smaller funds and are more sensitive to the size of the management fee. Corporations or other businesses are more willing to pay higher fees and tend to invest into larger funds. Insurance companies back younger funds,

while High net worth individuals prefer older, more established funds. State or municipal government entities prefer funds which are less risky. Charities are more likely to invest into funds which have a high-water mark in place.

In the third part of this study, I investigate whether investors not only differ in the funds they choose but also shape the funds' investment strategies. Using a methodology similar to a classical difference in differences estimation, I study the implications of changes in the holdings by the classes of investors on performance measures and the standard deviation of monthly returns, as a proxy for the risk-taking behavior of the fund manager. An increase by 10% in the investment by Individuals, Pension and profit sharing plans, Other investment advisers, or Insurance companies decreases the monthly standard deviation of the funds' returns over the subsequent periods by between -0.16 and -0.20. An increase in the holding of Banking or thrift institutions leads to an increase in the exposure to systematic factors and a decrease in abnormal performance.

Chapter 1

Birds of a Feather: Do Hedge Fund Managers Flock Together?

1.1 Introduction

Much work has been done to study the performance of hedge funds with their intriguing and secretive investment strategies. Traditionally, this has been achieved by looking at factor models in the style of Fung and Hsieh (2004), which are aimed at identifying performance that is left unexplained by exposure to systematic risk factors.[1] The nuanced message from this voluminous literature is that managerial leeway at hedge funds leaves a large portion of their returns unexplained by standard systematic factors and that the average fund generates significant abnormal (net-of-fee) returns.[2] However, while this alpha tends to be associated with managerial skill, its analysis has often been reduced to variation due to hedge fund-specific variables such as fees and investment styles, as in Joenväärä, Kosowski, and Tolonen (2012), or geography, as in Teo (2009).

In this paper, we contribute to the understanding of hedge funds' investment behavior by looking at social connections that arise among managers sharing a common prior employment history. The current literature largely ignores personal connections between managers and instead treats each hedge fund as being independently structured into systematic components (betas), abnormal return of the manager (alpha), and an idiosyncratic component (residuals). We contend that social ties developed at the prior industry or company employment are natural candidates for explaining differences in hedge fund returns. Managers may arguably learn valuable portable skills and strategies at their former workplace. Moreover, managers with the same background are likely to share a similar mix of exposures to risk factors, which are the result of developing common attitudes towards risk-taking or adopting similar trading strategies. Shared employment careers may also increase social interactions and the exchange of information through social networks. The impact of social ties may not be captured by simple replicating portfolios but rather may show up in the idiosyncratic portion of returns or may generate abnormal performance as managers trade on the same (valuable)

[1] Many details surround this literature, such as database biases, econometric issues, and omitted factors, see Joenväärä, Kosowski, and Tolonen (2012) for a current survey.

[2] For example, Patton and Ramadorai (2013) report an average adjusted R^2 of only 32% when adding intra-month dynamic trading strategies to standard factors (their Table VI).

signal.

The idea that managers' connections in the form of prior employment matter in the hedge fund industry is neatly illustrated by the case of the Commodity Trading Advisor (CTA) UK segment. In 1987, Messrs. Adam, Harding, and Lueck came together to set up their new commodity trading advisor fund, AHL. Before long, the fund was taken over by Man Group and, by 2015, Man AHL has some $13 billion in assets. After the takeover in 1994, the original founders created two new CTAs: Harding set up Winton Capital Ltd ($25 billion, 340 employees); Lueck and Adam set up Aspect Capital Ltd ($4.7 billion, 110 employees). Over the years, several more companies were spun off, such as the CTA Solaise Capital Management with key personal from Winton and Aspect, Kennox Assset Management (which runs long-only equity portfolios) set up by Adam yet again, and Altegris (which also offers mutual funds) with key personal from AHL. The case suggests that industry experience matters for setting up new firms in the same or potentially different investment styles. Also, the knowledge gained at one firm during past employment seems to travel with the managers as they set up new firms. And finally, time spent together at a past employment can create lasting social connections, which can lead to shared ownership at new firms.

Working on the universe of UK hedge funds, we find strong evidence that exposures to systematic risk factors (betas), abnormal performance (alphas), and idiosyncratic shocks (residuals) are more similar for hedge fund managers who are connected to each other through past employment at the same firm or past employment in the same industry. Results are unaffected by including a large number of controls such as fund characteristics and manager-specific details. We are thus first to establish the relevance of such social conducts for the investment decisions of hedge fund managers.

Our study relies on data from mandatory filings that are compiled by management companies domiciled in the UK that run hedge funds. The Financial Conduct Authority (FCA) requires these companies to disclose detailed information on the past employment histories of their key managers. This information includes relevant items such as the name of the former employer, the period of employment, and the role of the employee. The name of the manager and of the

hedge fund company is also disclosed, which allows us to match this source with commercial hedge fund databases. The resultant database is much larger and more encompassing than the hand-collected data sets used in the literature, see e.g. Engel, Kerllar, Millio, and Simon (2011). It avails us of a complete historical record of performance, fund characteristics, and work trajectories of the UK hedge fund industry, which is the basis for our analysis.[3]

The combined data set allows us to construct the following three measures of social connectedness among UK hedge fund management companies. A first variable, *Industry*, links two companies whose managers worked in the same industry at some point in time.[4] Sharing an industry experience may equip managers with a common set of knowledge that subsequently influences their portfolio choice. For a second variable, *Firm*, a tighter link is established for managers who worked for the same past employer, but at potentially non-overlapping times. Managers who worked for the same company may undertake similar investment decisions that reflect portable strategies they acquired at their former workplace. Finally, a third variable, *Overlap*, identifies network connections from managers overlapping for a significant time frame (in our setup, at least 24 months) while working for the same employer. This overlap is likely to generate an exchange of information among the people who are part of the same network, which may potentially inform their future investment choices.[5]

Examining the work trajectories of UK hedge fund managers through our definitions of social ties reveals a highly interconnected world. In fact, the great majority of funds in our dataset share connections of some sort. We utilize this information to ask whether social ties and work experience can explain similarities in hedge fund returns. Given the high degree of complexity in hedge funds trading, we test for the impact of employment history separately along the three dimensions of hedge fund performance, namely abnormal performance (alpha), systemic risk factors (beta), and idiosyncratic shocks (residuals). To that end, we resort to the widely used Fung and Hsieh (2004) 7-factor model, which we

[3]The FCA record starts in 2001 based on a legal requirement for filing as of that year. Some companies voluntarily filed even earlier employment records.

[4]The FCA record only requires firms in the financial industry to file. As a result, the 'industries' are fields within the financial sector such as banking.

[5]Note that the variables are nested in that overlapping managers always worked for the same *Firm*. Managers at the same *Firm* always share the same *Industry*.

estimate at the fund level. For each pair of funds, we then compute the average absolute distance in their factor exposures ($\Delta\beta$), the time-series average in the absolute difference in residuals ($\Delta\epsilon$), and the absolute difference in abnormal returns ($\Delta\alpha$). These three distances serve as dependent variables for our analysis.[6]

We document that social connections, in particular prior *Industry* and *Firm* experience, explain a significant fraction of cross-sectional differences across the three dimensions of returns. The corresponding coefficients are not only statistically but also economically large, as they imply that the distance in alpha for any fund pair is 0.25% per month closer for connected funds, or about 3% per year. For the distance in exposure to risk factors, connected funds have each factor exposure reduced by 0.27 on average. The idiosyncratic component, $\Delta\epsilon$, is even reduced by 0.62% on average, or more than 7% per year. The effect of overlapping times spent at a joint former employer (*Overlap*) does not affect $\Delta\alpha$ and $\Delta\beta$ but significantly impacts $\Delta\epsilon$. The idiosyncratic risk taking seems to depend more on social networks and personal interaction rather than industry and firm effects.

These results are robust to the inclusion of standard controls such as the distances in funds' size, age, and compensation structures, which may indirectly capture the effect of common work trajectories. We also include a style dummy, which guarantees that our findings do not merely originate from correlation between investment styles and employment opportunities or from funds relying on the same style-specific trading.

In various ways, we try to rule out the possibility that our findings simply reflect fund characteristics. First, we estimate our regression model across pairs of funds with similar strategies or size and ask whether the effects line up with expected differences in social ties. We find that an overlap in prior employment is more relevant when focusing on investment strategies for which information sharing is likely to play a crucial role, such as Event-Driven, Convertible Arbitrage, and Merger Arbitrage. Also, social ties tend to be more important for pairs of small funds, defined as funds with below median number of employees, for which key executives influence the fund strategy more. Taken together, these cross-sectional patterns

[6]Compare Fracassi (2015) for a related two-stage estimation of network effects on returns in a corporate finance setting.

lend further support to the claim that our measures capture network-related dynamics, rather than individual characteristics.

Employment history is potentially correlated with unobserved manager characteristics, such as gender, age, education, or skill.[7] We control for gender and age to proxy for personal attributes such as risk-aversion and career concerns.[8] We also check that network effects are based on employment histories and not simply driven by physical proximity, which also would facilitate exchange of information with other managers. Hong, Kubik, and Stein (2005) show that managers in the same city display correlated trades. Our measure of physical proximity is a dummy, which indicates if management companies are headquartered in the same postcode. While physical proximity enters with a significant coefficient, it does not absorb the effect of our measures of social ties, which suggests that they capture different information channels. Manager characteristics turn out to have a very limited role in explaining distances in the components of returns, after controlling for fund characteristics. Controlling for manager skill is more difficult. To do so, we first resort to a measure capturing the strength of the hedge fund labor market in the year the manager entered the fund, *Hiring Climate*. *Hiring Climate* is motivated by the evidence in Deuskar, Pollet, Wang, and Zheng (2011) that managers moving from the mutual fund industry to the hedge fund industry tend to do so when the latter is in a boom period. Importantly, these fund managers had poor performance track records in the mutual fund and continue to underperform in the hedge fund. This fact is consistent with hedge funds lowering their hiring standards during periods of rapid hedge fund growth, when the short term supply of managers is inelastic. We compute a manager's *Hiring Climate* as the number of people being newly employed minus people leaving the financial industry during the month when the manager was hired at the hedge fund. A management company's *Hiring Climate* is the average over all its managers. It proxies for average manager skill within a company. We use *Hiring Climate* either as an additional control or an instrumental variable. Alternatively, for ex-hedge fund managers,

[7] Grinblatt, Keloharju, and Linnainmaa (2012) find that investors with higher skill (measured by IQ) outperform their peers.

[8] Unfortunately, data on schooling or other personal details are not available in our data.

we compute their past alpha. The assumption here is that personal skills would induce persistence in performance across funds run by the same manager in different companies. Notwithstanding the inclusion of these variables, the economic and statistical significance of social ties from prior employment remains intact. We take this evidence as supportive of a direct effect of social ties on managers' decisions that goes beyond personal characteristics and innate skills.

Finally, we gauge the economic significance of hedge funds' employment background for the performance of individual funds, rather than pairs. Namely, we ask whether sorting funds on managers' prior industry training is associated with significant dispersion in abnormal performance. We find that industry experience of a manager significantly influences future alpha with managers from pension funds and banks outperforming and managers from investment management underperforming. We also explore the economic gains from loading on connected funds through a bootstrap exercise. There, we randomly group funds into portfolios and then sort these portfolios based on the degree of industry connectedness. We document that the decile of most connected funds outperforms the decile of least connected funds by a significantly positive abnormal return of about 60 basis points per month. Overall, the results lend further support to the claim that managers' connections have ultimately beneficial effects on performance, consistent with Pool, Stoffman, and Yonker (2015).

The remainder of the paper proceeds as follows. Section 1.2 relates our paper to the existing literature on social interactions in financial markets. Section 1.3 describes the data set and the construction of our measures of connectedness. Here, we also detail the dependent variables and their construction via auxiliary factor model regressions. Section 1.4 outlines our estimation strategy and presents the empirical results linking hedge fund performance to social connections via employment histories. Further results addressing managerial characteristics and endogeneity concerns follow in Section 1.5. Section 1.6 investigates the economic significance of our results. We report robustness results in Section 1.7 and conclude in Section 1.8.

1.2 Related literature

The paper contributes to the surging literature on the impact of social connections on investment and managerial decisions. A number of studies focus on retail investors and money managers. For households, Hong, Kubik, and Stein (2004) find that more socially interactive investors tend to participate more in the stock market, and the impact of sociability is higher in states with higher levels of participation. For mutual fund managers, the work of Hong, Kubik, and Stein (2005) and Pool, Stoffman, and Yonker (2015) are the closest to the spirit of our paper. Hong, Kubik, and Stein (2005) show that holdings and trades of mutual fund managers who work in the same city are closer to their peers. They interpret this evidence as a direct consequence of interpersonal word of mouth exchange of ideas among the agents. Pool, Stoffman, and Yonker (2015) find significant overlap in the holdings of managers who live in the same neighborhood and convincingly demonstrate that these effects arise from social interactions rather than similarities in preferences. They further show that the transmission of information through the network of neighboring managers generates abnormal performance. Here they investigate mutual fund managers who invest into the same company. Mutual fund managers who are are connected to the company CEO through educational background outperform unconnected managers (Cohen, Frazzini, and Malloy (2008)) and are more likely to vote against shareholder-initiated proposals to limit executive compensation (Butler and Gurun (2012)). We expand the evidence in these studies by documenting that social ties in the form of prior employment trajectories are first-order determinants for another class of institutional investors, namely hedge funds.

For hedge funds, the role of geographical distance on performance is explored by Teo (2009). He shows that funds whose physical presence is closest to the investment region outperform their peers, which he attributes to local information advantages. Information on hedge fund managers' prior employment is examined in Deuskar, Pollet, Wang, and Zheng (2011) for a subset of managers who switch from the mutual fund industry. These managers are found to exhibit persistent underperformance, and their hiring is concentrated in periods of expansion of the hedge fund industry. Also related is Papageorgiou, Parwada, and Tan

(2011), who look at the effect of past work experience on performance. We add to this literature by documenting that social ties among hedge fund managers induce similarity in their returns. We are also the first to measure the economic significance of these ties by showing that portfolios of funds that load on connected hedge managers on average deliver higher performance than unconnected funds.

A large body of the literature documents the pervasive importance of director and CEO networks. Hwang and Kim (2009) show that board independence is substantially weaker when considering social ties among the board members that facilitate personal connections. Cohen, Frazzini, and Malloy (2010) document that analysts who possess educational links to company senior managers outperform their peers in terms of precision of stock recommendations. Corporate policy and investment are found to be more similar for firms where the key employees share social ties, Fracassi (2015). Having a large network increases CEO compensation, as evidenced by Engelberg, Gao, and Parsons (2013). Educational and prior employment linkages between company and bank managers reduce the interest rate charged by syndicates (Engelberg, Gao, and Parsons (2012)), while those between directors and senior executives at acquiring and target firms instead tend to lower overall value creation (Ishii and Xuan (2014)). Our evidence suggests that social connections between hedge fund managers and corporate executives may also be an interesting venue of analysis.

Finally, our paper naturally adds to the discussion on the determinants of hedge fund returns. We demonstrate that an economically important fraction of the cross-sectional distribution of abnormal performance and idiosyncratic risk can be traced to social connections, which appear not to be captured by exposures to commonly used systematic risk factors.

1.3 Data and Variables Construction

Our analysis requires the intersection of three different data sources: hedge fund databases, managers' employment histories, and industry classification of prior employers. First, we gather information on hedge fund performance and attributes. Existing studies on hedge

funds mainly focus on few databases, the most commonly used being Lipper TASS, HFR, and Morningstar. Recently, Joenväärä, Kosowski, and Tolonen (2012) provide compelling evidence that individual hedge fund databases are not representative of the industry as a whole. They show that differences among databases may induce survivorship biases and alter the inference on the determinants of hedge fund performance, which is the focus of our study. For these reasons, we rely on a comprehensive dataset that is obtained by combining six major hedge fund databases, namely Morningstar, Eurekahedge, BarclayHedge, HFR, TASS, and CISDM. The merging procedure and filters follow Hodder, Jackwerth, and Kolokolova (2014) and are similar to Joenväärä, Kosowski, and Tolonen (2012).[9] We restrict to funds which report in USD.[10] The data consists of monthly information on 21,547 hedge funds (organized in 9,147 management companies) from January 1977 to December 2012, of which 16,374 are dead funds and 5,173 are live funds. Keeping the dead funds addresses potential survivorship bias. The backfill bias is due to the possibility to list older (and typically higher) returns in the database at the time of joining the database. If performance is correlated with prior work experience, as we demonstrate later, this practice would induce a selection bias and lead us to over-estimate the effect of social ties. We follow prior studies (see e.g. Kosowski, Naik, and Teo (2007) and Teo (2009)) and remove the initial 12 months of each fund's return data history.

Next, we retrieve information about the employment histories of hedge fund employees from the Financial Services Register (FSR) which is compiled by the Financial Conduct Authority (FCA). The FCA regulates insurance, investment, and banking companies that are domiciled in the UK ('onshore'). Importantly, the FSR includes the normally secretive management companies that control hedge funds. The Financial Services and Markets Act 2000, which came into force on December 1, 2001, requires all those companies to report detailed in-

[9]Specifically, we merge the databases on the names of the hedge funds' managing companies. We remove duplicates and different share classes of the same fund within each company by grouping the funds if their return correlations are above 0.99. Within each group, we keep the fund with the longest time series of returns.

[10]The great majority of managing companies have multiple share classes for the same strategy which are denominated in various currencies. We opt for the class denominated in USD as this is by far the most common.

formation on current and past employment of their key employees. The FCA makes the resultant database publicly available with full disclosure of the employee name.[11]

Using the FSR has clear advantages with respect to other available sources. The fact that the FCA requires reporting rather than voluntary disclosure increases the completeness and accuracy of the FSR information, which is comparable to existing databases on US executives such as the widely used Boardex.[12] The resulting sample should be devoid of any selection bias and is survivorship-bias free as the FSR also keeps track of dead companies. As the record is only available for UK companies and is only reliable as of 2002, we limit ourselves to the years 2002 to 2012 and to UK-domiciled management companies. Note that the records exist only at the level of the management company and not the individual hedge fund.

Our analysis utilizes the following information: the hedge fund management company name; the employee's name and a numeric ID; the full employment history with names of former employers (FCA-registered only) with entry and exit dates; an identifier (the Controlled Function (CF) Code that specifies the employee's role in the management company. The CF Code is of special importance to us as it identifies the various regulated functions within the management companies. The Financial Services and Markets Act lists a total of sixteen such functions for UK firms that are ranked based on their significant influence on the activity.[13] We later use this code to identify key hedge fund employees who form our network.

We match the FSR and the combined hedge fund dataset based on the management company name. For further consideration, we require a fund to report returns for at least 24 months.

[11] The FCA was formerly known as Financial Services Authority (FSA). The FSA was created in 1997 with responsibility for banking supervision, listing authority, and investment services regulation. With the Financial Services and Markets Act 2000, it started to exercise statutory powers to regulate the financial services industry. In the wake of the financial crisis of 2007–2008, the Financial Services Act of 2012 set out a new system for regulating financial services in order to protect and improve the UKs economy, and the FSA was abolished with effect from April 1, 2013. Its responsibilities were then split between two new agencies (the Prudential Regulation Authority and the Financial Conduct Authority) and the Bank of England. The FCA continues to maintain the FSR originally developed by the FSA. For the purpose of measuring the effect of social ties in the hedge fund industry, it is reasonable to consider the introduction of the act as an exogenous regulatory change.

[12] Reporting to FSA is not merely a formality as companies that fail to report for approval of a key employee may be subject to FSA investigations and ultimately to fines.

[13] See the full list at http://www.fsa.gov.uk/doing/regulated/approved/persons/functions. A detailed description of each CF code function can be found in the CFA handbook, http://fshandbook.info/FS/html/handbook.

The resulting sample comprises 685 UK-domiciled companies managing 2,930 distinct hedge funds (788 live and 2,142 dead) from January 2002 to December 2012. Consistent with the findings in Joenväärä, Kosowski, and Tolonen (2012), we find that only 45 funds are jointly reporting to all databases and that nearly half of them (1,545) report to only one database. In addition to net-of-fee returns, the hedge fund data includes a wealth of fund-level characteristics, such as management fee, performance fee, and investment style. It also contains a leverage indicator and the amount of assets under management, albeit for a much smaller set of funds. We complement this information with the number of employees. This number serves as an alternative measure of company size, as it is available in the FSR for the large majority of companies.

Finally, we classify FSR former employers into 11 industries within the financial services sector. We contend that managers acquire distinct skills in these different sectors: Banking, Brokerage firms, Consultancy firms, Hedge Funds, Insurance companies, Investment Banks, Investment Management, Mutual Funds, Pension Funds, Private Equity, and the residual group Other. The classification is obtained by matching the company name with the Registrar of Companies that is maintained by the UK Companies House database and by manual verification.[14]

1.3.1 Connection Measures

Our main goal is to capture the effect of past work experience on the investment decisions of hedge fund managers. We define three measures of social ties that capture different facets of hedge fund managers' work trajectories:

i) *Industry*: The variable equals one if two employees have been working for a company operating in the same industry at some, potentially different, point in time for a minimum of 12 months for each manager.

[14]Data on live companies are readily obtainable from http://www.companieshouse.gov.uk/. Hedge funds we can identify easily through our own merged database. Mutual funds we identify in the Morningstar database. Finally, we classify the remaining firms by manual web-based investigation. Investment management firms are investment advisers, which cannot be clearly subsumed under private equity, mutual fund, or hedge fund.

ii) *Firm*: The variable equals one if two employees have been working for the same company at some, potentially different, point in time for a minimum of 12 months for each manager.

iii) *Overlap*: The variable equals one if two employees have been working for the same company during the same period of at least 24 months.

We face two challenges in constructing these variables since our data document employment at the management company and not the individual hedge fund level. First, we focus on the senior managers of the management company, who determine the general strategy at all hedge funds owned: Director (CF code 1), Chief Executive (CF code 3), or Partner (CF code 4). Our choice is supported by our hedge fund data from which we know the names for a subset of 139 managers. These are mostly classified as either CF code 1 (40% of times), CF code 3 (16% of times), or CF code 4 (23% of times). Henceforth, we refer to any such employee as a (hedge fund) 'manager.'

Second, we construct all our variables at the management company level. Such data limitation should work against our empirical tests as we potentially classify unconnected funds as linked, implying that our empirical results should be considered as a lower bound for the relevance of social connections. Accordingly, we define two management companies as socially connected if at least two of their employees share a social tie. That is, *Overlap* equals 1 for the pair of funds (i, j) if an employee of management company of fund i worked at the same firm as an employee of management company of fund j during the same period of at least 24 months, and similarly for *Industry* and *Firm*.[15]

We realize that these variables reflect distinct channels leading to similar investment choices. On the one hand, hedge fund managers may acquire portable skills and expertise at a former employer or industry. For example, two managers who both worked at Goldman Sachs are likely to exhibit a similar propensity toward managing fixed income products due to the training in fixed income they received in the workplace. Similarly, former employees who

[15]To construct the network measures, we take into account all prior work experiences an employee had during the relevant network period. The median hedge fund employees worked in one prior industry and for two distinct employers.

worked in the life insurance industry may develop an attitude toward risk that is different than that of employees in the banking sector. On the other hand, employees are likely to establish personal interactions through mutual work experience. We contend that these connections are presumably stronger at the firm rather than the industry level and for employees who overlapped in their working experience. To the extent that managers continue to discuss ideas with their former colleagues, as evidenced by Simon, Millo, Kellard, and Engel (2012), these ties may lead to the exchange of information and induce correlated strategies. In what follows, we refer to the sharing of prior employment alternatively as social ties or networks, keeping in mind that the underlying economic mechanisms may be quite different.

1.3.2 Dependent Variables

We ask whether the investment decisions of hedge funds whose managers are socially connected are more similar vis-à-vis those of unconnected funds. Social ties could impact hedge fund returns through abnormal performance (alpha), systematic risk exposures (beta), and idiosyncratic risk (residuals). Following Kosowski, Naik, and Teo (2007), Deuskar, Pollet, Wang, and Zheng (2011), and others, we resort for the decomposition of hedge fund returns to the 7-factor model of Fung and Hsieh (2004).[16] For each hedge fund i in our sample we estimate the model

$$xr_{i,t} = \alpha_i + \beta_i' F_t + \epsilon_{i,t}, \tag{1.1}$$

where $xr_{i,t}$ denotes hedge fund i net-of-fees return in excess of the risk free rate in month t, F_t collects the contemporaneous factor returns, α_i measures the fund abnormal performance, and $\epsilon_{i,t}$ is the mean-zero idiosyncratic error term. We standardize each of the factors to exhibit unit standard deviation.

[16] The factors are: the excess return of the S&P 500; a size factor as the difference between the Russell 2000 and the S&P 500 indexes; the change in the 10-year treasury constant maturity yield; the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond; and the excess return on portfolios of lookback straddle options on currencies, commodities, and long-term bonds. We obtain the factors from https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

We construct three dependent variables that capture distances in the three components of hedge fund returns. For abnormal performance (alpha), we measure the absolute distance in the estimated intercept from equation (1.1):

$$\Delta\alpha_{i,j} \equiv |\alpha_i - \alpha_j| \tag{1.2}$$

For the systematic risk exposures (beta), we measure the average absolute distances in the funds' estimated βs:

$$\Delta\beta_{i,j} \equiv (1/7)\sum_{k=1}^{7} |\beta_{i,k} - \beta_{j,k}|. \tag{1.3}$$

Finally, for idiosyncratic risk (residuals), we measure the average absolute difference of the estimated residuals:

$$\Delta\epsilon_{i,j} \equiv (1/T)\sum_{t=1}^{T} |\epsilon_{i,t} - \epsilon_{j,t}|. \tag{1.4}$$

The smaller any distance between two funds is, the more similar are their investment strategies in terms of exposures to systematic risks ($\Delta\beta$), idiosyncratic risk ($\Delta\epsilon$), and abnormal performance ($\Delta\alpha$). In Section 1.7, we show that using alternative factor models does not markedly alter our findings.

1.3.3 Dataset Construction and Filters

To investigate whether social connections make two funds i and j behave more similarly, we relate similarities in hedge fund returns ($\Delta\beta$, $\Delta\epsilon$, and $\Delta\alpha$) to measures of manager connectedness (*Overlap*, *Firm*, and *Industry*). However, unlike other studies that look at the effect of social ties on holdings (Pool, Stoffman, and Yonker (2015)) or corporate outcomes (Fracassi (2015)), our dependent variables are not directly observable but need to be estimated over a period of time.

We tackle this issue by resorting to a 'wave' structure. In each wave, we estimate the performance model during a three-year 'evaluation' period and use the previous six-year 'network' period to construct our measures of social ties. We begin our analysis in 2002,

when FSR reporting became mandatory, thereby obtaining 3 evaluation waves starting in January of 2008, 2009, and 2010. To fix ideas, for the first 'wave' we estimate the auxiliary factor model on 2008-2010 return data and create our explanatory variables using data from 2002 to 2007 included. We next move our evaluation and network period forward by one, and then two, years.[17] Given the length of our data, the one-year gap between evaluation periods strikes a balance between sample availability and overlap in the estimation period. This estimation procedure approximates a dynamic panel, which would obtain by re-estimating our dependent variable every month. To make sure that the manager does not exit the evaluation period too early, thereby potentially diluting the proximity with other connected funds, we require the managers to be present in the same company for at least 24 months in the evaluation period. Also, funds need at least 24 time-series observations during the evaluation period to accurately estimate the factor model.

