

DOCTORAL THESIS

Hedge fund performance, capacity constraints, and relative skill

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“I would rather have questions that can’t be answered than answers that can’t be questioned”

Richard Feynman

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Abstract

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Doctor of Philosophy

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In this dissertation, I use empirical methods to examine the relative performance of hedge funds, as well as their capacity constraints. The research is motivated by the increasingly high allocation of assets to hedge funds combined with limited regulation of the industry, making it an important area for academic research. By introducing new methods to examine hedge fund performance and capacity constraints, I aim to add new knowledge to the increasing discussion by industry participants and financial commentators and to provide novel insight for further research.

This research takes the form of three studies.

The first study seeks to identify which investor types are most informed. Specifically, I examine the informativeness of quarterly disclosed portfolio holdings across four institutional investor types: hedge funds, mutual funds, pension funds, and private banking firms. I find that overweight positions outperform underweight positions only for hedge funds. By decomposing holdings and stock returns, I find that hedge funds are superior to other institutional investors; both at picking industries and stocks, and that they are better at forecasting long- and short-term returns.

The second study, proposes a novel method to investigate capacity constraints in the hedge fund industry. I introduce the concept of cohort size, which is measured by the total assets of all hedge funds applying similar strategies. Together, these funds impact on opportunity and execution costs, so that the total cohort size, rather than simply the individual fund size, is associated with fund performance. The study finds cohort size to be negatively related to future quarterly returns.

Finally, I introduce the cohort model, used to assess relative hedge fund manager skill. The model tested uses the correlation of monthly returns to locate cohorts, and forms peer-benchmarks by averaging returns across the cohort. The advantages of the cohort model are that it is able to address the omitted variable problem present in factor models, and it is better able to disaggregate skill from factor exposures common to particular investment strategies. Consistent with improved identification of manager skill, cohort alpha shows stronger persistence over longer horizons.

Statement of originality

I, David FORSBERG, declare that this thesis titled, 'Hedge fund performance, capacity constraints, and relative skill' and the work presented in it has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Signed:

David Forsberg

Date:

08-01-2018

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Dedicated to my Grandfather, Lars Berglund

Chapter 1

Introduction

1 Objectives and motivation

Hedge funds were first introduced in 1949 by A.W. Jones, who aimed to limit the impact of market risk by utilising short positions. By 1968, the number of United States (U.S.) hedge funds had grown to 140. Since then, the assets under management have continued to grow exponentially, now reaching over three trillion U.S. Dollars (USD).¹ Following this growth, hedge funds have emerged as one of the main categories of active investment management alongside mutual funds and pension funds, and have received increasing attention in academic literature. However, there remains several unanswered questions. Furthermore, the unregulated nature of hedge funds, and the secretiveness of the managers regarding their investment strategies, enhances the importance of additional studies to provide new insight and analysis.

In this dissertation, I present three studies which seek to answer some of the outstanding questions on hedge funds. The first paper, Forsberg (2016), seeks to determine if hedge funds, on average, are superior to other institutional investor types at predicting security returns. It analyses and compares hedge funds with mutual funds, pension funds and private banking firms, to determine which of these investor types is the most informed. For such a comparison to be valid, it is imperative that the analysis be based on consistent research design, data attributes, and examination period regardless of fund category. My motivation

¹Eichengreen and Mathieson (1999); BarclayHedge (2017).

for conducting this study is that the literature, to the best of my knowledge, does not contain such an analysis.

The second paper, Forsberg (2017a), seeks to improve the understanding of capacity constraints in the hedge fund industry. The impact of capacity constraints is a central issue to the active funds management industry. Having a better understanding of the impact such constraints can have on performance, would make a significant contribution to hedge fund performance evaluation. The absence of detailed assessment in the literature which is addressed in the paper, relates to a lack of understanding as to how capacity constraints are impacted by funds applying the same, or very similar, strategies. This topic is especially relevant following the exponential growth which the hedge fund industry has experienced, growth which increases the risk that the strategies may become over-crowded, resulting in diminishing returns.

The final paper, Forsberg (2017b), aims to improve understanding of another central topic to the active funds management industry; namely, how to assess the skill of a hedge fund manager. Multi-factor models traditionally applied for such analysis suffer from omitted variable biases, and the often-limited information on hedge fund strategies make it difficult to construct custom benchmarks for analyses of individual funds. Motivated by this shortcoming, I introduce a model that solves such issues, and improves the identification of relative hedge fund skill.

Through this dissertation, I hope to provide insight that will enhance the understanding of hedge funds; thereby, expanding relevant academic literature. I also hope that the original research presented will give a better understanding of active funds management overall. Further, the research is of interest to several stakeholders of the hedge fund industry, such as the hedge fund managers and their investors. Comparing hedge funds to other institutional investor types allows for further understanding of the value provided by hedge funds to their investors. This is of importance since hedge funds charge higher fees relative to other types of active investment managers, and these findings aim to help understand if these fees are warranted. The introduction of methods to comprehend the workings of capacity constraints, as well as models to identify relative hedge fund manager skill, are also of interest to these stakeholders.

All three papers presented in the dissertation are restricted to analyses of the U.S. hedge fund market. The U.S. market is one of the most developed, and has data available with the substantial history and breadth necessary for the analysis I present. Hence, I am providing analysis on, arguably, one of the most important hedge fund markets. Therefore, insight gained through this dissertation is highly relevant, and not restricted to a niche market. Additionally, a majority of previous studies involving hedge funds, focus on the U.S. market, making the results presented in this dissertation easily comparable to the literature.

2 Thesis content

The remainder of this dissertation is structured as follows:

Chapter 2 reviews the literature relevant to the topics covered in the dissertation. The review focuses on previous studies of performance of institutional investors, capacity constraints, relative performance of funds, as well as performance persistence.

Chapter 3 presents the study “Which institutional investor types are the most informed?”. Following the high fees characterising the hedge fund industry, it is of interest to investors to understand if they get value for these fees. To determine if hedge funds on average are more informed, the study compares the informativeness of equity holdings of hedge funds, mutual funds, pension funds, and private banking firms. By utilising a consistent research design and examination period regardless of fund type, as well as a dataset free of biases, the study is the first to compare institutional investor types on a like-for-like basis. I find that even though hedge funds are characterised by high fees, hedge fund managers are on average the most informed. This is true in regards to picking industries and picking stocks, as well as to forecasting short-term and long-term returns. Further analysis shows that the results are not due to hedge funds utilising commonly known factors in the Carhart (1997) four-factor model, or to hedge funds being able to invest in more illiquid assets.

Through Chapter 3, I identify that hedge fund managers represent the only institutional investor type that, on average, is informed regarding future security returns. Being informed investors introduces the issue of capacity constraints. Even though an informed fund may be able to identify investment opportunities, it may be unable to profit from these in the

presence of capacity constraints. Although capacity constraints in hedge funds have been analysed in the literature, previous studies often consider funds in isolation without considering the impact of other funds. However, funds with similar strategies are likely to pursue the same investment opportunities; thereby, impacting each other's opportunity costs and execution costs.

Chapter 4 consists of the paper "Capacity constraints in hedge funds: The information content in cohort alpha". It introduces the concept of 'fund cohorts', utilising the correlation in hedge fund returns to determine which funds apply similar strategies. Through cohorts, I am then able to estimate the total assets allocated to each fund's strategy, and investigate whether diseconomies of size exists at a cohort level or at a fund level. I find a negative and statistically significant relation between cohort size and future fund returns, indicating the importance of considering the total size of funds performing similar strategies when analysing capacity constraints. The chapter then provides an analysis of other ways whereby cohorts may influence funds, finding that they impact a fund's propensity to grow as well as the performance flow relation of individual funds.

Chapter 5 presents the paper "Relative hedge fund skill and the informativeness of cohort alpha". Traditional factor models commonly used to analyse hedge fund performance, such as Fung and Hsieh's (2004) seven-factor model, suffer from the impact of omitted variables. Furthermore, the unregulated nature of the hedge fund industry combined with hedge fund secrecy in terms of their strategy, makes it difficult to assign benchmarks to individual funds. This can further cause biases when estimating relative hedge fund skill. The chapter introduces the cohort model to identify hedge fund skill. The model finds benchmarks from within the thousands of funds reporting their returns to hedge fund databases. Chapter 5 provides an analysis of the cohort model and compares it to the traditional seven-factor model. The cohort model contributes to the existing literature by providing a method to analyse hedge fund performance that suffers less from the impact of omitted variables. Furthermore, cohort-adjusted performance is persistent over longer horizons compared to seven-factor alpha, and I provide analysis indicating that the cohort model can add value to fund-of-funds by investing in the best funds from within each cohort.

Chapter 6 concludes the dissertation and also provides a discussion of further research direction.

3 Publications and conference presentations

The papers presented in this dissertation are currently under review for publication, or are prepared to be submitted within the near future. All papers are targeted for either A*, or A rated journals according to the Australian Business Deans Council (ABDC) rating guide.² Furthermore, the paper presented in Chapter 4 has been presented at academic conferences.

- “Which institutional investor types are most informed?”, forthcoming: *Journal of Accounting and Finance* (A-rated journal)
- “Capacity constraints in hedge funds: The information content in cohort alpha”, working paper prepared for submission to A* rated journal, presented at:
 - The Role of Hedge Funds and other Collective Investment Funds in the Modern World, University of Manchester, United Kingdom
 - 7th Behavioural Finance and Capital Markets Conference, La Trobe University, Australia
- “Relative hedge fund skill and the informativeness of cohort alpha”, working paper prepared for submission to A* rated journal

The paper presented in Chapter 3 incorporates the feedback from Dr. Zhe Chen and Professor David Gallagher. The papers presented in Chapters 4 and 5 incorporates the feedback from Professor David Gallagher and Assoc. Professor Geoffrey Warren. They have provided help to refine the papers. However, I was the primary author, and a majority of the research and its originality is due to my own effort.

²Ratings are available on: <http://www.abdc.edu.au/master-journal-list.php>.

4 Summary

This dissertation aims to broaden the understanding of hedge funds in three dimensions. First, it investigates if hedge funds are more informed compared to other institutional investor types. Second, it introduces a new perspective to capacity constraints. Third, it develops a new method to estimate relative hedge fund skill.

The research presented in the dissertation is motivated by the increasing amount of capital allocated to the industry combined with an absence in the literature of the three areas of research. Furthermore, the industry's lack of regulation and the secretiveness of the funds, increases the importance of deepening our understanding of the hedge fund industry. Data used throughout the three papers presented is restricted to the U.S., making the findings highly relevant, as they are based on analyses of arguably the largest hedge fund market in the Western world.

Chapter 2

Literature review

1 Introduction

This chapter provides an overview of academic literature relevant to this thesis. Section 2 describes some of the key characteristics of hedge funds which distinguish them from other institutional investor types. Section 3 covers literature on performance of active funds managers. Section 4 focuses on studies of capacity constraints. Section 5 summarises literature regarding how relative fund skill can be assessed. Section 6 introduces literature related to performance persistence. Besides the review presented in this chapter, each of the papers presented throughout Chapters 3 to 5 include a literature review in the introduction or as a standalone section.

2 Distinguishing characteristics of hedge funds

The funds management industry is represented by passive and active managers. Whereas passive managers aim to replicate an index, active managers seek to identify mispriced securities to buy and sell to outperform market indices (Chen, Jegadeesh, and Wermers, 2000). However, Sharpe (1991) explains that all active managers impossibly can outperform passive managers. Sharpe further considers that, after taking transaction costs into consideration, the average performance of active managers would be less than the average performance of passive managers. Yet, a majority of the investments to the global funds management indus-

try is allocated to active managers (PwC, 2014). A possible explanation to this conundrum is that individuals or organisations investing in actively managed funds believe that they have located a subset of managers who are able to outperform passively managed funds.

Within the active funds management industry there are three types of managers; hedge funds, mutual funds, and pension funds. Among these types, hedge funds have several distinguishing characteristics which may be expected to impact the strategies they are able to apply, and therefore, also their performance relative to other institutions. Perhaps the most striking differences are related to their fee structure, the liquidity restrictions they apply on investors, and the industry's lack of regulation. A common compensation structure of hedge funds is to charge 2% in management fees and 20% in performance fees, which is substantially higher than fees charged by mutual funds and pension funds. One possible consequence of such higher fees is that hedge funds may be able to attract the most skilled managers because they can be paid at commensurately higher rate. Nohel, Wang, and Zheng (2010) and Deuskar, Pollet, Wang, and Zheng (2011) investigate this possibility in terms of hedge fund firms' ability to attract the most skilled mutual fund managers, but their results indicate that mutual funds are able to prevent this by providing the opportunity to manage mutual funds and hedge funds side-by-side. Li, Zhang, and Zhao (2011) argue that the high performance fees charged by hedge funds provide incentive to close the fund before its size makes it difficult for the managers to continue to achieve above average returns. Furthermore, according to Agarwal, Boyson, and Naik (2009a), the stronger incentives for hedge funds may be one of the reasons they earn higher returns than mutual funds.

In terms of liquidity constraints, hedge funds differ from other institutional investors in that they commonly apply constraints such as redemption, notice and lockup periods, thereby preventing the investors from accessing their capital in a timely manner. This allows hedge fund managers to enter positions in more illiquid assets. It is difficult to assess what impact these restrictions have on hedge fund performance relative to other institutional investor types by making a direct comparison in performance, since there are several other differences between the institutional types. Instead, it is possible to assess the significance of the restrictions indirectly, by examining the relation they have to performance within the hedge fund industry. Findings by Aragon (2007), Agarwal, Daniel, and Naik (2009b)

and [Titman and Tiu \(2011\)](#) indicate a positive relation between liquidity constrictions and hedge fund performance. Hence, it is reasonable to believe that redemption, notice, and lockup periods have a positive impact on the performance of hedge funds relative to other institutional types.

The regulatory landscape differentiates hedge funds from other institutional investors. Compared to mutual funds and pension funds, hedge funds experience less regulation. [Agarwal et al. \(2009a\)](#) argue that this is one of the reasons why hedge funds, in their sample, outperform mutual funds. [Aragon, Liang, and Park \(2014\)](#) compare the performance of offshore hedge funds (i.e. hedge funds with relatively low regulation) to U.S. onshore funds (i.e. hedge funds with relatively high regulation). They document that regulation impacts how hedge funds invest, in that offshore hedge funds, to a wider extent, invest in illiquid securities. [Cumming and Dai \(2009\)](#) find that hedge funds operating in countries with tougher capital requirements on average experienced lower performance, suggesting that regulations can have a significant impact on the performance of active managers.

Taken together, the differences across the dimensions of fee structure, liquidity constraints, and regulation, can be expected to impact hedge funds and their performance relative to other institutional investors. The fee structure may impact the decisions of hedge fund managers to reject further assets to protect performance, and may also impact their incentives to find strategies that generate high returns. The liquidity constraints hedge funds apply to their investors, allow the funds to apply strategies investing in more illiquid assets. Lastly, the absence of regulation of hedge funds, compared to the regulation faced by other investor types, can be expected to impact the strategies hedge funds are able to apply.

3 Performance of active funds

Several studies seek to analyse the ability of active managers in identifying mispriced securities. These studies often focus on one specific type of active manager, such as mutual funds, hedge funds, or pension funds. The methods applied in this branch of literature can be categorised as ‘holdings-based’ and ‘returns-based’ studies. I present articles related to the two categories below.

3.1 Returns-based approach

Early literature using fund returns to assess if actively managed funds are able to outperform passive counterparts include [Treynor \(1965\)](#), [Sharpe \(1966\)](#) and [Jensen \(1968\)](#). These studies focus on the returns of mutual funds, and find that mutual funds, on average, are able to provide value to investors. Since the 1960s, several studies have been published analysing performance of funds based on their returns, with a majority focusing on mutual funds. [Chang and Lewellen \(1984\)](#), and [Ippolito \(1989\)](#), find indications of mutual funds being informed based on their returns, although [Chang and Lewellen \(1984\)](#) only document returns high enough to offset the fees paid by investors. [Henriksson \(1984\)](#) documents that mutual funds are unable to time the market successfully, in that their market exposure is not correlated to market performance. [Elton, Gruber, Das, and Hlavka \(1993\)](#) control for returns of non-S&P stocks when assessing performance of U.S. mutual funds, and document that this reverses the result of [Ippolito \(1989\)](#). [Malkiel \(1995\)](#) provides insights into the significant impact of survivorship bias when studying fund performance. Malkiel states that when using a dataset free from such bias, mutual funds do not appear to be informed, in that their Jensen alpha on average is indistinguishable from zero. Besides survivorship bias, several other aspects appear to impact the results in studies of mutual fund returns. The country examined is one such factor. [Cai, Chan, and Yamada \(1997\)](#) find that Japanese mutual funds underperform, whereas [Otten and Bams \(2002\)](#) document aggregated out-performance of mutual funds in four out of five examined countries. Additionally, [Otten and Schweitzer \(2002\)](#) and [Rao, Ward, and Ward \(2007\)](#) show that European mutual funds in their sample outperformed U.S. mutual funds. [Redman, Gullett, and Manakyan \(2000\)](#) document that aggregated mutual fund performance may vary over time. They find that the international funds in their sample outperformed the U.S. stock market from 1985 to 1989, but underperformed between 1990 and 1994. [Busse \(1999\)](#) documents how results may differ depending on sample frequency. Utilising daily fund returns, a market timing ability of mutual funds is identified, something not found using lower frequency data.

In more recent studies using mutual fund returns to assess their average skill, the discrepancy continues. [Barras, Scaillet, and Wermers \(2010\)](#) control for false discoveries when

assessing fund skill, and find that the proportion of actually skilled managers has decreased over time, and that, by the end of their sample in 2006, more unskilled managers exist than skilled managers. [Angelidis, Giamouridis, and Tessaromatis \(2013\)](#) introduce a method of performance evaluation based on comparison between the fund and the fund's self-assigned benchmark. They find that U.S. mutual funds underperform, and that this mainly is due to stock selection. [Mateus, Mateus, and Todorovic \(2016\)](#) apply the method introduced by [Angelidis et al. \(2013\)](#) to analyse the performance of U.K. mutual funds, and document a positive average alpha. Overall, both early and recent studies on mutual fund performance sheds little light on whether the funds are able to provide positive risk-adjusted returns to their investors. The literature demonstrates the importance of method, time-period, and dataset, when assessing the performance of mutual funds.

Although a majority of literature utilising fund returns focuses on mutual funds, other types of institutional investors are also covered. One of the first studies to focus on hedge funds is by [Brown, Goetzmann, and Ibbotson \(1999\)](#), who find positive average risk-adjusted performance of hedge funds using a sample of U.S. offshore hedge funds. Hedge funds managers' ability to earn positive returns is supported in studies such as those by [Agarwal et al. \(2009a\)](#) and [Cao, Chen, Liang, and Lo \(2013\)](#). [Bali, Brown, and Demirtas \(2013\)](#) analyse the performance of different hedge fund indices. They observe that, whereas a few of the indices outperform the U.S. equity market, others outperform the U.S. treasury market, indicating that hedge funds are able to provide value to their investors. Similar to studies of mutual funds, the findings on performance of hedge funds have not been aligned. [Ackermann, McEnally, and Ravenscraft \(1999\)](#) document that hedge funds are able to outperform mutual funds, but still fail to outperform market indices. [Amin and Kat \(2003\)](#) find hedge funds to be associated with high risks, and state that the survivorship bias in previous studies most likely overstates the average performance of the funds.