1.4 Social Ties and Hedge Fund Returns

After applying the filters described above, the final database consists of 1,483 hedge funds which are run by 443 distinct management companies, or about 3 funds per company. Collectively, we identify a total of 1,799 managers who are employed at any time in a UK management company during our 2002-2012 time span. According to our definition of connectedness, we identify 1,138 managers who are linked to at least one other individual through past employment in the same (finance) industry. Thus, about 37% of the managers in the sample are 'outsiders' as they joined the hedge fund industry without prior experience in the finance sector.

[17] We move forward both the beginning and the ending dates. This guarantees that the network does not get increasingly dense, as 'old' social ties are severed once they exit a given six-year window.

Table 1.1: Dataset descriptive statistics

For each fund in the sample, we estimate the Fung and Hsieh (2004) 7-factor model separately during the evaluation period of each wave (2008-2010, 2009-2011, and 2010-2012) to obtain idiosyncratic risk (ϵ), systematic risk (β), and abnormal performance (α). Panel A reports descriptive statistics at the fund-wave level. Industry, Employer, and Overlap connection are dummy variables that equal 1 if a fund is connected through a corresponding social tie at any time. 'Adjusted R^2' is the adjusted R-squared from the 7-factor model. 'Age' is the the number of months since the fund entered the database with the longest history. 'EmpSize' is the log of the number of employees of the management company. 'MgmtFee' is the fund management fee (in percentage), while 'PerfFee' is the fund performance fee (also in percentage). 'Leverage' is one if the fund employs leverage, and zero otherwise. AuM are the fund's assets under management, in USD million. Panel B reports analogous statistics at the fund pair level. $\Delta\alpha$, $\Delta\beta$, and $\Delta\epsilon$ denote the distances between any pair of funds belonging to two distinct management companies, as explained in Section 1.4.1. *Industry*, *Firm*, and *Overlap* are the three measures of social ties, as defined in Section 1.3.1.

Panel A: Fund-wave level dataset

	No obs.	Avg	Median	Std	Min	Max
Industry connection	3,516	0.559	1	0.497	0	1
Employer connection	3,516	0.406	0	0.491	0	1
Overlap connection	3,516	0.270	0	0.444	0	1
α	3,516	0.144	0.155	0.932	-5.759	12.917
Adjusted R^2	3,516	0.479	0.477	0.215	0.019	0.986
Age	3,453	59.29	46	49.611	0	394
EmpSize	2,988	59.89	18	220.183	1	2679
MgmtFee	3,446	1.605	2	0.493	0	5
PerfFee	3,409	17.44	20	5.859	0	30
Leverage	1,983	0.309	0	0.462	0	1
AuM	1,438	375.2	106.623	1345	0.019	31,716

	Equity Long/Short	Global Macro	Event-Driven	Fixed-Income	Emerging Markets	Managed Futures
Fraction by style	47%	16%	7%	5%	4%	3%

Panel B: Pair-level dataset

	No obs.	Avg	Median	Std	Min	Max
$\Delta\alpha$	2,037,476	0.877	0.640	0.847	0.006	5.229
$\Delta\beta$	2,037,476	1.149	0.961	0.772	0.187	5.195
$\Delta\epsilon$	2,037,476	2.977	2.514	2.002	0.000	28.531
Industry	2,037,476	0.222	0	0.416	0	1
Firm	2,037,476	0.013	0	0.115	0	1
Overlap	2,037,476	0.005	0	0.071	0	1
logΔAge	1,965,271	3.553	3.738	1.076	0	5.979
log$\Delta EmpSize$	1,466,327	3.182	3.258	1.503	0	7.893
$\Delta MgmtFee$	1,957,074	0.515	0.5	0.472	0	4.5
$\Delta PerfFee$	1,914,714	4.701	0	6.853	0	30
log$AvgEmpSize$	1,466,327	3.465	3.401	0.941	0.693	7.519
log$AvgAge$	1,965,271	3.901	3.998	0.686	0	5.862
logΔAuM	341,107	18.783	18.786	1.794	0	24.180

As a prelude to our analysis, Panel A of Table 1.1 collects descriptive statistics at the fund level across the three waves. The first three rows collect statistics for the three measures of social ties: *Industry*, *Firm*, and *Overlap*. A fund is connected with another fund if there exists at least one connection in any of the three waves. About 56% of all hedge funds are connected through *Industry*, counting only connections to other management companies and excluding hedge funds at the same management company. The percentages of connections for work experience at the same firm, *Firm*, and during the same time, *Overlap*, are 41% and 27%. These numbers reinforce the view that social ties are not confined to a select few funds.

For the average fund in the sample, the monthly abnormal return, α, is about 0.14%. There is, however, considerable dispersion in α ranging from -6% to as high as 13% per month. The adjusted R^2 of the auxiliary regressions averages at 48%, but it too varies in a wide range from 2% to 99%.

The last six rows of Panel A report fund characteristics, which we use as control variables. These are: *Age*, measured by the number of months the fund appears in the hedge fund databases; *EmpSize*, the number of total employees of the management company (from the FSA); management fee ($MgmtFee$), in percent; performance fee ($PerfFee$), in percent; a *Leverage* dummy, which equals one if the fund utilizes positive leverage, and zero otherwise; and assets under management (AuM), in million USD. The median fund has been present in the database for about 60 months, has 18 employees (including all CF-codes), and utilizes compensation schemes in the form of a management fee (2%) and, especially, a performance-based fee (20%). About 31% of the funds make use of some degree of leverage in their operations, conditional on this variable being present (exists for only 57% of funds). Finally, the median fund has 106 million USD of assets under management, but the distribution is highly skewed. It is important to control for these variables as Joenväärä, Kosowski, and Tolonen (2012) report a significant relation between monthly alphas from the 7-factor Fung and Hsieh (2004) model and most of these characteristics.[18]

[18] Joenväärä, Kosowski, and Tolonen (2012) do not find a significant link between alphas and share restrictions (lockup period, redemption period, and redemption notice period) in their combined hedge fund database.

The second block in Panel A breaks down the distribution of funds by style, sorted in descending order among the six most numerous categories. Our sample mimics quite closely the industry in general as outlined in Lo (2007), with the great majority of the funds being classified as Equity Long/Short (about 45%) and Global Macro (about 16%). Overall, the funds in our sample are active in twelve distinct styles, plus a residual 'Other' group.

Panel B of Table 1.1 reports descriptive statistics at the fund-pair level that will be the basis for our econometric investigation. Since our measures of social connectedness are constructed at the management company level, we exclude from the analysis pairs of funds that belong to the same company. Hence, a unit is a pair of funds that are run by two distinct companies. The first block of rows collects statistics for our three dependent variables ($\Delta\alpha$, $\Delta\beta$, $\Delta\epsilon$), which are winsorized at the top and bottom 0.5% to reduce the influence of outliers. We observe an economically very large dispersion in abnormal performance. The average $\Delta\alpha$ is about 0.88% per month, or about 10.50% in annual terms. The standard deviation is comparable at 0.85%, and the distance in α is as large as 5% monthly. Considering that the average absolute excess return in the evaluation period is 2.92%, these figures underscore a large degree of cross-sectional heterogeneity.[19] The average distance in β between any two funds is 1.149. The large value is due to our factor scaling - as the Fung and Hsieh (2004) factors differ widely in standard deviation, we normalized them to have unit variance. There is, however, significant variation in this distance too, ranging from 0.19 to as high as 5.20. Finally, $\Delta\epsilon$ averages 2.98% with a standard deviation of 2.00%. The second three rows focus on the measures of connectedness (*Industry*, *Firm*, and *Overlap*), which are defined at the management company level, see Section 1.3.1. For about 22% of all possible fund pairs we observe a connection through *Industry*. This is the most common linkage. About 1.3% of the pairs share a former employer (*Firm*), while nearly 0.5% are connected via an overlap in the work experience of their managers (*Overlap*). While these numbers sound low, a third of all managers have at least one *Overlap* connection and more than half have at least one

Since data on these variables is also sparse, we do not include them in the analysis.

[19] The average $\Delta\alpha$ for funds in the same style is comparable at 0.85% per month. Hence, the variability is not just originating from comparing funds across different styles.

Industry connection. So managers are well embedded in social networks, just not everybody with everybody else.

Before turning to the results, we note that the distribution of prior employers is not dominated by any single industry or company. Panel A of Figure 1.1 in the appendix reports the distribution of the prior industry employment. Panel B shows the histogram of the number of managers that belong to the ten largest former employers. Together they are associated with 8% of all prior employments. Managers predominantly worked in investment management and at hedge funds, and a total of 224 managers belong to the top-5 prior employers.[20] Finally, Table 1.7 in the appendix contrasts the average and median fund characteristics in our sample with those from the full data set. As we can see, the differences are small and insignificant along many dimensions, which suggests that our UK funds are quite representative of the universe of hedge funds used in prior studies.

1.4.1 Methodology

We estimate the following pooled panel regression relating the distance in performance measures ($\Delta\beta$, $\Delta\epsilon$, $\Delta\alpha$) to the network variables (*Industry*, *Firm*, *Overlap*), cross-sectional controls, and style and time dummies:

$$\begin{aligned}\Delta y_{ij,t\to t+2} &= \text{const} + \beta_1 Industry_{ij,t-1} + \beta_2 Firm_{ij,t-1} + \beta_3 Overlap_{ij,t-1} + \gamma' X_{ij,t-1} + \\ &\quad \xi\,\text{StyleDummy} + \psi\,\text{TimeDummy} + u_{ij,t\to t+2} \qquad (1.5)\end{aligned}$$

where Δy denotes alternatively $\Delta\beta$, $\Delta\epsilon$, or $\Delta\alpha$. The subscripts highlight the fact that the dependent variable is constructed for each pair of funds i and j using data from year t to year $t+2$ (the 'evaluation' period) while the explanatory variables are measured using information up to the end of year $t-1$, with t being 2008, 2009, and 2010, respectively, accounting for the three waves.[21] Thus, our framework is predictive (in-sample) in the sense

[20] These are: Martin Currie Investment Management Ltd, Cheyne Capital Management (UK) LLP, Brevan Howard Asset Management LLP, Goldman Sachs International, and JPMorgan Chase Bank, N.A.

[21] That is, we estimate a pooled version of equation (1.5) where observations across difference 'waves' are stacked, and coefficients are assumed to be constant across waves.

that it amounts to asking how much of the future distance in the performance measures of any two funds can be captured by today's information. The style dummy is one if both funds follow the same style and zero otherwise. This implies that our results should be interpreted as capturing deviations from the common style. Standard errors are clustered at the fund-pair level, as in Pool, Stoffman, and Yonker (2015). We expect negative coefficients for the network measures, consistent with the view that socially connected managers exhibit more similar asset allocation and trading decisions.

1.4.2 Results

Do social networks influence investment behavior? We start by assessing the impact on differences in abnormal returns, $\Delta\alpha$. Results are collected in Table 1.2, Panel A. In model (1), we only include the network variables plus style and time dummies. Sharing a common industry background and employer has the expected negative sign on the distance in alphas. The loadings on *Industry* and *Firm* are -0.152 and -0.098, respectively, both significant at the 1% confidence level. In stark contrast to these findings is the evidence that an overlap in former mutual work experience is not accompanied by a significant reduction in $\Delta\alpha$. The coefficient on *Overlap* is positive but small at 0.032 and insignificant. The style dummy enters negatively (0.038 and a t-statistic of -1.9), which is expected as funds of same style should have more similar investment behavior.

Table 1.2: Social ties and hedge fund returns

For each fund in the sample, we estimate the Fung and Hsieh (2004) 7-factor model separately during the evaluation period of each wave (2008-2010, 2009-2011, and 2010-2012) to obtain idiosyncratic returns (ϵ), factor loadings (β), and abnormal performance (α). We then compute the average absolute distances ($\Delta\epsilon$, $\Delta\beta$, $\Delta\alpha$) between any pair of funds belonging to two distinct management companies as explained in Section 1.4.1. The table reports the OLS estimates of the pooled regression of the distances on the network connection measures (*Industry*, *Firm*, and *Overlap*) and distances (Δ) and averages (*Avg*) of cross-sectional characteristics, which are defined as in Table 1.1. The explanatory variables are measured using information up to December 2007, 2008, and 2009 respectively. Columns (3) of all panels exclude managers with no prior FSA-regulated employment (Excl. new MGRs). Standard errors clustered along the pair level appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	Panel A: Distance in abnormal performance, $\Delta\alpha$			Panel B: Distance in systematic risk, $\Delta\beta$			Panel C: Distance in idiosyncratic risk, $\Delta\epsilon$		
			Excl. new MGRs			Excl. new MGRs			Excl. new MGRs
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Industry	-0.152***	-0.104***	-0.048**	-0.141***	-0.098***	-0.041	-0.386***	-0.238***	-0.099
	(-6.49)	(-4.41)	(-2.21)	(-5.47)	(-3.98)	(-1.17)	(-5.79)	(-3.80)	(-1.01)
Firm	-0.098***	-0.093***	-0.097***	-0.130***	-0.107***	-0.104***	-0.238***	-0.198***	-0.186***
	(-5.97)	(-5.58)	(-6.03)	(-5.90)	(-4.69)	(-4.75)	(-4.74)	(-3.78)	(-3.68)
Overlap	0.032	0.033	0.027	-0.016	-0.022	-0.030	-0.140***	-0.139***	-0.155***
	(1.35)	(1.37)	(1.15)	(-0.67)	(-1.00)	(-1.41)	(-2.70)	(-2.72)	(-3.06)
logΔ*Age*		0.004	-0.003		0.008	-0.006		-0.014	-0.049***
		(0.67)	(-0.57)		(1.18)	(-0.90)		(-0.85)	(-3.02)
logΔ*EmpSize*		0.017**	0.024***		-0.007	0.008		-0.015	0.049***
		(2.21)	(2.74)		(-1.14)	(1.31)		(-1.01)	(3.28)
Δ*MgmtFee*		0.000	-0.035*		-0.011	-0.009		-0.079	-0.046
		(0.00)	(-1.95)		(-0.51)	(-0.39)		(-1.58)	(-1.05)
Δ*PerfFee*		0.001	0.000		0.006***	0.004**		0.001	-0.006
		(0.73)	(0.13)		(3.02)	(2.01)		(0.29)	(-1.59)
log*AvgEmpSize*		-0.094***	-0.075***		-0.077***	-0.084***		-0.221***	-0.281***
		(-4.42)	(-3.01)		(-5.16)	(-4.64)		(-5.98)	(-6.02)
log*AvgAge*		-0.043**	-0.003		-0.080***	-0.026		-0.114*	0.033
		(-2.10)	(-0.18)		(-3.36)	(-1.19)		(-1.88)	(0.62)
Style Dummy	-0.038*	-0.025	-0.027	-0.003	0.017	-0.015	0.087	0.104*	0.003
	(-1.90)	(-1.15)	(-1.16)	(-0.16)	(0.84)	(-0.61)	(1.57)	(1.84)	(0.05)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. ('000)	2,037	1,301	513	2,037	1,301	513	2,037	1,301	513
Adj. R-squared	0.011	0.02	0.014	0.007	0.026	0.017	0.031	0.055	0.064

We next augment the regression by including fund-level controls in model (2). If connected managers tend to establish or join funds with similar fund structures (say, because they develop similar attitudes toward performance-based compensation schemes), including the controls potentially captures part of the overall effect of managers' ties. Consistent with this argument, we see that the coefficients of *Industry* and *Firm* decrease in absolute value to -0.104 and -0.093. However, both of the effects remain significant, with t-statistics of around 5. The coefficient on *Overlap* is again positive and insignificant. From the controls, size (as proxied by the log of the average number of employees) and (log average) age stand out as important determinants, consistent with Joenväärä, Kosowski, and Tolonen (2012). Both controls have negative coefficients, leading to more similar alpha for larger and older firms. As the controls remain stable throughout most regression models, we only discuss them when needed.

We noticed that about a third of all managers are not part of a network as they do not have a prior employer who is regulated by the FCA. We label these managers 'outsiders.' Our results could be driven by similarities in managers who worked for a finance-related firm compared to these 'outsiders.' To address this issue, we restrict the sample in model (3) to pairs of managers with prior employment in the finance sector. As expected, the importance of *Industry* is now reduced, with the coefficient being halved at -0.048, but still significant at the 5% level. In contrast, the impact of *Firm* is comparable to the full sample figure, with a significant and large negative estimate of -0.097.

In Panel B of Table 1.2, we turn our attention to the regression for the distance in systematic risk exposures, $\Delta\beta$. In the specification without controls in model (1), the estimated loading on *Industry* is again negative at -0.141 and strongly significant with a t-statistic of -5.47. A common *Firm* has a comparably negative impact of -0.130, which is also significant at the 1% level. *Overlap* is again insignificant. The inclusion of control variables in model (2) decreases somewhat the coefficients of *Firm* and *Industry* to -0.098 and -0.107. Both remain highly significant, suggesting that social connections capture similarities in managers' systematic risk exposures that are not subsumed by differences in funds' characteristics.

When excluding 'outsiders' in model (3), the loading on *Firm* changes slightly to −0.104, while the coefficient on *Industry* decreases to −0.041 and loses significance.

Finally, Panel C of Table 1.2 presents the estimates for the regression of $\Delta\epsilon$. Without controls, we find for model (1) that the coefficients for *Industry* and *Firm* are negative at −0.386 and −0.238 and highly significant. Interestingly, the coefficient on *Overlap* is also negative, relatively large at −0.140, and significant at the 1% level. Thus, network connections originating from a common work experience seem to play a role in explaining idiosyncratic risk. This is consistent with 'word-of-mouth' transmission of information that propagates through the network of managers who know each other personally. Including control variables in model (2) decreases the coefficients on *Industry* and *Firm*, while leaving the results strongly significant. For *Overlap*, the coefficient is almost unchanged at −0.139 and significant. Excluding 'outsiders' in model (3) leaves *Firm* largely unaffected and reduces the effect of *Industry*. *Overlap* is now larger at −0.155 and again significant at the 1% level. This suggests that word-of-mouth effects, which can arise from close relationships established in the workplace, seem to affect the idiosyncratic return component of hedge fund managers. We show so far that social ties in the hedge fund industry play a relevant role in explaining differences among fund returns through differences in alpha, beta, and residuals. Sharing a common *Industry* and *Firm* has by far the most robust and significant effect. These effects are also economically quite large, which we document by comparing the joint effect of having worked for the same *Firm* (and thus in the same *Industry*) from model (1) in Table 1.2 to the averages of our differences in performance measures from Panel B of Table 1.1. For monthly abnormal returns ($\Delta\alpha$), social ties reduce the average of 0.88 by 0.25. In annual terms, this reduction (of 28%) translates into a large 3% figure. The average factor loading ($\Delta\beta$) of 1.15 is reduced by 0.27 (23% reduction) and the average residual ($\Delta\epsilon$) of 2.98 by 0.62 (21% reduction). Social ties thus account for about a quarter of the cross-sectional differences in performance measures. In contrast, network connections that arise from *Overlap* in the work experience appear to explain only the idiosyncratic part of returns, which may be capturing dynamic trading based on the sharing of ideas through the network. We revisit the discussion

about the economic significance of social ties in Section 1.6.

1.4.3 Subsample Analysis

The universe of hedge funds is characterized by a wide spectrum of investment strategies, both in terms of asset classes and types of financial products. A natural question that arises is whether cross-sectional differences in these strategies impact our findings on the influence of social ties on investment decisions.

We begin by grouping hedge funds by broad investment strategies based on the classification in Agarwal, Daniel, and Naik (2009). We then estimate equation (1.5) separately for pairs of funds belonging to the three largest strategies, namely, Security Selection (including Equity Long and Equity Long/Short, about 23% of all pairs), Directional Traders (including Emerging Markets and Global Macro, about 1.5% of all pairs), and Multiprocess and Relative Value (including Distressed, Event-Driven, Multi-Strategy, Bonds, Convertible Arbitrage, and Merger Arbitrage, about 1% of all pairs). Results are reported in Panel A of Table 1.3.

Table 1.3: Social ties and hedge fund returns, subsample analysis

For each fund in the sample, we estimate the Fung and Hsieh (2004) 7-factor model separately during the evaluation period of each wave (2008-2010, 2009-2011, and 2010-2012) to obtain idiosyncratic risk (ϵ), systematic risk (β), and abnormal performance (α). We then compute the average absolute distances ($\Delta\epsilon$, $\Delta\beta$, $\Delta\alpha$) between any pair of funds belonging to two distinct management companies as explained in Section 1.4.1. The table reports the OLS estimates of the pooled regression of the distances on the network connection measures (*Industry*, *Firm*, and *Overlap*) and distances (Δ) and averages (*Avg*) of cross-sectional characteristics, which are defined as in Table 1.1. The explanatory variables are measured using information up to December 2007, 2008, and 2009 respectively. In Panel A, the regression is estimated separately on the sample of fund pairs whose styles fall into the Security Selection, Directional Traders, or Multiprocess and Relative Value investment strategies. In Panel B, the regression is estimated separately on the sample of fund pairs where both funds are Small ($EmpSize < 18$) or Large ($EmpSize \geq 18$). The coefficients on the cross-sectional controls, time fixed effects, and style dummy are omitted to save space. Standard errors clustered along the pair level appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

Panel A: By investment strategy

	Security Selection			Directional Traders			Multiprocess and Relative Value		
	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$
Industry	-0.084***	-0.165***	-0.436***	-0.139**	-0.098*	-0.219*	-0.208***	-0.030	-0.213
	(-2.66)	(-4.58)	(-4.61)	(-2.18)	(-1.95)	(-1.79)	(-3.30)	(-0.60)	(-1.60)
Firm	-0.079***	-0.060**	-0.059	-0.149**	-0.229***	-0.354**	-0.104	0.074	0.204
	(-3.08)	(-2.55)	(-1.04)	(-2.44)	(-4.10)	(-2.23)	(-1.61)	(0.64)	(0.74)
Overlap	0.048	-0.012	-0.115	-0.022	0.035	-0.091	0.093	-0.390***	-0.706***
	(1.37)	(-0.37)	(-1.50)	(-0.29)	(0.49)	(-0.43)	(0.79)	(-3.36)	(-2.67)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. ('000)	296	296	296	33	33	33	11	11	11
Adj. R-squared	0.025	0.066	0.081	0.053	0.031	0.062	0.020	0.019	0.048

Panel B: By fund size

	Small funds			Large funds		
	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$
Industry	-0.109**	-0.173***	-0.388***	-0.056**	-0.044	-0.100
	(-2.28)	(-4.06)	(-3.39)	(-2.01)	(-1.52)	(-1.62)
Firm	-0.269***	-0.187***	-0.608***	-0.074***	-0.096***	-0.106*
	(-4.68)	(-3.01)	(-4.02)	(-4.26)	(-3.78)	(-1.85)
Overlap	0.007	-0.012	-0.068	0.045*	-0.005	-0.124**
	(0.08)	(-0.15)	(-0.34)	(1.66)	(-0.21)	(-2.12)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs. ('000)	308	308	308	333	333	333
Adj. R-squared	0.020	0.016	0.037	0.010	0.030	0.060

We note interesting patterns in the coefficients of the network measures across strategies. First, whenever significant, social ties impact investment decisions with the expected negative sign. Of the 27 coefficients (three distance measures times three investment measures times three strategies), 22 of them are negative and 14 are significant at the 10% level or better. This implies that our results are quite robust and not driven by any single strategy. Importantly, *Industry* and *Firm* are almost always significant drivers of the distance in alphas, the sole exception being *Firm* for Multiprocess where the t-statistics is -1.61. The strategies Security Selection and Directional Trading stay pretty close to the main results of Table 1.2 but lose the significance for *Overlap*. Multiprocess, comprising just 0.5% of the sample, loses significance for *Industry* and *Firm* for $\Delta\beta$ and $\Delta\epsilon$. It is then noteworthy that *Overlap* is especially relevant for Multiprocess with the largest loading of -0.706 in the case of $\Delta\epsilon$ (t-statistic of -2.67). We interpret the findings as evidence that Multiprocess is particularly sensitive to the sharing of information – e.g. for funds following Event-Driven, Convertible Arbitrage, and Merger Arbitrage styles. For these strategies, *Overlap* seems to capture word-of-mouth communications and exchange of investment ideas, which concern systematic ($\Delta\beta$) and idiosyncratic ($\Delta\epsilon$) risk. *Industry* and *Firm* effects seem to be less relevant for Multiprocess, except for the abnormal returns ($\Delta\alpha$).

In addition to strategies, we next analyze whether the effect of social ties varies with fund size. Small funds are characterized by a greater proximity of key employees to the fund strategic investment decision. Thus, the effect of connected key employees is likely to be greater. We test this prediction by running our analysis separately for pairs of Small and Large funds, defined as funds below (respectively, above) the median employee size, 18. We document in Panel B of the Table 1.3 that the results for Small funds mimic closely the main results from Table 1.2 but for *Overlap*. Large funds lose in economic significance as coefficients are about one-third of the coefficients for Small funds for *Industry* and *Firm*. Statistical significance also suffers for Large funds. The picture is less clear for *Overlap* where the results, perhaps counter-intuitively, strengthen for Large funds.

1.5 Testing for Alternative Hypotheses

It is tempting to conclude that our results provide support for a causal link from social ties to hedge fund investment decisions. Establishing causality is, however, a challenging endeavor. Using our initial example of the commodity trading adviser AHL, we would like to argue that similarities are being driven by having been employed in the same *Industry* (hedge fund), at the same *Firm* (AHL), and possibly at the same time, *Overlap*. This story nicely dovetails with Simon, Millo, Kellard, and Engel (2012), who report that managers continue to discuss ideas with their former colleagues.

Yet the alternative argument could be put forward that our findings are driven by managerial characteristics. These characteristics may be personal attributes (such as, manager risk aversion) or manager innate skill. Continuing with the example above, one may argue that only skilled managers join AHL and employ similar, skilled trading strategies. Given that more skilled investors exhibit higher trading performance, see Grinblatt, Keloharju, and Linnainmaa (2012), our evidence of social ties driving abnormal returns ($\Delta\alpha$) instead might simply measure similar managerial characteristics. This argument would imply that our estimates suffer from an endogeneity bias that leads to overestimating the impact of social ties.

We attempt to disentangle effects of social ties from those of managerial characteristics in various ways. First, we augment our regression with the following three controls that capture personal attitudes and other network-related effects: (i) the log difference in the managers' age, $\log\Delta MgrAge$; (ii) the difference in gender, $\Delta Gender$; and (iii) a dummy variable ΔZip that equals 1 if the two hedge fund management companies are headquartered in the same postcode district, and 0 otherwise.[22]

[22]The information for ΔZip and $\Delta MgrAge$ is obtained by manually looking for the manager name in the Companies House database at https://companycheck.co.uk. In the UK, filing with the Companies House is mandatory. Two postcodes are defined as being equal if they have the same outward code.

Table 1.4: Social ties and hedge fund returns, testing for alternative hypotheses

For each fund in the sample, we estimate the Fung and Hsieh (2004) 7-factor model separately during the evaluation period of each wave (2008-2010, 2009-2011, and 2010-2012) to obtain idiosyncratic risk (ϵ), systematic risk (β), and abnormal performance (α). We then compute the average absolute distances ($\Delta\epsilon$, $\Delta\beta$, $\Delta\alpha$) between any pair of funds belonging to two distinct management companies as explained in Section 1.4.1. The table reports the OLS estimates of the pooled regression of the distances on: the connection measures (*Industry*, *Firm*, and *Overlap*); distances (Δ) and averages (*Avg*) of cross-sectional characteristics, which are defined as in Table 1.1; a dummy that equals 1 if the two companies are headquartered in the same postcode district and 0 otherwise, ΔZip; the log distance in managers' age, $\log\Delta MgrAge$; the distance in gender, $\Delta Gender$, with 0 being of same gender and 1 otherwise; the distance in hiring climate, $\Delta HiringClimate$, constructed as explained in Section 1.5; the distance in the managers' previous alpha, ΔPrevious α, for the managers with prior employment in the hedge fund industry. The column 'IV' denotes the instrumental variable approach that uses the residuals from regressing the connection measures on $\Delta HiringClimate$. The explanatory variables are measured using information up to December 2007, 2008, and 2009 respectively. The coefficients on the cross-sectional controls, time fixed effects, and style dummy are omitted to save space. Standard errors clustered along the pair level appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	Panel A: Distance in abnormal performance, $\Delta\alpha$				Panel B: Distance in systematic risk, $\Delta\beta$				Panel C: Distance in idiosyncratic risk, $\Delta\epsilon$			
			IV				IV				IV	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Industry	-0.091***	-0.102***	-0.101***	0.039	-0.098***	-0.091***	-0.090***	0.091**	-0.231***	-0.237***	-0.226***	0.128*
	(-3.83)	(-4.01)	(-3.96)	(0.84)	(-3.89)	(-3.43)	(-3.37)	(2.47)	(-3.69)	(-3.58)	(-3.44)	(1.70)
Firm	-0.096***	-0.092***	-0.092***	-0.120***	-0.108***	-0.103***	-0.102***	-0.141***	-0.204***	-0.175***	-0.172***	-0.246***
	(-5.82)	(-5.88)	(-5.82)	(-6.17)	(-4.74)	(-4.65)	(-4.60)	(-5.37)	(-3.87)	(-3.40)	(-3.30)	(-3.87)
Overlap	0.041	0.035	0.036	0.073***	-0.000	-0.004	-0.003	0.017	-0.074	-0.103*	-0.098*	0.009
	(1.50)	(1.22)	(1.25)	(2.84)	(-0.00)	(-0.16)	(-0.13)	(0.75)	(-1.33)	(-1.78)	(-1.75)	(0.16)
ΔZip	0.028	0.025	0.027	0.075*	0.156***	0.142***	0.144***	0.097**	0.437***	0.417***	0.426***	0.183*
	(0.67)	(0.57)	(0.60)	(1.86)	(4.37)	(3.90)	(3.95)	(2.22)	(4.41)	(4.09)	(4.13)	(1.93)
$\log\Delta MgrAge$	-0.009	-0.018***	-0.017***	-0.008	0.000	-0.003	-0.002	0.003	-0.013	-0.034*	-0.029	-0.018
	(-1.14)	(-3.17)	(-3.12)	(-1.04)	(0.06)	(-0.34)	(-0.23)	(0.41)	(-0.58)	(-1.70)	(-1.52)	(-1.01)
$\Delta Gender$	0.041	0.103	0.098	0.018	0.058	0.151*	0.145*	0.090	-0.137	0.050	0.015	0.026
	(0.68)	(1.60)	(1.53)	(0.22)	(0.77)	(1.77)	(1.70)	(0.81)	(-0.88)	(0.30)	(0.09)	(0.12)
$\Delta HiringClimate$		0.032		-0.075		0.041		-0.070		0.277		-0.249
		(0.74)		(-0.86)		(0.90)		(-0.92)		(1.55)		(-1.13)
ΔPrevious α				-0.030				0.103**				0.131*
				(-1.05)				(2.53)				(1.77)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. ('000)	1,155	942	942	156	1,155	942	942	156	1,155	942	942	156
Adj. R-squared	0.019	0.021	0.02	0.014	0.027	0.026	0.025	0.023	0.055	0.061	0.055	0.07

The results in Table 1.4 are organized in three panels (A, B, and C) for $\Delta\alpha$, $\Delta\beta$, and $\Delta\epsilon$; mimicking the structure of Table 1.2. Models (1) in each panel of Table 1.4 show that the main results of Table 1.2 remain significant once we add managerial characteristics, although the coefficients shrink somewhat. Of the new controls, only ΔZip is significant for $\Delta\beta$ and $\Delta\epsilon$. The evidence that managers operating in the same postcode district exhibit correlated investment strategies is consistent with Hong, Kubik, and Stein (2005). The other two controls do not appear to be significant drivers of return distances.

Next, we strive to construct proxies for managers' skills. From an econometric viewpoint, exogenous changes in the composition of the hedge fund's managerial team (such as a manager's death) are too rare to draw any inference, and direct data on skills are unavailable for our sample. To circumvent this issue, we construct two variables that proxy for skill. The first variable is motivated by Deuskar, Pollet, Wang, and Zheng (2011)'s evidence that mutual fund managers who switch to the hedge fund industry tend to underperform relative to their peers in both the former and new employment and hence appear less skilled. Importantly, they document that these career changes are more likely to occur when the hedge fund industry is growing rapidly, which is consistent with hedge funds lowering their hiring standards during periods of extensive growth. This suggests that the 'hiring climate' might capture exogenous variation in market conditions that proxy for a fund's ability to select skilled versus unskilled managers. Following this reasoning, we define *Hiring Climate* as the net number of people hired in the financial industry at the time the manager was hired. We construct fund level *Hiring Climate* as the average of its managers' *Hiring Climate*. The underling assumption is that in times of great demand for money managers (*Hiring Climate* is high, as many managers are being newly employed), the management companies cannot be overly picky and need to hire whomever they can.

Models (2) in all panels of Table 1.4 add the distance in the funds' *Hiring Climate* as an additional control variable. Its loading has the expected positive sign across all distance measures. However, it is not statistically significant, and its inclusion does not alter the significance of our social ties measures that remain economically and statistically impor-

tant. As an alternative to using *Hiring Climate* as a control variable, we also employ an instrumental variable approach. Namely, we first regress *Industry*, *Firm*, and *Overlap* on *Hiring Climate* and store the resulting residuals. Under the assumption that *Hiring Climate* captures variations in managers' skills (intelligence), the residuals in this regressions should reflect social ties among fund managers that are orthogonal to their level of skills.[23] We next use these residuals in our main regression, omitting *Hiring Climate* from the set of controls. The results are reported in Models (3) of Table 1.4 and convey a similar message to those in Models (2).

In addition to *Hiring Climate*, we also track abnormal performance (Previous α) for the subset of managers who previously worked for a hedge fund and where we can track that hedge fund's returns in our databases. The sample size shrinks to about one-seventh of the original 1,155,000 fund-pair observations. Controlling for Previous α should go a long way towards absorbing skills that are innate to the manager. Models (4) in all panels of Table 1.4 add ΔPrevious α to the list of regressors, which is computed as the average alpha (with respect to the 7-factor Fung and Hsieh (2004) model) of the hedge funds the manager previously worked for (excluding the current ones).[24] As we can see, ΔPrevious α has significantly positive loadings for $\Delta\beta$ and $\Delta\epsilon$. Managers with more different Previous α invest in more different systematic and idiosyncratic risks, which confirms our expectation. The main results from Table 1.2 remain intact for *Firm* but weaken (and even flip the sign in Panel B) for *Industry*. Overall, we conclude that managerial characteristics and unobserved skills are not responsible for our main finding that social networks due to prior employment matter for similarity in investment behavior.

[23] Indeed, we verify that *Hiring Climate* negatively predicts future performance consistent with the claim that it captures some component of skill. In a panel regression of future alpha on fund controls and *Hiring Climate*, the latter enters with a negative coefficient and is statistically significant with a t-statistic of -2.50.

[24] If there is more than one manager for a given company, this figure is then defined as the average of the managers' previous alphas.

1.6 The Economic Significance of Hedge Funds Social Ties

Our analysis thus far uncovers proximity in the performance of hedge fund pairs due to social ties. But from an asset management perspective, it is also important to understand whether social ties ultimately impact the *level* of future individual hedge fund performance. In other words: Does grouping hedge funds based on the manager's prior employment background generate significant cross-sectional differences in alphas? Further, are there economic gains from loading on connected funds?

A priori, both economic and statistical arguments can be made for a link between managers' social ties and funds' performance. From an economic viewpoint, managers might learn valuable skills in the prior workplace, which allow them to make better investment decisions for the hedge fund. Being part of a specific social network might also provide valuable information sharing that improves the precision of any single manager information set. Pool, Stoffman, and Yonker (2015) provide compelling evidence that the exchange of information ultimately results in a significantly positive abnormal return. On the other hand, the evidence above that connected funds exhibit more similar return components suggests that loading on these funds may harm portfolio diversification. Moreover, correlated trades among funds of the same network may lead to the funds trading securities based on the same signals. This behavior could endogenously generate a liquidity spiral when the signal reverts, and depress their performance. Which one of these effects prevails is ultimately an empirical question.

From a statistical viewpoint, conditioning on social ties may lead to a better assessment of hedge funds' risk-return profile. It is well known that individual fund alphas tend to exhibit only modest persistence over long horizons when conditioning on past (abnormal) performance, Kosowski, Naik, and Teo (2007). Given our finding that social ties explain distances in hedge funds returns, it is natural to ask whether they could serve as valid predictors of performance. For example, finding that managers who are trained in a given

industry tend to generate on average higher performance than their peers would suggest that sorting funds across this dimension is a statistically more powerful predictor of future performance than individual funds' alphas.

To investigate the economic value of hedge fund managers' networks, we conduct two complementary analyses. First, we run regressions of future fund performance on industry dummies, where these are defined based on the prior managers' working experience. That is, we construct a 'Pension Fund' dummy that equals 1 for a fund with at least one manager with prior employment in a pension fund, and 0 otherwise. Similarly, we construct dummy variables for all the 10 other industries. We include a constant term for those managers with no prior experience reported in the FSA. We focus on the effect of industry rather than company background as the number of distinct industries is much more limited, which would in turn enhance statistical power. As measures of performance we consider alpha, Sharpe ratio (excess return divided by total volatility), and Information ratio (alpha divided by residual volatility). In analogy to our pair analysis, performance is computed over the evaluation period, while the industry dummies are defined at the end of the network period. Panel A of Table 1.5 reports the corresponding estimates for the constant, the industry dummy coefficients sorted in descending order based on alpha, and the p-value for the null that the dummies are jointly zero. We cluster the standard errors by time.

Table 1.5: Economic significance of hedge funds social ties

Panel A reports the estimates from the panel regression of a fund's Alpha, Sharpe Ratio, or Information Ratio on the manager's *Industry*. The last row reports the *p*-value for the F-test that all coefficients (excluding the constant) are zero. Panel B reports the Alpha, Sharpe Ratio, and Information Ratio for portfolios of hedge funds that are sorted into deciles according to the degree of *Industry* connectedness. The portfolios are formed using the bootstrap procedure described in Section 1.6. The last two rows report the statistics for a strategy that goes long portfolio D10 and short portfolio D1, along with its *p*-value. We cluster the standard errors by time.

Panel A: Past industry and future performance

	Alpha	Sharpe Ratio	Information Ratio
Constant	0.160***	0.166***	0.110***
Pension Fund	0.255***	0.070**	0.110***
Bank	0.110*	0.033*	0.056**
Other	0.069	0.011	0.035
Brokerage	0.046	-0.034	0.004
Private Equity	0.039	0.006	0.036
Investment Bank	0.034	-0.002	0.038
Hedge Fund	0.031	-0.002	0.000
Consultancy	-0.006	0.028	-0.01
Mutual Fund	-0.027	0.004	-0.012
Insurance	-0.048	0.003	0.028
Investment Management	-0.144***	-0.047***	-0.080***
Obs.	3,513	3,513	3,513
p-value F-test	0.016	0.026	0.001

Panel B: Loading on industry connection, bootstrap results

Industry connectedness deciles	Alpha	Sharpe Ratio	Information Ratio
D1=Low	0.205	0.656	0.126
D2	0.222	0.666	0.141
D3	0.230	0.665	0.151
D4	0.244	0.681	0.157
D5	0.239	0.690	0.161
D6	0.241	0.709	0.165
D7	0.239	0.687	0.165
D8	0.265	0.719	0.188
D9	0.251	0.721	0.179
D10=High	0.264	0.734	0.193
D10-D1	0.059	0.078	0.067
p-value	<0.001	<0.001	<0.001

The constant term for alpha is positive at 0.16, or 16 basis points per month, and highly significant. Among the industry dummies, we find that hedge funds whose managers worked at a Pension Fund and in the Banking industry deliver superior performance with respect to their peers. Alpha is more than doubled if the manager hails from the Pension Fund industry (0.26% per month), significant at the 1% level. The effect is somewhat smaller for the Banking industry (0.11%), significant at the 10% level. The remaining industries are insignificant but for Investment Management, where the negative effects dominate. Alpha is almost completely wiped out in that case due to a strongly significant coefficient of −0.14%. These results are consistent with expectations that a background in banking adds to performance due to social networks and skills acquired. Interestingly, the alpha for managers coming from the mutual fund industry is negative, at -3 basis points per month. This result is consistent with Deuskar, Pollet, Wang, and Zheng (2011) who find that fund managers with poor performance track records at their old mutual fund continue to underperform in the hedge fund industry. We obtain a similar (although insignificant) effect using a very different data set and time span. The null hypothesis that the industry dummies are zero is rejected with a p-value of 0.016, which implies that the estimates are not simply due to random differences. The cross-sectional patterns are fairly similar when looking at the Sharpe Ratio or the Information Ratio.

Our second approach of looking at economic significance involves bootstrapped funds of funds, when these are sorted according to their degree of connectedness.[25] If social networks expose managers to valuable trading ideas and investment strategies, then we expect funds of well-connected hedge funds to have higher out-of-sample performance than funds of little-connected hedge funds.

Our bootstrap procedure is as follows. Consider the first evaluation period which starts in January, 2008. Using the sample of funds available then, we randomly sample 10,000 portfolios consisting of 15 funds each. The sampling is done with replacement and is stratified to

[25]Bootstrap methods have been widely used in prior studies as a way to improve statistical inference given the relatively recalcitrant nature of hedge fund time series, see notably Kosowski, Naik, and Teo (2007).

preserve the same relative style concentration as in the whole industry.[26] We track each fund in the portfolio for the 3-year period ending in December, 2010 and compute the portfolio return as the equally-weighted average of the constituent funds' returns.[27] Next, we measure the level of network connectedness in the portfolio by the number of *Industry* connections among its funds, when these are based on the network period ending on December, 2007. To fix ideas, if only two funds in a portfolio are linked via their managers sharing a prior employment in the same industry, we assign a value of $2^2 - 2 = 2$. If four funds are linked, we assign a value of $4^2 - 4 = 12$. Based on this count, we sort the portfolios into deciles; D1 being the decile of portfolios with the lowest number of connections and D10 the decile with the highest number of connections.

We compute the alpha, Sharpe ratio, and Information ratio of each decile as the corresponding averages across the respective portfolios. We repeat this entire procedure for the other 3-year periods starting in January, 2009 and January, 2010. We report the average values across all three waves in Panel B of Table 1.5. We find that funds of most-connected hedge funds (portfolio D10) outperform funds of least-connected funds (D1) across all performance metrics. For alpha, funds of funds in D10 generate an abnormal return of about 0.264 compared to the 0.205 figure for D1. The difference of about 60 basis points per month is highly significant. Interestingly, the alpha increases almost monotonically as we move from D1 to D10. Analogous conclusions are drawn when considering the Sharpe ratio and the Information ratio, with D10 delivering better volatility-scaled performance than D1. Overall, these results corroborate the evidence in prior studies that network connections tend to enhance fund performance.

[26] For the 2008-2010 sample, this implies that the portfolios are composed of 8 funds from the Equity Long/Short category, 2 from Global Macro, 1 from Event-Driven, 1 from Fixed-Income, 1 from Emerging Markets, and 1 from Others. The stratification avoids that we erroneously pick up differences in performance across styles when sorting based on connectedness. This would arise, for example, if social ties and styles were correlated due to managers endogenously joining more popular styles.

[27] If a fund drops from the sample during the 3-year period, we invest the portfolio equally in the remaining funds.

1.7 Robustness analysis

We conduct further analyses to verify that our results are robust to the empirical design and collect the corresponding estimates for the social ties coefficients in Table 1.6.

First, we are concerned that our definition of distance in fund performance may be inadequate when funds use leverage. For example, it could be the case that two connected managers load on the same mix of risk factors, but only one of them levers up. Leverage would amplify the magnitude of betas and in turn their distance. To address this issue, we repeat our regressions focusing on fund pairs with the same leverage, as measured by our dummy variable. Results are reported in Panel A of Table 1.6. We note that the economic and statistical significance of our measures of connectedness is preserved. Interestingly, the effect of *Overlap* on $\Delta\beta$ is now significant at the 10% level.[28]

Our prior analysis uses hedge funds' self-reported styles. Throughout their life, hedge fund managers may well follow strategies that deviate quite significantly from that reported style. To control for this possibility, we group funds among 10 clustered styles that are identified by their rank correlation, similar to Siegmann, Stefanova, and Zamojski (2013). We report the resulting estimates in Panel B, and they are very close to those in Table 1.2.

We also explore two variations of the performance-attribution model. First, we add the Pastor and Stambaugh (2003) traded liquidity factor to the set of Fung and Hsieh (2004) factors. There is evidence that hedge funds differ significantly in terms of exposure to market and funding liquidity shocks, see Jylha, Rinne, and Suominen (2014) and Franzoni and Plazzi (2014). Alternatively, we resort to the Namvar, Phillips, Pukthuanthong, and Rau (2016) 10-factor model, where factors are constructed as the first 10 principal components from a large set of asset classes. Panels C and D of Table 1.6 present the estimates for the two models, respectively. We draw similar conclusions to our main set of results, namely, *Industry* and *Firm* are significant determinants across all distances in return components, while *Overlap* matters only for the distance in idiosyncratic risk.

[28] In unreported results, we use measures of distance scaled by idiosyncratic volatility and obtain similar results to those in Table 1.2.

Table 1.6: Social ties and hedge fund returns, robustness analysis

The Table shows six alternative specifications of model (2) in Table 1.2. In Panel A, we restrict the sample to funds with the same amount of leverage. In Panel B, the style dummy is defined with respect to 10 clustered styles based on rank correlation, rather than self-reported styles. In Panel C and D we use two alternative models to decompose funds returns. In Panel C, we augment the Fung and Hsieh (2004) 7-factor model with the traded liquidity factor of Pastor and Stambaugh (2003). In Panel D, we instead use the 10-factor model of Namvar, Phillips, Pukthuanthong, and Rau (2016). In Panel E we use assets under management instead of employee size as control variable. In Panel F we add the distance in fund flows to the set of controls. The coefficients on the cross-sectional controls, time fixed effects, and style dummy are omitted to save space. Standard errors clustered along the pair level appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	Panel A: Funds with same leverage			Panel B: Clustered-based styles		
	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$
Industry	-0.104***	-0.103***	-0.262***	-0.104***	-0.097***	-0.232***
	(-4.31)	(-4.09)	(-4.12)	(-4.44)	(-3.98)	(-3.75)
Firm	-0.068***	-0.078***	-0.159***	-0.094***	-0.106***	-0.196***
	(-3.47)	(-3.16)	(-2.93)	(-5.60)	(-4.67)	(-3.72)
Overlap	0.014	-0.045*	-0.144**	0.034	-0.022	-0.137***
	(0.45)	(-1.81)	(-2.42)	(1.38)	(-0.99)	(-2.65)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs. ('000)	474	474	474	1,301	1,301	1,301
Adj. R-squared	0.022	0.033	0.061	0.02	0.026	0.054
	Panel C: Adding Liquidity Factor			Panel D: NPPR 10-factor model		
	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$
Industry	-0.090***	-0.083***	-0.237***	-0.098***	-0.064***	-0.224***
	(-4.07)	(-3.58)	(-3.94)	(-4.63)	(-3.27)	(-3.91)
Firm	-0.089***	-0.106***	-0.182***	-0.060***	-0.100***	-0.184***
	(-5.26)	(-4.88)	(-3.62)	(-2.97)	(-4.26)	(-3.76)
Overlap	0.025	-0.024	-0.128**	-0.020	-0.031	-0.106**
	(1.00)	(-1.19)	(-2.56)	(-0.81)	(-1.59)	(-2.22)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs. ('000)	1,301	1,301	1,301	1,301	1,301	1,301
Adj. R-squared	0.022	0.026	0.057	0.032	0.049	0.061
	Panel E: Controlling for AuM			Panel D: Controlling for Flows		
	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$	$\Delta\alpha$	$\Delta\beta$	$\Delta\epsilon$
Industry	-0.256***	-0.202***	-0.588***	-0.187***	-0.141***	-0.419***
	(-6.02)	(-4.72)	(-4.77)	(-4.26)	(-3.60)	(-3.74)
Firm	-0.060	-0.033	-0.247**	-0.068	-0.006	-0.249**
	(-1.57)	(-0.67)	(-2.42)	(-1.64)	(-0.10)	(-2.01)
Overlap	0.042	-0.023	-0.050	0.041	-0.064	-0.006
	(0.88)	(-0.44)	(-0.50)	(0.76)	(-0.99)	(-0.05)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs. ('000)	103	103	103	61	61	61
Adj. R-squared	0.032	0.050	0.062	0.035	0.034	0.057

In Panel E, we use assets under management (AuM) in place of number of employees as a proxy for fund size. A drawback is that the number of observations is reduced by a factor of 10 to 103,000 pairs. We note that the sign of the measures of social ties remains negative, as expected. Statistical significance is, however, preserved only for *Industry* across all distances in performance and for *Firm* in the case of idiosyncratic risk (for abnormal performance, it is marginally insignificant with a p-value of 12%).

Finally, in Panel F we add the distance in funds' percentage flows to the set of control variables. Teo (2011) documents differences in risk-adjusted performance that are related to flows for the group of liquid funds. Including flows in the analysis shrinks our sample further to 61,000 pairs. We draw similar conclusions as in Panel E, namely, managers who share social ties display more similar performance figures, but the evidence is weaker in statistical terms which is probably due to the smaller sample size.[29]

[29] Another potential explanation could be that connected managers share the same investors, potentially inherited from their former common employer. This would imply that flows already capture away some of the direct effect of social connections. In an effort to test for this channel, we repeat our main analysis using distance in flows as dependent variable but cannot find a significant link with the social ties variables.

1.8 Conclusion

There is growing interest in understanding the determinants of hedge fund strategies. Much progress has been made on identifying risk factors that could explain the astonishingly large performance that hedge funds seem to be able to generate. Comparably little, however, is known about the role played by social connections in explaining differences in hedge fund returns. This study offers some steps in this direction.

Our results point towards a distinct role for social ties and work histories in explaining differences in hedge fund performance. Managers who overlap in their prior work experience at a firm are more similar in the idiosyncratic component of their hedge fund returns than non-overlapping managers. This result may be capturing the exchange of information among the managers in the network that leads to similar bets. This result seems to be driven by hedge funds betting on distressed securities, convertible securities, corporate events, and merger arbitrage - all hedge fund styles which rely on the communication of trading strategies and probability assessments among hedge fund managers. Managers having worked at the same firm or in the same (financial) industry has an economically relevant impact on all aspects of investment. Abnormal returns (alpha), systematic risks (beta), and idiosyncratic risks (epsilon) are all more similar for managers connected through *Industry* and *Firm*. As expected, smaller hedge funds, where connected managers matter more for the investment strategy, exhibit larger effects. Results are robust to numerous fund level and managerial control variables. In particular, we define hiring climate as the overall net number of hires in the financial industry. High numbers indicate on average less skilled managers as more people find jobs; low numbers mean that only the most skilled managers can secure employment. Our results survive intact when controlling for this exogenous measure of average skill.

In terms of economic significance, we find that connections within the Pension fund and the Banking industry influence hedge fund alpha positively and significantly, while connections within the investment management industry reduce alpha significantly. Finally, investing in funds of most connected hedge funds and (hypothetically) shorting funds of least connected hedge funds delivers significant performance in terms of alpha, Sharpe ratio, and Information ratio.

1.9 Appendix

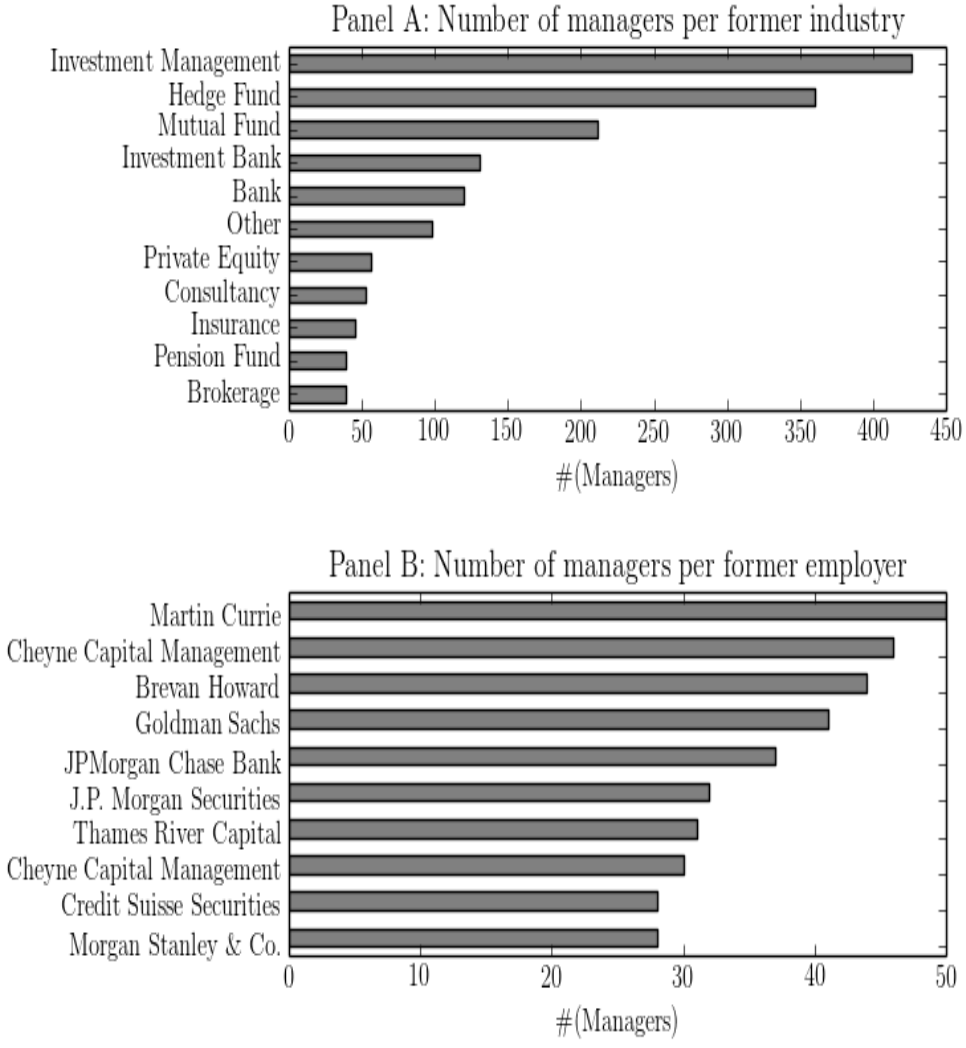
Table 1.7: Hedge Fund Data Representativeness

This table reports the regression of funds characteristics of the universe of hedge funds on a constant and an 'FSA' dummy for funds in the combined FSA data set that is used in our study. Variables definition follows from Table 1.1. 'Alive' is a dummy for funds that are alive by the end of the period. In parenthesis, we report t-statistics based on standard errors clustered on the level of the style and the managing company.