Lastly, pension funds are also examined in the literature, although not to the same extension as mutual funds and hedge funds. [Ippolito and Turner \(1987\)](#) analyse the performance of pension funds from 1977 to 1983. They show that pension funds underperformed mutual funds as well as the S&P 500. However, they also document that pension funds outperform a stock-bond index which is weighted according to each pension fund's holdings, indicating the

importance of benchmarks used when assessing performance. [Coggin, Fabozzi, and Rahman \(1993\)](#) analyse the market timing ability as well as the stock selection ability of pension funds, finding that the industry, on average, has stock selection ability, but not market timing ability. In a more recent study, [Timmermann and Blake \(2005\)](#) examine the market timing ability of U.K. pension funds while conditioning for publicly available information, and do not observe any indications of pension funds having timing skills.

Studies which address the topic of utilising fund returns to assess the performance of active funds, usually arrive at different conclusions. For each of the three institutional investor types described above, a subset of studies finds that the average performance of the fund type is high enough to justify the fees they charge, whereas some find that they are not. Factors such as examination period, dataset and method, may explain why the results differ between studies. Hence, for the purpose of distinguishing which of the institutions on average are more informed, it is important that differences across these dimensions are eliminated.

3.2 Holdings-based approach

Analysis based on holdings allows for a more detailed examination of institutional investors' ability to pick securities. This approach allows for a breakdown into the ability to pick securities within certain universes, giving the researcher more control of the research environment, and has resulted in several new methods of examining the performance of funds. Because of data limitation, most of the studies utilising holdings to assess performance are based on equity holdings.

One of the first studies to apply a holdings-based approach is by [Grinblatt and Titman \(1989\)](#). They use quarterly holdings to estimate the performance of mutual funds. They document positive performance for a subset of funds, but find that mutual funds do not out-perform their benchmarks on average. A common method to holdings-based analysis introduced by [Daniel, Grinblatt, Titman, and Wermers \(1997\)](#) is the DGTW method. Applied to examine the skill of fund managers across different dimensions, the DGTW method allows for analysis of characteristics (i.e. value, size and momentum) timing and stock picking. [Daniel et al. \(1997\)](#) document skill within the mutual fund industry in regards to picking

securities, but not for timing stock characteristics. [Chen et al. \(2000\)](#) analyse both holdings and trades of mutual funds and find that, whereas mutual fund trades are informative of future stock performance, their level of holdings are not. However, [Wermers \(2000\)](#) documents that stocks held by mutual funds outperform the market. In more recent studies of mutual fund holdings, [Baker, Litov, Wachter, and Wurgler \(2010\)](#) and [Jiang, Verbeek, and Wang \(2014\)](#) find indications of mutual funds on aggregate being informed of future stock returns. [Jiang, Yao, and Yu \(2007\)](#) and [Kacperczyk, Nieuwerburgh, and Veldkamp \(2014\)](#) both find that mutual funds, on average, have market timing ability.

Hedge fund holdings are also analysed in the literature; the first was a study by [Brunermeier and Nagel \(2004\)](#). Their results indicate hedge fund managers are, on average, informed investors. Hedge funds appear to have profited from the technology bubble (leading up to the year 2000) by holding technology stocks prior to the bubble bursting. They were then able to avoid the downturn by selling stocks prior to their decline. [Griffin and Xu \(2009\)](#) do not reach the same conclusion regarding the informativeness of hedge funds. They compare the relation between hedge fund holdings and future stock returns to the relation between mutual fund holdings and future stock returns. When controlling for the exposure of holdings and trades to stock characteristics such as size, value and momentum, they are unable to provide any evidence that hedge fund managers are superior at picking stock than mutual fund managers. Several recent studies exist analysing hedge fund holdings. [Aragon and Martin \(2012\)](#) utilise hedge fund holdings of options and stocks, documenting that stock holdings are informative of future stock returns, and that option holdings are informative of future returns and volatility. [Sias, Turtle, and Zykaj's \(2015\)](#) research into hedge fund 'herding', find that hedge funds do not tend to herd. However, the occasions when they do buy the same stock, are often related to future positive stock performance. Analysing holdings, [Gao and Huang \(2016\)](#) find that hedge funds are able to earn positive returns through lobbyist connections. The foundation to a majority of the literature on hedge fund holdings is the U.S. Securities and Exchange Commission (SEC) 13F filings. However, the filings only require long positions to be disclosed by institutional investors; therefore, studies of hedge fund holdings commonly do not include the short side of trades and holdings. [Jiao, Massa, and Zhang \(2016\)](#) solve this issue by combining hedge fund trading on the long side with

the change in short interest, thereby getting a more complete view of what hedge funds are trading. They find that changes in hedge fund long positions and changes in short interest moving in different directions is highly informative of future stock returns. [Agarwal, Jiang, Tang, and Yang \(2013b\)](#) and [Aragon, Hertz, and Shi \(2013\)](#) analyse the positions hedge funds deliberately hide from their portfolio disclosures. It appears that hedge funds delay reporting of long positions that will earn high future positive returns, consistent with the view that the funds want to hide their alpha-generating stock picks.

In summary, the literature using holdings to assess the performance of different institutional investor types is not homogeneous in its conclusions. Even though a majority of the studies analysing hedge fund holdings argue that the funds' managers, on average, are skilled investors, [Griffin and Xu \(2009\)](#) do not find them to be more skilled than mutual fund managers at picking stocks. Furthermore, the studies use different datasets of holdings depending on what institutional type is examined, and the examined time period rarely is consistent across two different studies. Therefore, even though the use of holdings allows for more controlled experiments compared to the returns-based approach, the literature does not make it possible to compare the informativeness of institutional investor types.

4 Capacity constraints

Capacity constraints in the active funds management industry is related to the negative impact of size on execution costs and opportunity costs ([Perold, 1988](#)). These two costs cause implementation shortfall, meaning that the actual portfolio underperforms the theoretical 'paper' portfolio.¹ Execution cost is the cost of trading a security, and includes commission fees as well as price impact. Opportunity cost is the cost associated with not holding the desired portfolio. [Perold and Salomon \(1991\)](#) argue that one of the costs can be reduced by increasing the other. For instance, a fund may choose to not trade in security A because of the high price impact such a trade would have, thereby decreasing the execution cost and increasing the opportunity costs. Although the costs can be seen as substitutes, [Perold and](#)

¹The 'paper' portfolio is the portfolio the fund would have held at each point in time if there were no costs associated with trading and if the market had unlimited liquidity.

Salomon (1991) show that implementation shortfall is expected to increase with the block size of the desired trade.

One common method to examine whether capacity constraints exist within the hedge fund industry is to investigate if there is a negative relation between size and performance. The literature regularly uses one of two definitions of size: the size of the individual fund, or the total size of the sector in which the fund resides. The fund size is expected to have a negative impact since it will increase the block size of the trades. For instance, a fund with \$10 million in Assets Under Management (AUM) will have to trade a higher amount to achieve a 5% weight in a security compared to a fund with \$1 million in AUM. Ammann and Moerth (2005) analyse the relation between hedge fund size and future returns. They document that a negative relation exists both in linear and quadratic terms. However, when analysing the relation between size and Sharpe ratio, Ammann and Moerth (2005) are unable to find a statistically significant impact of the linear term. Ammann and Moerth (2008) document that whereas larger hedge funds tend to have lower standard deviation, they also tend to have lower returns compared to small funds. When analysing the relation between size and risk-adjusted performance, they find that small funds outperform large funds. Ramadorai (2013) and Yin (2016) also document a negative impact of hedge fund size on performance. One of the possible explanations is, according to Yin (2016), the fee structure of hedge funds. Even though diseconomies of size exist and hedge funds commonly are rewarded for high performance through a performance fee, they have incentive to accept new inflows. Contrary to these studies, Gregoriou and Rouah (2002) and Aggarwal and Jorion (2010) do not find a negative relation between hedge fund size and future performance.

Whereas the data availability of hedge funds is limited in areas other than returns and AUM, this is not the case for active mutual funds. Through regulations, mutual funds in several countries report their holdings. Hence, studies of capacity constraints within mutual funds have enabled additional insight in regards to explanations to the relation between size and performance within the active funds industry. Chen, Hong, Huang, and Kubik (2004) and Yan (2008) find that portfolio liquidity has a significant impact on diseconomies of size, in that funds with more illiquid portfolios experience capacity constraints to a higher degree compared to other funds. This is consistent with the fact that execution costs will

have a more significant impact within illiquid securities. [Chan, Faff, Gallagher, and Looi \(2009\)](#) utilise daily transaction data of mutual funds, and find that capacity constraints are driven by transaction costs. Large funds in their study experience higher market impact, leading to lower percentage return. Furthermore, diseconomies of size are present to a higher degree within mutual funds with higher turnover. [Agnesens \(2013\)](#) analyses how a wide range of mutual fund characteristics can be used to predict future fund performance using a generalised calendar time regression approach. Agnesens documents that the only characteristics informative of future performance are fund size (negative impact), fund family size (positive impact), and past return (positive impact).

The negative impact of sector size is related to competition for mispriced securities. As the size of a hedge fund sector increases, more funds will seek to buy and sell the same securities, leading to increasing implementation shortfall for the involved funds. This relation is examined by [Naik, Ramadorai, and Stromqvist \(2007\)](#), who find a negative and significant impact of sector size, within four out of eight examined sectors, in that sector performance decreases following high inflows. A similar relation is also documented by [Pástor, Stambaugh, and Taylor's \(2015\)](#) examination of the active mutual fund industry. They document that as the total size of the active mutual fund industry increases, the performance of the funds reduces.

Capacity constraints in hedge funds has, to the best of my knowledge, not been examined besides the fund or sector size approaches presented above. For instance, one unexplored area is how peer-groups of funds with very similar trading strategies may impact the implementation shortfall of funds.

5 Relative hedge fund skill

One strand of literature discussed in Section [3](#) is the performance of hedge funds as a type of institutional investors, performance which can be used to assess if hedge fund managers, as a group, are skilled investors. In this section, I focus on literature concerning methods to observe fund manager skill relative to other fund managers. One of the most common methods to assess the skill of a fund manager is the use of factor models. This branch of

literature was first introduced by Jensen (1968), who utilised a one-factor model to analyse performance of fund managers. By regressing the returns of a mutual fund against the return of the market portfolio, the fund's forecasting ability (Jensen alpha) could be estimated. Several attempts have since then been made to improve the estimation of fund skill by introducing additional factors. Several of these studies can be traced back to Ross's (1976) Arbitrage Pricing Theory (APT), which describes asset returns by linear combinations of the returns of systematic factors. Chang and Lewellen (1984) and Lehmann and Modest (1987) extend the APT to analysis of actively managed funds by allowing the intercept of the regression to not pass through the origin, thereby enabling the analysis of a fund's forecasting ability. Perhaps the two most common multi-factor models applied to analysis of mutual fund performance are the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model.

Whereas the above models have proven useful in the analysis of traditional long-only equity investment strategies, they have been proven insufficient to the analysis of hedge fund performance. Fung and Hsieh's (1997) analysis of hedge funds reveals that hedge fund strategies often differ from those followed by mutual funds. Whereas they document the Sharpe (1992) style factor model to explain more than 50% of returns for 92% of mutual funds, the same model explains less than 25% of returns for almost half of the hedge funds they examine. In light of this finding, other studies have introduced new risk factors to suit the strategies of hedge funds. Fung and Hsieh (2001) introduce lookback straddles, that are capable of explaining a significant proportion of returns of trend-following hedge funds. These lookback straddles were later added to Fung and Hsieh's (2004) seven-factor model, now one of the most common factor models utilised in performance analysis of hedge funds. Fung and Hsieh (2004) document their seven-factor model to explain a significant proportion of indices of hedge fund returns. However, they also explain that their model may not be suitable for the hedge funds applying niche strategies, for which tailored models may be necessary. In a more recently developed model, Buraschi, Kosowski, and Trojani (2013) append correlation risk to the seven-factor model. Agarwal and Naik's (2004) multi-factor model is an alternative to the seven-factor model. Their model controls for asset returns as well as returns on options on these assets, and indicates that several hedge fund strategies

are exposed to the returns of these options. Other recent studies suggest new factors for analysis of hedge funds. For instance, [Bali, Brown, and Caglayan \(2011\)](#), [Bali, Brown, and Caglayan \(2014\)](#), and [Avramov, Barras, and Kosowski \(2013\)](#) include macroeconomic variables in models of hedge fund returns.

The factor models above have proven useful for analysis of hedge fund performance, increasing the explanatory power compared to the models used to examine mutual fund performance. However, although the models have proven useful for analysis of average hedge fund returns, some studies have found the models to be insufficient for analysis of individual funds. For instance, [Titman and Tiu \(2011\)](#) document the average R^2 of the seven-factor model to be 26% when applied to individual hedge funds, which is substantially lower than the results on the hedge fund indices analysed by [Fung and Hsieh \(2004\)](#). [Bollen's \(2013\)](#) analysis of individual hedge funds indicates that one third of the funds in their sample had an R^2 insignificantly different from zero, and explain that these zero- R^2 funds are likely to be exposed to omitted risk factors. The findings of [Titman and Tiu \(2011\)](#) and [Bollen \(2013\)](#) are consistent with [Fung and Hsieh's \(2004\)](#) suggestion that the seven-factor model is more suitable when the purpose is to analyse the returns of diversified portfolios of hedge funds.

An alternative to the risk-factor approach of the studies above, is to use style-benchmarks. [Brown and Goetzmann \(1997\)](#) introduce a style classification algorithm to the analysis of mutual funds, which classifies mutual funds into eight separate styles. Dividing the funds into the styles, allows for analysis of relative performance. [Brown and Goetzmann \(2003\)](#) implement the same algorithm to the universe of hedge funds. [Jagannathan, Malakhov, and Novikov \(2010\)](#) utilise 32 Hedge Fund Research (HFR) style indices to estimate style-adjusted performance of individual funds. Their model adjusts the returns of hedge funds by the return of the market, the return of the self-reported hedge fund style, and the return of the model-selected hedge fund style. Through their model, they are able to explain a higher proportion of return of individual hedge funds compared to the seven-factor model. [Hunter, Kandel, Kandel, and Wermers \(2014\)](#) introduce a peer-benchmark for analysis of mutual funds. They allocate each fund to one of nine different peer-groups, and create a peer benchmark based on the average excess return of the funds in the peer-group. They then augment the [Carhart \(1997\)](#) four-factor model by appending the peer-benchmark. Their

model increases the identification of skilled and unskilled managers compared to the standard four-factor model.

As per the literature presented above, there is a wide range of methods available for analysis of hedge fund performance. However, the risk of omitted variables remains, and [Lehmann and Modest \(1987\)](#) document the importance of factor-selection in performance analysis. A subset of studies aims to bypass this issue by benchmarking funds against a peer group. However, the total number of existing strategies within the growing number of hedge funds is unknown, and may very well exceed the number of hedge fund sectors controlled for in the literature.

6 Performance persistence

Performance persistence of hedge funds is examined by a range of authors, providing mixed evidence with regard to the duration of persistence. [Agarwal and Naik \(2000\)](#), [Baquero, Horst, and Verbeek \(2005\)](#), [Barès, Gibson, and Gyger \(2003\)](#) and [Harri and Brorsen \(2004\)](#) document persistence in performance at a quarterly horizon. However, as the persistence horizon increases to one or more years, the results become less homogeneous. [Brown et al. \(1999\)](#) and [Brown and Goetzmann \(2003\)](#) do not find past hedge fund performance to be indicative of their future performance at a one-year horizon. Similar results are documented by [Herzberg and Mozes \(2003\)](#) and [Barès et al. \(2003\)](#). On the other hand, the study by [Agarwal and Naik \(2000\)](#) indicates past hedge fund performance to be informative over a one-year horizon, and [Edwards and Caglayan \(2001\)](#) find evidence of persistence at a two-year horizon.

In more recent studies of hedge fund returns, methods have been introduced revealing persistence at one or more years. [Kosowski, Naik, and Teo \(2007\)](#) employ a Bayesian approach to deal with short-sample issues in hedge fund returns, and document persistence over a one-year horizon. [Horst and Verbeek \(2007\)](#) adjust for hedge fund database biases and conclude that performance persists up to an annual horizon. They also find style persistence to explain some of the perseverance identified in the literature. [Boyson \(2008\)](#) incorporates factors such as fund size and fund age, and conclude that persistence exists for up to two

years. Lastly, Jagannathan et al. (2010) adjust returns for hedge fund styles, and find that hedge fund returns over the past three years are informative of the performance over the next three years. However, their method does not explain if the persistence is driven by perseverance over the full three-years, or by a shorter sub-period.

Overall, the duration of persistence in hedge fund returns varies in the literature. One trend is that recent studies tend to find a slightly longer persistence of between one and two years. A possible explanation to this trend is that new methods to identify relative past hedge fund performance have been introduced, improving the identification of skilled managers. Yet the question remains as to whether further improvements could be made to enhance the ability to predict future hedge fund performance. By eliminating omitted variables to the widest extent possible, pure fund skill may be more accurately identified, which can be expected to persist over long horizons.

7 Summary

Parallel to the growth of the hedge fund industry is an increasing amount of literature. In a recent literature review, Agarwal, Mullally, and Naik (2015) document that the number of publications related to hedge funds in the top financial journals in 2015 had increased by a factor of 6.6 compared to 2005. Besides summarising studies relevant to this dissertation, this chapter helps to highlight shortcomings in the literature. First, it is difficult to assess which institutional investor types on average are more skilled at security selection. In Chapter 3, the informativeness of hedge funds, mutual funds, pension funds and private banking firms, are compared using a consistent method, dataset, and examination period, regardless of institutional type. The results indicate that hedge fund managers are more able to pick stocks, compared to other types of institutional investors. Second, the review highlights a potential gap in studies of capacity constraints in hedge funds. In Chapter 4 the concept of fund cohorts is introduced, and it provides evidence of how funds with closely related strategies impact capacity constraints. Lastly, models utilised in the literature to analyse relative hedge fund performance may still suffer from omitted variables. Chapter 5 discusses how models of hedge fund performance can be improved through the construction of peer

benchmarks based on the average return of funds performing the same, or very similar, strategies.

Chapter 3

Which institutional investor types are the most informed?

1 Introduction

The global funds management industry continues to grow rapidly and is forecast to exceed USD 100 trillion by 2020, half of which are funds from North America (PwC, 2014). The majority of assets in the industry are delegated to active managers seeking higher risk-adjusted returns compared to passive benchmarks, reflecting an industry-wide belief that active managers are genuinely informed. Within active management, there is a wide variety of institutional investor types: hedge funds, mutual funds, pension funds and private banking firms, each with differing characteristics, capabilities and incentive arrangements. For allocators to these institutions, it is of significant interest to understand if these differences translate into institutional investor types having differential abilities in generating alpha.

In order to draw conclusions on which institutional investor type provides the highest value to investors, it is imperative to make comparisons in an environment with a consistent research design, time period and data attributes. I argue that if one of these points differs across different institutional types, it cannot validly be concluded whether the results are driven by these dissimilarities or by actual differences among the investor types. Unfortunately, prior research does not always fulfil these requirements. Further, previous findings are inconclusive given that several studies find no evidence of institutions being able to earn

abnormal returns.^[1] whereas others conclude the opposite.^[2] In addition, previous research has largely focused on mutual funds, as well as hedge funds to a limited extent; whereas pension funds and particularly private banking firms, have received little attention. Hence, this paper aims to bridge this knowledge gap by comparing the stock-picking ability of different institutional investor types using a consistent method and time period, as well as sourcing holdings data from the same dataset regardless of institutional investor type.