	MgmtFee (1)	PerfFree (2)	Age (3)	Leverage (4)	Aum (5)	Alive (6)
Constant	1.545***	18.170***	106.399***	0.373***	460.771	0.665***
	(47.53)	(65.45)	(51.51)	(14.77)	(2.53)	(39.09)
FSA	0.046	-0.819*	-6.824**	-0.057	-119.512	-0.006
	(1.17)	(-1.95)	(-2.46)	(-1.47)	(-0.54)	(-0.20)
Obs.	7,199	7,175	7,470	4,358	4,407	4,247
R-squared	0.001	0.003	0.002	0.002	0.000	0.000

Figure 1.1: Distribution of Prior Industries and Employers

Panel A displays the distribution of the number of managers by former employer industry, while Panel B displays the distribution of managers for the top-10 former employers in the data set.



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Chapter 2

Manager Alpha

2.1 Introduction

Traditionally, both practitioners and researchers, focus on the hedge fund when studying properties of returns, as opposed to, articles in the popular media which highlight the individual fund managers.[1] What are the ultimate drivers of abnormal returns?

If we adapt the view of a hedge fund as a firm producing a sole good (abnormal returns) we may come up with various different models for the production function. For example, Siegmann, Stefanova, and Zamojski (2013) group hedge funds by their institutional structure (fund details and assets the fund trades in). This renders the institutional setting behind the fund or the fund's managing company as the driving force behind abnormal returns. Most other studies focus on the fund (including its structure, as well as human capital and intellectual property). In this view, estimates of alpha are always a mixture of the institutional setting and the human capital within the fund.

Acknowledging that many hedge funds are managed by multiple managers over the course of their lifetime, or single managers manage multiple funds at the same time, this paper takes a complimentary stance on this issue and focuses on the human capital represented by the hedge fund manager. First, I ask whether alpha is a property of the hedge fund or the hedge fund *manager*. Acknowledging, that alpha is a property of both, the hedge fund, and the hedge fund manager, I investigate the effect of a turnover in management on the hedge fund's performance and fund flows. Finally, I study the drivers behind the probability of a turnover event.

Using a novel data set, which allows me to observe key employees of hedge funds domiciled in the UK, I am able to identify the exact periods at which a hedge fund is managed by a specific manager. This allows for the identification of managerial fixed effects. By showing that these fixed effects are highly significant in performance regressions, I provide first evidence for the importance of the individual hedge fund manager for producing alpha.

Next, I show that at the change of management there is a structural break in the intercept

[1] As an example, a headline in the Financial Times reads "Hedge fund manager Bill Ackman seizes 7.5% Mondelez stake", see: http://on.ft.com/1DsumCk

of the Fung and Hsieh (2004) seven factor model. I construct a panel model relating a fund's excess returns to a fund fixed effect and the seven factors proposed by Fung and Hsieh (2004). The factor exposure is allowed to vary across the funds and I account for a potential trend in the average abnormal returns using time fixed effects and control for a linear trend in average returns over a fund's lifetime, as well as potentially diminishing returns to scale. Dummy variables capture the effects of different periods on alpha. One dummy represents the period during which we can identify the manager and a second dummy represents the period after the manager has left. If the coefficients on these dummies are not equal to zero, there is evidence in favor of a structural break in alpha. According to an F-test, these dummy variables are significantly different from zero. Estimating a cross-sectional average effect for the two sets of dummy variables, I document a negative effect between -2.71% and -3.04% on annualized alpha whenever a manager leaves a fund. Conditioning on relative past performance reveals that this negative effect is driven by outperforming managers leaving. The departure of an outperforming manager (as defined by performing above the cross-sectional median of average returns before replacement) decreases annual alpha by -4.57%. Next, I study the implications of a change of management on fund flows. Consistent with existing evidence for mutual funds, I document an inverse relationship between past performance and future fund flows around a replacement event. I find that if an underperforming manager leaves, subsequent fund flows increase by 3.8%. If an outperforming manager is replaced, fund flows decrease by -1.9% on a monthly basis.

Finally, I focus on the determinants of a replacement event. Using a Probit model, I estimate probabilities of replacement conditional on the fund's age, assets under management, past performance, and past fund flows. I find that the probability of replacement increases with the age of the fund and is a concave function of the fund's past absolute performance.

The remainder of this paper proceeds by putting my contribution into context of the literature in Section 2.2. Section 2.3 describes the data set and the methodology to extract time series of returns associated with individual hedge fund managers. Besides, I present descriptive statistics for the data set. Section 2.4 presents evidence for the presence of a

managerial fixed effect, shows evidence for the existence of a structural break in alpha at the change of management, and estimates conditional probabilities of managerial turnover. Finally, Section 2.5 concludes.

2.2 Literature

This paper relates to literature on the management's role in the context of investment management and on the implications of management turnover on firm performance and policy. In the context of firms in general, Bertrand and Schoar (2003) are among the first to study the impact of a firm's management on performance and the firm's policy. Using panel regressions, similar to the ones employed in this paper, the authors document strong managerial fixed effects for both, a firm's performance and policy.

In the context of investment management, there is a growing literature on the relationship between the performance of investment funds and characteristics of the funds' managers. Golec (1996) finds that abnormal performance is larger for younger mutual fund managers with longer tenure at the fund and an MBA degree. Also studying mutual funds, Chevalier and Ellison (1999a) focus more directly on the mutual fund manager's ability, as proxied by the average SAT score of the manager's undergraduate university's students. They find a positive relationship between the manager's ability and mutual fund performance. Kempf, Manconi, and Spalt (2014), exploiting strategy-specific experience of mutual fund managers for identification, document a positive effect of experience on performance. Huang and Wang (2015) estimate manager-level fixed effects and find a positive relationship between a mutual fund manager's fixed effect and fund performance. Li, Zhang, and Zhao (2011) focus on characteristics of hedge fund managers. Their results are similar to the ones found for mutual funds. Namely, higher managerial ability (proxied using a similar method as applied by Chevalier and Ellison (1999a)) is associated with higher abnormal performance.

All these studies document significant explanatory power of mutual and hedge fund managers' characteristics for explaining abnormal performance of the funds. These studies pro-

vide a motivation for why we should care about differences between the fund's and the manager's ability to generate abnormal performance. Especially since the distinction between the manager and the fund seems to be even more pronounced for hedge funds than for mutual funds because of the entrepreneurial nature of a hedge fund business, as Li, Zhang, and Zhao (2011) argue. As opposed to mutual fund managers, hedge fund managers have much more freedom in shaping the investment strategy of the virtually unrestricted hedge fund. Therefore, we would expect the effect of the ability of an individual hedge fund manager on performance to be even stronger. This paper contributes to this literature by examining whether there is a manager-specific component in abnormal performance of a hedge fund and in this spirit is close to the work by Huang and Wang (2015), who focus on mutual funds.

The second strand of the literature this paper relates to focuses on the implications of managerial turnover on both, investors, and fund performance. Since I use the change of management to identify the time series of returns associated with the manager, my study closely relates to studies focusing on performance and fund flows around a replacement event. The major part of this literature studies the response of past or future fund flows and performance to turnover in management. Khorana (1996) is the first to study the relationship between past performance, portfolio turnover, expenses, and the replacement of mutual fund managers. In a follow-up paper, Khorana (2001) investigates the performance of mutual funds after the replacement event has taken place. He documents an inverse relationship between the probability of replacement and the performance of the manager. Besides, funds which underperformed have better performance after the replacement of the management and the replacement of outperforming managers leads to a decrease in performance. Chevalier and Ellison (1999b) show that managers take their individual replacement probability into account when making decisions. Younger managers take on less unsystematic risk as a response to their higher sensitivity of replacement probabilities to past abnormal performance. Wermers, Wu, and Zechner (2008) study the relationship between the replacement of mutual fund managers and closed-end fund discounts. They provide evidence suggesting

that investors anticipate changes of management. Huij, Lansdorp, and Verbeek (2012) find that investors react to the replacement of the management. They find that if a fund was outperforming and the manager is replaced fund flows decrease. Underperforming funds which replace the management have lower flows than their underperforming peers. Kostovetsky and Warner (2012) argue that this finding clashes with the rationality of investors. They study the effect of manager replacement for internally and externally managed mutual funds. By studying externally managed funds they argue that replacement is more likely of an involuntary nature. Using this sample they are able to identify a positive effect of replacement on future fund flows for underperforming funds. Jin and Scherbina (2011) use the managerial turnover event to study the disposition effect for mutual fund managers.
The existing literature focuses almost exclusively on the mutual fund industry when studying a manager's impact on performance and the implications of turnover events. Using a novel data set, this paper is the first to study these questions in the context of the hedge fund industry.

2.3 Data

In Section 2.3.1, I describe the steps to construct a combined data set which consists of data on performance, characteristics, and information on the work histories of the management of hedge funds. Section 2.3.2 discusses summary statistics for the data set.

2.3.1 Data Set Construction

The analysis is based on the intersection of two different data sources. Data on historical time series of hedge fund returns, assets under management, and characteristics are obtained by merging six hedge fund databases - BarclayHedge, CISDM, Eurekahedge, HFR, Morningstar, and TASS. Aggregating data from different database vendors is important to obtain a sufficiently complete coverage of the hedge fund industry, as Joenväärä, Kosowski, and Tolonen (2012) point out. I merge the data sets on the names of the hedge funds' managing

companies. Then, within every company I remove duplicates and different share classes of the same fund by grouping the funds by their correlations in returns (when two funds have a correlation coefficient above 0.99 they belong to the same group). Finally, within every group I keep the fund with the longest time series of returns. The merge results in a rather complete coverage of the publicly available hedge fund universe. The resultant data set consists of monthly information on 21,546 funds (9,146 management companies) ending in June, 2013. All six database vendors include delisted funds and are thus free of any survivorship bias.

Data on hedge funds is associated with various biases (Fung and Hsieh (2000)), stemming from the voluntary nature of reporting by the hedge funds to the database vendors. Additionally, hedge funds often undergo an incubation period in which they try to establish a track record and do not manage investors' money. In some databases hedge funds are allowed to back-fill one year of past performance when entering the database. Therefore, funds which do well enter the databases and back-fill one year of good performance and hedge funds which did not do well during their incubation period never make it into the databases in the first place. In general, this results in estimates of mean returns which are biased. To mitigate this effect I follow Kosowski, Naik, and Teo (2007) and drop the first 12 monthly observations of returns for every hedge fund. I drop funds with less than 24 months of return observations, reporting in any other currency than USD, and drop returns below -90% and above 300%.

For every hedge fund managing company, I collect employment histories for key employees through the Financial Services Register (FSR), which is distributed by the Financial Conduct Authority (FCA). In the UK, the FCA regulates the financial services industry. Among other information, the FCA collects information on all current and past employment relations for employees of hedge fund managing companies domiciled in the UK. The information relevant for my analysis is contained in the following items: the name of the hedge fund managing company; the employees' names and numeric IDs; start and end dates of the employment relationship. I extract information on all key employees within a hedge fund managing

company by matching the company names in the hedge fund databases on the company names in the FSR. This results in a sample of 633 unique managing companies, managing 2,520 hedge funds. From the subset of employees registered in the FSR and employed by the fund's corresponding managing company, I extract the employment records of the hedge fund manager by matching the name of the hedge fund manager, as registered in the hedge fund databases, on the names of the employees associated with the respective managing company in the FSR. Using this procedure, I focus on funds which are managed by a single manager and not by a team of managers. I am able to identify 143 distinct hedge fund managers. Since a manager can work in different regulatory positions within a management company (e.g. CEO, director), I define the first starting date and the last exit date of employment, regardless of the position, as the points in time defining the management period of the manager. I split the time series of every hedge fund into three disjoint periods. *Pre* is the period before the manager has entered the management company. *Mgr* is the period during which the manager is working at the management company, and *Post* is the period after the manager has left the firm. For every fund-manager pairing I extract the returns during the *Pre*, *Mgr*, and *Post* periods. Since the FSR data set starts in January 2002, I truncate the time series of hedge fund returns before January 2002 to make the samples of manager returns and fund returns comparable. The next Section (2.3.2) discusses descriptive statistics for the merged database and returns during the different subperiods.

2.3.2 Summary Statistics

Table 2.1 provides summary statistics for the merged data set. Panel A shows the number of hedge funds, managing companies, and the number of managers. In total, there are 2,520 hedge funds managed by 633 managing companies. I am able to identify 143 fund managers in the FSR data set. This results in 221 fund-manager pairings. On average a manager operates 1.55 hedge funds, not necessarily at the same time.

Table 2.1: Data Set Descriptive Statistics

This table reports summary statistics for the final data set used in the analysis. *Pre* is defined as the period before we can identify the manager. *Mgr* is the period when the manager registered in the hedge fund databases is employed at the managing company, as reported in the FSR. *Post* is the period after the manager has left. Fund level refers to the whole period which is equivalent to the union of *Pre*, *Mgr*, and *Post*. All subsets are extracted from a full sample ranging from January 2002 to June 2013. Panel A shows the number of hedge funds, managing companies, managers, and fund-manager pairings in the final data set. Panel B shows descriptive statistics for the distribution of the number of observations grouped by the different periods. Panel C depicts descriptive statistics on the time series of returns grouped by the different periods.

Panel A: Combined hedge fund - FSR database

Number of	Hedge Funds	Managing Companies	Managers	Fund-Manager Pairings
	2,520	633	143	221

Panel B: Distribution of number of observations

	Mean	Median	Std	Min	Max	Skew
Fund level	67.32	60	33.49	24	139	0.69
*Pre*pre	11.86	0	22.49	0	98	2.01
Mgr	47.23	39	34.17	0	139	0.71
Post	10.43	0	22.80	0	104	2.33

Panel C: Distribution of average returns

	Mean	Median	Std	Min	Max	Skew
Fund level	0.53	0.56	4.53	-90.00	221.06	1.04
Pre	0.85	0.79	4.01	-51.85	24.91	-0.72
Mgr	0.48	0.54	4.21	-86.25	63.14	-0.69
Post	0.32	0.39	4.79	-29.13	101.06	4.19

Panel B shows statistics for the distribution of the number of observations across the three different periods (*Pre*, *Mgr*, and *Post*). Changes in management are not very frequent in the hedge fund industry. More than half of the funds are managed by a single manager for the whole time. This can be seen by noting that the median number of observations is equal to zero for the *Pre* and *Post* periods. The average number of return observations before and after we can identify the manager are 11.86 and 10.43. On average there are 47.23 return observations for which we can identify the manager.

Panel C shows statistics for the returns during the periods. There is a pronounced downward trend in both the mean and the median of returns over the periods. The mean return during the *Pre* period is equal to 85 bps and drops to 32 bps during the *Post* period. A potential reason for this effect is a general downward trend in average returns combined with a higher propensity for returns from the later phase of the sample to belong to the *Mgr* and *Post* periods.

Table 2.2: Data Representativeness

This table reports estimates for a regression of fund characteristics, using the complete universe of hedge funds in the six databases reporting at least 24 months of return observations between January 2002 and June 2013, on a dummy variable (FSR) which is equal to one if the fund is present in the merged sample that is used in this study. The table shows estimates for the following dependent variables: management fee (MgmtFee); performance fee (PerfFee); time-series average of the age of the fund in months since first reporting to any database (Age), dummy variable for the use of leverage (Leverage); times-series average of the assets under management in millions (AuM). All data is extracted from January 2002 to June 2013. T-statistics, based on standard errors clustered at the level of the managing company, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	MgmtFee	PerfFee	Age	Leverage	AuM
FSR	-0.015	-0.017	-4.849	0.161***	-160.657
	(-0.33)	(-0.03)	(-1.55)	(3.24)	(-1.60)
Constant	1.512***	17.852***	56.481***	0.397***	335.094***
	(134.25)	(161.60)	(58.63)	(32.59)	(3.46)
Observations	13,004	13,045	13,558	8,300	8,841
R-squared	0.000	0.000	0.000	0.002	0.000

Table 2.2 shows estimates for a regression, using data for the whole universe of hedge funds reporting in USD and with more than 24 months of return observations between January 2002 and June 2013, of fund characteristics on a dummy variable which is equal to one if the fund is contained in the merged sample used in this study (FSR). Standard errors are clustered at the level of the managing company. I calculate time-series averages for time-varying variables (Age and AuM). The coefficient on the dummy variable captures the deviation in means between the sample of the whole hedge fund population and the merged sample used in this study. Funds in the merged sample are younger, smaller, and charge lower fees. However, none of these differences is statistically significant at the 10% level. Funds in the merged sample are by 16% more likely to employ leverage. This effect is statistically significant at the 1% level.

2.4 Empirical Analysis

To show that managers indeed matter for the generation of alpha, in the framework of a factor model, I estimate manager fixed effects and test whether these fixed effects are jointly significant. Having collected evidence in favor of the presence of a fixed effect tied to the manager, I study the implication of a change of management on a hedge fund's abnormal performance (alpha) and fund flows. Finally, I condition the observed changes in performance and fund flows on different potential drivers and estimate conditional probabilities of replacement.

2.4.1 Manager's Alpha or Fund's Alpha?

To test whether a fund's alpha is solely tied to the fund or if a manager's ability influences alpha, I test for the presence of manager-specific fixed effects. This approach is similar to the one applied by Bertrand and Schoar (2003). Identification of the manager fixed effects hinges on changes in management. If a manager only manages one fund and is present during the whole lifetime of the fund, the manager's fixed effect is collinear with the fund fixed effect.

I drop these manager fixed effects and only estimate the remaining 86 manager fixed effects which are identified by either, the manager not being present for the whole lifetime of the fund, and/or the manager managing multiple funds. I regress funds' monthly excess returns on the set of seven factors proposed by Fung and Hsieh (2004), manager fixed effects, and control variables to account for any other correlated drivers of abnormal returns:

$$xr_{i,t} = \alpha_i + \alpha_j^{Mgr} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \tag{2.1}$$

Where $xr_{i,t}$ is the net excess return of fund i at time t, α_i is a fund-specific fixed effect, β_i are the fund-specific factor loadings of fund i on the seven factors proposed by Fung and Hsieh (2004), denoted by X_t. To control for any industry-wide heterogeneity in average performance across time, I include a full set of monthly time dummies ($TIME_t$). Compatible with the theoretical model by Berk and Green (2004), there is evidence for a deterioration in performance over a fund's lifetime. Thus, if the manager fixed effect correlates with the age of a fund this may introduce a bias in the estimate of the manager fixed effects. I control for the age of the fund in terms of the number of years passed since the fund's first appearance in any database ($\text{Age}_{i,t}$). For a sample of mutual funds, Pastor, Stambaugh, and Taylor (2015) document diminishing returns to scale. Performance seems to be decreasing in the amount of assets under management. To make sure that this fact does not contaminate the results, I include the fund's assets under management ($\text{AuM}_{i,t}$) in millions USD. α_j^{Mgr} denotes the manager-specific fixed effect.

To test for the presence of manager fixed effects, I test for the joint significance of α_j^{Mgr} using an F-test. Table 2.3 shows estimation results for four specifications of model (2.1). Information on assets under management is only available for a subset of the sample, reducing the number of identifying changes of management to 41. Thus, I estimate the first three models without including the funds' assets under management. Row (1) shows estimates including fund and manager fixed effects and the set of Fung and Hsieh (2004) factors. A joint F-test on the manager fixed effects results in a test statistic equal to 1.89. The

Table 2.3: F-Tests for Manager Fixed Effects

This table shows test results of joint F-tests on the manager fixed effects in the following model:

$$xr_{i,t} = \alpha_i + \alpha_j^{Mgr} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t},$$

where $xr_{i,t}$ is the net excess return of fund i at time t, α_i is a fund-specific fixed effect, β_i are the factor loadings of fund i on the seven factors proposed by Fung and Hsieh (2004), denoted by X_t. α_j^{Mgr} denotes the manager-specific fixed effect. $\text{Age}_{i,t}$ denotes the age of the fund in terms of months passed since the appearance of the fund in any database. $\text{AuM}_{i,t}$ denotes the assets under management of the fund in millions. $TIME_t$ is a full set of monthly time dummies. Model (1) only includes fund fixed effects and the seven Fung and Hsieh (2004) factors. Model (2) adds the age of the fund, model (3) adds the age and time dummies, while row (4) includes the fund's assets under management (AuM). In the column "Manager Fixed Effects" the table shows the values of the test statistic for an F-test for the hypothesis of all manager fixed effects being jointly equal to zero. The corresponding p-value and the number of restrictions is displayed in parentheses. Columns "Age" and "AuM" show the estimated coefficient on the age and the assets under management of the fund and the corresponding t-statistics and p-values in parentheses.

	Manager Fixed Effects	Age	AuM	Time Dummies?	N
(1)	1.89 (0.00, 86)	-	-	No	15,365
(2)	1.81 (0.00, 85)	-0.0917 (-6.43, 0.00)	-	No	15,365
(3)	1.69 (0.00, 66)	-0.2496 (-0.52, 0.60)	-	Yes	15,365
(4)	2.38 (0.00, 41)	-0.6145 (-0.59, 0.55)	-0.0003 (-1.38, 0.17)	Yes	9,804

hypothesis of all manager fixed effects being jointly equal to zero is rejected at the 1% significance level. Row (2) includes the age of the fund as a control variable. Compatible with the theoretical model by Berk and Green (2004), the coefficient on the age of the fund is negative and statistically significant at the 1% level. This coefficient implies a decrease in monthly abnormal performance equal to 9.17 bps for every additional year the fund is alive. Controlling for age, the hypothesis of all manager fixed effects being jointly equal to zero is rejected at the 1% significance level with a test statistic equal to 1.81. Row (3) shows results for a model including time fixed effects. The significance of the manager fixed effects is robust to the inclusion of time fixed effects. However, the effect of age on abnormal performance turns statistically insignificant. When controlling for industry-wide trends in average abnormal performance, the age of a fund has no significant impact on abnormal performance. Row (4) shows estimates for a model including the fund's assets

under management. The test statistic for the hypothesis of the manager fixed effects being jointly equal to zero increases and the hypothesis is rejected at the 1% significance level. Besides, the coefficient on the assets under management has the expected negative sign but is not statistically significant. Thus, statistical significance of the managerial fixed effects does not seem to be an artifact of diminishing returns to scale.

There is statistical evidence for the presence of fixed effects tied to the manager. This result is robust to controlling for the fund's age and assets under management, as well as to the inclusion of time fixed effects. The manager fixed effects are identified by either managers managing multiple funds and/or the turnover of management. In undocumented tests, I verify that the fund-fixed effects are jointly significant, showing that the average abnormal performance of a fund is indeed a mixture of fund-level and manager-level performance. In the next Section, I investigate the turnover event in more detail and estimate models for the structural breaks in abnormal returns and fund flows.

2.4.2 Structural Breaks at the Change of Management

As stated above, the identification of the manager fixed effects hinges on a turnover in management or managers running multiple funds. A change in management induces a structural break in the time series of a fund's abnormal returns. In this Section, I focus on the unconditional and conditional magnitude of these structural breaks.

Khorana (1996, 2001) documents a relation between the replacement event of the management of mutual funds and past and future performance. Is there also an effect for hedge funds? I test for a structural break in the intercept of the Fung and Hsieh (2004) seven factor model at the change of management. The FSR data set allows me to identify the month in which the management of a hedge fund changes. Using the following panel model, I test for a structural break in the intercept (alpha) between the period before we can identify the manager (Pre) and the period in which we can identify the manager (Mgr), as well as

between the *Mgr* period and the period in which the manager has left the fund (*Post*):

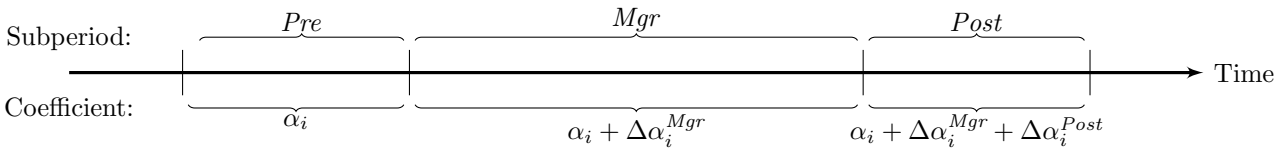
$$xr_{i,t} = \alpha_i + (Mgr_{i,t} + Post_{i,t})\Delta\alpha_i^{Mgr} + Post_{i,t}\Delta\alpha_i^{Post} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \tag{2.2}$$

$Mgr_{i,t}$ and $Post_{i,t}$ denote dummy variables being equal to one for the periods *Mgr* and *Post*. $\Delta\alpha_i^{Mgr}$ captures the incremental change of the fund-specific alpha from the *Pre* to the *Mgr* period. $\Delta\alpha_i^{Post}$ measures the incremental effect of a change from the *Mgr* to the *Post* period on top of the effect of the change from the *Pre* to the *Mgr* period. Figure 2.1 illustrates the timing of the three periods and the effect of the three coefficients ($\alpha_i, \Delta\alpha_i^{Mgr}$ and $\Delta\alpha_i^{Post}$). To account for any effects induced by the age of the fund or diminishing returns to scale, I include the age of the fund ($Age_{i,t}$) and the fund's assets under management in millions ($\text{AuM}_{i,t}$) as control variables. $TIME_t$ is a full set of time fixed effects, potentially capturing trends in alpha across the whole hedge fund industry. To allow for potential cross-sectional correlation in the residuals, I cluster the standard errors by time (see Petersen (2009)).

Figure 2.1: Timing of the periods and coefficients

This Figure shows the timing of the three subperiods: *Pre*, *Mgr*, and *Post*. The *Pre* period is defined as the period from the listing event of the hedge fund until the first start of a working relationship of the fund's manager. The *Mgr* period is the period between the first start and the last end of a working relationship between the fund's manager and the hedge fund's managing company. The *Post* period is defined as the period after the last working relationship has ended. The figure also illistrates the timing of the coefficients for the following regression:

$$xr_{i,t} = \alpha_i + (Mgr_{i,t} + Post_{i,t})\Delta\alpha_i^{Mgr} + Post_{i,t}\Delta\alpha_i^{Post} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}.$$



To test for a structural break in alpha at the change of management I test the following hypothesis:

$$H_0 : \Delta\alpha_i^{Mgr} = \Delta\alpha_i^{Post} = 0, \quad \forall i.$$

An F-test of hypothesis H_0 results in a test statistic equal to 11.82, corresponding to a p-value equal to 0.00. H_0 is clearly rejected, indicating the presence of at least one structural break at the change of management from *Pre* to *Mgr* or from *Mgr* to *Post*.
Testing the two individual hypotheses:

$$H_0^{Mgr} : \Delta\alpha_i^{Mgr} = 0, \quad \forall i,$$
$$H_0^{Post} : \Delta\alpha_i^{Post} = 0, \quad \forall i,$$

yields test statistics equal to 3.71 for H_0^{Mgr} and 6.06 for H_0^{Post}. Both test statistics correspond to p-values equal to 0.00. Both hypotheses being rejected at all conventional significance levels provides strong support for the presence of structural breaks at the change of management.
Having established that there exist structural breaks in the intercept of the factor model when the management changes, what is the average effect of a change of management on alpha? I estimate the following model:

$$\begin{aligned} xr_{i,t} = \quad & \alpha_i + (Mgr_{i,t} + Post_{i,t})\Delta\alpha^{Mgr} + Post_{i,t}\Delta\alpha^{Post} + \\ & X_t\beta_i + TIME_t + \mathrm{Age}_{i,t}\gamma + \mathrm{AuM}_{i,t}\delta + \varepsilon_{i,t}. \end{aligned} \tag{2.3}$$

$\Delta\alpha^{Mgr}$ and $\Delta\alpha^{Post}$ denote the average incremental effects of the periods *Mgr* and *Post* on fund-specific alpha (α_i). Again, standard errors are clustered by time allowing for cross-sectional correlation in the residuals.

Table 2.4: Model for structural breaks in $xr_{i,t}$

Columns (1), (2), (5), and (6) present estimates for the structural break model (2.3):

$$xr_{i,t} = \alpha_i + (Mgr_{i,t} + Post_{i,t})\Delta\alpha^{Mgr} + Post_{i,t}\Delta\alpha^{Post} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}.$$

I regress excess returns ($xr_{i,t}$) on a fund-specific intercept (α_i), the set of seven Fung and Hsieh (2004) factors (X_t) with fund-specific factor loadings (β_i), a set of time fixed effects ($TIME_t$), the age of the fund ($\text{Age}_{i,t}$) in years, the fund's assets under management ($\text{AuM}_{i,t}$) in millions, and dummy variables for the *Mgr* ($Mgr_{i,t}$) and *Post* ($Post_{i,t}$) periods. $\Delta\alpha^{Mgr}$ and $\Delta\alpha^{Post}$ measure the average incremental effect of the *Mgr* and *Post* periods on alpha. Columns (3), (4), (7), and (8) show estimates for model (2.4):

$$\begin{aligned} xr_{i,t} = \quad & \alpha_i + (Mgr_{i,t} + Post_{i,t})Pre_i^-\Delta\alpha^{Mgr-} + (Mgr_{i,t} + Post_{i,t})Pre_i^+\Delta\alpha^{Mgr+} \\ & + Post_{i,t}Mgr_i^-\Delta\alpha^{Post-} + Post_{i,t}Mgr_i^+\Delta\alpha^{Post+} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \end{aligned}$$

Columns (3) and (7) show estimates for Pre_i^- and Pre_i^+ being dummy variables equal to one if the fund's mean return was ranked below or above the cross-sectional median of all funds' mean returns during the *Pre* period. Columns (4) and (8) show results for a ranking of the funds according to the first and fourth quantile. Mgr_i^- and Mgr_i^+ are equal to one if the fund was ranked below or above the respective percentile during the *Mgr* period. T-statistics, based on standard errors clustered by time, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1) $xr_{i,t}$	(2) $xr_{i,t}$	(3) $xr_{i,t}$	(4) $xr_{i,t}$	(5) $xr_{i,t}$	(6) $xr_{i,t}$	(7) $xr_{i,t}$	(8) $xr_{i,t}$
$\Delta\alpha^{Mgr}$	-0.138	-0.253*			-0.328	-0.458**		
	(-0.802)	(-1.736)			(-1.368)	(-2.040)		
$\Delta\alpha^{Post}$	-0.171	-0.226			-0.548*	-0.597*		
	(-0.823)	(-1.151)			(-1.709)	(-1.938)		
$\Delta\alpha^{Mgr-}_{50\%}$			-0.016				-0.430	
			(-0.067)				(-1.584)	
$\Delta\alpha^{Mgr+}_{50\%}$			-0.381**				-0.499*	
			(-2.144)				(-1.884)	
$\Delta\alpha^{Post-}_{50\%}$			-0.131				-0.172	
			(-0.246)				(-0.181)	
$\Delta\alpha^{Post+}_{50\%}$			-0.350				-0.764**	
			(-1.616)				(-2.312)	
$\Delta\alpha^{Mgr-}_{25\%}$				0.121				-0.485
				(0.233)				(-1.105)
$\Delta\alpha^{Mgr+}_{25\%}$				-0.547***				-0.691**
				(-2.662)				(-2.100)
$\Delta\alpha^{Post-}_{25\%}$				-1.542				-1.082
				(-0.753)				(-0.500)
$\Delta\alpha^{Post+}_{25\%}$				-1.550***				-2.092***
				(-2.950)				(-3.137)
Age	-0.099***	-0.307***	0.180***	0.201***	-0.082**	-0.565***	722.655	738.016
	(-3.349)	(-8.209)	(3.152)	(3.506)	(-2.403)	(-4.555)	(0.221)	(0.234)
AuM					-0.000	-0.000	-0.000	-0.000
					(-0.985)	(-1.431)	(-1.394)	(-0.912)
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Beta	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	15,365	15,365	15,365	15,365	9,804	9,804	9,804	9,804
R-squared	0.338	0.402	0.406	0.408	0.332	0.386	0.390	0.392

Information on the funds' assets under management is only available for 64% of the observations in the sample. Thus, first I focus on regressions without controlling for the funds' assets under management. Columns (1) and (2) in Table 2.4 show estimates for model (2.3) without and with time fixed effects. Because of a pronounced downward trend in the returns over the sample period, I focus on the results shown in column (2), including the time fixed effects. The coefficient on the age of the fund has the expected negative sign (compatible with diminishing returns to scale, as proposed by Berk and Green (2004)) and is statistically significant at the 1% level. The *Mgr* period decreases monthly alpha by -25.3 bps. This effect is statistically significant at the 10% level. The *Post* period decreases alpha by -22.6 bps. However, the coefficient is not statistically significant. Thus, the total incremental effect of two changes of management (from *Pre* to *Mgr* and from *Mgr* to *Post*) on subsequent abnormal performance is in the magnitude of -47.9 bps monthly. This translates into an annualized effect equal to -5.7%. Noting that the average annualized alpha in the whole sample of hedge fund returns (before merging with the FSR register) is 2.76%, renders this effect economically sizable. The results are statistically weaker and point into the same direction if I do not account for the trend in average returns across the industry.

Columns (5) and (6) contain estimates of regressions controlling for the funds' assets under management. The sample size drops considerably but the documented effects are robust to the inclusion of the assets under management and statistically even stronger. Now, the effect of the transition from the *Mgr* to the *Post* period turns statistically significant at the 10% level and decreases annual alpha by -7.16%.

Studying mutual funds, Khorana (2001) finds that performance deteriorates whenever an outperforming manager leaves a fund and increases whenever an underperforming manager leaves. To investigate this issue for the sample of hedge funds I estimate the following model:

$$\begin{aligned} xr_{i,t} = \; & \alpha_i + (Mgr_{i,t} + Post_{i,t}) Pre_i^- \Delta\alpha^{Mgr-} + (Mgr_{i,t} + Post_{i,t}) Pre_i^+ \Delta\alpha^{Mgr+} \\ & + Post_{i,t} Mgr_i^- \Delta\alpha^{Post-} + Post_{i,t} Mgr_i^+ \Delta\alpha^{Post+} \\ & + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \end{aligned} \tag{2.4}$$

where Pre_i^- and Pre_i^+ are dummy variables equal to one if, during the *Pre* period, the fund's mean return was ranked below or above a certain cross-sectional percentile of all funds' mean returns. Mgr_i^- and Mgr_i^+ are equal to one if the fund was ranked below or above some percentile during the *Mgr* period. Thus, the coefficients on these interacted dummies ($\Delta\alpha^{Mgr-}$, $\Delta\alpha^{Mgr+}$, $\Delta\alpha^{Post-}$, and $\Delta\alpha^{Post+}$) capture the average incremental effect of a change of management conditional on the relative performance of the fund during the preceding period. I estimate the regressions for a ranking according to the fund ranking above or below the median ($\Delta\alpha_{50\%}^{\cdot+}$ and $\Delta\alpha_{50\%}^{\cdot-}$) and the upper and lower quantiles ($\Delta\alpha_{25\%}^{\cdot+}$ and $\Delta\alpha_{25\%}^{\cdot-}$). For example, $\Delta\alpha_{25\%}^{Post-}$ captures the incremental effect of a change of management from the *Mgr* to the *Post* period conditional on a relative underperformance of the fund (according to the fund ranking in the lower quantile of mean returns) during the *Mgr* period. Again, first, I discuss results for regressions not controlling for the assets under management and then proceed with showing that the findings are robust to the inclusion of the assets under management. Columns (3) and (4) show estimates for model (2.4) for the relative past performance according to the medians and quantiles. Surprisingly, for both specifications, the coefficient on the age of the fund turns positive and stays statistically significant at the 1% level. The effect ranges from an increase of 2.16% in annual abnormal performance to an increase of 2.41% for every additional year the fund is alive. Thus, it seems that once accounting for the conditional replacement of a fund manager the abnormal performance of hedge funds increases with the age of the funds. Column (3) shows estimates for a ranking based on the median. Only $\Delta\alpha_{50\%}^{Mgr+}$ is statistically significant at the 5% level. Whenever an outperforming manager (modeled as exhibiting above-median performance during the *Pre* period) leaves, a fund at the end of the *Pre* period subsequent performance during the *Mgr* period drops by -38.1 bps monthly. The direction of this effect is consistent with the findings by Khorana (2001) for mutual funds. The coefficient for the change of an outperforming manager from the *Mgr* to the *Post* period ($\Delta\alpha_{50\%}^{Post+}$) is not significant but of the same magnitude and direction (-35.0 bps). Column (4) shows results for rankings based on the quantiles. The basic results do not change but turn out even stronger. Whenever

an outperforming manager leaves, subsequent performance deteriorates significantly between -6.56% annually for the *Mgr* period and -18.60% annually for the *Post* period. The other conditional effects are not statistically significant. For this sample of hedge funds, I am not able to identify an improvement in performance once an underperforming manager leaves, as Khorana (2001) finds for mutual funds. Thus the deterioration of hedge fund performance after a turnover in management seems to be driven by the effect of the replacement of well-performing managers. This story is compatible with high search costs in the labor market for hedge fund managers, making it very costly and difficult to find a replacement of well-performing managers. Also, the proprietary nature of the hedge fund strategies might render it difficult for new managers to adapt to the environment in existing funds.

Columns (6), (7), and (8) repeat the regression results including the assets under management as a control variable. The effects are of larger magnitude and the statistical significance increases, rendering the conclusions robust to the inclusion of the funds' assets under management.

For mutual funds, Kostovetsky and Warner (2012) examine the effect of a change of management on subsequent fund flows. In order to study this issue for hedge funds, I explain fund flows by dummy variables for the changes of management, time fixed effects, the fund's age and assets under management:

$$FFLOW_{i,t} = F_i + (Mgr_{i,t} + Post_{i,t})\Delta F^{Mgr} + Post_{i,t}\Delta F^{Post} + TIME_t + \mathrm{Age}_{i,t} + \mathrm{AuM}_{i,t}\delta + \varepsilon_{i,t}, \tag{2.5}$$

where F_i denotes the fund-specific average fund flow. ΔF^{Mgr} and ΔF^{Post} denote the average responses of fund flow to a change of management at the end of the *Pre* and the *Mgr* period. The net fund flow (adjusted for fluctuations due to investment returns) is defined as:

$$FFLOW_{i,t} := \frac{AUM_{i,t} - AUM_{i,t-1}(1 + r_{i,t})}{AUM_{i,t-1}},$$

where $AUM_{i,t}$ denotes the assets under management of fund i at the end of period t. I winsorize the fund flow at the 1% level to mitigate the impact of outliers.

Table 2.5: Model for structural breaks in $FFLOW_{i,t}$

Columns (1) and (2) present estimates for the structural break model (2.5):

$$FFLOW_{i,t} = F_i + (Mgr_{i,t} + Post_{i,t})\Delta F^{Mgr} + Post_{i,t}\Delta F^{Post} + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}.$$

I regress fund flows ($FFLOW_{i,t}$) on a fund-specific intercept (α_i), the set of seven Fung and Hsieh (2004) factors (X_t) with fund-specific factor loadings (β_i), a set of time fixed effects ($TIME_t$), the age of the fund ($\text{Age}_{i,t}$) in years, the fund's assets under management ($\text{AuM}_{i,t}$) in millions, and dummy variables for the *Mgr* ($Mgr_{i,t}$) and *Post* ($Post_{i,t}$) periods. $\Delta\alpha^{Mgr}$ and $\Delta\alpha^{Post}$ measure the average incremental effect of the *Mgr* and *Post* periods on alpha. Columns (3) and (4) show estimates for model (2.6):

$$\begin{aligned} FFLOW_{i,t} = \quad & F_i + (Mgr_{i,t} + Post_{i,t})Pre_i^{-}\Delta F^{Mgr-} + (Mgr_{i,t} + Post_{i,t})Pre_i^{+}\Delta F^{Mgr+} \\ & + Post_{i,t}Mgr_i^{P}\Delta F^{Post-} + Post_{i,t}Mgr_i^{+}\Delta F^{Post+} + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \end{aligned}$$

Column (3) shows estimates for Pre_i^{-} and Pre_i^{+} being dummy variables equal to one if the fund's mean return was ranked below or above the cross-sectional median of all funds' mean returns during the *Pre* period. Column (4) shows results for a ranking of the funds according to the first and fourth quantile. Mgr_i^{-} and Mgr_i^{+} are equal to one if the fund was ranked below or above the respective percentile during the *Mgr* period. T-statistics, based on standard errors clustered by time, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1) $FFLOW_{i,t}$	(2) $FFLOW_{i,t}$	(3) $FFLOW_{i,t}$	(4) $FFLOW_{i,t}$
ΔF^{Mgr}	-0.007	-0.001		
	(-0.958)	(-0.146)		
ΔF^{Post}	0.012**	0.011*		
	(2.227)	(1.888)		
$\Delta F_{50\%}^{Mgr-}$			0.002	
			(0.228)	
$\Delta F_{50\%}^{Mgr+}$			-0.004	
			(-0.504)	
$\Delta F_{50\%}^{Post-}$			0.038***	
			(2.679)	
$\Delta F_{50\%}^{Post+}$			0.000	
			(0.041)	
$\Delta F_{25\%}^{Mgr-}$				0.021
				(1.133)
$\Delta F_{25\%}^{Mgr+}$				-0.019**
				(-2.276)
$\Delta F_{25\%}^{Post-}$				-0.012
				(-0.543)
$\Delta F_{25\%}^{Post+}$				-0.011
				(-1.252)
Age	-0.006***	-0.003	-0.002	-0.000
	(-8.084)	(-1.482)	(-1.235)	(-0.208)
AuM	0.000***	0.000***	0.000***	0.000***
	(4.400)	(5.078)	(5.141)	(5.258)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	Yes	Yes
N	9,627	9,627	9,627	9,627
R-squared	0.049	0.080	0.082	0.081

Table 2.5 shows estimates for model (2.5). As opposed to the estimates for returns, the number of observations are reduced by roughly one third due to only a reduced number of funds reporting information on assets under management. Column (1) shows estimates without time fixed effects. Only the effect of the change from the *Mgr* to the *Post* period is statistically significant at the 5% level and increases fund flows by 1.2% monthly. Column (2) shows estimates including time fixed effects and the statistical significance of this effect drops to the 10% level. Thus, there seems to exist a small unconditional effect of a change of management on future fund flows which is robust to the inclusion of time fixed effects. Kostovetsky and Warner (2012) identify an increase in fund flow after an underperforming external mutual fund manager leaves. To test this hypothesis for the sample of hedge funds I estimate the following model:

$$\begin{aligned} FFLOW_{i,t} = \; & F_i + (Mgr_{i,t} + Post_{i,t}) Pre_i^- \Delta F^{Mgr-} + (Mgr_{i,t} + Post_{i,t}) Pre_i^+ \Delta F^{Mgr+} \\ & + Post_{i,t} Mgr_i^P \Delta F^{Post-} + Post_{i,t} Mgr_i^+ \Delta F^{Post+} \\ & + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \end{aligned} \tag{2.6}$$

Analogous to the performance regressions, the coefficients on the interacted dummies (ΔF^{Mgr-}, ΔF^{Mgr+}, ΔF^{Post-}, and ΔF^{Post+}) capture the incremental effect of a replacement of the management on subsequent fund flows conditional on the ranking with respect to the relative past performance. Columns (3) and (4) show estimates for the conditional model (2.6) for the median and the quantile. Column (3) shows estimates for model (2.6) for the ranking of the funds' past performance according to the median. Consistent with the findings by Kostovetsky and Warner (2012) for mutual funds managed by external managers, an underperforming manager who leaves between the *Mgr* and the *Post* period increases subsequent fund flows by 3.8% monthly. This effect is statistically significant at the 1% level. Column (4) shows the estimate for a ranking based on the quantiles of past performance. Whenever an outperforming manager leaves between the *Mgr* and the *Post* period future fund flows decrease by -1.9% monthly. This effect is statistically significant at the 5% level. To summa-

rize, there is evidence in favor of investors paying attention to the turnover in management. Fund flows seem to increase if an underperforming manager is replaced, while fund flows decrease if an outperforming manager is replaced. These results are broadly in line with the findings of Kostovetsky and Warner (2012).

Consistent with the study by Jin and Scherbina (2011), there might exist a disposition effect for hedge fund managers. Hedge fund managers might hold on to losing positions for too long and a change of management might induce a sell-off of these losing positions. Due to illiquidity or price-pressure effects this might contaminate the results for returns and fund flows and bias estimates on the average incremental effects of a change of management discussed in Section 2.4.2. To make sure that results are not driven by a potential disposition effect, I exclude observations associated with the subsequent quarter of monthly returns and fund flows following a change of management. The Tables 2.6 and 2.7 show the results for a structural break in excess returns ($xr_{i,t}$) and fund flows ($FFLOW_{i,t}$). Likely, because of the decrease in the number of observations, the results weaken statistically but do not change qualitatively.

The *Pre* and *Post* periods contain on average 11.86 and 10.43 return observations. Therefore, I refrain from testing for the presence of a structural break in the funds' factor loadings from the *Pre* to the *Mgr* period and from the *Mgr* to the *Post* period since for more than half of all the fund-manager pairings the model would not be identified when we interact the fund-specific factor loadings with the *Mgr* and *Post* periods.

Having found an effect of managerial turnover on future performance I now turn to the question whether the replacement event is assigned randomly. In the following Section, I estimate the probability of replacement conditional on past performance and fund flow.

Table 2.6: Model for structural breaks in $xr_{i,t}$, excluding the subsequent quarter

Excluding the subsequent quarter after the replacement of management, columns (1), (2), (5), and (6) present estimates for the structural break model (2.3):

$$xr_{i,t} = \alpha_i + (Mgr_{i,t} + Post_{i,t})\Delta\alpha^{Mgr} + Post_{i,t}\Delta\alpha^{Post} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}.$$

I regress excess returns ($xr_{i,t}$) on a fund-specific intercept (α_i), the set of seven Fung and Hsieh (2004) factors (X_t) with fund-specific factor loadings (β_i), a set of time fixed effects ($TIME_t$), the age of the fund ($\text{Age}_{i,t}$) in years, the fund's assets under management ($\text{AuM}_{i,t}$) in millions, and dummy variables for the *Mgr* ($Mgr_{i,t}$) and *Post* ($Post_{i,t}$) periods. $\Delta\alpha^{Mgr}$ and $\Delta\alpha^{Post}$ measure the average incremental effect of the *Mgr* and *Post* periods on alpha. Columns (3), (4), (7), and (8) show estimates for model (2.4):

$$\begin{aligned} xr_{i,t} = \quad & \alpha_i + (Mgr_{i,t} + Post_{i,t})Pre_i^-\Delta\alpha^{Mgr-} + (Mgr_{i,t} + Post_{i,t})Pre_i^+\Delta\alpha^{Mgr+} \\ & + Post_{i,t}Mgr_i^-\Delta\alpha^{Post-} + Post_{i,t}Mgr_i^+\Delta\alpha^{Post+} + X_t\beta_i + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \end{aligned}$$

Columns (3) and (7) show estimates for Pre_i^- and Pre_i^+ being dummy variables equal to one if the fund's mean return was ranked below or above the cross-sectional median of all funds' mean returns during the *Pre* period. Columns (4) and (8) show results for a ranking of the funds according to the first and fourth quantile. Mgr_i^- and Mgr_i^+ are equal to one if the fund was ranked below or above the respective percentile during the *Mgr* period. T-statistics, based on standard errors clustered by time, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1) $xr_{i,t}$	(2) $xr_{i,t}$	(3) $xr_{i,t}$	(4) $xr_{i,t}$	(5) $xr_{i,t}$	(6) $xr_{i,t}$	(7) $xr_{i,t}$	(8) $xr_{i,t}$
$\Delta\alpha^{Mgr}$	-0.099	-0.243			-0.213	-0.403		
	(-0.523)	(-1.461)			(-0.788)	(-1.503)		
$\Delta\alpha^{Post}$	-0.138	-0.122			-0.562	-0.511		
	(-0.570)	(-0.533)			(-1.511)	(-1.438)		
$\Delta\alpha^{Mgr-}_{50\%}$			-0.095				-0.202	
			(-0.502)				(-0.717)	
$\Delta\alpha^{Mgr+}_{50\%}$			-0.327				-0.507	
			(-1.618)				(-1.638)	
$\Delta\alpha^{Post-}_{50\%}$			-0.015				-0.464	
			(-0.025)				(-0.428)	
$\Delta\alpha^{Post+}_{50\%}$			-0.228				-0.566	
			(-0.974)				(-1.580)	
$\Delta\alpha^{Mgr-}_{25\%}$				-0.247				-0.351
				(-0.752)				(-0.766)
$\Delta\alpha^{Mgr+}_{25\%}$				-0.542**				-0.685*
				(-2.474)				(-1.828)
$\Delta\alpha^{Post-}_{25\%}$				-1.011				-1.075
				(-0.426)				(-0.429)
$\Delta\alpha^{Post+}_{25\%}$				-1.428**				-1.812**
				(-2.433)				(-2.475)
Age	-0.092***	0.167***	0.178***	0.203***	-0.061*	1452.873	1460.697	1444.150
	(-2.969)	(3.711)	(3.687)	(4.208)	(-1.795)	(0.456)	(0.399)	(0.429)
AuM					-0.000	-0.000	-0.000	-0.000
					(-0.978)	(-1.419)	(-1.389)	(-0.976)
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Beta	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	15,365	15,365	15,365	15,365	9,804	9,804	9,804	9,804
R-squared	0.338	0.402	0.406	0.408	0.332	0.386	0.390	0.392

Table 2.7: Model for structural breaks in $FFLOW_{i,t}$, excluding the subsequent quarter

Excluding the subsequent quarter after the replacement of management, columns (1) and (2) present estimates for the structural break model (2.5):

$$FFLOW_{i,t} = F_i + (Mgr_{i,t} + Post_{i,t})\Delta F^{Mgr} + Post_{i,t}\Delta F^{Post} + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}.$$

I regress fund flows ($FFLOW_{i,t}$) on a fund-specific intercept (α_i), the set of seven Fung and Hsieh (2004) factors (X_t) with fund-specific factor loadings (β_i), a set of time fixed effects ($TIME_t$), the age of the fund ($\text{Age}_{i,t}$) in years, the fund's assets under management ($\text{AuM}_{i,t}$) in millions, and dummy variables for the *Mgr* ($Mgr_{i,t}$) and *Post* ($Post_{i,t}$) periods. $\Delta\alpha^{Mgr}$ and $\Delta\alpha^{Post}$ measure the average incremental effect of the *Mgr* and *Post* periods on alpha. Columns (3) and (4) show estimates for model (2.6):

$$\begin{aligned} FFLOW_{i,t} = \quad & F_i + (Mgr_{i,t} + Post_{i,t})Pre_i^{-}\Delta F^{Mgr-} + (Mgr_{i,t} + Post_{i,t})Pre_i^{+}\Delta F^{Mgr+} \\ & + Post_{i,t}Mgr_i^{P}\Delta F^{Post-} + Post_{i,t}Mgr_i^{+}\Delta F^{Post+} + TIME_t + \text{Age}_{i,t}\gamma + \text{AuM}_{i,t}\delta + \varepsilon_{i,t}. \end{aligned}$$

Column (3) shows estimates for Pre_i^{-} and Pre_i^{+} being dummy variables equal to one if the fund's mean return was ranked below or above the cross-sectional median of all funds' mean returns during the *Pre* period. Column (4) shows results for a ranking of the funds according to the first and fourth quantile. Mgr_i^{-} and Mgr_i^{+} are equal to one if the fund was ranked below or above the respective percentile during the *Mgr* period. T-statistics, based on standard errors clustered by time, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1) $FFLOW_{i,t}$	(2) $FFLOW_{i,t}$	(3) $FFLOW_{i,t}$	(4) $FFLOW_{i,t}$
ΔF^{Mgr}	0.000	0.008		
	(0.001)	(1.152)		
ΔF^{Post}	0.016***	0.013**		
	(2.694)	(2.041)		
$\Delta F^{Mgr-}_{50\%}$			0.021**	
			(2.163)	
$\Delta F^{Mgr+}_{50\%}$			0.001	
			(0.101)	
$\Delta F^{Post-}_{50\%}$			0.024*	
			(1.713)	
$\Delta F^{Post+}_{50\%}$			0.006	
			(0.888)	
$\Delta F^{Mgr-}_{25\%}$				0.040**
				(2.377)
$\Delta F^{Mgr+}_{25\%}$				-0.018**
				(-2.113)
$\Delta F^{Post-}_{25\%}$				-0.034
				(-1.474)
$\Delta F^{Post+}_{25\%}$				-0.013
				(-1.411)
Age	-0.006***	-0.005***	-0.004**	-0.002
	(-7.104)	(-2.785)	(-2.234)	(-0.927)
AuM	0.000***	0.000***	0.000***	0.000***
	(4.416)	(5.020)	(5.102)	(5.141)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	Yes	Yes
N	8,901	8,901	8,901	8,901
R-squared	0.049	0.083	0.084	0.084

2.4.3 Determinants of Replacement

In this Section, I aim to shed light on the drivers of a manager's replacement event. There exist different potential reasons for a manager to leave. Results could have been disappointing, leading to a forced replacement of the manager. Other potential reasons are that the manager did well and has very good outside opportunities or retires, rendering the leave voluntary. Lastly, the replacement event could be assigned randomly. Brown, Goetzmann, and Park (2001) model the exit event of a hedge fund as a function of past performance, risk, age, and a linear time trend. They find that the conditional probability of delisting is lower for older, less risky funds which have high relative and absolute performance. This points into the direction of a forced replacement of the management.

For a story centering around the forced replacement of the management because of disappointing results, we would expect the replacement probability to be decreasing in past performance and fund flows. If changes in management are mostly induced by managers leaving for better opportunities, past performance and flows in the right tail of the cross-sectional distribution should increase the replacement probabilities. If both effects are at play we would expect a convex relationship between past performance and flows and the probability of management turnover.

I categorize every beginning and every end of a work relationship as a replacement/exit event. Thus, the events occur at the transitions from the *Pre* to the *Mgr* and from the *Mgr* to the *Post* periods. Using the following Probit model, I estimate the conditional replacement probability as a function of absolute and relative past performance, fund flow, assets under management, and age:

$$\begin{aligned} P(\text{Replacement}) = \; & \Phi(\alpha + xr_{t-T,t}\beta_{xr} + \text{rank}_{t-T,t}\beta_{\text{rank}} + FFLOW_{t-T,t}\beta_{FFLOW} \\ & + \text{Age}_{i,t}\beta_{\text{Age}} + \text{AuM}_{i,t}\beta_{\text{AuM}}). \end{aligned} \tag{2.7}$$

For a specific time window T (3, 6, and 12 months), I include the fund's past average excess returns ($xr_{t-T,t}$), the percentage cross-sectional rank of the fund's average excess returns

($\text{rank}_{t-T,t}$), the past average fund flow ($FFLOW_{t-T,t}$), the age of the fund ($\text{Age}_{i,t}$), and the fund's assets under management ($\text{AuM}_{i,t}$) as explanatory variables. As mentioned in the previous paragraph, the shape of the relationship between past performance, flows, and replacement probabilities might be non-linear. To account for these effects, I include squared terms of past performance and flows.