In this study I examine the quarterly portfolio holdings, available on an aggregated fund company level, of hedge funds, mutual funds, pension funds, and private banking firms holistically.^[3] These institutional investor types have many differences in characteristics. For instance, hedge funds commonly apply redemption, notice and lockup periods which allow them to enter positions in more illiquid securities compared to other institutional investors, thereby earning a liquidity premium.^[4] Furthermore, the compensation structure of hedge funds can be expected to attract fund managers with an ability to earn abnormal returns.^[5] and motivation to maximise the fund's risk-adjusted performance.^[6] Meanwhile, mutual funds, pension funds and private banking firms commonly only charge fixed management fees, thereby motivating the fund to increase aggregate assets under management (AUM) rather than maximising returns. Institutional investor types have also been found to have different performance-flow relations, which, in the presence of management fees, impacts fund incentives. For example, [Del Guercio and Tkac \(2002\)](#) find that pension funds are punished for negative performance and tracking error to a wider extent than mutual funds,

¹Mutual funds: [Chang and Lewellen \(1984\)](#); [Elton et al. \(1993\)](#); [Carhart \(1997\)](#); [Quigley and Siquefield \(2000\)](#); [Barras et al. \(2010\)](#). Hedge funds: [Ackermann et al. \(1999\)](#); [Amin and Kat \(2003\)](#); [Malkiel and Saha \(2005\)](#). Pension funds: [Ippolito and Turner \(1987\)](#).

²Mutual funds: [Ippolito and Turner \(1987\)](#); [Ippolito \(1989\)](#); [Busse \(1999\)](#). Hedge funds: [Brown et al. \(1999\)](#); [Kosowski et al. \(2007\)](#); [Cao et al. \(2013\)](#). Pension funds: [Coggin et al. \(1993\)](#).

³The source of the portfolio holdings is the Securities and Exchange Commission EDGAR 13F filings, which are reported on a firm level, and a filer may therefore represent several underlying funds. However, since I aggregate holdings to an institutional investor type level, I argue that this only has a minor impact on the findings and is consistent with the approach used by other studies. Throughout the paper, I use the term 'fund' to represent 'fund company'.

⁴[Aragon \(2007\)](#), [Agarwal et al. \(2009b\)](#) and [Titman and Tiu \(2011\)](#) all find that hedge funds with restrictions on investor liquidity outperform hedge funds without these restrictions.

⁵[Nohel et al. \(2010\)](#) and [Deuskar et al. \(2011\)](#) investigate the possibility of hedge funds being able to attract the best mutual fund managers and find that mutual fund firms avoid this by providing the opportunity to manage mutual funds and hedge funds side-by-side.

⁶[Li et al. \(2011\)](#) argue that the incentive fees applied by hedge funds make them more likely to have an optimal fund size that allows for abnormal returns, whereas funds with low or no incentive fees will allow the AUM to increase to the point at which the fund is not able to earn abnormal returns. In addition, hedge fund managers commonly invest their own wealth in the fund, which is not the case for mutual funds ([Aggarwal and Jorion, 2010](#)).

and Li et al. (2011) observe the performance-flow relation of hedge funds to be symmetric, whereas it is asymmetric for mutual funds. With all these differences in mind, investors can expect to find varying levels of average skill across different institutional investor types.

Using portfolio holdings instead of returns has several advantages in creating a coherent comparison. For instance, it allows me to restrict the research to a known set of securities, in this case U.S. equities listed on the AMEX, NASDAQ or NYSE, compared to returns which will be impacted by investments in different asset classes and security universes. In addition, to the best of my knowledge, there is no fund return database with mandatory reporting covering hedge funds, mutual funds, pension funds and private banking firms, and several fund return databases available suffer from reporting biases.⁷ In contrast, the portfolio holdings data used in this study do not suffer from such biases, as the Securities and Exchange Commission (SEC) legally requires disclosure of equity positions.

Analysing holdings also allows me to decompose fund exposures into an industry and stock component, as well as into static (long-term forecast) and trade (short term forecast) components. This enables me to better assess if fund managers can successfully forecast industry or stock returns, as well as if they are able to make these forecasts over a short-term or long-term horizon. Additionally, by decomposing stock returns into a systematic and a non-systematic component I can distinguish between market timing and industry/stock picking. Historically, market timing has commonly been estimated using fund returns, and most studies examine the market timing ability of either mutual funds or hedge funds. Findings in these studies point towards hedge funds, on average, having market timing ability, and mutual funds do not.⁸ In this context, holdings analysis is an important complement to returns when assessing market timing ability. Since I only analyse equity holdings, I am focusing on the ability of managers to time the market from selecting industries and stocks, thereby excluding the timing ability driven by holdings of other asset classes.

⁷See Brown, Goetzmann, Ibbotson, and Ross (1992); Goetzmann, Ingersoll, Spiegel, and Welch (2007); Evans (2010); Aiken, Clifford, and Ellis (2013); Agarwal, Fos, and Jiang (2013a).

⁸For instance, Henriksson (1984), Chang and Lewellen (1984), Ferson and Schadt (1996), Bollen and Busse (2001) and Bali et al. (2014) find that mutual funds have no ability to time the market, whereas Busse (1999) find that they are able to time volatility. Chen and Liang (2007), Cao et al. (2013) and Bali et al. (2014) find proof of market timing of hedge funds. Coggin et al. (1993) find no proof of market timing of pension funds.

The results reveal a number of novel findings. Firstly, hedge funds have the highest information content in their holdings. The most overweight hedge fund positions outperform their most underweight positions by 10.7% per year (with an annualised Carhart four factor alpha of 8.46%) whereas the evidence does not support the view that other institutional investor types have stock-picking skills.⁹ This finding contradicts Griffin and Xu (2009), who determine that the informativeness of hedge fund holdings does not exceed that of mutual fund holdings, which I attribute to the different time period examined as well as to differences in method. Instead, the findings support Brown et al. (1999), Brunnermeier and Nagel (2004), Kosowski et al. (2007), Agarwal et al. (2009a), Bali et al. (2013), Cao et al. (2013) and Shive and Yun (2013), who find that hedge funds earn abnormal returns.¹⁰ Furthermore, this finding is consistent regardless of whether I compare long-only positions or include an approximation for the short positions of hedge funds, and is also consistent across different methods to aggregate holdings. Hence, I provide evidence that, when compared over the same time period with a consistent research design, and holdings being collected from the same source, hedge funds appear to be significantly more informed compared to mutual funds, pension funds and private banking firms, and this finding has not been possible to conclude using previous available research.

Secondly, I find that the difference in stock picking ability is not explained by hedge funds being able to exploit illiquid positions, to a greater extent, than other institutional investors. I show that hedge funds are better at picking more liquid stocks, and that they outperform mutual funds, pension funds and private banking firms irrespective of stock liquidity. Furthermore, I find that the results are robust regardless of whether I analyse only large-cap stocks, small-cap stocks, or micro-cap stocks. The results are therefore supportive of the view that the hedge fund industry attracts more skilled fund managers, or that hedge funds, to a wider degree, have greater incentives in stock picking compared to other institutional types.

⁹Results based on returns between March 1999 and June 2015.

¹⁰However, these papers are based on analysis of returns of hedge funds. Therefore, it cannot be concluded if these findings are driven by hedge funds having access to financial instruments not available to mutual funds, pension funds and private banking funds, or if they are driven by superior skills at picking securities available to all institutional investor types.

Thirdly, the results show the informativeness of hedge fund holdings is driven by their ability to pick industries and stocks, both based on their trades and long-term holdings. The results also indicate that pension funds are skilled at picking stocks based on longer term forecasts, but that this skill is neutralised by their poor ability to forecast short-term returns. I do not find that mutual funds or private banking firms have stock or industry picking ability.

Lastly, I find evidence that hedge funds, mutual funds and pension funds are able to successfully time the market. Mutual funds exhibit this skill by timing systematic returns through their industry holdings, whereas pension funds time systematic returns through their stock holdings. Hedge funds are able to achieve market timing through both industry and stock selection. Meanwhile, the evidence indicates that private banking firms do not time the market.

The remainder of the paper is organised as follows. Section 2 provides a literature review. Section 3 summarises the data. Section 4 provides a description of the method. Section 5 presents empirical results, and Section 6 concludes.

2 Literature review

Over the last three decades, studies have analysed fund manager holdings. The question of whether fund managers are skilled stock pickers is addressed in a subset of these studies by examining how holdings and trades predict future stock returns. Some studies (see Jiang et al. (2007) and Kacperczyk et al. (2014)), have also used holdings to examine the market timing ability of fund managers.

Grinblatt and Titman (1989) use quarterly holdings to compute the gross returns of each fund in their sample, and find that while positive performance exists for a subset of funds, mutual funds do not outperform their benchmarks on average. Daniel et al. (1997) introduce characteristic-based benchmarks to analyse stock characteristic timing and stock characteristic selectivity among mutual funds, in turn giving further insight into the value provided by fund managers. They document that mutual funds are skilled at picking securities, but are not able to time stock characteristics (i.e., value, size and momentum). Chen et al.

(2000) examine the holdings and trades of mutual funds and find that stocks with substantial shareholdings by mutual funds do not outperform stocks for which the level of mutual fund ownership is low. However, they conclude that stocks bought by mutual funds outperform the stocks they sell, implying that stock selection skill exists among mutual funds. Wermers (2000) documents that mutual fund holdings do indeed predict future stock returns, but that transaction costs and poor performance of nonstock holdings results in underperformance in terms of net returns. Baker et al. (2010) analyse the ability of mutual funds to forecast company earnings announcements, and find a positive relation between mutual fund holdings and abnormal earnings announcement returns; and therefore, conclude that mutual funds are able to forecast earnings. Jiang et al. (2014), introduce an additional measure of aggregated mutual fund belief in a stock called the ‘deviation from benchmark’ (*DFB*). Using their measure, they find that from 1984 to 2008, stocks with a positive deviation (i.e., an aggregated overweight by mutual funds) outperformed stocks with a negative deviation (i.e., an aggregated underweight by mutual funds), thereby providing additional evidence of informativeness within mutual funds.

Brunnermeier and Nagel (2004) were the first to analyse the holdings of hedge funds. They conclude that hedge funds were able to profit from the pre-2000 technology bubble by being heavily invested in tech stocks when the bubble was growing, and were able to predict which stocks would drop in value as the bubble burst. Griffin and Xu (2009) determine whether hedge funds are superior to mutual funds by comparing the information in their holdings and trades. Their study is similar to this paper. They find that hedge funds only exhibit marginally superior stock picking ability over mutual funds. Furthermore, they find no evidence that hedge funds are able to time stock characteristics such as momentum, value and size, and question whether hedge fund performance justifies the 20% performance fees they typically charge. However, in more recent studies, Agarwal et al. (2013b) and Aragon et al. (2013) find that the subset of hedge fund holdings disclosed with a deliberate delay earn positive abnormal returns, indicating that hedge funds are informed stock pickers.

Two studies use portfolio holdings to confirm the existence of market timing ability among mutual funds. Jiang et al. (2007) conclude that mutual funds decrease their aggregated beta at times when future market returns are low. Kacperczyk et al. (2014) add an additional

dimension by analysing how the stock picking and market timing ability depends on the current market state, and document that mutual funds appear to have stock selection ability during booms and market timing ability during recessions.

3 Data

The source of portfolio holdings data used is the SEC EDGAR 13F reports. The SEC requires these reports to be filed quarterly by investors owning more than USD 100 million in 13F securities,^[11] within 45 days after each quarter end. Through the report, institutions are required to disclose their long positions, as at the end of the quarter, for every security in which the dollar value invested is higher than USD 200,000.^[12] The reported holdings may be aggregated over several funds, however, as I do not perform fund level analysis, this should not have a significant impact on the findings presented. Throughout the paper, I use the term ‘fund’ to represent these fund companies. I collect holdings from March 1999 to March 2015, and the dataset is free from survivorship bias. The 13F holdings dataset is combined with securities level data from FactSet, and is filtered so that I only include equity securities listed on the AMEX, NASDAQ or NYSE.

One of the advantages in using 13F data, is that holdings for all four institutional investor types can be collected from the same data source. This is especially important since different databases apply different filters to the data. For instance, the SEC N- 30D form, commonly used in studies of mutual funds, does not apply the same reporting frequency or size filter as the 13F filings, and is made on a fund level rather than a fund company level. Hence, if comparing the informativeness of hedge fund holdings from 13F data, with mutual fund holdings from N-30D data, the results could be driven by these dissimilarities rather than by actual differences in informativeness. To avoid such issues, I collect the holdings of the four institutional investor types from the 13F filings.

To classify each institution by type, I combine the holdings dataset with institutional type classifications provided by FactSet. FactSet examines each 13F filer, and determines

¹¹A list of securities updated quarterly, available on <https://www.sec.gov/divisions/investment/13flists.htm>.

¹²Since the fund is required to own at least USD 100 million in 13F securities, the USD 200,000 threshold corresponds to a maximum of 0.2% of the value invested in 13F securities.

the institutional type. I include all reports filed by hedge funds, mutual funds, pension funds, and private banking firms.¹³

Panel A in Table 1 summarises the number of reporting institutions and their average number of reported positions over time. Since 1999, the number of filers for each institutional type has increased. Compared to other studies that use hedge fund holdings extracted from 13F reports, I have the highest number of identified hedge funds.¹⁴ FactSet classifications have enabled a broader sample compared to methods used in previous studies. According to Table 1 (Panel A), hedge funds and pension funds have become less concentrated over time in terms of the average number of stocks held, whereas mutual funds have moved in the opposite direction. Over the entire sample period, hedge funds have had the highest concentration, and pension funds the lowest.

Throughout the sample period, the average number of stocks held by the different institutional investor types is higher than what may be expected of individual funds, especially in regards to mutual funds and pension funds. This high average is due to the fact that holdings are reported on a fund company level rather than on a fund level. Hence, the average number of stocks owned by the individual funds is likely to be lower than what is presented in Table 1. However, since the analysis in Section 5 is completed based on holdings on an aggregate institutional investor type level, this is unlikely to have a significant impact on the results.

¹³13F reports have been used in several studies to analyse holdings of institutional investors. In the case of hedge funds, Brunnermeier and Nagel (2004), Griffin and Xu (2009), Ben-David, Franzoni, and Moussawi (2011), Agarwal et al. (2013b) and Aragon et al. (2013) all use 13F filings, inferring that the holdings are representative of hedge fund's equity positions. I also assess hedge fund holdings in the sample and time period used in this study. I construct portfolios containing all equity holdings of hedge funds, and compare these to the performance of two hedge fund indices: the Barclay Hedge Equity Long Bias Index and the Barclay Hedge Equity Long/Short Index. For the holdings to be representative, I would expect the correlation to be high between the hedge fund portfolio and the indices. The results confirm this, revealing a correlation, based on returns adjusted for market beta, of 0.80 (0.68) between the hedge fund portfolio and the long bias index (long/short index). If I do not adjust the portfolio and indices returns for market beta, the correlations increase to 0.96 and 0.81 respectively. Given the way the SEC collects fund data, I would see no reason for the data to be unrepresentative of mutual funds, pension funds and private banking firms. Furthermore, in terms of the impact of the USD 100 million cut-off applied to 13F reports, it is important to note that this rule is applied on a firm level rather than on a fund level. Therefore, the sample used will indirectly contain several funds with an AUM lower than USD 100 million.

¹⁴For example, in 2004, Griffin and Xu (2009) identified 191 hedge funds, whereas I have 561, and in 2000, Brunnermeier and Nagel (2004) identified 48 hedge funds, whereas this study has 300.

Table 1: Holdings data summary statistics

Table 1 provides key statistics for reported entity holdings between March 1999 and March 2015, for Hedge funds, Mutual funds, Pension funds and Private banking firms. Panel A reports yearly statistics of numbers of funds filing a 13F report, and average number of unique stocks reported per filing, per manager type. Panel B reports the average USD distribution, both as percentage allocated and relative to the market, across large-cap, small-cap and micro-cap stocks respectively, for each manager type.

Panel A: Number of funds reporting and their average holdings								
	Number of reporting entities				Average number of stocks owned			
	Hedge funds	Mutual funds	Pension funds	Private banking	Hedge funds	Mutual funds	Pension funds	Private banking
1999	242	76	34	160	84.2	624.2	697.9	177.3
2000	300	81	35	180	86.8	632.1	745.8	190.4
2001	363	83	35	202	89.6	592.7	857.4	176.1
2002	392	83	35	207	95.3	582.5	910.3	174.3
2003	466	85	40	214	106.4	580.2	925.2	191.2
2004	561	89	41	235	105.4	618.2	959.4	202.3
2005	687	99	39	264	105.7	594.4	980.4	199.3
2006	802	108	42	291	104.4	555.0	959.1	210.9
2007	920	118	42	314	102.2	521.5	931.6	199.5
2008	934	116	42	324	84.5	492.1	881.4	186.3
2009	860	120	44	331	83.0	491.2	890.5	170.7
2010	832	118	44	353	94.9	496.4	947.5	167.5
2011	869	120	49	379	88.5	493.9	882.8	168.7
2012	904	123	51	402	90.0	489.3	875.2	171.3
2013	942	124	57	468	95.8	487.1	876.8	177.4
2014	1022	125	62	521	99.7	487.2	895.4	178.6
2015	945	125	61	517	101.6	486.6	832.7	174.8

Panel B: Average weight distribution across size universes				
	Hedge funds	Mutual funds	Pension funds	Private banking
% weight in large stocks	80.839	93.019	94.312	94.049
Relative to market	0.887	1.020	1.035	1.032
% weight in small stocks	13.712	5.772	4.703	4.601
Relative to market in	2.157	0.885	0.737	0.714
% weight in micro stocks	5.449	1.208	0.985	1.349
Relative to market in micro stocks	2.222	0.479	0.391	0.542

Panel B in Table 1 provides statistics on the USD distribution of holdings in large-cap stocks, small-cap stocks, and micro-cap stocks,¹⁵ as well as their weightings relative to the market. In terms of relative distribution, hedge funds prefer small-cap and micro-cap stocks, where they have over twice the market exposure as mutual funds, pension funds and private banking firms, which all appear to prefer large-cap stocks. This is consistent with the theory that the redemption period required by hedge funds enables them to enter illiquid positions in small-cap and micro-cap stocks.

¹⁵The breakpoints used are the same as in Fama and French (2008). Large-cap stocks contain all stocks with a market capitalisation above the 50th percentile for NYSE stocks, small-cap stocks contain all stocks with a market capitalisation between the 20th and 50th percentile for NYSE stocks, and micro stocks contain all stocks with a market capitalisation below the 20th percentile for NYSE stocks.

4 Measure of average institutional conviction

While holdings and trades have been analysed in previous studies to determine whether fund managers are informed stock pickers, different institutional investor types have rarely been compared; Griffin and Xu (2009) being an exception.