Table 2.8 shows estimation results for the Probit model for various specifications. Column (1) includes past relative and absolute performance, as well as fund flows measured over the previous quarter. Column (2) adds squared terms of past performance and fund flows. Conflicting with the evidence provided by Brown, Goetzmann, and Park (2001), the fund's age seems to have a positive impact (significant at the 5% level) on the replacement probability. The coefficient on the past average performance has the expected negative sign (the higher the performance the lower the probability of replacement) but is not statistically significant. The squared terms are not statistically significant. Column (3) shows estimates for a window length equal to 6 months. Column (4) includes squared terms and the coefficient on the average past performance over the previous six months turns significantly negative at the 10% level. The age of the fund still has a positive effect on the replacement probability. Columns (5) and (6) show the results for a window length equal to 12 months. In general, the qualitative results do not change. Columns (7) and (8) show a joint Probit regression including the average performance and fund flows over all window lengths without and with squared terms. The only significant coefficients are the ones on absolute past performance over a window length equal to 6 months. Both, the linear and the squared term are significant at the 10% level and point towards a decreasing and (weakly) concave relationship between past absolute performance and the replacement probability. This points towards forced replacement being the dominating driver. There is evidence for the probability of replacement to increase over a fund's lifetime. This paints the picture of replacement events being driven mostly by involuntary turnover resulting from poor past performance. These decisions tend to be made on the basis of the past 6 months of returns. Fund Flows do not seem to matter for the probability of managerial replacement.

Table 2.8: Probit model for the replacement of the management cont.

This Table shows estimation results for the following Probit model:

$$P(\text{Replacement}) = \Phi(\alpha + xr_{t-T,t}\beta_{xr} + \text{rank}_{t-T,t}\beta_{\text{rank}} + FFLOW_{t-T,t}\beta_{FFLOW} + \text{Age}_{i,t}\beta_{\text{Age}} + \text{AuM}_{i,t}\beta_{\text{AuM}}).$$

I model the probability of a replacement event as a function of past average excess returns ($xr_{t-\Delta,t}$), past average cross-sectional ranks of fund excess returns ($\text{rank}_{t-\Delta,t}$), and past average fund flows ($FFLOW_{t-\Delta,t}$) over window lengths (Δ) equal to 3, 6, and 12 months. Age is the age of the fund in terms of the number of years since the fund's first appearance in any database. $\text{AuM}_{i,t}$ denote the fund's assets under management in millions. The replacement event is defined as the transition from the *Pre* to the *Mgr* period or from the *Mgr* to the *Post* period. T-statistics appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$xr_{t-3,t}$	-0.025	-0.025					0.000	-0.008
	(-1.471)	(-1.225)					(0.008)	(-0.272)
$\text{rank}_{t-3,t}$	0.239	0.481					0.251	0.941
	(1.265)	(0.800)					(0.949)	(1.163)
$FFLOW_{t-3,t}$	0.000	0.000					0.000	0.000
	(0.283)	(0.268)					(0.397)	(0.488)
$xr_{t-6,t}$			-0.040	-0.069*			-0.064	-0.122*
			(-1.641)	(-1.855)			(-1.315)	(-1.911)
$\text{rank}_{t-6,t}$			0.094	0.144			-0.220	-0.504
			(0.475)	(0.234)			(-0.666)	(-0.554)
$FFLOW_{t-6,t}$			0.000	0.000			-0.000	-0.000
			(0.139)	(0.035)			(-0.670)	(-0.754)
$xr_{t-12,t}$					-0.040	-0.040	0.033	0.047
					(-1.023)	(-0.914)	(0.572)	(0.790)
$\text{rank}_{t-12,t}$					0.116	-0.140	0.120	-0.255
					(0.531)	(-0.216)	(0.404)	(-0.309)
$FFLOW_{t-12,t}$					0.000	0.000	0.000	0.000
					(0.482)	(0.374)	(0.782)	(0.569)
$xr^2_{t-3,t}$		-0.000						0.002
		(-0.037)						(1.445)
$\text{rank}^2_{t-3,t}$		-0.238						-0.675
		(-0.411)						(-0.870)
$FFLOW^2_{t-3,t}$		-0.000						-0.000
		(-0.047)						(-0.287)
$xr^2_{t-6,t}$				-0.004				-0.014*
				(-1.014)				(-1.917)
$\text{rank}^2_{t-6,t}$				0.076				0.552
				(0.125)				(0.634)
$FFLOW^2_{t-6,t}$				0.000				0.000
				(0.004)				(0.094)
$xr^2_{t-12,t}$						-0.001		0.006
						(-0.107)		(0.786)
$\text{rank}^2_{t-12,t}$						0.274		0.332
						(0.420)		(0.411)
$FFLOW^2_{t-12,t}$						0.000		0.000
						(0.695)		(0.439)
Age	0.021**	0.021**	0.019*	0.020*	0.017	0.017	0.017	0.017
	(2.039)	(2.051)	(1.804)	(1.822)	(1.423)	(1.419)	(1.475)	(1.416)
AuM	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(-0.254)	(-0.236)	(-0.076)	(0.020)	(-0.386)	(-0.555)	(-0.163)	(-0.046)
N	9,292	9,292	8,688	8,688	7,637	7,637	7,637	7,637

2.5 Conclusion

A question of practical and academic importance is whether investors should focus on the individual hedge fund or the hedge fund *manager* when making their investment decisions. In Section 2.4.1 I show that there exists a manager fixed effect in the average abnormal performance of hedge funds. Alpha is not solely a property of the hedge fund but is a mixture of the alpha of the hedge fund and the hedge fund manager.

As I show in Section 2.4.2, the change of management induces a structural break in alpha. On average, performance deteriorates after a change of management. Conditioning on previous performance reveals an inverse relationship between past performance and subsequent performance. Whenever an outperforming manager leaves, future performance decreases. Consistent with existing evidence for mutual funds, fund flows increase once an underperforming manager leaves and decrease once an outperforming manager leaves.

Section 2.4.3 documents a negative and concave relationship between the probability of a manager's replacement event and performance over the previous six months.

These findings have important implications for the investment decision of hedge fund investors. Investors should not only focus on the fund's ability to generate abnormal returns but also factor in the influence of the manager. Hedge fund investors facing the question whether to invest, or potentially stay invested, after the replacement of the management of a hedge fund should consider the past track record of the leaving manager.

Going forward, repeating the study for a sample of non-UK hedge fund managers could increase the number of observations. Potentially, this would enable us to study whether there also exist structural breaks in the factor loadings at the change of a hedge fund's management.

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Chapter 3

Hedge Fund Investors

3.1 Introduction

This paper studies the realized performance and investment objectives of different classes of hedge fund investors, as well as potential influences the investors exert on the fund managers' strategies.

There is an enormous body of literature focusing on the question whether hedge funds are worth their fees and are able to deliver abnormal performance (Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2000), Liang (2000), Kosowski, Naik, and Teo (2007)). The consensus evolves along the lines of some hedge funds being able to consistently outperform the market. However, this result holds for the average hedge fund investor who has no preference for specific fund characteristics and does not engage in any market timing activity. Few studies take the presence of different groups of investors into account. Potential hedge fund investors include high net worth individuals, pension funds, sovereign wealth funds, charities, insurance companies, asset managers, to name a few. Most likely, these types of investors differ strongly in their investment objectives and degree of sophistication. This paper demonstrates that, indeed, the universe of potential hedge fund investors is heterogeneous. Existing evidence on investment returns in the hedge fund industry do not necessarily translate to every group of investors. Hedge fund investments by different classes of investors differ in their realized performance. Besides, I present evidence compatible with hedge fund investors exerting influence on the hedge fund managers to align the managers' strategies with the investors' objectives.

Using a sample of Form ADV filings and data on hedge fund performance and characteristics, I estimate the performance which different classes of investors realize. I differentiate between the following classes of investors: Individuals (other than high net worth individuals); High net worth individuals; Banking and thrift institutions; Investment companies; Business development companies; Pension and profit sharing plans (but not the plan participants); Charitable organizations; Corporations or other businesses not listed above; State or municipal government entities; Other investment advisers; Insurance companies.

In the first part of this study, I employ cross-sectional and panel regressions in order to

estimate the raw, abnormal, and risk-adjusted performance the groups of investors realize. I find that Corporations or other businesses tend to earn larger raw returns than other investment companies. However, this outperformance can be attributed to systematic risk factors and fund-level characteristics. The hedge fund investments by Banking or thrift institutions perform poorly in terms of raw returns, as well as in terms of abnormal returns. This result is robust to the inclusion of fund-level control variables. An increase in the holding of Banking or thrift institutions by 10% decreases annual abnormal returns by -0.83%. To account for differences in the attitudes towards risk among the investors, I study risk-adjusted performance measures. Hedge fund investments by Banking or thrift institutions underperform on a risk-adjusted basis. An increase by 10% in the holding of Banking or thrift institutions decreases the annualized Sharpe Ratio by -0.12. State or municipal government entities realize a larger risk-adjusted performance, corresponding to an increase by 0.19 in the annual Sharpe Ratio for an increase by 10% in the holding of State or municipal government entities. In the second part of this study, I estimate the revealed investment objectives of the classes of investors. By regressing the relative size of the investors' allocations to different funds on fund characteristics, I document heterogeneity in the preferences across the groups of investors. Charities and High net worth individuals prefer smaller funds and are more sensitive to the size of the management fee. Corporations or other businesses are more willing to pay higher fees and tend to invest into larger funds. Insurance companies back younger funds, while High net worth individuals prefer older, more established funds. State or municipal government entities prefer funds which are less risky. Charities are more likely to invest into funds which have a high-water mark in place.

In the third part of this study, I investigate whether investors not only differ in the funds they choose but also shape the funds' investment strategies. Using a methodology similar to a classical difference in differences estimation, I study the implications of changes in the holdings by the classes of investors on performance measures and the standard deviation of monthly returns, as a proxy for the risk-taking behavior of the fund manager. An increase by 10% in the investment by Individuals, Pension and profit sharing plans, Other investment

advisers, or Insurance companies decreases the monthly standard deviation of the funds' returns over the subsequent periods by between -0.16 and -0.20. An increase in the holding of Banking or thrift institutions leads to an increase in the exposure to systematic factors and a decrease in abnormal performance. Unfortunately, this part of the analysis is prone to endogeneity concerns and I cannot rule out any reverse causality.

The paper is organized as follows: Section 3.2 summarizes the literature on the realized performance of different investors and investor preferences. Section 3.3 describes the construction of the data set and provides descriptive statistics. Section 3.4 focuses on the performance the different classes of investors realize. In Section 3.5, I estimate the investment objectives and preferences of different classes of investors. Section 3.6 studies the effect of changes in the investor structure on the investment policy and performance of the hedge funds under consideration. Section 3.7 discusses the robustness of the results found in Section 3.5. Section 3.8 concludes.

3.2 Literature

The literature directly focusing on heterogeneity in realized performance across classes of investors is very limited. Most studies treat investors in certain asset classes as a homogeneous group and focus on heterogeneity in performance across asset classes. Up to my knowledge, there is no paper focusing on the realized performance different classes of investors realize in their hedge fund investments.

Focusing on equity investments, Bogle and Twardowski (1980) are the first to analyze the average performance realized by different types of institutional investors. The authors distinguish between the performance of equity investments by banks, investment counselors, insurance companies, and mutual funds. The authors find evidence for mutual funds outperforming other classes of investors. Lerner, Schoar, and Wongsunwai (2007) focus on differences in realized performance across different classes of private equity investors. They find that private equity investments by endowment funds outperform the average private

equity investment by 21% annually. Hooke and Walters (2015) study the performance of private equity and hedge fund investments by state pension funds. They find a relative underperformance of the funds the states invest in.

A second strand of the literature this paper is related to, is the literature on the investment objectives of different types of investors. Gerakos, Linnainmaa, and Morse (2015) focus on the demand for asset management services by institutional investors. They document a demand for exposure to systematic factors which clashes with the popular notion that providing exposure to systematic factors does not warrant fees. Bennett, Sias, and Starks (2003) study the demand for small cap stocks by different classes of institutional investors. They find an increasing trend in the demand for small cap stocks by institutional investors over time. Berk and van Binsbergen (2016) employ a revealed preferences approach to determine which model investors employ to value equity securities.

3.3 Data

The data set consists of a merge of hedge fund data, obtained from two data providers, and mandatory Form ADV filings obtained from the SEC. In the following, I provide descriptive statistics on the individual data sources and describe the merging procedures, as well as the filtering techniques.

3.3.1 Hedge Fund Data

Joenväärä, Kosowski, and Tolonen (2012) note that in order to obtain a complete coverage of the hedge fund industry it is crucial to not only rely on a single data source but to construct a merged data set consisting of data provided by different sources. To obtain a sample which is as complete as possible, I merge the BarclayHedge and Eurekahedge commercial hedge fund data bases. These data bases include time-series information on the hedge funds' returns and assets under management. Besides, the data bases track static information on various fund characteristics. I extract the following information, with the

names of the variables in parentheses: raw net returns (Return); assets under management (AuM); age of the fund defined as the number of months passed since the first reported return observation (age); management fee (mgmtFee); performance fee (perfFee); the length of the lockup period in days (lockupPeriod); a dummy variable indicating the presence of a high-water mark (HWM); a dummy variable indicating the use of leverage (leverage); a dummy variable indicating whether the fund is classified as a fund of hedge funds (FOF). To avoid including duplicates of the same fund I standardize the names of the funds' managing companies (I drop legal forms, delete special characters, and capitalize all letters). Next, within a group of funds having the same standardized name of the managing company, I select groups of funds with correlation coefficients larger than 0.99 and keep the fund with the longest time series of returns. I only keep funds reporting returns in USD. I drop return observations below -90% and above 300% and winsorize assets under management at the 5% level to mitigate the influence of outliers and data errors. To avoid any backfill bias, I drop every fund's first 12 monthly return observations.

The resulting data set covers the period from January 1994 until August 2014. Since 1994, data base providers keep defunct funds. Thus, the data set should be free of any survivorship bias. Panel A of table 3.1 shows descriptive statistics on the resulting data set. In total, I observe 10,838 funds, managed by 4,202 different managing companies.

The average fund in the sample of hedge funds has an average monthly net (of fees) return equal to 0.53%, $238.64 mio. in assets under management, charges a 1.46% management and 14.32% performance fee, reports since 77.75 months to one of the two databases, and has a lockup period equal to 75.04 days. 75% of the funds have a high-water mark in place, 42% employ leverage, and 20% of the sample are funds of hedge funds.

Table 3.1: Descriptive statistics: Hedge fund and merged sample

This table shows descriptive statistics on the sample. Panel A presents descriptive statistics for the sample of hedge funds before merging with the data from the Form ADV filings. The upper sub-panel shows the number of hedge funds and the number of hedge fund managing companies. The lower sub-panel shows the average, standard deviation, minimum, 25%, 50%, 75% percentiles, and maximum for the following variables: raw return (Return); assets under management in millions USD (AuM); management fee (mgmtFee); performance fee (perfFee); age measured as the number of months passed since the first appearance in any database (age); length of the lockup period in days (lockupPeriod); dummy for the presence of a high-water mark (highwaterMark); dummy for the use of leverage (leverage); dummy for funds of hedge funds (FOF).
Panel B shows the same statistics for the sample consisting of the data on hedge funds merged with the Form ADV filings.
Panel C shows the average, standard deviation, minimum, 25%, 50%, 75% percentiles, and maximum for the following performance measures: raw return (Return); Fung and Hsieh (2004) abnormal return ($\alpha + \varepsilon$); Fung and Hsieh (2004) average abnormal return (α); Sharpe Ratio (SR); Appraisal Ratio (AR); Goetzmann, Ingersoll, Spiegel, and Welch (2007) Manipulation proof performance measure (MPPM).

Panel A: Hedge fund data

Number of	Hedge funds	Managing companies							
	10,838	4,202							
	Return	AuM	mgmtFee	perfFee	age	lockupPeriod	HWM	leverage	FOF
Average	0.53	238.64	1.46	14.32	77.75	75.04	0.75	0.42	0.20
Std	3.80	807.90	0.60	8.22	59.78	191.17	0.43	0.49	0.40
Min	-89.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
25%	-0.63	12.87	1.00	10.00	30.00	0.00	1.00	0.00	0.00
50%	0.52	45.00	1.50	20.00	64.00	0.00	1.00	0.00	0.00
75%	1.72	152.00	2.00	20.00	112.00	0.00	1.00	1.00	0.00
Max	300.00	27,408	20.00	60.00	251.00	2,160.00	1.00	1.00	1

Panel B: Hedge fund data and Form ADV

Number of	Hedge funds	Managing companies							
	3,066	1,053							
	Return	AuM	mgmtFee	perfFee	age	lockupPeriod	HWM	leverage	FOF
Average	0.56	252.35	1.41	13.71	90.38	111.26	0.76	0.45	0.22
Std	3.11	390.25	0.52	8.27	64.60	218.84	0.42	0.50	0.41
Min	-89.99	4.57	0.00	0.00	0.00	0.00	0.00	0.00	0
25%	-0.53	29.00	1.00	10.00	38.00	0.00	1.00	0.00	0.00
50%	0.57	83.60	1.50	20.00	77.00	0.00	1.00	0.00	0.00
75%	1.67	266.00	1.85	20.00	132.00	180.00	1.00	1.00	0.00
Max	300.00	1,500	5.00	50.00	251.00	2,160.00	1.00	1.00	1

Panel C: Performance measures

	Return	$\alpha + \varepsilon$	α	SR	AR	MPPM
Average	0.56	0.09	0.09	0.35	0.18	-0.01
Std	3.11	2.40	0.88	0.38	0.59	0.02
Min	-89.99	-46.85	-14.03	-0.54	-1.26	-0.11
25%	-0.53	-0.67	-0.24	0.10	-0.16	-0.01
50%	0.57	0.18	0.14	0.33	0.13	0.00
75%	1.67	0.91	0.46	0.54	0.47	0.00
Max	300.00	235.70	9.06	1.58	2.24	0.01

3.3.2 Form ADV

According to the Investment Adviser Act of 1940, investment advisers who manage more than $100 million have to register with the SEC and file a Form ADV. In order to obtain data on the classes of investors and their hedge fund holdings, I rely on these publicly available Form ADV filings collected by the SEC. The filing process is mandatory. Thus, it should not introduce any selection bias beyond the fact that the managing companies have to have assets under management in excess of $100 mio. I download the data directly from the SEC investment adviser website.[1]

The first part of Form ADV filings is composed of 12 items. Items 1 to 4 contain general information on the company, such as the address and the structure of the company. Item 6 contains information on other business activities. Items 7 and 8 refer to potential conflicts of interest. Item 9 and 10 provide information on the custody of the assets and on control persons within the firm. Item 11 provides information on disciplinary history on key persons within the firm. Brown, Goetzmann, Liang, and Schwarz (2009) use this information to develop a measure for the magnitude of operational risk within a hedge fund - the ω-score. Item 12 contains information on the effect of regulation by the SEC on small entities.

Item 5, which is of special interest for this study, contains information on the company's clients. The item becomes available in Form ADV in May 2012. Among others, investment advisers have to provide information on the percentage of total assets under management certain groups of clients represent. The SEC distinguishes between the following groups: Individuals (other than high net worth individuals); High net worth individuals; Banking and thrift institutions; Investment companies; Business development companies; Pooled investment vehicles (other than investment companies); Pension and profit sharing plans (but not the plan participants); Charitable organizations; Corporations or other businesses not listed above; State or municipal government entities; Other investment advisers; Insurance companies. Investment advisers are required to tick boxes representing the following ranges of values: None, up to 25%, up to 50%, up to 75%, $>$ 75%. I encode this information on bins

[1] http://www.sec.gov/foia/iareports/inva-archive.htm

of the data by assuming that values are distributed uniformly within each bin and compute the average value of the bin edges within each bin. I exclude the category Pooled investment vehicles (other than investment companies). Pooled investment vehicles themselves combine capital from different investors. To make sure that I observe allocations by the ultimate end investor, I exclude this category. Finally, for every fund, I normalize the relative allocations by the groups of investors to sum up to one.

3.3.3 Merged Sample

I merge data from Form ADV filings and data on hedge funds by standardizing the names of the management companies from the hedge fund databases and the names of the investment advisers in the Form ADV filings (I exclude legal forms, replace special characters, and capitalize every letter). Next, I match on the company names. If a company has multiple ADV filings I take the average of the reported values.

The ADV information becomes available in May 2012, while the hedge fund data ends in August 2014. This results in a sample spanning 28 months in the time dimension.

In total, I am able to identify 3,066 funds managed by 1,053 companies in the intersection of the Form ADV filings and the hedge fund data set. Panel B of table 3.1 shows descriptive statistics on the merged sample.

In terms of average performance, fees, the presence of high-water marks, use of leverage, and the frequency of funds of hedge funds, both samples are virtually identical. Funds in the merged sample tend to be larger ($252.35 mio. assets under management compared to $238.64 mio.), older (90.38 months compared to 77.75 months), and have longer lockup periods (111.26 days compared to 75.04). Since fund managing companies have to register with the SEC above a threshold of $100 mio. in assets under management, the difference in the average size of the funds is not surprising. The amount of assets under management correlates positively with age (the correlation coefficient is equal to 0.1), thus that is the most likely reason for funds in the merged sample being older. The length of the lockup period correlates negatively with the assets under management of a fund (the correlation coefficient

is equal to -0.06). Thus, the longer average lockup period in the merged sample does not seem to be a direct result of the implicit conditioning on managing companies having more than $100 mio. in assets under management.

Table 3.2: Descriptive statistics: Hedge fund investors

This table shows descriptive statistics on the absolute dollar allocations and the relative allocations, as found in the Form ADV filings, of the different classes of investors in the hedge funds. The average absolute holdings are computed as the average sum of the relative allocations multiplied by the assets under management of the funds. The table shows the average, standard deviation, minimum, 25%, 50%, 75% percentiles, and maximum.

	Average absolute holding (millions)	Proportional holding						
		Average	Std	Min	25%	50%	75%	Max
Business development companies	604	0.00	0.03	0.00	0.00	0.00	0.00	1.00
Individuals	5,654	0.04	0.11	0.00	0.00	0.00	0.00	1.00
Banking or thrift institutions	9,931	0.03	0.10	0.00	0.00	0.00	0.00	1.00
Other investment advisers	21,501	0.06	0.18	0.00	0.00	0.00	0.00	1.00
State or municipal government entities	23,975	0.05	0.11	0.00	0.00	0.00	0.10	1.00
High net worth individuals	24,383	0.14	0.25	0.00	0.00	0.00	0.14	1.00
Insurance companies	29,058	0.06	0.14	0.00	0.00	0.00	0.08	1.00
Charities	29,853	0.08	0.14	0.00	0.00	0.00	0.13	1.00
Pension and profit sharing plans	61,968	0.20	0.27	0.00	0.00	0.11	0.25	1.00
Investment companies	62,981	0.17	0.29	0.00	0.00	0.00	0.20	1.00
Corporations or other businesses	73,798	0.16	0.26	0.00	0.00	0.08	0.17	1.00

Table 3.2 shows descriptive statistics on the average absolute and relative holdings of the different classes of investors. Relative holdings are the relative size of a fund's assets under management which can be attributed to a specific class of investors. I compute the average absolute holdings by multiplying the relative holdings for every pairing of fund and class of investor by the assets under management of the fund. Next for every month and class of investor, I calculate the sum of all absolute holdings. Finally, I compute the average for every class of investors across time.

On average, Business development companies represent $604 mio. of assets under management and represent the smallest group of investors. Corporations and other businesses are the largest group of investors with average assets under management equal to $73,798

mio. On a relative basis, Pension and profit sharing plans represent 20% of the assets under management of a hedge fund. Business development companies are the smallest group of investors, owning virtually 0% of the average hedge fund.

In this Section, I have presented the data sources, merging and filtering techniques, as well as descriptive statistics on the data. In the following sections, I turn to the empirical analysis of the data.

3.4 Realized Performance of Hedge Fund Investors

The hedge fund industry's self-proclaimed goal is the generation of abnormal performance, providing sophisticated investors with an orthogonal (to systematic risk factors) source of investment returns. In the first part of this Section, I estimate the unconditional ability of different groups of hedge fund investors to harvest these abnormal returns. This unconditional analysis sheds first light on the realized performance of the groups of investors.

Omitting other potential determinants of heterogeneity in realized performance may result in biased estimates. As highlighted by Gerakos, Linnainmaa, and Morse (2015), institutional investors do not only focus on abnormal performance but also seek exposure to certain classes of known systematic factors. Sophisticated investors should be able to manufacture these exposures themselves. In the light of the high fees charged by the average hedge fund, this renders the allocation of these investors towards funds providing mainly systematic exposures puzzling. To incorporate the effect of the hedge funds' systematic exposure, I include raw performance measures in the following analysis.

Investors might not only differ in their ability to detect funds which generate abnormal returns or their sophistication - they might also differ in their attitudes towards risk. For example, average abnormal performance might be elevated by an increase in the amount of leverage. Thus, investors who are less risk averse might realize larger average abnormal performance. To control for the investors' risk attitudes, I include risk-adjusted measures of raw and abnormal performance.

There exists empirical evidence for hedge fund performance to vary across observable characteristics.[2] If investors also vary in their preferences for certain characteristics (e.g. restrictions on share redemptions), this could explain differences in realized performance. I control for fund characteristics in the above-mentioned performance regressions to account for a potential heterogeneity in the investors' preferences for fund characteristics.

In the following, I present the risk measures used in the performance analysis. As a measure of realized raw performance I include the mean net of fees return of every fund.

To estimate abnormal performance, I estimate the following regression for every fund i reporting more than 12 monthly return observations:

$$r_{i,t} - r_{f,t} = \alpha_i + X_t\beta_i + \varepsilon_{i,t}, \tag{3.1}$$

where r denotes the fund's net return after fees. r_f denotes the risk-free rate.[3] X_t is the set of seven hedge fund risk factors proposed by Fung and Hsieh (2004).[4]

As a measure of abnormal performance, I include every fund's average abnormal return (α_i). This results in one cross section of alphas. To obtain a time-varying measure of abnormal performance, I include the time series of abnormal returns of every fund ($\alpha_i + \varepsilon_{i,t}$). This introduces a lookahead-bias because I estimate the factor model on the whole sample. However, in the light of the very limited size of the time dimesion of this data set, I refrain from estimating the factor model using a rolling-window methodology.

To account for differences in attitudes towards risk, I include the Sharpe Ratio (SR), the Appraisal Ratio based on the Fung and Hsieh (2004) model (AR), and the Manipulation Proof Performance Measure proposed by Goetzmann, Ingersoll, Spiegel, and Welch (2007) (MPPM). I choose the level of the coefficient of risk aversion in the MPPM so that the time series of total S&P500 index returns results in an MPPM equal to zero during the period

[2] An example is Aragon (2007), who focuses on the relationship between share restrictions and performance.
[3] I obtain the risk-free rate from the website of Ken French: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[4] I obtain the factors from the website of David Hsieh: https://faculty.fuqua.duke.edu/~dah7/HFData.htm.

from May 2012 until August 2014. This results in a level of risk aversion equal to 32.61. To mitigate the impact of outliers, I winsorize the risk-adjusted performance measures at the 1% level. For every fund, I estimate the performance measures for the full sample period (May 2012 until August 2014). Panel C of Table 3.2 shows descriptive statistics for the performance measures computed for the merged sample.

3.4.1 Grouped Means

First, I estimate realized averages of the performance measures for every class of investors. For a fixed class of investors, I calculate the average performance measure weighted by the investor's relative dollar allocation in the fund. I assign weights to the observations, which are equal to the dollar allocation, to account for the severe heterogeneity of the hedge funds with respect to their size. Additionally, the ultimate object of interest is the average return the investors realize.

Table 3.3: Realized performance: Grouped means

This table shows grouped means weighted by the relative dollar allocation of the groups of investors of the following performance measures: Appraisal Ratio (AR), Goetzmann, Ingersoll, Spiegel, and Welch (2007) Manipulation proof performance measure (MPPM), Sharpe Ratio (SR), Fung and Hsieh (2004) seven factor alpha (α), Fung and Hsieh (2004) abnormal return ($\alpha + \varepsilon$), raw return (Return).