In this paper I set out to answer the question of which institutional investor type on average is the most informed, and to do so I first need to define a metric to estimate the average investor type's conviction in a security. This conviction can then be used determine average stock picking ability, by assessing how different levels of conviction predicts future stock performance. This paper's method adopts the argument by Griffin and Xu (2009) that the holdings of any one fund manager contain scant information, but if a certain group of institutional investor is skilled, then their aggregated holdings should be informative of future stock returns. The measure applied takes foundation in the estimation for fraction of ownership, which has been used in several previous studies (see e.g. Chen et al. (2000) and Griffin and Xu (2009)):

$$\begin{aligned}
 f_{s,t} &= \frac{\sum_{m=1}^M \text{Shares held}_{s,m,t}}{\text{Shares outstanding}_{s,t}} \\
 &= \frac{\sum_{m=1}^M \text{Shares held}_{s,m,t} \times \text{Price}_{s,t}}{\text{Shares outstanding}_{s,t} \times \text{Price}_{s,t}} \\
 &= \frac{\sum_{m=1}^M \text{Value held}_{s,m,t}}{Mcap_{s,t}}
 \end{aligned} \tag{1}$$

$\text{Shares held}_{s,m,t}$ is the number of shares manager m holds in security s

$\text{Shares outstanding}_{s,t}$ is the number of shares outstanding in security s

$\text{Value held}_{s,m,t}$ is the dollar value manager m has invested in security s

$Mcap_{s,t}$ is the market capitalisation of security s

By scaling the measure for fraction of ownership by a constant equal to the sum of the market capitalisation across all stocks in the selected stock universe, divided by the sum of the total institutional Assets Under Management (AUM) within the same stock universe (see equation (2)), a critical attribute of the fraction of ownership becomes evident: Fraction of ownership is equivalent to the ratio between the AUM weighted average fund weight in

the stock and the weight of the stock in a market capitalisation weighted universe portfolio. The fact that the metric gives different weights to institutions depending on their size is problematic, given that I set out to answer the question of which institutional investor type on average are superior stock pickers. For instance, an institution with AUM of one billion USD, will impact the fraction of ownership 10 times more compared to an institution with 100 million USD in size, making the measure unsuitable when estimating the average institutional investor confidence in a security.

$$\begin{aligned}
 Scaled\ f_{s,t} &= \frac{\sum_{m=1}^M Value\ held_{s,m,t}}{Mcap_{s,t}} \times \frac{Universe\ Mcap_t}{\sum_{m=1}^M AUM_{m,t}} \\
 &= \frac{\frac{\sum_{m=1}^M Value\ held_{s,m,t}}{\sum_{m=1}^M AUM_{m,t}}}{\frac{Mcap_{s,t}}{Universe\ Mcap_t}} \\
 &= \frac{\frac{\sum_{m=1}^M AUM_{m,t} \times w_{s,m,t}}{\sum_{m=1}^M AUM_{m,t}}}{\frac{Mcap_{s,t}}{Universe\ Mcap_t}}
 \end{aligned} \tag{2}$$

$AUM_{m,t}$ is the assets under management of manager m

$w_{s,m,t}$ is manager m 's weight in security s

$Universe\ Mcap_t$ is the market capitalisation of all stocks in the universe

I only need to make a small modification to adjust for the issue highlighted above; namely, replace the AUM weighted average weight with the equal weighted average weight. Since this measures the average weight across all funds relative to the market weight, I name the measure the Relative Excess Weight (REW).¹⁶

$$REW_{s,t} = \frac{FW_{s,t}}{UW_{s,t}} \tag{3}$$

$FW_{s,t}$ is the average weight across all funds in security s

$UW_{s,t}$ is the market capitalisation weighted universe weight in security s

¹⁶As an example of how the REW differs to the scaled fraction of ownership, I consider two managers (A and B). Manager A has an AUM of 10 million, and a weight in security X of 5%. Manager B has an AUM of 90 million, and a weight in security X of 10%. Security X has a market weight of 7.5%. In this case, the equal weighted weight in the stock is 7.5%, and the REW is therefore 1. The AUM weighted weight in security X is 9.5%, and the scaled fraction of ownership is therefore 1.27. Hence, even though the managers on average have the same weight in the security as the market, the scaled fraction of ownership indicates that the managers on average are overweight in the security, driven by the fact that the large manager is overweight.

In other words, the *REW* is the average weight of institutional investors in a security relative to the market weight in the security, and can be seen as the average institutional investor belief in a security relative to the belief of the market in the same security.¹⁷ Hence, if the measure exceeds one, the average institutional investor has a weight in the security higher than the rest of the market, indicating that the institutional investors have a more positive expectation of future returns of the security compared to the rest of the market. Similarly, on average, a *REW* below one indicates a pessimistic view of the security compared to the rest of the market. If the managers on average have stock picking ability, then the *REW* will be higher in those stocks which will outperform the other stocks in the universe, and lower in the stocks which will underperform. I estimate the *REW* separately for each institutional investor type; and therefore, estimate four different *REW* estimates for each quarter for each stock.¹⁸

One of the aspects differentiating hedge funds from mutual funds, pension funds and private banking firms is that they commonly enter short positions, either as a bet on future negative stock returns, or as a hedge to a long position. The 13F reports only contain long positions, and the *REW* measure therefore ignores the short side of hedge fund holdings. For completeness, I therefore define an alternative measure (REW^{LS}) which takes into consideration the short interest in each stock.¹⁹ Throughout this paper I consequently present

¹⁷Holdings have been used for analysis of fund performance in many instances. *REW* is a measure of aggregate institutional investor belief in a security, resulting in one estimate per security at each point in time, and therefore shares resemblance with fraction of ownership (see Chen et al. (2000) and Griffin and Xu (2009)) and with the deviation of benchmark measure (see Jiang et al. (2014)). Since these estimates are similar to *REW* both in how they are constructed and what they aim to measure, I include the measures in the analysis in Section 5. In other instances, holdings have been used for fund-level estimates. One such example is the active share estimate introduced by Cremers and Petajisto (2009). Active share differs from *REW* in that it is an estimate of how active a fund is in terms of its holdings deviating from a benchmark, therefore resulting in one estimate per fund at each point in time.

¹⁸In some cases, the fund family for which I capture the holdings may contain index-tracking products. However, since the *REW* is measuring the deviation from the market capitalisation weighted weight, such index products would only bring the measure closer to 1 for all stocks (assuming that the index is market capitalisation weighted). In Section 5, I focus either on portfolio sorts or standardised *REW* (so that each cross-section has a mean of 0 and a standard deviation of 1). Therefore, the fact that some institutional investor types includes families with a higher proportion of index products will not have a significant impact on the results.

¹⁹Short interest is the number of stocks sold short, and is not restricted to hedge funds. Therefore, it is an approximation of the short side of hedge funds, and not a perfect measure. To confirm that short interest can be used as an approximation for the short side of hedge funds, I estimate the following regression:
$$\frac{\sum SI_t}{\sum MCAP_t} = \alpha + \beta_1 \frac{\sum HF_t}{\sum MCAP_t} + \beta_2 \frac{\sum MF_t}{\sum MCAP_t} + \beta_3 \frac{\sum PB_t}{\sum MCAP_t} + \beta_4 \frac{\sum PF_t}{\sum MCAP_t} + \epsilon_t$$
 (where SI is the value of all short interest at time, MCAP is the market capitalisation, and HF, MF, PB, PF are the values of total ownership of each of the fund types). The results from the regression indicate that only the hedge fund proportion of ownership has a statistically significant relation with the proportion of short interest (the t-

results for both REW and REW^{LS} when discussing hedge funds, and only REW for other institutional investor types. This allows me to compare fund types, like for like, through the long-only measure, and also to analyse the more complete picture of hedge fund holdings through the long-short measure.

$$REW_{s,t}^{LS} = \frac{FW_{s,t} - SW_{s,t}}{UW_{s,t}} \quad (4)$$

$SW_{s,t}$ is the short interest weighted universe weight in security s

4.1 Industry or stock driven conviction

One contribution of this paper is the decomposition of the informativeness of institutional stock conviction into industry-driven conviction and stock-driven conviction. To accomplish this, I split REW into two separate measures which aim to capture the component of REW due to belief in an industry ($REW_{Industry}$) and the component due to belief in a stock within an industry (REW_{Stock}). REW_{Stock} is designed to measure the REW in a stock relative to other stocks within the same industry, thereby eliminating the component of REW driven by a belief in an industry. Hence, I define REW_{Stock} as the average weight in the stock within the stock's industry divided by the market's weight in the stock within the industry:

$$\begin{aligned} REW_{Stock,s,t} &= \frac{FW_{s,i,t}}{UW_{s,i,t}} \\ &= \frac{\frac{FW_{s,t}}{FW_{i,t}}}{\frac{UW_{s,t}}{UW_{i,t}}} \\ &= \frac{FW_{s,t}}{UW_{s,t}} \times \frac{UW_{i,t}}{FW_{i,t}} \end{aligned} \quad (5)$$

$FW_{s,i,t}$ is defined as $FW_{s,t}/FW_{i,t}$

$UW_{s,i,t}$ is defined as $UW_{s,t}/UW_{i,t}$

stats from the regression above are 4.13 (β_1), 1.53 (β_2), 1.22 (β_3) and 1.38 (β_4). This is to be expected if the short interest is a valid approximation, since it shows that when hedge funds grow on the long side, the short interest grows simultaneously. Furthermore, short interest has previously been used as an approximation of short hedge fund positions by Ben-David et al. (2011), and Goldman Sachs (as cited in Ben-David et al. (2011)) estimates that hedge funds represent 85% of all short positions.

$FW_{i,t}$ is the average institutional investor weight in industry i

$UW_{i,t}$ is the market capitalisation weight in industry i

From equation (5), it becomes apparent that REW_{Stock} will be highest in stocks where the REW is high compared to the REW of other stocks in the same industry, and lowest in stocks where the REW is low compared to the REW of other stocks in the same industry. Furthermore, the measure can also be seen as a scaled REW , which adjusts for the component of REW which is driven by an industry bet. For instance, in industries where the institutional investors on average are underweight ($\frac{UW_{i,t}}{FW_{i,t}} > 1$), the REW_{Stock} will be scaled upwards, thereby adjusting the REW for the fact that the institutional investors made an industry bet. I define $REW_{Industry}$ as the difference between REW and REW_{Stock} :

$$\begin{aligned} REW_{Industry,s,t} &= REW_{s,t} - REW_{Stock,s,t} \\ &= \frac{FW_{s,t}}{UW_{s,t}} - \frac{\frac{FW_{s,t}}{FW_{i,t}}}{\frac{UW_{s,t}}{UW_{i,t}}} \\ &= \frac{FW_{s,t}}{UW_{s,t}} \left(1 - \frac{UW_{i,t}}{FW_{i,t}} \right) \end{aligned} \tag{6}$$

Equation (6), reveals two interesting attributes of $REW_{Industry}$. Firstly, the measure will be high if the REW is high, but not driven by a high REW_{Stock} . Secondly, $REW_{Industry}$ will be negative for all stocks in industries where the institutions are underweight, and positive for all stocks within industries in which the institutions are overweight.

5 Empirical results

5.1 Portfolio sorts

In this section I apply the commonly used portfolio sort method to assess the informativeness of the standard REW estimate. Each quarter, the stocks are split into decile portfolios based on the REW of each institutional investor type as of the end of the previous quarter.²⁰ The

²⁰It could be argued that different institutions may have different investment horizons, and that their informativeness therefore should be analysed over these horizons. However, I argue that the REW , since it is based on aggregate level of holdings, rather than trades, does not suffer from this issue. A fund with a long investment horizon will most likely keep the same stock overweighted for a long time period, and the

portfolios are equal weighted and I include all equity securities listed on the AMEX, Nasdaq and NYSE.²¹

Panel A in Table 2 provides the average monthly return of portfolios, in excess of the equally weighted index, based on holdings of hedge funds, mutual funds, pension funds, and private banking firms.²² Hedge funds are the only institutional investor type where holdings are informative of future stock returns. The most underweight positions (the bottom decile) underperform the benchmark universe, and the most overweight positions (the top decile) outperform the rest of the stocks in the universe. Over the sample period, a portfolio buying the most heavily overweight positions and selling the most underweight positions (the top minus bottom portfolio) has an average annualised performance of 10.7%.

Including short interest in the measure of hedge fund holdings increases the performance difference between the most overweight and most underweight positions to 14.2% per year (from 10.7%), driven mainly by increasingly negative performance of the most underweight positions. The finding that hedge funds are able to predict future returns is not surprising, since several previous studies have found that hedge funds are informed investors.²³ However, I conclude that part of the abnormal returns of hedge funds is driven by their stock picking ability, which cannot be easily established using fund returns. Mutual funds, pension funds and private banking firms do not appear to have information in their holdings, as overweight positions do not outperform underweight positions for any of these fund types. The results for mutual funds confirm results from Chen et al. (2000), but also contradict the findings by, for example, Baker et al. (2010) and Jiang et al. (2014). To the best of my knowledge, the results for private banking firms are new to the literature.

Griffin and Xu (2009) find that the excess informativeness of hedge fund holdings can be explained by exposure to the momentum factor, and in Table 1 I document how hedge

REW will capture the stock as overweight for each of the quarters. If the stock is then sold, so that it is no longer overweight, and the stock earns high positive returns in the subsequent months, it would be wrong to consider the investor as informed on the basis that the institution used to hold the stock many quarters ago.

²¹In this section, I winsorise the data used in the analysis to ensure that a subset of extreme outliers are not driving the results. In the instances winsorisation is used, I have validated that the conclusions remain even if the outliers are not cleaned.

²²I define the return of the benchmark universe as the equal weighted return of all stocks in the universe, which contains all stocks listed on the AMEX, Nasdaq and NYSE.

²³See Brown et al. (1999), Brunnermeier and Nagel (2004), Kosowski et al. (2007), Cao et al. (2013) and Shive and Yun (2013).

Table 2: Returns of decile portfolios

Table 2 provides average monthly returns of equally weighted decile portfolios, between March 1999 and June 2015. The deciles are constructed by sorting the *REW*, and then splitting the stocks into 10 deciles. Top contains the 10% stocks with highest *REW*, and Bottom contains the 10% stocks with lowest *REW*. The top minus bottom portfolio is formed by buying the Top portfolio, and selling the Bottom portfolio. All portfolios are updated quarterly, and the stock universe is all stocks listed on AMEX, Nasdaq and NYSE. The stock returns used to estimate portfolio performance are winsorised at the 1st and 99th percentile. The returns presented in Panel A are net of the equal weighted return of the stock universe. The returns presented in Panel B, C and D are the four-factor alphas estimated through the following regression: $r_t = \alpha + \beta_1 MktRf_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \epsilon_t$. Where r is the portfolio return estimated using the same method as in Panel A, *MktRf* is the market return net the risk free rate, *SMB* is the return of the Small-minus-Big portfolio, *HML* is the return of the High-minus-Low portfolio and *UMD* is the return of the Up-minus-Down portfolio.

	Hedge funds (1)	Hedge funds ^{LS} (2)	Mutual funds (3)	Private banking (4)	Pension funds (5)
Panel A: Mean adjusted returns					
Top	0.521*** (4.651)	0.479*** (4.711)	0.135 (1.352)	0.199*** (2.687)	0.119 (1.115)
Decile 9	0.430*** (4.399)	0.446*** (4.975)	-0.040 (0.471)	-0.107 (1.189)	-0.015 (0.120)
Decile 8	0.347*** (4.488)	0.289*** (4.010)	-0.164* (1.848)	-0.138* (1.664)	-0.158 (1.397)
Decile 7	0.149** (2.111)	0.042 (0.671)	-0.126 (1.554)	-0.195*** (2.712)	-0.053 (0.542)
Decile 6	-0.030 (0.453)	0.080 (1.001)	-0.142* (1.810)	-0.019 (0.317)	0.023 (0.253)
Decile 5	-0.198*** (3.639)	0.226 (1.595)	-0.088 (1.284)	-0.082 (1.593)	-0.024 (0.292)
Decile 4	-0.225*** (3.263)	-0.012 (0.113)	0.077 (1.087)	0.034 (0.447)	-0.017 (0.184)
Decile 3	-0.280*** (3.382)	-0.294*** (4.207)	0.028 (0.386)	0.046 (0.516)	0.014 (0.103)
Decile 2	-0.326*** (3.115)	-0.549*** (5.476)	0.050 (0.415)	0.076 (0.713)	0.087 (0.531)
Bottom	-0.369*** (3.393)	-0.702*** (4.244)	0.271 (1.387)	0.189 (1.459)	0.024 (0.123)
Top-Bottom	0.889*** (5.224)	1.181*** (5.631)	-0.136 (0.581)	0.010 (0.061)	0.095 (0.354)
# of Obs	195	195	195	195	195
Panel B: Four-factor alpha					
Top	0.463*** (4.456)	0.411*** (4.262)	0.030 (0.338)	0.194*** (2.979)	0.092 (1.023)
Decile 9	0.320*** (3.974)	0.360*** (4.520)	-0.068 (0.845)	-0.030 (0.430)	0.026 (0.327)
Decile 8	0.249*** (4.082)	0.254*** (3.899)	-0.174** (2.154)	-0.063 (0.948)	-0.125 (1.507)
Decile 7	0.108* (1.930)	0.029 (0.500)	-0.123* (1.743)	-0.179*** (2.995)	-0.037 (0.449)
Decile 6	-0.061 (0.960)	0.124** (1.995)	-0.113* (1.789)	0.015 (0.286)	-0.032 (0.393)
Decile 5	-0.197*** (4.169)	0.387*** (4.166)	-0.099 (1.525)	-0.114** (2.233)	-0.102 (1.386)
Decile 4	-0.210*** (3.402)	0.067 (0.875)	0.026 (0.425)	-0.049 (0.830)	-0.070 (0.948)
Decile 3	-0.199*** (3.260)	-0.282*** (4.082)	-0.006 (0.082)	-0.023 (0.326)	-0.003 (0.032)
Decile 2	-0.217*** (2.634)	-0.564*** (5.804)	0.110 (1.012)	0.045 (0.470)	0.144 (1.080)
Bottom	-0.242*** (3.079)	-0.782*** (6.073)	0.416** (2.245)	0.205 (1.660)	0.107 (0.647)
Top-Bottom	0.704*** (5.066)	1.193*** (6.084)	-0.386* (1.794)	-0.011 (0.074)	-0.015 (0.069)
# of Obs	195	195	195	195	195