	AR	MPPM	SR	α	$\alpha + \varepsilon$	Return
Banking or thrift institutions	0.0417	-0.0044	0.2985	-0.0809	-0.0887	0.3712
Individuals	0.0658	-0.0049	0.2853	0.0704	-0.0026	0.3950
Investment companies	0.1914	-0.0011	0.3814	0.1246	0.1004	0.4806
Other investment advisers	0.1220	-0.0032	0.3422	0.0740	0.0725	0.5021
High net worth individuals	0.2543	-0.0026	0.4056	0.1647	0.1301	0.5051
State or municipal government entities	0.2703	-0.0015	0.4306	0.1636	0.1389	0.5458
Charities	0.1714	-0.0043	0.3525	0.1174	0.0873	0.5559
Pension and profit sharing plans	0.2853	-0.0031	0.4077	0.1956	0.1806	0.5751
Insurance companies	0.2339	-0.0035	0.3749	0.1802	0.1521	0.5837
Corporations or other businesses	0.2903	-0.0034	0.4243	0.2252	0.2204	0.6284
Business development companies	-0.0589	-0.0046	0.2601	-0.0829	0.1701	0.6827

Table 3.3 shows the estimation results. The whole table is sorted by the average raw return.

The ranking of the different classes of investors shows a fair amount of persistence. However, this is not surprising since most of the performance measures are rather similar in their conception. One exception are Business development companies. According to time-varying measures (raw returns and abnormal returns), which take into account the time-varying nature of the allocations, this group of investors ranks towards the top of all groups. When neglecting this time variation in the allocations, Business development companies fare poorly. This indicates a relatively large timing ability of this group.

Banking or thrift institutions and Individuals rank relatively poorly, while hedge fund investments made by Insurance companies and Corporations or other businesses tend to perform well.

To formally test for the differences between the realized performance of the different groups of investors and to also take into account fund characteristics, I turn to a panel model in the following Section.

3.4.2 Conditional Analysis

Hedge fund investors might differ in their preferences for certain fund characteristics. If these characteristics correlate with average performance, this might introduce a bias in the analysis of grouped means. For example, Aragon (2007) documents a correlation between the share restrictions of a hedge fund and the fund's average performance, resulting in a liquidity premium in the hedge fund industry. To account for these otherwise omitted variables, I estimate the following panel regression:

$$Y_{i,t} = \beta_0 + \sum_k \beta_k \text{PercentageAllocation}_{i,t,k} + \text{Time}_t + \text{Style}_i + \text{Controls}_{i,t} + \varepsilon_{i,t}.$$

This model is similar to the one employed by Lerner, Schoar, and Wongsunwai (2007) in the context of private equity investments. Y is either the raw return ($r_{i,t}$) or the abnormal return ($\alpha_i + \varepsilon_{i,t}$) of fund i at time t. Time_t denotes a full set of monthly time dummies.

Style_i is set of dummies for the self-reported investment style of the funds.[5] $\text{Controls}_{i,t}$ is a set of variables including the following static controls: management fee; performance fee; length of the lockup period; dummy for the presence of a high-water mark; dummy equal to one if the fund employs leverage. I include the following time-varying control variables: age of the fund as measured by the time passed since the first reporting of the fund to any database; assets under management. $\text{PercentageAllocation}_{i,t,k}$ is the relative allocation by investor class k into fund i at the beginning of period t. I drop the investor class "Investment companies" and consider this class as the baseline case.[6]

Table 3.4 shows estimation results for a panel regression weighted by the funds' assets under management (measured at the beginning of month t), to take into account the size of the absolute investment. Standard errors are clustered at the managing company level to account for the residuals potentially being correlated within the managing companies.

[5]I map the self-reported styles of the funds to the following categories: Bonds; Convertible Arbitrage; Distressed; Emerging Markets; Equity Long; Equity Long/Short; Event Driven; Fund of Funds; Global Macro; Managed Futures; Merger Arbitrage; Multi Strategy.

[6]I have to drop one category of investors in order to avoid the dummy variable trap.

Table 3.4: Realized performance: Conditional analysis

This table shows estimates for the following regression:

$$Y_{i,t} = \beta_0 + \sum_k \beta_k \text{PercentageAllocation}_{i,t,k} + \text{Time}_t + \text{Style}_i + \text{Controls}_{i,t} + \varepsilon_{i,t}.$$

$Y_{i,t}$ denotes either the raw return ($r_{i,t}$) or the abnormal return ($\alpha_i + \varepsilon_{i,t}$). $\text{PercentageAllocation}_{i,t,k}$ denotes the percentage allocation of investor class k to fund i at the beginning of period t. Time_t is a full set of monthly time dummies. Style_i is a set of dummies for the self-reported investment styles. $\text{Controls}_{i,t}$ is a set of control variables consisting of the following controls: management fee; performance fee; length of the lockup period; dummy for the presence of a high-water mark; dummy equal to one if the fund employs leverage; age of the fund measured by the time passed since the first reporting of the fund to any database; assets under management in millions USD. To save space, the estimates for the control variables are omitted. The regression is weighted by the assets under management of fund i at the beginning of period t. T-statistics, based on standard errors clustered at the level of the managing company, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1) r	(2) r	(3) r	(4) $\alpha+\varepsilon$	(5) $\alpha+\varepsilon$	(6) $\alpha+\varepsilon$
Individuals	-0.473	-0.444	-0.070	-0.382	-0.373	-0.133
	(-1.225)	(-1.208)	(-0.259)	(-1.000)	(-0.991)	(-0.322)
Pension and profit sharing plans	0.124	0.112	0.074	0.220*	0.204*	0.137
	(0.859)	(0.811)	(0.620)	(1.885)	(1.726)	(1.191)
Business development companies	0.944	1.081	1.119	0.567	0.540	0.196
	(0.654)	(0.776)	(1.065)	(0.450)	(0.456)	(0.253)
State or municipal government entities	0.138	0.120	-0.079	0.186	0.188	0.050
	(0.814)	(0.750)	(-0.556)	(0.631)	(0.640)	(0.296)
Other investment advisers	0.077	0.086	-0.004	-0.085	-0.072	-0.151
	(0.569)	(0.595)	(-0.033)	(-0.504)	(-0.413)	(-1.043)
Charities	0.191	0.113	-0.145	-0.206	-0.229	-0.073
	(0.996)	(0.596)	(-0.718)	(-1.079)	(-1.200)	(-0.444)
Corporations or other businesses	0.216**	0.200**	0.150	0.248*	0.236*	0.098
	(2.091)	(1.989)	(1.602)	(1.952)	(1.871)	(0.914)
Insurance companies	0.239	0.210	-0.050	0.080	0.081	0.120
	(0.965)	(0.952)	(-0.280)	(0.404)	(0.412)	(0.728)
High net worth individuals	0.029	0.023	-0.123	0.113	0.113	0.074
	(0.156)	(0.127)	(-0.871)	(1.048)	(1.070)	(0.725)
Banking or thrift institutions	-0.787**	-0.642***	-0.407**	-1.095***	-1.023***	-0.693***
	(-2.305)	(-2.746)	(-2.120)	(-4.050)	(-4.330)	(-3.460)
FOF	-0.144***	-0.148***	-0.129	-0.011	-0.020	-0.128
	(-2.610)	(-2.645)	(-1.170)	(-0.190)	(-0.326)	(-1.300)
Constant	0.524***	-1.948***	-1.780***	0.094	-0.238**	-0.222
	(6.654)	(-7.147)	(-6.312)	(1.283)	(-2.034)	(-1.298)
Time Fixed Effects	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Style Dummies	No	No	Yes	No	No	Yes
N	38,087	38,087	33,022	35,872	35,872	31,181
R-squared	0.002	0.118	0.195	0.003	0.035	0.094

Banking or thrift institutions earn significantly lower raw and abnormal returns than Investment companies. This effect is robust to the inclusion of time dummies, control variables, and style dummies. An increase by 10% in the holding of Banking or thrift institutions results in a decrease of -0.48% p.a. for raw returns and -0.83% p.a. for abnormal returns with significance ranging from the 1% to the 5% level.

Corporations and other businesses earn raw returns which are significantly larger by 0.18% annually for an increase by 10% in the holding of Corporations and other businesses. Without the control variables and style dummies, this group of investors also earns abnormal returns which are significantly larger by 0.28% annually for an increase by 10% in their holding. This effect is still positive but turns statistically insignificant if I include control variables and style dummies.

There is also slight evidence for an outperformance by the hedge fund investments of Pension and profit sharing plans in terms of abnormal returns. An increase by 10% in the holding of Pension and profit sharing plans increases the annualized abnormal returns by 0.24%. The effect is significant at the 5% level without control variables and style dummies and turns insignificant if I include the set of fund-level control variables and style dummies. When controlling for time fixed effects, Charities seem to underperform with respect to their realized abnormal returns. This effect is only significant at the 10% level and vanishes once I include control variables.

To summarize, I find that the realized raw performance of the hedge fund investments by Corporations or other businesses is statistically larger than the performance realized by other Investment companies. This group of investors also realizes larger abnormal returns, not taking into account the influence of fund-level controls and style dummies. Hedge fund investments by Banking or thrift institutions seem to underperform on a raw, as well as on an abnormal basis. There is also slight evidence for Pension and profit sharing plans to realize larger abnormal returns if I do not include fund-level controls.

Raw measures of raw and abnormal performance do not adjust for risk and can be inflated by an increase in risk taking. To mitigate the risk of falsely classifying groups of investors as

being either skilled or unskilled at their hedge fund investment choices because of differences in their attitudes towards risk, I turn to risk-adjusted measures of raw and abnormal performance in the following Section. Since I have to resort to a cross-sectional analysis this will neglect the potential market timing ability of the groups of investors and is complementary to the analysis in this Section.

3.4.3 Risk-adjusted Performance

In the previous Section, I study mean raw returns and abnormal returns. Both performance measures do not take the influence of risk into account. Under the assumption of positive raw and abnormal returns, a fund can artificially increase the mean return and mean abnormal return by levering up existing positions. Since hedge fund investors might differ in their tolerance for risk, it is crucial to investigate risk-adjusted measures of performance. As mentioned in the previous Section, this also has a drawback. Since I have to estimate the risk measures on a data set which is very limited in the time dimension, I have to resort to a cross-sectional analysis. This does not allow to detect the potential benefits of the market timing ability of certain classes of investors on the performance measures.

The allocations from the Form ADV filings document time-varying allocations by the investors while the risk-adjusted performance measures are cross sectional in nature. Thus, for every fund, I have to select a certain point in time at which I measure the allocation by the different classes of investors. For every fund, I fix the investors' allocation at the beginning of the sample (May 2012). I apply the same logic to the time-varying control variables (age of the fund and assets under management). Using the resulting cross-section of allocations by the classes of investors, I estimate the following model:

$$RM_i = \beta_0 + \sum_k \beta_k \text{PercentageAllocation}_{i,k} + \text{Style}_i + \text{Controls}_i + \varepsilon_{i,t}. \tag{3.2}$$

RM denotes one of the following risk measures: Appraisal Ratio (AR), Sharpe Ratio (SR), and the MPPM (MPPM). Standard errors are clustered by the hedge fund managing com-

pany to account for correlations in performance within fund families.

Table 3.5 shows the results for regressions weighted by the funds' assets under management. Banking or thrift institutions exhibit significantly lower risk-adjusted performance. Except for the MPPM including control variables and style dummies, all risk measures are significantly lower at least at the 5% significance level. The effect corresponds to a reduction of the annualized Sharpe Ratio by -0.12 if the holdings by Banking or thrift institutions are increased by 10%. Comparing the effect to the average Sharpe Ratio within the hedge fund industry during the sample period of 1.10 renders the effect economically sizable. The effects are robust to the inclusion of control variables and style dummies.

Investments by Other investment advisers seem to underperform according to the MPPM at the 5% significance level, including control variables and style dummies.

State or municipal government entities tend to exhibit higher Sharpe Ratios and MPPMs. If I include control variables and style dummies the effects are significant at the 5% level and correspond to an increase by 0.19 in the annualized Sharpe Ratio for an increase in the holdings equal to 10%.

Corporations and other businesses, Pension and profit sharing plans, and High net worth individuals outperform in terms of their Appraisal Ratios. However, these effects are only significant at the 10% level if I include control variables and style dummies.

Table 3.5: Realized performance: Risk-adjusted performance

This table shows estimates for the following regression:

$$RM_i = \beta_0 + \sum_k \beta_k \text{PercentageAllocation}_{i,k} + \text{Style}_i + \text{Controls}_i + \varepsilon_{i,t}.$$

RM_i denotes one of the following risk measures: Appraisal Ratio (AR); Sharpe Ratio (SR); MPPM (MPPM). $\text{PercentageAllocation}_{i,k}$ denotes the percentage allocation of investor class k to fund i in May 2012. Style_i denotes a set of dummies for the self-reported investment styles. Controls_i is a set of the following control variables: management fee; performance fee; length of the lockup period; dummy for the presence of a high-water mark; dummy equal to one if the fund employs leverage; age of the fund measured by the time passed since the first reporting of the fund to any database; assets under management in millions USD. To save space, the estimates for the control variables are omitted. The time-varying control variables (age and assets under management) are measured in May 2012. The regression is weighted by the funds' assets under management. T-statistics, based on standard errors clustered at the level of the managing company, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1) AR	(2) AR	(3) SR	(4) SR	(5) MPPM	(6) MPPM
Individuals	-0.334	-0.251	-0.153	-0.022	0.001	0.004
	(-0.761)	(-0.693)	(-0.771)	(-0.104)	(0.281)	(0.767)
Pension and profit sharing plans	0.355*	0.251*	0.107	0.056	0.001	0.001
	(1.906)	(1.833)	(0.691)	(0.448)	(0.158)	(0.280)
Business development companies	0.263	0.513	0.009	0.248	0.001	0.008
	(1.023)	(1.276)	(0.071)	(0.986)	(0.085)	(0.550)
State or municipal government entities	0.368	0.186	0.501*	0.539**	0.011**	0.010**
	(0.956)	(0.619)	(1.817)	(2.050)	(2.197)	(2.320)
Other investment advisers	-0.218	-0.252	-0.139	-0.188	-0.007*	-0.008**
	(-1.285)	(-1.611)	(-1.097)	(-1.563)	(-1.796)	(-2.400)
Charities	0.016	-0.006	-0.044	-0.066	-0.001	0.000
	(0.081)	(-0.034)	(-0.342)	(-0.552)	(-0.148)	(0.009)
Corporations or other businesses	0.314***	0.211*	0.184**	0.104	0.002	-0.000
	(2.588)	(1.784)	(1.996)	(1.125)	(0.686)	(-0.041)
Insurance companies	0.003	0.206	-0.080	0.003	-0.005	-0.001
	(0.014)	(1.364)	(-0.512)	(0.025)	(-0.897)	(-0.442)
High net worth individuals	0.293**	0.231*	0.103	0.053	-0.001	0.001
	(2.067)	(1.784)	(0.738)	(0.434)	(-0.440)	(0.541)
Banking or thrift institutions	-0.710***	-0.514***	-0.454***	-0.341**	-0.009**	-0.005
	(-3.674)	(-2.713)	(-3.546)	(-2.432)	(-2.023)	(-0.945)
Constant	-0.004	0.353**	0.228***	0.440***	-0.007***	-0.002
	(-0.047)	(1.976)	(3.027)	(3.134)	(-2.908)	(-0.555)
Controls	No	Yes	No	Yes	No	Yes
Style dummies	No	Yes	No	Yes	No	Yes
N	1,271	1,103	1,480	1,292	1,510	1,321
R-squared	0.077	0.279	0.074	0.287	0.090	0.278

Summarizing, there is evidence for severe heterogeneity in risk-adjusted performance across the groups of hedge fund investors. Banking and thrift institutions tend to underperform, while High net worth individuals, Corporations or other businesses, State or municipal government entities, and Pension and profit sharing plans outperform on a risk-adjusted basis. Comparing the results to the non-risk adjusted results from Section 3.4.2, I find that State or municipal government entities and High net worth individuals outperform on a risk-adjusted basis but do not outperform on a non-risk adjusted basis. This points towards a story of State or municipal government entities and High net worth individuals being more risk averse but being able to select outperforming hedge funds on a risk-adjusted basis. For Pension and profit sharing plans and Banking or thrift institutions, I find results consistent with the results obtained for the non-risk adjusted performance measures.

In this Section, I take the fund characteristics of the funds the groups of investors invest in as given and include them as control variables. This allows me to separate the effects of investors being skilled at picking funds with characteristics (e.g. illiquidity) which generate alpha from the effect of investors being skilled at capturing alpha which cannot be explaining by funds' characteristics. In the next Section, I drill deeper into the investment objectives of the hedge fund investors. I employ a revealed preferences approach and study the investors' preferences for certain fund characteristics in more detail.

3.5 Revealed Preferences

In the previous sections, we saw that - to a certain extent - funds' characteristics explain a part of the difference in realized performance between hedge funds. Are there groups of investors which systematically differ in their demand for certain characteristics? In the flavor of Berk and van Binsbergen (2016), I take the perspective of a revealed preferences approach and estimate the preferences of hedge fund investors for a hedge fund's characteristics. Taking the allocations of the investors as given, I estimate the preferences for fund characteristics which are compatible with these observed allocations. I estimate the preferences for the

control variables used in the previous Section: management fee (MgmtFee); performance fee (PerfFee); age of the fund, measured as the number of years passed since the first entry of the fund in any database (Age); assets under management in millions USD (AuM); length of the lockup period in days (LockupPeriod); a dummy equal to one if the fund has a high-water mark in place (High-waterMark); a dummy equal to one if the fund uses leverage (Leverage). To measure the risk tolerance of the groups of investors, I include the standard deviation of the funds' returns, measured over the full sample period (σ) as a proxy for risk. Additionally, I control for the investment styles of the funds by including dummy variables. For every class of investor k, I estimate the following cross-sectional regression:

$$\text{PercentageAllocation}_{i,k} = \beta_0 + X_i\beta_k + \text{Style}_i + \varepsilon_{i,k}, \tag{3.3}$$

where X_i denotes the vector of characteristics of fund i. $\text{PercentageAllocation}_{i,k}$ denotes the allocation by investor class k into fund i. I measure the time-varying characteristics (age, assets under management) and the allocations at the beginning of the sample (May 2012). Style_i is a set of style dummies. I cluster the standard errors at the level of the managing company. Table 3.6 shows estimates for OLS regressions weighted by the assets under management.[7]

[7]The dependent variable, being a percentage, is bounded. See the robustness Section 3.7 for a model and estimation results taking into account the bounded support of the dependent variable.

Table 3.6: Revealed preferences

This table shows estimates for the following regression:

$$\text{PercentageAllocation}_{i,k} = \beta_0 + X_i\beta_k + \text{Style}_i + \varepsilon_{i,k}.$$

$\text{PercentageAllocation}_{i,k}$ denotes the allocation by investor class k into fund i in May 2012. X_i denotes a vector of the following fund characteristics: management fee (MgmtFee); performance fee (PerfFee); age of the fund measured as the number of years passed since the first entry of the fund in any database (Age); assets under management in millions USD (AuM); length of the lockup period in years (LockupPeriod); a dummy equal to one if the fund has a high-water mark in place (High-waterMark); a dummy equal to one if the fund uses leverage (Leverage); standard deviation of the fund's returns during the full sample period (σ). I measure the time-varying characteristics (age, assets under management) in May 2012. Style_i is a set of style dummies. The regression is weighted by the funds' average assets under management during the full sample period. T-statistics, based on standard errors clustered at the level of the managing company, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	Individuals	Pension and profit sharing plans	Business development companies	State or municipal government entities	Other investment advisers
MgmtFee	-0.005	-0.018	-0.001	-0.012	0.021
	(-1.035)	(-0.687)	(-0.458)	(-0.874)	(1.340)
PerfFee	-0.001	-0.003	0.000*	-0.002*	-0.002
	(-1.160)	(-0.798)	(1.867)	(-1.727)	(-1.520)
Age	-0.000	0.001	-0.000	0.002	0.001
	(-0.540)	(0.259)	(-0.199)	(0.906)	(0.333)
AuM	-0.000**	-0.000	-0.000	0.000	0.000
	(-2.574)	(-1.647)	(-0.615)	(0.574)	(1.061)
LockupPeriod	0.000	-0.000	-0.000	0.000	-0.000
	(0.160)	(-0.069)	(-0.861)	(0.499)	(-0.731)
σ	-0.002	-0.015	-0.001	-0.014***	0.029
	(-0.901)	(-1.055)	(-0.377)	(-2.623)	(1.481)
High-waterMark	0.016	0.020	-0.003	0.016	-0.006
	(1.314)	(0.389)	(-1.224)	(0.672)	(-0.102)
Leverage	0.011	-0.020	0.002	-0.010	0.022
	(1.401)	(-0.489)	(0.886)	(-0.781)	(0.906)
Constant	0.030**	0.287***	-0.001	0.130**	-0.016
	(1.970)	(2.741)	(-0.292)	(2.081)	(-0.364)
N	1,306	1,306	1,306	1,306	1,306
R-squared	0.112	0.095	0.043	0.071	0.168

Table continued on next page ...

	Charities	Corporations or other businesses	Insurance companies	High net worth individuals	Banking or thrift institutions
MgmtFee	-0.047***	0.087*	0.019	-0.028*	-0.016
	(-3.055)	(1.845)	(0.767)	(-1.934)	(-1.323)
PerfFee	-0.003**	0.009**	0.001	0.000	-0.001
	(-2.042)	(2.180)	(0.888)	(0.202)	(-0.616)
Age	0.002	-0.001	-0.003*	0.005**	-0.002
	(1.314)	(-0.294)	(-1.837)	(2.358)	(-1.030)
AuM	-0.000**	0.000**	0.000	-0.000***	0.000
	(-2.068)	(2.131)	(0.586)	(-3.088)	(0.047)
LockupPeriod	-0.000	-0.001	-0.000	0.002*	-0.000*
	(-0.320)	(-0.859)	(-0.430)	(1.801)	(-1.953)
σ	0.000	0.027	-0.004	-0.007	0.004
	(0.045)	(1.028)	(-0.696)	(-1.162)	(1.075)
High-waterMark	0.056**	-0.092	-0.039	0.009	0.018
	(2.305)	(-1.516)	(-1.566)	(0.323)	(0.645)
Leverage	0.012	0.037	-0.019	0.009	0.011
	(0.689)	(0.662)	(-0.685)	(0.483)	(1.474)
Constant	0.117***	0.258*	0.042	0.060*	0.028
	(3.104)	(1.789)	(0.909)	(1.767)	(1.286)
N	1,306	1,306	1,306	1,306	1,306
R-squared	0.112	0.186	0.135	0.095	0.055

Table continued from previous page.

Turning to the preferences of the groups of investors for specific fee structures, I find that Charities seem to prefer lower management and performance fees. An increase by 1% in the management fee leads to a decrease of -4.7% in the relative holding of charities. The effect of the fund's performance fee is only statistically significant at the 5% level and economically not relevant. Corporations or other businesses seem to tolerate higher fees. An increase by 1% in the management fee translates to an increase equal to 8.7% in the relative holding of Corporations and other businesses. The effect of the performance fee is significant at the 5% level but economically not significant. High net worth individuals seem to prefer lower management fees. An increase by 1% in the management fee results in a decrease of -2.8% in the relative holding of High net worth individuals.

Turning to the age and the size of the funds - both closely related to how well-established the funds are - reveals that Individuals, Charities, and High net worth individuals prefer smaller funds. The assets under management of the funds are measured in millions and all coefficients are virtually equal to zero. Thus, the effect is likely economically negligible. High

net worth individuals tend to invest in older funds, while Insurance companies are willing to invest into younger funds. An increase by ten years in the age of the fund leads to a decrease equal to -3% and an increase by 5% in the holdings by Insurance companies and High net worth individuals.

High net worth individuals seem to accept longer lockup periods. An increase in the lockup period by 30 days results in an increase in the holding of High net worth individuals of approximately 6%. Banking or thrift institutions prefer shorter lockup periods. However, with a coefficient being virtually equal to zero this effect is economically irrelevant.

Charities seem to prefer funds which have a high-water mark in place. The presence of a high-water mark increases the relative holding of Charities by 5.6%. This effect is significant at the 5% level.

As conjectured in Section 3.4.3, State or municipal government entities indeed seem to prefer funds which are less risky. A 1% increase in the monthly standard deviation of the fund's returns decreases the relative holding of State or municipal government entities by -1.4%.

Summarizing, there is heterogeneity in the preferences of the groups of investors for fund characteristics. Charities and High net worth individuals are sensitive with respect to the management fees they are charged and prefer smaller funds. On the other hand, Corporations or other businesses are willing to pay higher fees and invest in larger funds. Insurance companies are willing to invest into younger funds, while High net worth individuals prefer older funds. Compatible with evidence from prior Sections, State or municipal government entities prefer funds which are less risky. Charities prefer funds with high-water marks in place.

This Section establishes that hedge fund investors differ in their investment objectives and therefore choose different funds based on their characteristics. In the next Section, I study whether hedge fund investors not only choose different funds but also influence the investment strategies employed by the funds.

3.6 The Effect of the Investor Structure on Funds' Investment Decisions

The previous two sections document a severe heterogeneity in the realized performance of different groups of investors, as well as heterogeneity in the investment objectives of the groups of investors. In this Section, I investigate whether investors tend to influence the investment strategies employed by the managers.

Hedge fund investors might exert a certain pressure on hedge fund managers to align their strategy with the investor's investment objectives. If the investment objectives of investors correlate with the group they are assigned to - which the results from previous sections suggest - and investors indeed influence the investment decision by fund managers, we would expect that changes in the investor composition induce changes in the investment strategy. Using a model similar to a classical difference in differences model, I exploit changes in the hedge fund's structure of investors to estimate correlations between changes in the investor composition and changes in the fund's performance and risk.

I split the sample into two periods. The first part ranges from May 2012 to June 2013. The second part ranges from July 2013 to August 2014. The key idea is to estimate a model featuring fund fixed effects interacted with a dummy for the second period and time dummies for the two parts of the sample. This is similar to a difference in differences approach with continuous covariates:

$$Y_{i,t} = \beta_i + \text{Time}_t + \sum_k \beta_k D^+_{i,t} \Delta\text{PercentageAllocation}_{i,t,k} + \varepsilon_{i,t}, \quad t \in \{1,2\}. \tag{3.4}$$

Y denotes one of the following measures: Appraisal Ratio (AR); Sharpe Ratio (SR); MPPM (MPPM); alpha (α) based on the Fung and Hsieh (2004) model; standard deviation (σ); mean net return (μ). Time_t and β_i are full sets of time and fund fixed effects. $D^+_{i,t}$ is a dummy variable representing the second part of the sample. $\Delta\text{PercentageAllocation}_{i,t,k}$ denotes the changes in the percentage allocation from the start of the first part of the sample (May 2012)

to the start of the second part of the sample (July 2013). Thus, the coefficient β_k measures the average effect of a change in the relative holding by investor class k, from the first to the second period, on the change in the dependent variable, accounting for time trends and fund-level heterogeneity in performance. Standard errors are clustered at the managing company level to allow for fund family-level correlations in performance changes.

Table 3.7 shows the estimation results for a regression weighted by the funds' average assets under management over the full sample period. In the previous sections we observed that Banking and thrift institutions realize lower average performance in their hedge fund investments. Turning to the results for changes in performance, I find that an increase in the investment by Banking and thrift institutions correlates with an increase in the average Sharpe Ratio, MPPM, and average net return over the subsequent period. For an increase equal to 10% in the holding of Banking or thrift institutions the Sharpe Ratio increases by 0.45 on an annual basis. However, annualized alpha drops by -2.48% and the Appraisal Ratio is not significantly changed. There is no effect on risk. This is compatible with the following story: after an increase in the investment by Banking or thrift institutions, funds tend to substitute exposure to strategies which generate abnormal performance for exposure to systematic risk factors.