Continued on next page

Table 2 Continued from previous page

	Hedge funds 2001-2004 (1)	Hedge funds 1999-2015 (2)	Mutual funds 1999-2015 (3)	Private banking 1999-2015 (4)	Pension funds 1999-2015 (5)
Panel C: Griffin and Xu (2009) fraction of ownership (four-factor alpha)					
Top	0.427** (2.409)	0.315*** (3.960)	-0.202* (1.939)	0.044 (0.743)	0.059 (0.716)
Decile 9	0.355** (2.537)	0.291*** (3.769)	-0.193** (2.144)	-0.202*** (3.084)	0.019 (0.239)
Decile 8	-0.203 (1.429)	0.120** (1.972)	-0.099 (1.391)	-0.136** (2.289)	0.072 (0.796)
Decile 7	-0.099 (0.984)	-0.013 (0.272)	-0.072 (1.138)	-0.048 (0.717)	-0.111 (1.122)
Decile 6	-0.049 (0.379)	-0.036 (0.632)	-0.053 (1.079)	-0.104 (1.621)	-0.135* (1.717)
Decile 5	-0.095 (0.832)	-0.109** (2.218)	0.009 (0.173)	-0.005 (0.094)	-0.010 (0.157)
Decile 4	-0.297** (2.122)	-0.149*** (2.737)	-0.081 (1.351)	0.025 (0.482)	-0.160* (1.783)
Decile 3	-0.154 (1.124)	-0.132** (2.181)	0.090 (1.145)	0.080 (1.208)	-0.005 (0.049)
Decile 2	0.088 (0.641)	-0.073 (1.134)	0.118 (0.978)	0.111 (1.049)	0.151 (1.234)
Bottom	0.043 (0.249)	-0.207*** (2.745)	0.484*** (2.764)	0.236* (1.775)	0.118 (0.809)
Top-Bottom	0.385 (1.418)	0.522*** (4.142)	-0.686*** (2.616)	-0.192 (1.187)	-0.059 (0.306)
# of Obs	48	195	195	195	195
	Hedge funds (1)	Mutual funds (2)	Private banking (3)	Pension funds (4)	
Panel D: Jiang et al. (2014) deviation from benchmark (four-factor alpha)					
Top		0.053 (0.715)	-0.207** (2.416)	-0.187** (2.389)	-0.131 (1.433)
Decile 9		-0.071 (0.995)	-0.150* (1.878)	-0.125 (1.608)	-0.094 (1.267)
Decile 8		-0.004 (0.067)	-0.147** (2.168)	-0.133* (1.913)	-0.091 (1.137)
Decile 7		0.007 (0.129)	-0.113 (1.597)	0.027 (0.481)	-0.078 (0.954)
Decile 6		0.005 (0.094)	-0.056 (0.828)	0.007 (0.130)	0.100 (1.285)
Decile 5		-0.021 (0.420)	0.027 (0.501)	0.072 (1.276)	0.284*** (3.265)
Decile 4		-0.029 (0.487)	0.246*** (3.142)	0.363*** (2.712)	0.649*** (3.807)
Decile 3		0.159** (2.192)	0.772*** (4.276)	0.523*** (3.619)	0.046 (0.395)
Decile 2		0.205** (2.003)	-0.062 (0.641)	-0.094 (1.004)	-0.315*** (3.616)
Bottom		-0.297*** (4.597)	-0.315*** (4.544)	-0.452*** (5.459)	-0.372*** (3.836)
Top-Bottom		0.349*** (3.539)	0.108 (1.023)	0.266*** (2.596)	0.242* (1.948)
# of Obs		195	195	195	195
Absolute <i>t</i> statistics in parentheses					
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$					

funds are more overweight in small-cap and micro-cap stocks compared to other institutional types. To ensure that my findings are not explained by these factors I estimate the Carhart

(1997) four-factor alpha of each of the portfolios and present the results in Panel B of Table 2.²⁴

The results indicate that the difference between hedge funds and other institutional investors holds true even after controlling for exposure to risk factors. The top minus bottom portfolio of the most overweight/underweight hedge fund holdings has an annualised four-factor alpha of 8.4%, indicating that the majority of the information in hedge fund holdings is not explained by exposure to risk factors. Furthermore, the REW^{LS} of hedge fund holdings increases the annualised four-factor alpha of the top minus bottom portfolio to 14.3% (from 8.4%). Conversely, the four-factor alpha of the same portfolio based on holdings of mutual funds is negative and statistically significant at a 10% level, revealing poor stock selection ability among mutual funds.

The significant difference in information between hedge funds and mutual funds, after controlling for risk factors, contradicts Griffin and Xu (2009). One possible reason why my findings are different is that Griffin and Xu's (2009) result is based on fund holdings from 1992 to 2004, whereas this paper's analysis spans from 1999 to 2015. Moreover, their estimation of the fraction of ownership also differs from REW in that it gives higher weight to funds with higher AUM. To understand the degree to which these differences impact my findings, I re-estimate the results for hedge funds over the overlapping period from 2001 to 2004, and adopt Griffin and Xu's (2009) fraction of ownership definition.²⁵ The results, presented in Panel C of Table 2, indicate that the top minus bottom portfolio of the most overweight and underweight hedge fund positions earned a positive, but statistically insignificant four-factor alpha from 2001 to 2004, in line with Griffin and Xu's (2009) own published findings. Computing the performance of the same portfolio over the full-time period reveals a positive and statistically significant performance in line with the results achieved using REW (6.3% annualised four-factor alpha compared to 8.4%). These findings indicate that the difference between studies is driven by the different time period and the measure of ownership.²⁶

²⁴The data utilised to estimate the four-factor alpha is sourced from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

²⁵I exclude the years 1999 and 2000 in the comparison as Griffin and Xu (2009) and Brunnermeier and Nagel (2004) find that hedge funds earned abnormal returns during the dotcom bubble.

²⁶An additional difference between the studies is this study's use of the FactSet classification database, which allows me to identify almost 3 times the number of hedge funds as Griffin and Xu (2009) in 2004 alone.

AIMA (2015) argue that the outperformance during the dotcom era led to increasing money flows to the hedge fund industry, especially from institutions. To profit from these flows, hedge funds were forced to reach institutional requirements, which may have improved their performance through more robust standards and risk controls. Furthermore, Scholes (2004) argues that fund inflows to hedge funds have increased their ability to attract talented investors and resulted in more resources spent on research, which is supported by my findings. That talent matters in funds management is also confirmed by Li et al. (2011), in that funds with talented managers outperform other funds.

As a robustness test of the results presented in Panels A and B of Table 2, I also include the decile performance of portfolios based on the fraction of ownership of the remaining fund types, as well as portfolios based on the Jiang et al. (2014) deviation from benchmark (*DFB*) measure.²⁷ The results reveal that hedge funds are the top performing investor type, regardless of method. When applying the fraction of ownership estimate, the results are highly comparable to the results presented in Panel B. All institutional types except hedge funds overweight stocks that underperform the ones they underweight, with mutual funds being the worst performing type. In terms of the *DFB* estimate, the overall results are less monotonic compared to when analysing the *REW* or the fraction of ownership. For instance, whereas private banking firms appear to have stock selection ability based on the top minus bottom portfolio, this is purely driven by the poor performance of the bottom portfolio, and the stocks most overweight by private banking firms do in fact underperform the rest of the universe.

One possible explanation as to why hedge funds may appear more informed, compared to other institutional investor types, is their ability to enter positions in illiquid securities owing to characteristics such as redemption periods, and that ability is commonly seen as one of the explanations of the performance of hedge funds.²⁸ To understand the extent to which my results are explained by this difference, I apply a double sort method. I first split

²⁷The *DFB* measure was introduced by Jiang et al. (2014) and is, similarly to fraction of ownership and the *REW*, an approach to aggregate holdings of several institutional investors to one estimate of stock belief. I estimate the *DFB* based on the second method described in Jiang et al. (2014), in which an institution's benchmark portfolio is the value weighted portfolio of all stocks included in the manager's portfolio.

²⁸See e.g. Agarwal et al. (2009b), Aragon (2007) and Titman and Tiu (2011).

the stocks into quintiles based on liquidity to form different liquidity universes.²⁹ For each quintile, I then construct decile portfolios based on the *REW* of each institutional investor type. Table 3 provides the average monthly performance of the top minus bottom portfolios of the most overweight and most underweight positions, for each liquidity universe. If the superior performance of hedge funds is indeed driven by the redemption period allowing them to take more illiquid positions, hedge funds should have similar stock picking ability as other institutional investors in liquid stocks, whereas they should have superior stock picking ability in illiquid stocks.

The results presented in Table 3 show that the discrepancy in ability to enter illiquid positions is not the driving factor for the difference in holdings informativeness across different institutional investor types. Hedge funds outperform mutual funds, pension funds and private banking firms regardless of the liquidity universe, both in terms of raw performance and four-factor alpha. In fact, hedge fund holdings contain more information regarding the future stock performance of more liquid stocks, compared to illiquid stocks. Instead, it appears that hedge funds motivate stock picking and are able to attract the most talented investors. Elton, Gruber, and Blake (2003) argue that high incentive fees can be expected to increase management effort and attract the best fund managers since the pay-off is lucrative for funds producing a positive return. Similarly, Li et al. (2011) posit that funds with no or low incentive fees will allow their AUM to increase to a level at which the fund is unable to earn abnormal returns, whereas funds with high incentive fees will have an optimal fund size which still allows for abnormal returns. Hedge funds are the institutional investor type charging the highest incentive fees, hence this paper's findings support these arguments.

As with hedge funds, both mutual funds and private banking firms have higher information content in their holdings in universes of more liquid stocks. However, even in the universe of the most liquid stocks, the performance of mutual funds and private banking firms is lower relative to hedge funds.

To further extend the liquidity analysis, I also present results of quintile portfolios based on the *REW* within size universes of large, small, and micro stocks, based on the Fama and French (2008) size cut-offs. The advantage of such an analysis is that size likely will

²⁹I define liquidity as the natural logarithm of stock turnover, which is defined as the average monthly volume divided by shares outstanding over the past year.

Table 3: Returns of decile portfolios across stock liquidity universes

Table 3 provides average monthly returns of portfolios formed by buying the 10% stocks with highest *REW*, and selling the 10% stocks with lowest *REW* across five liquidity universes. The High-Low liquidity universe portfolio is formed by buying the High liquidity universe portfolio and selling the Low liquidity universe portfolio. The time period examined is between March 1999 and June 2015, and liquidity is defined as the natural logarithm of stock turnover, which is defined as the average monthly volume divided by shares outstanding over the past year. All portfolios are updated quarterly, and the stock universe is all stocks listed on AMEX, Nasdaq and NYSE. Columns 1, 3, 4 and 5 use long-only positions when determining the *REW* of respective institutional investor type. Column 2 uses a combination of the long hedge fund positions and the reported short interest when determining the *REW* of hedge funds. The stock returns used to estimate portfolio performance are winsorised at the 1st and 99th percentile. The returns presented in Panel A are net of the equal weighted return of the stock universe. The returns presented in Panel B are the four-factor alphas estimated through the following regression: $r_t = \alpha + \beta_1 MktRf_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \epsilon_t$. Where r is the portfolio return estimated using the same method as in Panel A, *MktRf* is the market return net the risk free rate, *SMB* is the return of the Small-minus-Big portfolio, *HML* is the return of the High-minus-Low portfolio and *UMD* is the return of the Up-minus-Down portfolio.

	Hedge funds (1)	Hedge funds ^{LS} (2)	Mutual funds (3)	Private banking (4)	Pension funds (5)
Panel A: Mean adjusted returns					
High liquidity universe	1.609*** (6.192)	1.333*** (5.223)	0.526 (1.305)	0.483 (1.502)	0.460 (1.211)
Quintile 4	1.333*** (4.944)	1.183*** (4.625)	-0.221 (0.600)	-0.258 (0.940)	-0.378 (1.038)
Quintile 3	1.084*** (3.749)	1.146*** (4.108)	-0.366 (1.171)	-0.125 (0.504)	-0.045 (0.132)
Quintile 2	0.717*** (3.344)	0.738*** (2.690)	-0.034 (0.121)	-0.172 (0.828)	-0.490* (1.656)
Low liquidity universe	0.632*** (2.933)	0.650*** (2.811)	-0.153 (0.790)	-0.132 (0.800)	0.396* (1.813)
High-Low liquidity universe	0.977*** (2.914)	0.683** (2.094)	0.679 (1.562)	0.615* (1.837)	0.063 (0.149)
# of Obs	195	195	195	195	195
Panel B: Four-factor alpha					
High liquidity universe	1.432*** (5.536)	1.304*** (5.261)	0.525 (1.433)	0.567* (1.931)	0.433 (1.295)
Quintile 4	1.008*** (4.037)	0.986*** (4.068)	-0.251 (0.825)	-0.250 (1.050)	-0.214 (0.732)
Quintile 3	0.787*** (3.157)	1.008*** (3.740)	-0.451* (1.762)	-0.115 (0.525)	0.096 (0.328)
Quintile 2	0.633*** (2.975)	0.740*** (2.677)	-0.255 (0.950)	-0.150 (0.743)	-0.407 (1.481)
Low liquidity universe	0.617*** (2.934)	0.700*** (2.957)	-0.338* (1.830)	-0.125 (0.795)	0.263 (1.193)
High-Low liquidity universe	0.815** (2.438)	0.604* (1.902)	0.863** (2.279)	0.692** (2.115)	0.170 (0.447)
# of Obs	195	195	195	195	195
Absolute <i>t</i> statistics in parentheses					
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$					

be an important factor in determining investable universes for a fund. Large funds may be impacted by liquidity constraints as they try to invest in smaller stocks. Similarly, the transaction costs are likely to be larger in universes of micro stocks compared to large stocks, and hence it is important to understand if the results are driven purely by informativeness within more investable universes such as large and small stocks, or if the results are driven by the ability to predict performance of micro stocks.

Table 4: Returns of quintile portfolios across stock size universes

Table 4 provides performance of equally weighted quintile portfolios, between March 1999 and June 2015. The quintiles are constructed by sorting the *REW*, and then splitting the stocks into 5 quintiles. Top contains the 20% stocks with highest *REW*, and Bottom contains the 20% stocks with lowest *REW*. The top minus bottom portfolio is formed by buying the Top portfolio, and selling the Bottom portfolio. All portfolios are updated quarterly, and the stock universe is all stocks listed on AMEX, Nasdaq and NYSE. The stock returns used to estimate portfolio performance are winsorised at the 1st and 99th percentile. Panels A to C present results for three separate stock universes, where I apply Fama and French (2008) breakpoints to determine the universes. The performances presented are the four-factor alphas estimated through the following regression: $r_t = \alpha + \beta_1 MktRf_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \epsilon_t$. Where r is the portfolio return estimated using the same method as in Panel A of Table 2. *MktRf* is the market return net the risk free rate, *SMB* is the return of the Small-minus-Big portfolio, *HML* is the return of the High-minus-Low portfolio and *UMD* is the return of the Up-minus-Down portfolio.

	Hedge funds (1)	Hedge funds ^{LS} (2)	Mutual funds (3)	Private banking (4)	Pension funds (5)
Panel A: Large stocks					
Top	0.382*** (4.451)	0.503*** (6.005)	0.128* (1.784)	0.183*** (2.805)	0.122 (1.421)
Quintile 4	0.051 (0.748)	0.112** (2.111)	-0.046 (0.924)	0.027 (0.532)	0.085 (1.553)
Quintile 3	-0.044 (0.997)	-0.077 (1.227)	0.044 (1.055)	0.028 (0.695)	0.042 (0.699)
Quintile 2	-0.112** (2.342)	-0.132** (2.525)	-0.012 (0.256)	0.006 (0.105)	-0.029 (0.514)
Bottom	-0.266*** (2.784)	-0.397*** (3.974)	-0.115 (1.286)	-0.246*** (3.131)	-0.222 (1.864)
Top-Bottom	0.684*** (3.805)	0.899*** (5.374)	0.242* (1.643)	0.429*** (3.233)	0.344* (1.829)
# of Obs	195	195	195	195	195
Panel B: Small stocks					
Top	0.310*** (3.239)	0.365*** (3.863)	0.028 (0.378)	0.110* (1.915)	0.266*** (3.071)
Quintile 4	0.097 (1.304)	0.218*** (2.592)	0.172*** (2.728)	-0.004 (0.067)	0.102 (1.271)
Quintile 3	-0.011 (0.177)	-0.041 (0.603)	-0.041 (0.673)	0.057 (1.001)	0.001 (0.015)
Quintile 2	-0.163*** (2.759)	-0.165** (1.987)	-0.034 (0.531)	0.029 (0.530)	-0.191** (2.474)
Bottom	-0.226** (2.451)	-0.370*** (3.241)	-0.128 (1.396)	-0.190*** (2.589)	-0.180* (1.708)
Top-Bottom	0.536*** (3.100)	0.735*** (3.977)	0.156 (1.086)	0.300*** (2.775)	0.447*** (2.891)
# of Obs	195	195	195	195	195
Panel C: Micro stocks					
Top	0.189** (2.556)	0.331*** (4.372)	-0.010 (0.109)	-0.035 (0.485)	-0.030 (0.219)
Quintile 4	0.089 (1.352)	0.173** (2.241)	-0.062 (0.831)	0.001 (0.018)	-0.107 (1.115)
Quintile 3	-0.021 (0.311)	-0.220*** (2.917)	-0.014 (0.229)	0.023 (0.301)	0.078 (0.816)
Quintile 2	-0.110 (1.477)	-0.127* (1.872)	-0.176** (2.555)	-0.006 (0.072)	0.043 (0.397)
Bottom	-0.145 (1.604)	-0.588*** (4.438)	0.261* (1.862)	0.016 (0.188)	0.018 (0.129)
Top-Bottom	0.333** (2.391)	0.919*** (5.030)	-0.270 (1.323)	-0.051 (0.381)	-0.047 (0.193)
# of Obs	195	195	195	195	195
Absolute t statistics in parentheses					
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$					

Table 4 presents the analysis across the three size universes, and shows that hedge funds once again outperform other institutional investor types, regardless of selected universe.

Furthermore, the results indicate that hedge funds are able to more accurately pick stocks within the universe of large stocks, compared to their ability to pick micro stocks. A likely explanation to this finding is that the database threshold to only include institutions with at least USD 100 million in AUM, causes the sample used to be skewed towards large institutions. These large institutions may find the transaction costs to be too large within micro stocks, and therefore have to limit their information advantage to more investable universes. Including short interest in the estimate of hedge fund holdings improves the informativeness across all three size universes, with the most significant improvement within the micro stock universe.

The breakdown into size universes shows a more positive picture of the ability of private banking firms to pick stocks. Within both large and small stock universes, stocks overweight by private banking firms significantly outperform the ones they underweight. Whereas pension funds show some limited positive ability within the universe of small stocks, they appear to have no ability to pick stocks within universes of large and micro stocks. Although the results point towards stock selection abilities within private banking firms and pension funds within certain stock universes, my conclusion remains that they lack informativeness compared to hedge funds.

5.2 Cross-sectional regressions

One of the disadvantages of decile portfolio analysis is that focus is often on the performance of the two extreme portfolios, and that the performance of the remaining portfolios is consequently forgotten. Furthermore, portfolio analysis also ignores differences in the measure, as well as the entire span of performance, within the same portfolio. Hence, in this section I apply an alternative approach to portfolio sorts to assess the informativeness of different institutional investor types, namely cross-sectional regressions. Furthermore, I also extend the analysis by applying a decomposition to holdings and to stock returns. I decompose stock returns into systematic and non-systematic components to distinguish market timing

ability from stock picking ability in institutional investors:

$$R_{s,t} = \underbrace{(R_{s,t} - \beta_{s,t-1} \times R_{M,t})}_{\text{Non-systematic return}} + \underbrace{\beta_{s,t-1} \times R_{M,t}}_{\text{Systematic return}} \quad (7)$$

$R_{s,t}$ is the return of security s adjusted for the risk-free rate

$\beta_{s,t-1}$ is the market beta of security s ³⁰

$R_{M,t}$ is the excess return of the market³¹

Kacperczyk et al. (2014) argue that a skilled market timer will be more exposed to the market portfolio when the market return is high, thereby earning systematic returns. Furthermore, a skilled stock picker will be able to pick stocks with high non-systematic returns. Hence, the systematic return will be used to assess the market timing ability of institutional investors, and the non-systematic component will be used to assess the ability to pick specific stocks and industries.

Holdings are decomposed in two dimensions. First, I aim to differentiate between stock bets and industry bets by decomposing the REW into $REW_{Industry}$ and REW_{Stock} .³² Next, I distinguish information in static holdings from information in trades. Static holdings are defined as the holdings as of the previous quarter end, thereby capturing longer-term forecasts. Trades are the change in holdings from the previous quarter end, thereby capturing short-term forecasts. For example, if the REW as of the previous quarter end was 1.5 and the current REW is 2, then the trade component will have a value of 0.5, whereas the static component will have a value of 1.5. Combining the two dimensions gives the following decomposition of REW :

$$REW_{s,t} = \underbrace{REW_{Industry,s,t-1} + REW_{Stock,s,t-1}}_{\text{Static holdings}} + \underbrace{\Delta REW_{Industry,s,t} + \Delta REW_{Stock,s,t}}_{\text{Trades}} \quad (8)$$

$REW_{Industry,s,t-1}$ is the static component of $REW_{Industry}$

$REW_{Stock,s,t-1}$ is the static component of REW_{Stock}

³⁰I estimate the beta quarterly, based on the past one year of daily returns.

³¹See Fama and French (1993).

³²See equations (6) and (5) for descriptions of how I calculate $REW_{Industry}$ and REW_{Stock} .

$\Delta REW_{Industry,s,t}$ is the trade component of $REW_{Industry}$

$\Delta REW_{Stock,s,t}$ is the trade component of REW_{Stock}

I apply cross-sectional regression to estimate the degree to which the components of holdings explain future stock returns. Fama and French (2008) explain that results of cross-sectional regressions can differ widely depending on whether micro-cap stocks are included or excluded from the regression. Since the majority of the stocks are classified as micro-cap stocks, there is a risk that this group, which represents only a small fraction of the overall market capitalisation, have an abnormal impact on the regression results. Hence, rather than running one regression over the full stock universe, I run separate regressions for each stock size universe, and then calculate the average estimates across the three universes at each point in time. This method is similar to Chen, Hong, and Stein (2002). I use monthly returns; and therefore, derive 192 estimates per explanatory variable. As per Fama and MacBeth (1973), I present the average of the estimates.

I begin the analysis by assessing the ability of institutional investors to forecast non-systematic returns. The results are presented in Columns 1 to 3 of Table 5. Consistent with the portfolio sort results, hedge funds are the most informed investors. However, my decomposition provides additional insights into the skills and investment behaviour of hedge funds. It appears that hedge funds have the ability to predict future industry performance and the ability to identify individual mispriced securities. The aggregated hedge fund industry therefore acts as an informed top-down investor; first identifying which industries will outperform, and then picking individual stocks within these industries. Furthermore, the decomposition into static holdings and trades indicates that hedge funds are able to forecast both long-term and short-term returns. These findings hold true whether I analyse long-only hedge fund holdings or the long-short measure, taking into account the short interest.

The informativeness of the holdings of other institutional investors also provides novel insight. Absence of information in mutual fund trades contradicts Chen et al. (2000). However, there is no overlap between my examination period and theirs, indicating that mutual funds may have become less skilled at picking stocks in more recent periods. I also document that private banking firms are not skilled in picking industries and stocks, and that there is no information in their trades. Static holdings of pension funds are informative of future

Table 5: Informativeness of fund holdings

Table 5 provides information on the informativeness of $REW_{Industry}$ and REW_{Stock} . Columns 1, 2 and 3 contain the average coefficients from the following regression: $R_{s,t} - \beta_{s,t-1} \times R_{M,t} = \alpha + \beta_1 REW_{Industry,s,t-1} + \beta_2 REW_{Stock,s,t-1} + \beta_3 \Delta REW_{Industry,s,t} + \beta_4 \Delta REW_{Stock,s,t} + \beta_5 X_{s,t} + \epsilon_{s,t}$. Columns 4, 5 and 6 contain the average coefficients from the following regression: $\beta_{s,t-1} \times R_{M,t} = \alpha + \beta_1 REW_{Industry,s,t-1} + \beta_2 REW_{Stock,s,t-1} + \beta_3 \Delta REW_{Industry,s,t} + \beta_4 \Delta REW_{Stock,s,t} + \beta_5 X_{s,t} + \epsilon_{s,t}$. Where $R_{s,t}$ is the return of security s at time t , $\beta_{s,t-1} \times R_{M,t}$ is the systematic return of security s at time t , $R_{s,t} - \beta_{s,t-1} \times R_{M,t}$ is the non-systematic return of security s at time t , $REW_{Industry,s,t-1}$ is a vector of $REW_{Industry}$ at time $t-1$, $REW_{Stock,s,t-1}$ is a vector of REW_{Stock} at time $t-1$, $\Delta REW_{Industry,s,t}$ is a vector of the change in $REW_{Industry}$ between $t-1$ and t , $\Delta REW_{Stock,s,t}$ is a vector of the change in REW_{Stock} between $t-1$ and t , and $X_{s,t}$ is a vector of control variables which are only included in Columns 2, 3, 5 and 6. The model is estimated monthly, and the results provided are the averages of the estimated coefficients. *Size* is the natural log of market capitalisation, *Momentum* is the past 12 months stock return, *Book to Price* is the equity book value divided by the market capitalisation of the company, and *Liquidity* is the natural algorithm of the average monthly stock turnover (defined as the monthly volume divided by shares outstanding) over the past year. Columns 1, 2, 4 and 5 use long-only positions when determining the REW of hedge funds. Columns 3 and 6 use a combination of the long hedge fund positions and the reported short interest when determining the REW of hedge funds. All independent variables are winsorised at the 1st and 99th percentile, and are standardised to have a mean of 0 and a standard deviation of 1, across each cross-section.

	$R_{S,t} - \beta_{S,t-1} \times R_{M,t}$			$\beta_{S,t-1} \times R_{M,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Hedge funds						
$REW_{Industry,t-1}$	0.100** (2.218)	0.136*** (3.443)	0.089 (1.590)	0.026*** (2.839)	0.012** (2.320)	0.020*** (2.895)
$REW_{Stock,t-1}$	0.115*** (2.922)	0.122*** (3.262)	0.171*** (3.850)	0.016* (1.665)	0.010 (0.831)	-0.002 (0.163)
$\Delta REW_{Industry}$	0.088** (2.154)	0.101*** (2.645)	0.101** (2.462)	0.007 (0.712)	0.006 (1.291)	0.002 (0.423)
ΔREW_{Stock}	0.222*** (5.705)	0.212*** (6.082)	0.200*** (4.976)	0.020*** (2.777)	0.008* (1.919)	-0.002 (0.316)
Mutual funds						
$REW_{Industry,t-1}$	0.000 (0.008)	0.050 (1.569)	0.019 (0.595)	0.029** (1.993)	0.025*** (3.233)	0.026*** (3.560)
$REW_{Stock,t-1}$	0.020 (0.639)	0.059* (1.952)	0.062** (2.222)	0.004 (0.472)	0.005 (0.861)	0.001 (0.130)
$\Delta REW_{Industry}$	-0.041 (1.341)	-0.046 (1.539)	-0.014 (0.567)	0.017* (1.818)	0.007 (1.315)	0.007 (1.215)
ΔREW_{Stock}	-0.050* (1.841)	-0.019 (0.687)	-0.017 (0.568)	0.013* (1.673)	0.000 (0.116)	-0.003 (0.771)
Private banking firms						
$REW_{Industry,t-1}$	0.029 (0.826)	0.041 (1.241)	0.062** (2.027)	0.004 (0.519)	0.004 (0.657)	0.003 (0.590)
$REW_{Stock,t-1}$	-0.032 (1.091)	-0.036 (1.100)	-0.013 (0.504)	-0.005 (0.759)	-0.001 (0.271)	-0.003 (0.682)
$\Delta REW_{Industry}$	-0.017 (0.491)	-0.001 (0.016)	-0.045* (1.652)	0.004 (0.544)	0.002 (0.425)	0.002 (0.392)
ΔREW_{Stock}	0.010 (0.312)	0.016 (0.459)	0.026 (1.059)	-0.003 (0.461)	-0.001 (0.139)	-0.001 (0.166)
Pension funds						
$REW_{Industry,t-1}$	0.065 (1.293)	0.063 (1.390)	0.067 (1.596)	0.009 (0.408)	-0.013 (1.007)	-0.013 (1.059)
$REW_{Stock,t-1}$	0.052 (1.473)	0.081*** (2.820)	0.097*** (3.091)	0.033** (2.015)	0.010 (1.454)	0.008 (1.461)
$\Delta REW_{Industry}$	-0.028 (0.924)	-0.011 (0.337)	-0.030 (1.142)	0.009 (1.203)	0.003 (0.553)	0.003 (0.624)
ΔREW_{Stock}	-0.100*** (3.211)	-0.071** (2.173)	-0.023 (0.861)	0.013** (2.224)	0.000 (0.006)	0.001 (0.256)

Continued on next page

stock-specific returns when introducing control variables, but their trades are poor predictors

Table 5 Continued from previous page

	$R_{S,t} - \beta_{S,t-1} \times R_{M,t}$			$\beta_{S,t-1} \times R_{M,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Control variables						
Size		-0.230*** (3.124)	-0.208*** (2.989)		0.021 (0.976)	0.028 (1.262)
Book-to-Price		0.138* (1.844)	0.163** (2.228)		0.010 (0.542)	0.016 (0.769)
Momentum		0.180 (1.614)	0.229** (2.341)		0.031 (0.693)	0.023 (0.535)
Liquidity		-0.195** (2.001)	-0.098 (1.023)		-0.012 (0.157)	-0.009 (0.128)
Observations	192	192	192	192	192	192
Average R2	0.018	0.057	0.059	0.082	0.344	0.352
Absolute t statistics in parentheses						
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$						

of future performance. This suggests that pension funds are able to predict which stocks will outperform in the longer term, but have no ability to predict short-term returns.

The market timing ability of institutional investors is presented in Columns 4 to 6 in Table 5. Hedge funds, mutual funds and pension funds all appear to have market timing ability, although the results for pension funds are not statistically significant when introducing control variables. The presence of market timing among mutual funds is consistent with Kacperczyk et al. (2014). My finding provides further insight into previous studies in showing that this skill is driven by the ability of mutual funds to forecast long-term market returns, which they implement through their strategic industry weights. In other words, I find that mutual funds take long-term bets on high-beta industries during up-markets, whereas they take long-term bets on low-beta industries during down-markets.

As with mutual funds, pension funds are able to forecast longer term market performance. However, pension funds leverage this skill through stock selection rather than industry selection. The observation that pension funds are able to time the market contradicts Coggin et al. (1993), although their study is based on an earlier time period and uses fund returns rather than holdings.

Hedge funds' long-term industry and stock bets, as well as their trade directions, are indicative of future market returns, making them the only institutional investor type able to forecast the market on both long-term and short-term bases. The finding that hedge funds are skilled at timing the market is not surprising in itself, since this has been shown

in previous studies.³³ However, my findings add depth to the understanding of this ability. When comparing hedge funds' market timing ability with their ability to pick mispriced stocks and industries, it is clear that market timing only contributes a small fraction to the overall outperformance of their holdings. This finding is potentially explained by the fact that funds which focus on market timing are a minority among hedge funds. Therefore, if I were to focus only on funds targeting market timing, I would probably find that market timing has a more significant impact on the overall informativeness of hedge fund holdings. For instance, [Chen and Liang \(2007\)](#) focus only on hedge funds which describe themselves as market timers, whereas [Chen \(2007\)](#) focuses on several different hedge fund styles. Not surprisingly, [Chen and Liang \(2007\)](#) find stronger evidence of hedge funds being able to time the equity market.

6 Conclusion

I provide the first comparison of the ability of hedge funds, mutual funds, pension funds and private banking firms to predict stock returns, using the same dataset, as well as a consistent method and time period, regardless of institutional investor type. My approach uses 13F filings by aggregating weights of fund companies across each of the institutional investor types. The findings presented support the view that hedge funds are more informed than other institutional investors. By analysing the returns of decile portfolios based on holdings, only hedge funds appear to be able to predict stock performance both in terms of raw stock returns and risk-adjusted alpha. This finding is not explained by the redemption period commonly applied by hedge funds, which allows them to enter positions in illiquid stocks. I demonstrate that my results are driven by hedge funds surpassing other institutional investors at predicting industry returns as well as at identifying mispriced securities, and that there is information both in their trading and static holdings. Furthermore, the findings remain consistent regardless of whether I compare long-only positions, or apply an approximation for the short side of hedge fund holdings.

³³See for example [Chen and Liang \(2007\)](#), [Cao et al. \(2013\)](#), and [Bali et al. \(2014\)](#).

The finding that hedge funds appear to be more informed than other institutional investors highlights the value they add to investors in the fund industry. Whilst not refuting the contention that there is a subset of informed mutual funds, pension funds and private banking firms, I struggle to find, on average, that they provide equivalent value. This study also provides conflicting evidence with [Griffin and Xu \(2009\)](#), who argue that hedge funds are no better than mutual funds at picking stocks after adjusting for risk factors. One of the drivers of the difference in conclusion is that I examine the performance over a more recent time period, which indicates that hedge funds have become more skilled over time. I suggest that this is due to the high inflows of capital to the hedge fund industry after the dotcom era, which has increased the ability of hedge funds to attract talented managers and increased the industry's investment on proprietary research. In addition to the different time periods, the disparities between my findings and those of [Griffin and Xu \(2009\)](#) are driven by different methods used to aggregate holdings.

While this study provides novel insight into the skills of institutional investors, it leaves three important questions for further research, in particular for hedge funds. Firstly, while I find valuable information in the quarterly changes of hedge fund holdings, having access to portfolio information at a higher frequency would allow for a more detailed analysis of portfolio construction and trade timing. Secondly, an analysis of hedge fund holdings when they are actually disclosed (i.e. filed) would improve our understanding of the potential costs of mandatory holdings disclosure. If return predictability is still present as at that date, then mandatory reporting could potentially be harmful to hedge funds, since outside investors could replicate hedge fund holdings instead of investing in the funds. Finally, more detailed classifications (such as event driven funds, activists, market neutral funds, and directional traders) within the hedge fund universe would lead to a more granular understanding of whether my results are driven by specific types of hedge funds, as well as whether different hedge fund types have diverse skills.

Chapter 4

Capacity constraints in hedge funds: The impact of cohort size on fund performance

1 Introduction

Capacity constraints are important in the active funds management industry, causing diminishing returns with size, and having significant consequences for funds and investors (Perold, 1988; Perold and Salomon, 1991). Perold (1988) asserts that capacity constraints are driven by execution costs and opportunity costs, which can cause an implementation shortfall (where the actual portfolio underperforms a theoretical ‘paper’ portfolio). As a fund grows, higher dollar amounts are required to achieve the same portfolio weight in a security. The higher dollar amount results in increased implicit execution costs through higher price impact, which decreases the percentage fund return. To decrease execution costs, the fund may delay trades or invest in a different security, which, if the fund is a skilled investor,¹ will instead increase opportunity costs.

Historically, capacity constraints within the hedge fund industry have been examined by analyzing the relation between fund performance and the individual fund size, or the aggregate size of the hedge fund sector.² While increasing fund size will lead to higher exe-

¹Given that this statement is based on the assumption of funds being informed, I am more likely to find evidence of capacity constraints if analyzing hedge funds compared to other fund types. Several studies, such as Ackermann et al. (1999), Amin and Kat (2003), Malkiel and Saha (2005), and Forsberg (2016), find that hedge funds are able to earn abnormal returns, and Agarwal and Naik (2000) state that successful mutual fund managers are likely to move to the hedge fund industry.

²See e.g. Naik et al. (2007), Ammann and Moerth (2008), Aggarwal and Jorion (2010), Ramadorai (2013) and Yin (2016).

cution and opportunity costs, it has also been argued by Naik et al. (2007) that, as a specific hedge fund sector grows in size, the competition for mispriced securities increases. This can cause decreasing returns to all funds within the sector through increasing opportunity and execution costs.

While the relation between performance and fund size or sector size has been widely researched, the literature does not fully consider all the implications of capacity constraints and how they arise. If there are several hedge funds applying similar strategies, these funds form a cohort that is likely to pursue the same investment opportunities.³ As a consequence, implementation shortfall and hence capacity constraints may be more closely related to cohort size than to fund size. On the other hand, a hedge fund sector will contain funds with significant differences in terms of strategy. These funds do not necessarily trade in the same direction with similar timing, and therefore may not have severe impacts on each other's ability to implement their strategy. Therefore, focusing on the sector size is also limited when analyzing capacity constraints. Since neither fund size nor sector size are able to fully identify how funds applying similar strategies impact implementation shortfall (and hence capacity constraints), I argue there is a knowledge gap in the literature. To improve our understanding of capacity constraints, the focus should shift to the size of fund cohorts.

The primary research question in this paper is whether capacity constraints exist in hedge funds as a consequence of diminishing returns with cohort size. To answer this, I analyze how cohort size impacts future fund performance, and document that funds belonging to small cohorts significantly outperform funds in large cohorts. In terms of economic significance, I find that a one standard deviation increase of the cohort size is associated with a 185.6 basis point decrease in annual returns, adjusted for exposure to the Fung and Hsieh (2004) seven-factor model, and a 44.2 basis point decrease in annual returns (adjusted for the mean sector performance). Furthermore, when controlling for cohort size, I find no negative relation between fund size and performance. Overall, the findings confirm that capacity constraints exist in hedge funds and that they exist in terms of diseconomies of cohort size, rather than in terms of diseconomies of fund or sector size. The negative relation between

³Barberis and Shleifer (2003) discuss investment styles and their importance in institutional investors. A cohort can be seen as a group of funds applying the same investment style.

cohort size and future fund performance also highlights the importance of cohorts when making investment decisions.⁴

The impact of cohort size on capacity constraints is further supported by the finding that fund size only predicts negative returns for funds that form their own cohort. In other words, diseconomies to scale of fund size only exist when the fund is representing the full cohort; and hence, not competing with other funds to profit from a particular investment strategy. For cohorts containing multiple funds, there is no relation between individual fund size and performance.

Aside from documenting a relation between cohort size and future performance, I also find a positive relation between past performance and future flows to cohorts. This is consistent with the [Berk and Green \(2004\)](#) model of capital flows, modified to consider cohort flows rather than individual fund flows. Their model assumes that investors learn of fund skill by observing past performance, and allocate more assets to past-performing funds. My analysis indicates that the model can be expanded to cohorts, as investors appear to direct flows into cohorts with high past returns.

The results discussed above provide an important insight that may impact on fund behavior. As a fund performs well, assets will not only flow to the fund itself, but will also flow to other funds in the cohort. Since I also find that performance is negatively impacted by the size of the cohort, this raises the question of how funds behave in either accepting or rejecting assets depending on whether they are the only fund in the cohort. If a fund is forming its own cohort, it may reject inflows as it reaches a size which could cause the return to fall below a certain minimum threshold.⁵ However, competition within a cohort may change the situation. If the fund rejects the assets, investors may invest with another fund within the cohort, which in turn will have a negative impact on both the cohort and the fund's performance. Therefore, regardless of whether the fund accepts or rejects the new assets, it will experience a negative impact of a growing cohort size. If the assets are accepted, the fund will at least profit from higher total dollar management fees. Therefore, funds that do not form their own cohort have an incentive to accept inflows, rather than

⁴For instance, it may be disadvantageous to launch a fund in an already crowded space. Similarly, it may be preferable to invest in a fund belonging to a small cohort compared to a large cohort.