An increase in the allocation by Insurance companies leads to a decrease in net returns but also to a decrease in the standard deviation. This provides evidence in favor of Insurance companies possessing the ability to influence the investment strategy of the fund manager in order to decrease the risk-taking behavior. An allocation by Other investment advisers, Business development companies, and Individuals also decreases the risk of the fund but does not change the average return or other performance measures.

An increase in the investment by Corporations and other businesses by 10% tends to decrease alpha by -1.17% on an annual basis. A 10% increase in the investment by High net worth individuals correlates with an increase by 0.24 in the annualized Sharpe Ratio.

Table 3.7: Funds' investment decisions and changes in investor structure

This table shows estimates for the following regression:

$$Y_{i,t} = \beta_i + \text{Time}_t + \sum_k \beta_k D^+_{i,t} \Delta\text{PercentageAllocation}_{i,t,k} + \varepsilon_{i,t}, \quad t \in \{1, 2\}.$$

Y denotes one of the following measures: Appraisal Ratio (AR); Sharpe Ratio (SR); MPPM (MPPM); Fung and Hsieh (2004) alpha (α); standard deviation (σ); mean net return (μ). Time_t and β_i are full sets of time and fund fixed effects. $D^+_{i,t}$ is a dummy variable representing the time period from July 2013 to August 2014. $\Delta\text{PercentageAllocation}_{i,t,k}$ denotes the changes in the percentage allocation from May 2012 to July 2013. The regression is weighted by the average assets under management of the fund over the full sample period. T-statistics, based on standard errors clustered at the level of the managing company, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	(1) AR	(2) SR	(3) MPPM	(4) α	(5) σ	(6) μ
Individuals	-0.799	-0.237	0.008	0.361	-1.918*	-0.612
	(-0.350)	(-0.321)	(0.384)	(0.101)	(-1.828)	(-0.402)
Pension and profit sharing plans	1.492	0.498	0.001	0.147	-0.402	-0.075
	(1.481)	(1.238)	(0.071)	(0.211)	(-0.584)	(-0.106)
Business development companies	1.779	1.608	0.065	1.513	-1.156*	3.709
	(1.539)	(1.623)	(1.364)	(0.881)	(-1.911)	(1.152)
State or municipal government entities	0.954	0.010	-0.020	-0.599	-1.257	-1.264
	(0.662)	(0.018)	(-0.939)	(-0.499)	(-1.129)	(-0.984)
Other investment advisers	0.700	0.202	0.030***	-0.256	-1.992***	0.455
	(0.600)	(0.732)	(2.635)	(-0.402)	(-3.417)	(0.856)
Charities	0.287	0.543	0.005	-0.324	0.503	0.597
	(0.284)	(1.037)	(0.495)	(-0.406)	(0.570)	(0.799)
Corporations or other businesses	-0.089	0.468	0.009	-0.979*	-1.220	0.164
	(-0.171)	(1.062)	(0.989)	(-1.760)	(-1.597)	(0.346)
Insurance companies	1.636	-0.462	-0.001	-0.481	-1.594*	-1.130*
	(1.579)	(-1.114)	(-0.140)	(-0.802)	(-1.955)	(-1.742)
High net worth individuals	0.501	0.690*	0.008	-0.594	-0.854	0.364
	(0.692)	(1.846)	(0.920)	(-0.715)	(-1.463)	(0.547)
Banking or thrift institutions	-0.061	1.309***	0.025**	-2.067*	-1.411	1.892**
	(-0.039)	(2.602)	(2.131)	(-1.690)	(-1.397)	(2.067)
Constant	0.339***	0.341***	-0.003***	0.172***	2.027***	0.511***
	(10.455)	(24.127)	(-8.737)	(5.969)	(79.804)	(15.603)
N	2,091	2,393	2,450	2,091	2,434	2,450
R-squared	0.037	0.134	0.052	0.035	0.149	0.057

Summarizing, there is evidence in favor of a potential influence of certain types of investors on the fund managers' investment policies. An increase in the allocation by Individuals, Business development companies, Other investment advisers, and Insurance companies correlates with a subsequent decrease in risk. An allocation by Banking and thrift institutions correlates with higher subsequent raw performance but lower abnormal performance. Allocations by High net worth individuals and Other investment advisers tend to increase raw performance. These findings are not about causality but only document correlations. With the data at hand I cannot rule out any reverse causality. Namely, my findings are consistent with certain classes of hedge fund investors anticipating changes in the fund strategies and basing their investment decisions on these changes.

3.7 Robustness

In Section 3.5, I estimate the revealed investment objectives of the hedge fund investors by regressing the percentage allocation of the different groups of investors on fund-level explanatory variables. However, in this case, the variable on the left hand side of the regression has a bounded support between zero and one. Thus, standard assumptions underlying ordinary least squares regressions are violated. In this Section, I follow Papke and Wooldridge (1996) and estimate model (3.3) using a quasi-likelihood method. More specifically, I estimate a generalized linear model belonging to the binary family using a logit link function. Again, as in Section 3.5, I assign weights to the observations equal to the funds' average assets under management. Table 3.8 shows the estimation results.

Table 3.8: Robustness: Revealed preferences (truncated regressions)

This table shows estimates for the following model:

$$\text{PercentageAllocation}_{i,k} = \beta_0 + X_i\beta_k + \text{Style}_i + \varepsilon_{i,k}.$$

$\text{PercentageAllocation}_{i,k}$ denotes the allocation by investor class k into fund i in May 2012. X_i denotes a vector of the following fund characteristics: management fee (MgmtFee); performance fee (PerfFee); age of the fund measured as the number of years passed since the first entry of the fund in any database (Age); assets under management in millions USD (AuM); length of the lockup period in years (LockupPeriod); a dummy equal to one if the fund has a high-water mark in place (High-waterMark); a dummy equal to one if the fund uses leverage (Leverage); standard deviation of the fund's returns during the full sample period (σ). I measure the time-varying characteristics (age, assets under management) in May 2012. Style_i is a set of style dummies. The regression is weighted by the funds' average assets under management during the full sample period. I follow the methodology developed by Papke and Wooldridge (1996) and estimate a generalized linear model belonging to the binary family using a logit link function. T-statistics, based on standard errors clustered at the level of the managing company, appear in parenthesis below the estimates. Statistical significance at the 1%, 5%, and 10% level is denoted by ***,**, * respectively.

	Individuals	Pension and profit sharing plans	Business development companies	State or municipal government entities	Other investment advisers
MgmtFee	-0.215	-0.126	-0.449	-0.184	0.109
	(-1.169)	(-0.668)	(-0.792)	(-0.651)	(0.498)
PerfFee	-0.046	-0.018	0.112***	-0.050*	-0.048*
	(-1.518)	(-0.809)	(4.364)	(-1.693)	(-1.682)
Age	-0.009	0.004	-0.005	0.030	0.011
	(-0.276)	(0.270)	(-0.115)	(0.890)	(0.286)
AuM	-0.001**	-0.000*	-0.001	0.000	0.000
	(-2.150)	(-1.686)	(-0.561)	(0.580)	(1.542)
LockupPeriod	0.001	-0.000	-0.014	0.005	-0.006
	(0.134)	(-0.022)	(-0.669)	(0.524)	(-0.522)
σ	-0.144	-0.097	-0.168	-0.348***	0.558**
	(-1.107)	(-1.021)	(-0.331)	(-2.766)	(2.251)
High-waterMark	0.797*	0.157	-0.899*	0.400	0.018
	(1.685)	(0.420)	(-1.714)	(0.816)	(0.031)
Leverage	0.385	-0.123	0.811	-0.163	0.421
	(1.435)	(-0.478)	(1.071)	(-0.626)	(1.494)
Constant	-3.902***	-0.829	-10.153***	-1.533	-4.207***
	(-3.859)	(-1.303)	(-5.743)	(-1.602)	(-4.085)
N	1,306	1,306	1,306	1,306	1,306

Table continued on next page ...

	Charities	Corporations or other businesses	Insurance companies	High net worth individuals	Banking or thrift institutions
MgmtFee	-0.741***	0.500**	0.253	-0.390**	-0.729**
	(-2.897)	(2.053)	(0.853)	(-1.974)	(-1.975)
PerfFee	-0.047*	0.057**	0.021	0.008	-0.029
	(-1.876)	(2.205)	(0.995)	(0.334)	(-0.646)
Age	0.035	-0.008	-0.050**	0.077***	-0.061
	(1.366)	(-0.344)	(-2.079)	(2.848)	(-1.157)
AuM	-0.000**	0.000**	0.000	-0.001***	-0.000
	(-2.319)	(2.308)	(0.575)	(-2.654)	(-0.148)
LockupPeriod	-0.001	-0.006	-0.004	0.014**	-0.017
	(-0.189)	(-0.861)	(-0.328)	(2.015)	(-1.538)
σ	-0.001	0.157	-0.075	-0.126	0.149
	(-0.011)	(1.201)	(-0.637)	(-1.277)	(1.577)
High-waterMark	0.974**	-0.566	-0.539	0.151	0.794
	(2.292)	(-1.486)	(-1.557)	(0.408)	(0.642)
Leverage	0.148	0.213	-0.226	0.115	0.404*
	(0.628)	(0.688)	(-0.582)	(0.472)	(1.671)
Constant	-2.222***	-1.539**	-3.336***	-3.235***	-3.891***
	(-3.425)	(-2.143)	(-3.967)	(-4.792)	(-3.922)
N	1,306	1,306	1,306	1,306	1,306

Table continued from previous page.

All conclusions I came to in Section 3.5 translate to these estimation results. Not accounting for the boundedness of the left hand side variable results in an under-rejection of the null hypothesis of no significant effect. If I account for the boundedness more coefficients are significantly different from zero. Thus, the conclusions I come to in Section 3.5 can be seen as a conservative lower bound.

3.8 Conclusion

This paper demonstrates that hedge fund investors form a heterogeneous group. Investors differ in their realized performance and their revealed investment objectives. Banking and thrift institutions tend to realize smaller risk-adjusted and non-risk-adjusted returns. High net worth individuals, Corporations or other businesses, State or municipal government entities, and Pension and profit sharing plans realize larger risk-adjusted returns.

Employing a revealed preferences approach, I show that groups of investors also differ in their preferences for fund characteristics. State or municipal government entities, Charities, and

High net worth individuals are sensitive to the management fees they are charged. On the other hand, Corporations or other businesses and Business development companies tolerate larger management fees. State or municipal government entities tend to invest in funds which are less risky. High net worth individuals prefer older funds and accept longer lockup periods, while Insurance companies are willing to back younger funds.

Apart from differing in their preferences and realized performance, investors also seem to influence the investment strategies of hedge funds. An allocation by Individuals, Business development companies, Other investment advisers, and Insurance Companies tends to correlated with a decrease in the future risk taking of the fund manager. An investment by Banking or thrift institutions tends to correlate with a decrease in idiosyncratic risk and alpha, while increasing the systematic exposure.

These findings shed first light on the relationship between hedge fund managers and their investors. The correlations between a fund's investor composition and the fund's strategy highlight the importance of putting investors' objectives into the equation when studying hedge fund performance. Studying the interrelations between investors and managers could provide further fruitful insights for investors, hedge fund administrators, and managers, alike.

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Summary in German

Diese Dissertation besteht aus drei separaten Forschungsarbeiten zum Thema Hedgefunds. Die Forschungsarbeiten sind auf drei Kapitel aufgeteilt. Das erste Kapital beschäftigt sich mit dem Einfluss von Sozialbeziehungen zwischen Hedgefund Managern auf die von den Managern getätigten Investitionsentscheidungen. Das zweite Kapitel macht sich biographische Informationen über Hedgefund Manager zunutze um abnormale Renditen auf Basis des Investmentfonds von abnormal Renditen auf Basis des Managers zu trennen. Das dritte Kapitel beschäftigt sich mit realisierten Renditen von Hedgefund Investoren. Die Forschungsfragestellungen, angewandte Methodik und Hauptergebnisse der drei Studien werden im folgenden zusammengefasst.

Birds of a Feather: Do Hedge Fund Managers Flock Together?

Das erste Kapitel basiert auf einer Forschungsarbeit in Kooperation mit Jens Jackwerth von der Universität Konstanz und Alberto Plazzi von der Università della Svizzera Italiana.
In dieser Studie betrachten wir das Investitionsverhalten von Hedgefunds unter Einbeziehung von Sozialbeziehungen, welche auf einer gemeinsamen Biografie basieren. Wir vermuten, dass Sozialbeziehungen aus gemeinsamen Industrie- oder Unernehmensumfeldern, wichtige Aspekte darstellen, um Unterschiede in Hedgefund Renditen zu erklären.
Unsere Studie macht sich verpflichtende Berichte von Hedgefunds, mit Sitz in Großbritannien, zunutze. In Kombination mit kommerziellen Hedgefund Datenbanken erlaubt uns dieser

Datensatz, komplette historische Zeitreihen von Renditen, Fonds-Charakteristiken und beruflichen Laufbahnen der Hedgefund Industrie in Großbritannien zu konstruieren.

Mit diesem kombinierten Datensatz können wir die folgenden drei Maße für den Grad der Sozialbeziehungen innerhalb der Hedgefund Industrie in Großbritannien konstruieren. Die erste Variable, *Industry* verbindet zwei Firmen, deren Manager in der Vergangenheit in derselben Industrie gearbeitet haben. Die zweite Variable, *Firm* verbindet zwei Firmen falls deren Manager in der Vergangenheit für denselben Arbeitgeber gearbeitet haben. Schließlich verbindet *Overlap* zwei Firmen, deren Manager in der Vergangenheit gleichzeitig (mindestens 24 Monate) für denselben Arbeitgeber gearbeitet haben.

Wir nutzen diese Information, um Erkenntnisse über die Fragestellung zu gewinnen, ob Sozialbeziehungen und Arbeitserfahrungen Rückschlüsse auf Hedgefund Renditen zulassen. Wir testen für den Einfluss des beruflichen Werdegangs auf folgende drei Dimensionen der Hedgefund Renditen: abnormale Renditen (Alpha), systematische Renditen (beta) und idiosynkratische Komponenten (Residuen). Für diese Zerlegung nutzen wir das populäre Fung and Hsieh (2004) Faktormodell, welches wir für jeden Hedgefund separat schätzen. Für jedes Paar bestehend aus zwei Hedgefunds berechnen wir die durchschnittliche absolute Distanz der Faktorsensitivitäten ($\Delta\beta$), die durchschnittliche absolute Distanz der Residuen ($\Delta\epsilon$) und die durchschnittliche absolute Distanz der abnormalen Renditen ($\Delta\alpha$). Diese drei Variablen dienen als abhängige Variablen in der folgenden Analyse.

Wir zeigen, dass Sozialbeziehungen, im Besonderen frühere *Industry* und *Firm* Erfahrungen, einen signifikanten Bestandteil der Unterschiede im Querschnitt der drei Dimensionen von Hedgefund Renditen erklären. Die korrespondierenden Koeffizienten sind nicht nur statistisch sondern auch ökonomisch signifikant. Die durchschnittliche absolute Distanz in Alpha ist monatlich um 0.25% kleiner (3% pro Jahr). Durch Sozialbeziehungen verbundene Hedgefunds haben eine um 0.27 kleinere durchschnittliche absolute Distanz in ihren Faktorsensitivitäten. Die absolute Distanz in der idiosynkratische Komponente $\Delta\epsilon$ wird im Durchschnitt um 0.62% monatlich oder mehr als 7% jährlich reduziert. Der Effekt von vorheriger gemeinsamer Arbeitserfahrung (*Overlap*) wirkt sich nicht auf $\Delta\alpha$ und $\Delta\beta$ aus, jedoch auf $\Delta\epsilon$. Die

idiosynkratische Komponente der Hedgefund Renditen scheint somit mehr von persönlicher Interaktion und sozialen Netzwerken als von Firmen- oder Industrie-Effekten getrieben zu sein.

Diese Ergebnisse sind robust bezüglich der Aufnahme von diversen Kontrollvariablen. Wir kontrollieren für die Größe, das Alter und die Kompensationstrukturen der Hedgefunds, sowie für eine Variable, welche den Investitionsstil des Hedgefunds abbildet. Unsere Ergebnisse sind stärker für kleinere Hedgefunds, welche in Investitionsstilen operieren, in denen der Informationsaustausch eine größere Rolle spielt. Um zu zeigen, dass unserer Ergebnisse kein Produkt von Manager Charakteristiken sind, kontrollieren wir für das Geschlecht und das Alter der Manager, sowie für ein Maß der räumlichen Distanz zwischen den Manager-Paaren. Wir kontrollieren für die individuelle Befähigung der Manager mittels eines Maßes für die Stärke des Arbeitsmarktes zum Zeitpunkt der Einstellung des Managers bei dem spezifischen Hedgefund (*Hiring Climate*). Wir definieren das Maß *Hiring Climate* als die Anzahl der Arbeiter, welche in einem spezifischen Monat in der Finanzindustrie angestellt wurden, minus die Anzahl der Menschen, welche die Finanzindustrie verließen, zum Stichtag des Beginns des Anstellungsverhältnisses des Managers in dem spezifischen Hedgefund. Wir benutzen *Hiring Climate* als Kontrollvariable sowie als Instrument. Alternativ kontrollieren wir, für ex-Hedgefund Manager, für das durchschnittlich erzielte Alpha in früheren Hedgefunds. Die ökonomische sowie statistische Signifikanz ist nicht beeinflusst durch diese weiteren erklärenden Variablen.

Schließlich schätzen wir die ökonomische Signifikanz von bestimmten früheren Arbeitsverhältnissen der Manager für die Rendite von individuellen Hedgefunds. Wir dokumentieren, dass vorherige Industrie-Erfahrung signifikante Auswirkungen auf die künftig erzielte Rendite von Hedgefund Managern hat. Manager mit Erfahrung in Pensionsfonds und Banken erzielen überdurchschnittliche Renditen. Manager mit allgemeiner Erfahrung in der Vermögensverwaltung erzielen unterdurchschnittliche Renditen. Des Weiteren nutzen wir eine Bootstrap-Methode zur Schätzung des Einflusses des Grades der Vernetzung von Hedgefunds auf Renditen. Das Dezil der Hedgefunds mit der größten Anzahl an Sozialbeziehungen generiert eine um 60 Basispunkte höhere

monatliche Rendite als das Dezil mit der geringsten Anzahl an Beziehungen.

Manager Alpha

Das zweite Kapitel basiert auf einer Forschungsarbeit welche sich mit den Unterschieden von Renditeschätzungen basierend auf dem Hedgefund oder dem individuellen Hedgefund Manager beschäftigt.

Während ihrer Lebenszeit werden viele Hedgefunds durch mehrere Manager verwaltet. Außerdem verwaltet ein Manager oft auch mehrere Hedgefunds zur gleichen Zeit. Diese Forschungsarbeit macht sich diesen Umstand zunutze und formuliert die Frage ob Alpha eine Eigenschaft des Hedgefunds oder des Hedgefund Managers ist. Unter Anerkennung, dass das Alpha eines Hedgefunds eine Mischung von Manager-bezogenem und Hedgefund-bezogenem Alpha ist, beschäftige ich mich des Weiteren mit dem Effekt von Manager Fluktuationen auf Renditen und Kapitalflüsse. Zuletzt studiere ich die determinierenden Variablen hinter der Wahrscheinlichkeit für ein Fluktuationsereignis.

Mittels eines neuartigen Datensatzes, welcher mir biographische Informationen über wichtige Mitarbeiter von Hedgefunds in Großbritannien verfügbar macht, ist es mir möglich, die exakten Perioden von Arbeitsbeziehungen zwischen Hedgefunds und deren Mitarbeitern zu beobachten. Das erlaubt die Identifikation von Manager-basierten Fixed-Effects. Die Studie zeigt die statistische Signifikanz dieser Fixed-Effects in Rendite-erklärenden Regressionen.

Des Weiteren zeigt diese Studie signifikante Strukturbrüche in der Intercept (Alpha) des populären Fung and Hsieh (2004) Faktormodells zu Zeiten der Manager-Fluktuation auf. Die Faktorsensitivitäten können über die Hedgefunds variieren und potentielle Zeit-Trends und Trends über die Lebenszeit eines Hedgefunds werden mittels Time-Fixed-Effects und einem linearen Trend über das Alter des Hedgefunds modelliert. Potentiell abnehmende Skalenerträge werden berücksichtigt. Mittels Indikatorvariablen werden die Effekte der verschiedenen Perioden auf Alpha modelliert. Eine Indikatorvariable repräsentiert die Periode, in welcher wir den aktuellen Manager identifizieren können. Eine weitere Indikatorvariable

modelliert die Periode nach dem Ausscheiden des Managers. Mittels eines F-Tests zeige ich die statistische Signifikanz dieser Indikatorvariablen und damit die Existenz eines Strukturbruchs. Schätzungen des durchschnittlichen Querschnittsseffekts ergeben einen negativen Effekt der Managerfluktuation zwischen -2.71% und -3.04% auf das annualisierte Alpha wann immer ein Manager aus einem Hedgefunds ausscheidet. Konditional auf vergangene, relative Durschschnittsrenditen zeigt sich, dass dieser negative Effekt durch den Weggang von Managern mit überdurchschnittlichen Renditen getrieben wird. Der Weggang eines Managers, welcher über dem Querschnitts-Median der durchschnittlichen Renditen lag, resultiert in einer Verschlechterung der annualisierten Renditen um -4.57%. Die Studie beschäftigt sich auch mit der Auswirkung von Manager-Fluktuationen auf Kapitalflüsse. Konsistent mit Ergebnissen für Publikumsfonds ergibt sich ein positiver Effekt von 3.8% auf monatliche Kapitalflüsse bei dem Weggang eines Managers mit unterdurchschnittlichen Renditen und ein negativer Effekt von -1.9% bei dem Weggang eines Managers mit überdurchschnittlichen Renditen. Schließlich schätze ich ein Probit Modell, um die Wahrscheinlichkeiten für den Weggang eines Hedgefund Managers mittels vergangenen, durchschnittlichen Renditen, Kapitalflüssen und dem Alter des Hedgefunds zu erklären. Ich dokumentiere, dass die Wahrscheinlichkeit für den Weggang eines Managers im Alter des Hedgefunds steigt und eine fallende, konkave Funktion vergangener Renditen darstellt.

Hedge Fund Investors

Das dritte Kapitel präsentiert eine Forschungsarbeit über die durchschnittlich realisierte Rendite und Investitionsziele von verschiedenen Klassen von Hedgefund Investoren. Ausserdem beschäftigt sich diese Studie mit potentiellen Einwirkungen von Investoren auf Hedgefunds. Es existiert eine enorme Literatur über die Fragestellung ob Hedgefunds abnormale Renditen generieren. Wenige Studien beachten jedoch die Präsenz von verschiedenen Investorengruppen. Diese Studie zeigt, dass Hedgefund Investoren eine heterogene Gruppe darstellen. Existierende Forschungsergebnisse über die abnormalen Renditen von Hedgefunds lassen sich

nicht auf jede einzelne Gruppe von Investoren übertragen. Hedgefund Investitionen von verschiedenen Investorengruppen unterscheiden sich in ihren realisierten Renditen. Des Weiteren, präsentiere ich Ergebnisse, welche kompatibel mit einer Einwirkung von Hedgefund Investoren auf die Strategien der Hedgefund Manager sind.

Mittels einer Stichprobe von Form ADV Dokumenten und Daten über Hedgefund Renditen und Charakteristiken schätze ich die durchschnittlichen, realisierten Renditen der folgenden Investorenklassen: Individuals (other than high net worth individuals); High net worth individuals; Banking and thrift institutions; Investment companies; Business development companies; Pension and profit sharing plans (but not the plan participants); Charitable organizations; Corporations or other businesses not listed above; State or municipal government entities; Other investment advisers; Insurance companies.

In dem ersten Teil dieser Studie nutze ich Querschnitts-Regressionen und eine Paneldatenanalyse, um die durchschnittlichen Renditen, abnormalen Renditen und Risikoadjustierten Renditen dieser Investorengruppen zu schätzen. Corporations or other businesses realisieren größere Renditen als andere Investment-Unternehmen. Diese Überrenditen können jedoch auf systematische Faktoren und Hedgefund Charakteristiken zurückgeführt werden. Investitionen von Banking or thrift institutions erzielen geringe Renditen sowie abnormale Renditen. Dieses Ergebnis ist robust bezüglich der Aufnahme von Hedgefund-spezifischen Kontrollvariablen. Ein Anstieg von 10% des relativen Investments von Banking or thrift institutions resultiert in einem Rückgang von -0.83% der monatlichen abnormalen Renditen. Um für unterschiedliche Risikoneigungen der Investoren zu kontrollieren, schätze ich des Weiteren risikoadjustierte Renditekennzahlen. Hedgefund Investitionen von Banking or thrift institutions erzielen eine unterdurchschnittliche risikoadjustierte Rendite. Ein Anstieg von 10% des relativen Investments von Banking or thrift institutions resultiert in einem Rückgang von -0.12 der Sharpe Ratio. State or municipal government entities realisieren überdurchschnittliche risikoadjustierte Renditen. Ein Anstieg von 10% des relativen Investments von State or municipal government entities resultiert in einem Anstieg der annualisierten Sharpe Ratio um 0.19.

Im zweiten Teil dieser Studie schätze ich, mittels einer Regression der relativen Investitionsgröße der Investorenklassen auf Hedgefund Charakteristiken, die abgeleiteten Investitionspräferenzen der Investorenklassen. Charities und High net worth individuals präferieren kleinere Hedgefunds mit geringeren Verwaltungsgebühren. Corporations or other businesses sind bereit höhere Gebühren zu entrichten und investieren in größere Hedgefunds. Insurance companies investieren in jüngere Hedgefunds und High net worth individuals ziehen ältere Hedgefunds vor. State or municipal government entities investieren in Hedgefunds mit geringerem Risiko. Charities achten auf die Präsenz einer Highwater Mark.

Im dritten Teil dieser Studie untersuche ich, ob die verschiedenen Klassen von Hedgefund Investoren die Investitionsstrategien der Hedgefunds formen. Mittels einer Methodik, welche nahe der klassischen Difference-in-Difference Methode ist, mache ich mir Änderungen in der Investorenstruktur zunutze, um Änderungen von Renditekennzahlen und Risikomaßen zu untersuchen. Ein Anstieg von 10% in der relativen Investition von Individuals, Pension and profit sharing plans, Other investment advisers oder Insurance companies resultiert in einer geringeren Standardabweichung der Renditen des Hedgefunds im Bereich zwischen -0.16 und -0.2. Ein Anstieg in der relativen Investitionsgröße von Banking or thrift institutions erhöht die Sensitivität der Hedgefund Renditen bezüglich systematischer Faktoren und reduziert die durchschnittlichen abnormalen Renditen.

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Eigenabgrenzung

Kapitel 1 entstammt einer gemeinsamen Arbeit mit Prof. Dr. Jens Jackwerth (Universität Konstanz) und Prof. Dr. Alberto Plazzi (Università della Svizzera Italiana). Meine individuelle Leistung bei der Erstellung dieser Arbeit beträgt 33%.

Kapitel 2 entstammt meiner eigenständigen Arbeit. Meine individuelle Leistung bei der Erstellung dieser Arbeit beträgt 100%.

Kapitel 3 entstammt meiner eigenständigen Arbeit. Meine individuelle Leistung bei der Erstellung dieser Arbeit beträgt 100%.

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