⁵The propensity to reject assets to achieve high performance may be enhanced by the incentive fee structure in the hedge fund industry.

reject them to protect performance. To test this proposition, I examine the relation between cohort structure and a fund's propensity to accept or reject inflows.⁶ I find that funds which form their own cohort, and funds which comprise a larger component of their cohort, have less tendency to accept flows, consistent with this proposition.

Lastly, I document that cohorts impact the relation between past performance and future fund flows. According to Berk and Green (2004), investors follow performance when making allocation decisions. Accordingly, the flow into hedge funds have been found to be related to past fund performance.⁷ Furthermore, Lim et al. (2015) examine the importance of indirect income earned through the positive fund inflow (outflow) following good (poor) performance, and document this income to be of significant importance even when compared to the direct income earned through performance fees. While I find a positive relation between past performance for the full sample of funds, this relation is stronger among funds that experience less competition from other funds within their cohort. Therefore, it appears that cohorts have a significant impact on how funds are rewarded for performance.

I make several contributions to the understanding of implementation shortfall and capacity constraints in hedge funds. To date, capacity constraints within the hedge fund industry have mainly been researched by investigating the relation between performance and fund size or sector size, with inconclusive findings. The impact of sector size is examined by Naik et al. (2007), who find that half of the hedge fund sectors experience decreasing returns with capital inflows, thereby providing limited proof of capacity constraints. Ammann and Moerth (2005) document a relation between hedge fund size and performance, that includes both negative linear and quadratic terms, implying that very small and very large funds underperform. Ammann and Moerth (2008) extend this analysis, and conclude that, even though small hedge funds are riskier compared to large funds, the returns are high enough to compensate for this risk. In more recent studies, Ramadorai (2013) and Yin (2016) both find a negative relation between hedge fund size and performance. Yin (2016) suggests this is explained by the fee structure of hedge funds, such that hedge funds have incentive to accept new fund inflows, even in the presence of performance fees and the potential diseconomies of

⁶The cohort circumstances I examine the relation for are whether the fund is forming its own cohort, and the fund's AUM relative to the cohort's AUM.

⁷See e.g. Fung, Hsieh, Naik, and Ramadorai (2008) and Lim, Sensoy, and Weisbach (2015).

scale. Studies by [Gregoriou and Rouah \(2002\)](#) and [Aggarwal and Jorion \(2010\)](#), document no relation between hedge fund size and performance. My findings relating diseconomies to cohort size suggest that implementation shortfall is not primarily related to the size of the fund or sector. Instead, it appears to be driven by funds applying similar strategies, due to the impact on prices and capacity to trade in volume which increase implementation shortfall for all funds utilizing that strategy. My findings raise the possibility that the mixed results reported in the literature may be due to failure to observe cohort size as the key driver of capacity constraints.

The impact of fund size has also been examined for mutual funds. [Yan \(2008\)](#) provides evidence that the negative relation between size and performance is stronger among funds holding illiquid portfolios, and [Chan et al. \(2009\)](#) document that the negative impact of fund size on performance is related to transaction cost effects. Both studies imply that portfolio construction and turnover are important aspects when considering capacity constraints. [Chen et al. \(2004\)](#) also find a negative relation between mutual fund size and performance, and that the relation is strongest among funds investing in small and illiquid stocks. [Pástor et al. \(2015\)](#) show that a negative relation exists between the size of the active mutual fund industry and the ability of the funds to outperform passive benchmarks.⁸ By introducing cohort size, I extend this literature by considering the total size of funds applying the same strategy when analyzing capacity constraints.

I also provide important insight into the relation between performance and assets allocated to specific strategies, while adding to the literature on strategy distinctiveness. [Hanson and Sunderam \(2014\)](#) indicate that performance diminishes as more assets are allocated to value and momentum strategies. I confirm that the impact of assets allocated to specific strategies is a general phenomenon not unique to value and momentum. Furthermore, [Sun, Wang, and Zheng \(2012\)](#) document how funds with more distinctive strategies outperform other funds. The cohort-based method identifies funds applying a similar strategy, hence focusing on similarities rather than differences. My findings support those of [Sun et al. \(2012\)](#), while indicating the importance of considering the total size of all funds implementing a specific strategy.

⁸The mutual fund size and performance relation has also been examined by e.g. [Indro, Jiang, Hu, and Lee \(1999\)](#), and [Pollet and Wilson \(2008\)](#).

I also contribute to the literature on how funds can impact each other. [Wahal and Wang \(2011\)](#) evaluate fund competitors by analyzing the overlap of mutual fund holdings, and thus provide insight. For instance, investors become more sensitive to fund fees when close substitutes are available, and consequently the entrance of new competitors causes existing funds to decrease their fees in competition for new investors.⁹ While data limitations prohibit me from performing the same fee analysis for hedge funds, my findings nonetheless help to explain the response of hedge funds and hedge fund investors to the existence of fund substitutes.

The findings are also useful for hedge funds and their investors. By defining cohorts based on information available at each point in time, I show that cohort size is informative for investors who wish to avoid investing in funds likely to be affected by capacity constraints in the future. Hedge fund firms may also be able to make more informed decisions when launching new funds, avoiding cohorts that have already grown too large.

The remainder of the paper is as follows. Section [2](#) summarizes the hedge fund data applied in the study. Section [3](#) describes the method. Section [4](#) presents my empirical findings. Section [5](#) provides robustness tests, and Section [6](#) concludes.

2 Data

The data is sourced from Hedge Fund Research (HFR) and eVestment (EV) from January 1997 to March 2016.¹⁰ Following previous literature, I only keep funds reporting returns net of fees, and that report both returns and assets in U.S. Dollars (USD). One issue with hedge fund databases is the presence of duplicates, both within and across databases. For instance, the same fund may exist in different classes or through denomination in different currencies. I remove duplicates from each database by defining duplicate funds as those with a returns correlation exceeding 95% and which are managed by the same firm. I then estimate the assets under management (AUM) of the funds within each duplicate group, over time. I find the reporting of AUM to sometimes be inconsistent between different firms. In some cases,

⁹In addition, they find that new competitors cause decreasing performance and increasing attrition rates.

¹⁰HFR was established in 1992 and has long been seen as one of the industry standard hedge fund databases. EV acquired HedgeFund.net in 2011, making it one of the largest sources of hedge fund data worldwide. HedgeFund.net was founded in 1997.

the AUM is different for each duplicate, whereas in other cases the same AUM is reported for all duplicates. Since one likely explanation to duplicates is the feeder and master fund relationship, there is a risk of double counting if I were to calculate the sum of the AUM across the duplicates. Therefore, I estimate the AUM of the fund as the largest reported value across the duplicates at each point in time.¹¹

To merge the databases, I first match firms by firm names.¹² and manually confirm each match to eliminate inaccuracies. To remove duplicates reported in both databases, I repeat the correlation analysis. Since not all funds update their AUM with a monthly frequency, I only analyze the size as of each quarter's end.¹³ Following Yin (2016), I limit the data to hedge funds with AUM of at least USD 10 million.

Fund information collected as control variables includes: performance fee, management fee, minimum investment, redemption frequency, redemption notice period, subscription frequency and lock-up period.¹⁴ Fund flow is estimated in two steps. First, flow in USD is estimated by equation (1):

$$Fund\ Flow\ (USD)_{i,t} = Fund\ AUM_{i,t} - Fund\ AUM_{i,t-1} \times (1 + R_{i,t}) \quad (1)$$

$Fund\ AUM_{i,t}$ is the fund AUM in million USD

$R_{i,t}$ is the fund's return between time $t-1$ and t

In the second step, I calculate the fund flow rate, using equation (2):

$$Fund\ Flow\ (rate)_{i,t} = 100 \times \ln\left(1 + \frac{Fund\ Flow\ (USD)_{i,t}}{Fund\ AUM_{i,t-1}}\right) \quad (2)$$

A summary of the data is provided in Table 1. The statistics reported in Panel A are consistent with previous literature applying hedge fund data, such as Yin (2016) and Sun

¹¹I represent the fund's return by the return of the duplicate with the longest history.

¹²Firm names are often reported differently to different databases and I therefore allow for differences in the names.

¹³I use monthly fund returns when estimating factor exposure and when generating fund cohorts. Otherwise, I use quarterly data throughout the analysis.

¹⁴In the cases when a fund has not reported one of the control variables, I replace the missing value with the median from the full fund sample.

et al. (2012).¹⁵ Panel B of Table 1 reveals that a majority of the funds exit the sample by the end of the sample period. This reflects the long examination period (1997-2016), which includes two significant market crises, in combination with the fact that both HFR and EV retain graveyard funds in their databases.

The main objective of this paper is to analyze the relation between hedge fund returns and AUM at the cohort level. It is important that the sample is representative of entire cohorts. A comparison of the total number of funds included in my sample with the total number of funds included in previous hedge fund studies, indicates that the combination of the HFR and EV databases provides substantial coverage. After applying these filters, I have access to returns and fund AUM for 7,406 different funds over the 20 years from 1997 to 2016. This is high compared to previous hedge fund studies. For example, Yin's (2016) study from 1994 to 2009 includes a total of 2,563 funds, and Sun et al.'s (2012) analysis of hedge funds from 1996 to 2009 covers 3,896 funds. Hence, my sample has a higher degree of representativeness of the U.S. hedge fund industry than previous studies.

Panel C of Table 1 presents summary statistics of the natural logarithm of fund AUM, summarized per hedge fund sector. The values indicate that the multi-process funds on average are larger compared to other sectors.¹⁶ and that relative value funds on average are the smallest in terms of the natural logarithm of fund AUM.

A well-known issue with hedge fund databases is that they are based on self-reported data rather than regulatory reported data. Therefore they are susceptible to biases such as survivorship bias, backfill bias, and delisting bias. These biases may impact my analysis if they are related to cohort size. For instance, if small cohorts suffer more from overestimation of performance, then an observed negative relation between cohort size and performance may be driven by data biases rather than by diseconomies of cohort size. I aim to follow previous literature by eliminating these biases as much as possible. The fact that all databases utilized in this paper contain graveyard funds, means that my analysis is unlikely to be impacted by survivorship bias.

¹⁵The main difference is higher average fund AUM observed in this study, which likely is a result of different time periods and my method to remove duplicates, where I only keep the largest reported AUM for a set of duplicate funds.

¹⁶Multi-process covers event-driven and multi-strategy funds (see Appendix A).

Table 1: Summary statistics

Table 1 provides summary statistics for the data used in the study, based on the period January 1997 until March 2016. Panel A shows summary statistics across all hedge funds in the sample. Quarterly Return is the quarterly percentage return, Fund AUM is the AUM in million USD, Fund flow is defined as per equation (2), Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the Lock-up measured in number of months. Panel B shows the number of funds per hedge fund sector. In Panel B, Column 1 presents the total number of funds per sector, Column 2 presents the total number of funds still reporting as of the end of the sample, Column 3 presents the number of funds no longer reporting their returns, Column 4 presents the percentage of funds still reporting their returns as of the end of the sample, and Column 5 presents the proportion of funds within each sector. Panel C shows summary statistics of the natural logarithm of fund AUM (\$M), presented for each hedge fund sector.

Panel A: Summary statistics - individual hedge funds					
	Mean (1)	25th pct (2)	Median (3)	75th pct (4)	Std (5)
Quarterly Return (%)	1.25	-1.74	1.33	4.32	8.74
Fund AUM (\$M)	333.38	29.70	74.00	221.00	1438.82
Fund Flow (rel)	0.64	-4.85	0.00	5.58	21.54
Performance Fee (%)	17.79	20.00	20.00	20.00	6.15
Management Fee (%)	1.51	1.00	1.50	2.00	0.73
Minimum Investment (\$M)	1.17	0.25	1.00	1.00	2.68
Redemption Frequency (days)	62.70	30.00	30.00	90.00	67.78
Redemption Notice Period (days)	39.75	15.00	30.00	60.00	33.33
Subscription Frequency (days)	30.87	30.00	30.00	30.00	23.77
Lock-up Period (months)	4.53	0.00	0.00	12.00	7.27
Panel B: Funds per hedge fund sector					
	Total (1)	Still Reporting (2)	No longer reporting (3)	% reporting (4)	% of sample (5)
Directional traders	1407	508	899	36.11%	19.00%
Fixed income	678	161	517	23.75%	9.15%
Macro	1090	284	806	26.06%	14.72%
Multi-process	1670	671	999	22.55%	22.55%
Other	418	187	231	11.20%	5.64%
Relative value	134	38	96	28.36%	1.81%
Security selection	2009	533	1476	26.53%	27.13%
Total	7406	2382	5024	32.16%	100%
Panel C: Natural logarithm of fund AUM (\$M) per hedge fund sector					
	Mean (1)	25th pct (2)	Median (3)	75th pct (4)	Std (5)
Directional traders	4.30	3.26	4.11	5.14	1.31
Fixed income	4.71	3.58	4.56	5.65	1.42
Macro	4.48	3.26	4.23	5.44	1.52
Multi-process	4.78	3.63	4.58	5.72	1.49
Other	4.66	3.35	4.36	5.73	1.64
Relative value	4.08	3.00	3.97	4.89	1.25
Security selection	4.30	3.30	4.12	5.12	1.28

Backfill bias is caused by funds electing to commence reporting of their returns to a database several months or years after the inception date, but only report to the database if they have good performance since inception. Fung and Hsieh (2000) estimate a median backfill period of 12 months among hedge funds, and that the backfilled return has an upward bias of 1.4% per year. In the hedge fund literature it has become standard to discard the first 12 or 24 months of performance. I elect an alternative method in only

keeping returns after the date the fund was added to the database, thereby eliminating only backfilled performance.¹⁷

Delisting bias is caused by hedge funds choosing to delist from a database if they perform poorly. Agarwal, Daniel, and Naik (2011) analyze the impact of delisting bias in hedge funds, and find that funds delisting from databases earn lower returns in the subsequent periods. I perform a robustness check in Section 5.1 in which I examine how the probability of delisting depends on the cohort size, to understand how delisting bias may impact my findings. I find that the funds in large cohorts are more likely to delist. Therefore the diseconomies of cohort size I observe do not appear to be driven by a delisting bias, and if anything, delisting bias is attenuating my results.

3 Research method

3.1 Cohort identification

I define a cohort as funds which apply a similar strategy and, as a consequence, hold similar portfolios and trade in the same securities in the same direction at the same time. Given that I am unable to directly observe strategies, portfolio holdings or trades, I use correlations of monthly fund returns as a measure of similarity in strategy in order to identify cohorts. Two funds are assigned to the same cohort if:

The correlation of returns is higher than 75%¹⁸

and

The funds have a minimum of 12 months overlapping returns.

The correlation method aims to identify funds with similar strategies. These funds are likely to trade the same securities with similar timing, and subsequently may increase execution and opportunity costs of the funds applying the strategy, causing diminishing returns to cohort size. As the purpose of this paper is to analyze capacity constraints, rather than to develop a strategy to pick funds, I argue that an in-sample analysis is preferable, where

¹⁷In certain cases within the EV database, the date added is not reported correctly, which is likely a result of the acquisition of HFN in 2011. In these cases, I eliminate the first 24 months of reported returns.

¹⁸In Section 5.2 I examine the sensitivity of the correlation threshold.

cohorts are identified based on all available information. This is done for two reasons. First, correlation is likely to be a more accurate description of similarity in strategy the longer the available history. Second, for analysis of capacity constraints, it is of importance that the funds belong to the same cohort during the examination period, rather than only during a period of time before the performance is examined. For instance, if cohorts were identified using the short subset of information available at time t , then are used for performance analysis between time t and $t+1$, an issue arises in that the funds may not always apply the same strategy between time t and $t+1$. Therefore, I elect to use a long-term cohort definition based on the full dataset when analyzing how cohorts impact fund performance, as well as how cohorts impact fund and investor behavior. To investigate whether the look-ahead factor in the cohort definition is driving my results, I analyze an alternative definition based only on information available at time t in Section 5.5.¹⁹

An important aspect of the cohort assignments is that they are specific to each fund. For example, fund A's cohort may contain funds A, B and C. However, fund C may not belong to fund B's cohort. This could potentially be driven by funds B and C each applying strategies that overlap with the strategy applied by fund A, but having only limited resemblance with each other. This paper aims to estimate the relation between hedge fund returns and the aggregated AUM of funds exploiting similar strategies, and I argue my method is appropriate for such analysis. If all three funds were assigned to the same cohort, the size of fund B and fund C's cohort would be overstated. Hence, I identify cohorts that are specific to each fund, reflecting the funds applying similar strategies to the fund itself.

3.2 Cohort size and fund size

I create measures of cohort size and fund size that adjust for sector size. One common measure is the natural logarithm of fund AUM.²⁰ However, the limitation of this measure is that it does not take into account the total scope of a market in a sector. A fund within a large sector with a high scope may be able to operate at a larger size without experiencing diseconomies of scale. Furthermore, the scope of a market may change over time. While I

¹⁹The correlation between the cohort size based on the full sample and the one based on information available as of time t is 0.73, indicating a significant overlap for the two definitions of cohort size.

²⁰See e.g. Yin (2016) and Ammann and Moerth (2005).

am unable to observe a fund's total market scope, I utilize the average size within the fund's sector as an approximation, on the basis that a large market sector will be accompanied by high average fund and cohort size.

Fund size is thus defined using equation (3):

$$Fund\ Size_{i,t} = \ln(Fund\ AUM_{i,t}) - \overline{\ln(Fund\ AUM_t)} \quad (3)$$

$\ln(Fund\ AUM_{i,t})$ is the natural logarithm of fund AUM

$\overline{\ln(Fund\ AUM_t)}$ is the mean of the natural logarithm of fund AUM across all funds in the sector

To estimate cohort size, I first define cohort AUM using equation (4), and then use cohort AUM to calculate cohort size using equation (5).

$$Cohort\ AUM_{i,t} = \sum_{n=1}^N Fund\ AUM_{n,t} \quad (4)$$

$$Cohort\ Size_{i,t} = \ln(Cohort\ AUM_{i,t}) - \overline{\ln(Cohort\ AUM_t)} \quad (5)$$

$Fund\ AUM_{n,t}$ is the fund AUM

N is the number of funds within the cohort

$\ln(Cohort\ AUM_{i,t})$ is the natural logarithm of cohort AUM

$\overline{\ln(Cohort\ AUM_t)}$ is the mean of the natural logarithm of cohort AUM across all cohorts in the sector

3.3 Cohort flow and fund flow

To support the analysis of flows to and from cohorts, I introduce measures of cohort flows. The first is the flow measured in USD:

$$Cohort\ Flow\ (USD)_{i,t} = \sum_{n=1}^N Fund\ Flow\ (USD)_{n,t} \quad (6)$$

$Fund\ Flow\ (USD)_{n,t}$ is the USD flow of fund n , defined in equation (1)

N is the number of funds within the cohort

The second measure is cohort flow rate, estimated using equation (7):

$$Cohort\ Flow\ (rate)_{i,t} = 100 \times \ln\left(1 + \frac{Cohort\ Flow\ (USD)_{i,t}}{Cohort\ AUM_{i,t-1}}\right) \quad (7)$$

For both estimates of cohort flow, I estimate values adjusted for the mean within the fund's sector, to control for flows to and from the sector. These estimates are used in the analysis of the relation between past performance and future cohort flows (Section 4.3).

$$Cohort\ Flow\ (USD)_{i,t}^{adj} = Cohort\ Flow\ (USD)_{i,t} - \overline{Cohort\ Flow\ (USD)_t} \quad (8)$$

$\overline{Cohort\ Flow\ (USD)_t}$ is the mean of the *Cohort Flow (USD)* across all cohorts in the sector

$$Cohort\ Flow\ (rate)_{i,t}^{adj} = Cohort\ Flow\ (rate)_{i,t} - \overline{Cohort\ Flow\ (rate)_t} \quad (9)$$

$\overline{Cohort\ Flow\ (rate)_t}$ is the mean of the *Cohort Flow (rate)* across all cohorts in the sector

I apply the same method to estimate a mean-adjusted measure of fund flow rate for the analysis of flows in Section 4.4:

$$Fund\ Flow\ (rate)_{i,t}^{adj} = Fund\ Flow\ (rate)_{i,t} - \overline{Fund\ Flow\ (rate)_t} \quad (10)$$

$\overline{Fund\ Flow\ (rate)_t}$ is the mean of the *Fund Flow (rate)* across all funds in the sector

3.4 Fund performance

I apply two definitions of fund performance. The first definition is sector-adjusted return, following the method of Yin (2016).²¹ This method does not require estimates of factor exposures, and represents the actual return an investor in the fund would have earned, net

²¹The term style-adjusted return is used by Yin (2016).

of management fees and performance fees, relative to the average fund within the same sector. I estimate the sector-adjusted return using equation (11):

$$SAR_{i,t} = R_{i,t} - \overline{R}_t \quad (11)$$

$R_{i,t}$ is the fund return net of fees

\overline{R}_t is the mean of the return net of fees across all funds in the sector

The second measure is alpha estimated using the Fung and Hsieh (2004) seven-factor model. The model controls for a fund's exposure to the equity market factor (represented by the S&P 500 return), the size spread factor (represented by the difference between Russell 2000 return and S&P 500 return), the bond market factor (represented by the change in 10-year constant maturity yield), the credit spread factor (represented by the change in the Moody's Baa yield less 10-year treasury constant maturity yield), and the bond, currency and commodity trend-following factors.²² The seven-factor model explains a significant proportion of hedge fund returns, and has become a standard approach in the hedge fund literature.²³ This model provides an estimate of the component of fund returns that is not explained by exposures to factors. The factor-adjusted return (FAR) is estimated in two steps. First, the fund return is adjusted for factor exposures (equation (12)). I then adjust the return for sector averages, ensuring that each sector has a mean of zero, so that performance is evaluated relative to other funds in the same sector (equation (13)).

$$R_{i,t}^{adj} = R_{i,t} - \sum_{j=1}^7 \beta_{j,i,t} \times X_{j,t} \quad (12)$$

$R_{i,t}$ is the fund return net of fees

$\beta_{j,i,t}$ is fund i 's exposure to factor j , estimated by regression using monthly returns for the previous two years

$X_{j,t}$ is the return of the j 'th factor

$$FAR_{i,t} = R_{i,t}^{adj} - \overline{R_t^{adj}} \quad (13)$$

²²The bond, currency and commodity trend-following factors were introduced in Fung and Hsieh (2001) and are available to download from: <http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls>.

²³See e.g. Yin (2016) and Ramadorai (2013).

$\overline{R_t^{adj}}$ is the mean of the adjusted return across all funds in the sector

3.5 Regression method

The analysis uses panel regressions, as those used by Yin (2016), to examine the relation between fund size and performance.²⁴ The equations I estimate under the panel regressions are described in Section 4, including descriptions of the dependent and independent variables.

The dependent variable throughout most of the analysis is hedge fund performance, as measured by *SAR* and *FAR*. Subsequent tests examine cohort flows or fund flows as the dependent variable, as defined by equations (8), (9) and (10). Since the dependent variables in all instances are adjusted by the mean within the fund's sector, the dependent variable represents a value relative to the other funds in the sector. This removes the need to include sector and time dummies in the regressions.

The independent variables in the regressions vary depending on the analysis. The regressions also include control variables for past fund return net of fees, fund age, performance fee, management fee, minimum investment, redemption frequency, redemption notice period, subscription frequency, and lock-up period.

4 Empirical results

4.1 Summary of cohorts

This paper's key innovation is the introduction of fund cohorts, representing the funds that apply similar strategies. Summary statistics for cohorts are provided in Panel A of Table 2. Cohort AUM (in millions of USD) is substantially higher than fund AUM (see Table 1 for statistics of fund AUM), as expected. For instance, the median of cohort AUM is four times as high as the 75th percentile of fund AUM. The summary statistics for number of funds

²⁴Pástor et al. (2015) argue that size and performance are correlated to skill, causing an omitted variable bias in analysis of capacity constraints, and therefore introduce a recursive demeaning (RD) method. However, Choi, Kahraman, and Mukherjee (2016) argue that RD is dependent on a long time series, making it unsuitable for fund level analysis. In light of this issue, I decide to apply the traditional OLS regression approach used in e.g. Yin (2016).

per cohort, presented in Panel A of Table 2, show that more than 75 percent of fund-quarter observations represent funds with at least one other fund in their cohort.

Figure 1 illustrates the proportion of funds with cohorts exceeding different thresholds in terms of number of funds. If a hedge fund applies a completely unique strategy, they will form their own cohort. For cohorts to be meaningful, it is important that not every fund belong to such a category. Figure 1 shows that the proportion of cohorts with more than one fund varies between 63% and 83% over the sample period. In other words, a majority of funds pursue a strategy that is applied by at least one other fund. This suggests that cohorts' effects may impact a significant proportion of the hedge funds in the sample.

Figure 1: Number of funds in cohorts

Figure 1 illustrates the proportion of funds with cohort size, in terms of number of funds, over a certain threshold. The number of funds in a fund's cohort (N) as of time t is estimated as the number of funds within the cohort that reported returns for month t .

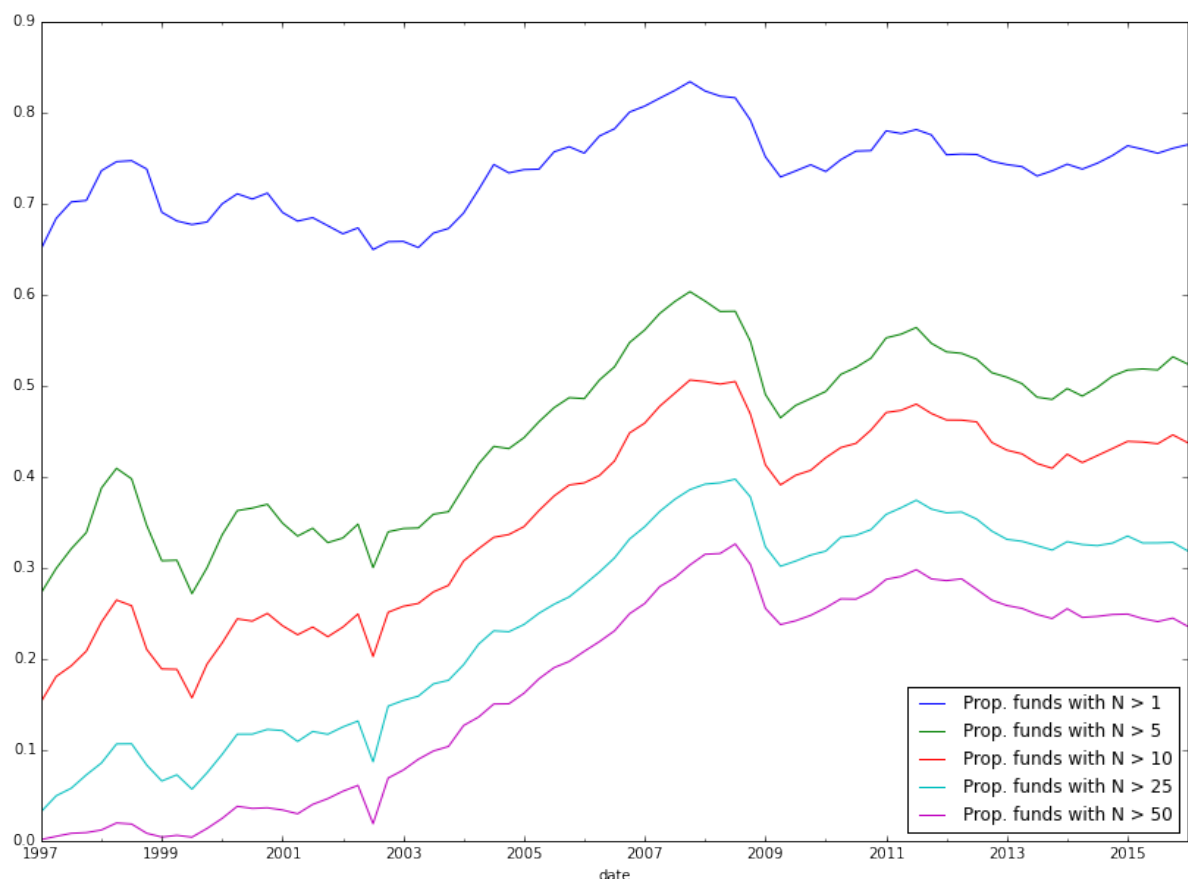


Figure 1 also shows that the proportion of cohorts with high number of funds (more than 25 or 50 funds) has increased over time. To understand what is driving this increase, I estimate regressions described by equation (14), which examines if the increase is driven by

an increasing total number of funds reporting returns:

$$\text{Proportion of funds}_t = \alpha + \beta_1 \text{Number of Funds}_t + \beta_2 \text{Month Count}_t + \epsilon_t \quad (14)$$

Proportion of funds is the proportion of funds with more than X number of funds in their cohort at time t

Number of Funds is the total number of funds reporting returns at time t

Month Count is an integer of the number of months since sample start in 1997

Panel B of Table 2 presents the coefficients from estimating equation (14), with X equal to 1, 5, 10, 25, and 50. The coefficients for the number of funds are positive and statistically significant at a 1% level for each of the proportions examined. As the number of funds increases, it becomes more likely that several funds will apply similar strategies. This also implies that cohorts may have an even more important impact on hedge funds in the future, if the industry continues to expand. The time effect is captured by the month count variable, and gives different results depending on the value of X . The proportion of funds with more than one fund in the cohort has decreased over time, indicating that the proportion of funds applying a unique strategy has increased with time. With respect to the number of funds with more than 25 or 50 funds in the cohort, the time effect is positive and statistically significant. It appears that the proportion of funds in very crowded strategies has increased with time, after controlling for the total number of funds in the sample.

Following Section 3.2, the natural logarithm of cohort AUM has a central role in the estimation of cohort size. Panel C of Table 2 presents summary statistics of the natural logarithm of cohort AUM (\$M) per hedge fund sector. The statistics show that relative value funds generally belong to cohorts with lower AUM, and that the multi-process sector contains large cohorts. The average natural logarithm of cohort AUM is substantially higher than the natural logarithm of fund AUM (see Panel C of Table 1 for statistics of fund AUM) across each hedge fund sector.

Table 2: Summary of Cohorts

Table 2 provides summary statistics for cohorts, based on the period from January 1997 until March 2016. Panel A shows basic summary statistics. Cohort AUM is the cohort AUM in million USD, Cohort Flow is defined as per equation (7), Funds per cohort is the number of funds in the fund's cohort that reported a return during the month. Panel B provides regression estimates for equation (14). Number of Funds is an integer of the total number of funds reporting their return at time t , and Month Count is an integer of the number of months since sample start in 1997. The dependent variable in the regression is the percentage of funds with a number of funds in its cohort higher than a certain threshold. This threshold is indicated by the column name. Panel C shows summary statistics of the natural logarithm of cohort AUM (\$M), presented for each hedge fund sector.

Panel A: Cohort summary statistics					
	Mean (1)	25th pct (2)	Median (3)	75th pct (4)	Std (5)
Cohort AUM (\$M)	17602.36	129.00	886.02	10699.69	39654.66
Cohort Flow (rate)	1.67	-2.92	0.73	5.78	18.89
Funds per Cohort	38.81	2.00	5.00	34.00	75.75
Panel B: Regression estimates for equation (14)					
Proportion of funds with number of funds in cohort > X	> 1 (1)	> 5 (2)	> 10 (3)	> 25 (4)	> 50 (5)
Intercept	61.637*** (56.225)	19.135*** (14.641)	6.277*** (6.069)	-6.808*** (8.786)	-13.329*** (16.850)
Number of Funds	0.007*** (8.299)	0.013*** (12.011)	0.013*** (15.899)	0.014*** (21.953)	0.014*** (21.083)
Month Count	-0.084*** (3.003)	-0.006 (0.174)	0.051* (1.914)	0.079*** (3.963)	0.071*** (3.501)
# of Obs	77	77	77	77	77
Adj. R^2	0.637	0.877	0.940	0.971	0.968
Absolute t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$					
Panel C: Natural logarithm of cohort AUM (\$M) per hedge fund sector					
	Mean (1)	25th pct (2)	Median (3)	75th pct (4)	Std (5)
Directional traders	7.04	4.85	7.09	9.04	2.61
Fixed income	7.38	5.26	7.34	9.56	2.56
Macro	5.88	4.14	5.61	7.16	2.23
Multi-process	8.01	5.57	8.01	10.80	2.84
Other	6.32	4.28	5.86	8.05	2.53
Relative value	5.25	3.89	4.96	6.35	1.91
Security selection	6.90	4.79	6.64	9.01	2.58

4.2 Relation between cohort size and future fund return

I extend the literature examining capacity constraints among hedge funds through investigating the role of cohorts with respect to the assets allocated to specific strategies. I examine the relation between cohort size and fund performance by estimating panel regressions as

described by equations (15) (linear relation) and (16) (quadratic relation):

$$\begin{aligned} Performance_{i,t} = & \alpha + \beta_1 Cohort\ Size_{i,t-1} + \beta_2 Fund\ Size_{i,t-1} + \\ & Controls_{i,t} + \epsilon_{i,t} \end{aligned} \quad (15)$$

$$\begin{aligned} Performance_{i,t} = & \alpha + \beta_1 Cohort\ Size_{i,t-1} + \beta_2 Cohort\ Size_{i,t-1}^2 + \\ & \beta_3 Fund\ Size_{i,t-1} + \beta_4 Fund\ Size_{i,t-1}^2 + Controls_{i,t} + \epsilon_{i,t} \end{aligned} \quad (16)$$

Performance is defined in Section 3.4

Cohort Size is defined in equation (5)

Fund Size is defined in equation (3)

Controls are control variables

Estimates of the equations are presented in Table 3. I find a negative and highly significant linear relation between cohort size and performance, regardless of whether performance is based on sector-adjusted returns (*SAR*) or factor-adjusted returns (*FAR*). Estimates are economically significant: a one standard deviation increase in cohort size is associated with an annualized 44.2 basis point decrease in *SAR*, and a 185.6 basis point decrease in *FAR*.²⁵ In Columns 2 and 4, I report results including a quadratic term for cohort size and fund size. These results differ depending on performance definition. Cohort size appears to have a positive and statistically significant quadratic relation with *SAR*, indicating that the negative impact of cohort size is higher if the fund belongs to a small cohort compared to a large cohort. For *FAR*, I find no significant quadratic relation, suggesting that the linear relation between cohort size and *FAR* is relatively consistent regardless of the fund's cohort size.

Once controlling for cohort size, the relation between fund size and performance is *positive*, although the results are only statistically different from zero for *FAR*. The positive relation differs from Ammann and Moerth (2005), Ammann and Moerth (2008), Ramadorai (2013) and Yin (2016), all of which do not control for the size of cohorts. My results indicate that diseconomies exist at the cohort level, but that this potentially occurs in conjunction with economies of scale at a fund level. Therefore, it appears that funds reap the benefits of

²⁵I estimate the impact by annualizing the quarterly impact of a one standard deviation increase in cohort size: $((1 + \beta_{CohortSize}/100 \times \sigma_{CohortSize})^4 - 1) \times 10000$. $\beta_{CohortSize}$ is the cohort size coefficient presented in Table 3 and $\sigma_{CohortSize}$ is the standard deviation of cohort size (which in the sample is 2.46).

a larger fund size, perhaps through relatively lower fixed costs; while being disadvantaged by cohort size, likely through increased execution and opportunity costs.

Table 3: Relation between cohort size and future fund performance

Table 3 reports results on the analysis of the relation between cohort size and returns, estimated through panel regressions of equations (15) and (16) using quarterly data. Cohort Size is defined by equation (5), Cohort Size SQ is the squared cohort size, Fund Size is defined by equation (3), Fund Size SQ is the squared fund size, Return₂₄₋₂ is the annualized fund return net of fees over the period $t-24$ to $t-2$, Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the Lock-up measured in number of months. Columns 1 and 2 report results with fund sector-adjusted return (*SAR*) as the dependent variable. Columns 3 and 4 report results with fund factor-adjusted return (*FAR*) as the dependent variable, estimated using the Fung and Hsieh (2004) seven-factor model. As per Petersen (2009), standard errors are clustered by fund.

	SAR, %		FAR, %	
	(1)	(2)	(3)	(4)
Intercept	-0.617*** (2.745)	-0.711*** (3.097)	-0.482* (1.889)	-0.506* (1.954)
Cohort Size	-0.045*** (3.514)	-0.045*** (3.506)	-0.190*** (13.652)	-0.190*** (13.673)
Cohort Size SQ		0.011** (2.226)		0.004 (0.721)
Fund Size	0.009 (0.423)	0.020 (0.805)	0.094*** (4.150)	0.103*** (3.682)
Fund Size SQ		0.000 (0.005)		-0.005 (0.413)
Return ₂₄₋₂	-0.004 (1.228)	-0.004 (1.161)	0.005 (1.273)	0.005 (1.289)
Fund Age	0.099** (2.341)	0.091** (2.343)	0.095** (1.965)	0.096** (1.983)
Performance Fee	0.003 (0.651)	0.004 (0.941)	-0.002 (0.389)	-0.002 (0.316)
Management Fee	0.032 (0.595)	0.036 (0.680)	-0.030 (0.506)	-0.029 (0.487)
Minimum Investment	0.017 (0.810)	0.018 (0.826)	0.082*** (3.618)	0.083*** (3.634)
Redemption Frequency	0.000 (0.525)	0.000 (0.498)	0.000 (0.385)	0.000 (0.409)
Redemption Notice Period	0.002** (2.019)	0.002* (1.867)	0.003*** (2.609)	0.003** (2.546)
Subscription Frequency	0.000 (0.267)	0.000 (0.172)	0.002 (1.628)	0.002* (1.652)
Lock-up Period	0.014** (2.522)	0.014** (2.486)	0.000 (0.053)	0.000 (0.035)
# of Obs	97531	97531	97531	97531
Adj. R^2	0.001	0.001	0.003	0.003

Absolute t statistics in parentheses
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To understand if my results are consistent across all hedge fund sectors, I estimate the regressions for each sector individually, and present the findings in Table 4. The negative relation between cohort size and *FAR* exists across all sectors. Cohort size has the largest negative impact among relative value funds. These funds trade based on temporary

mis-pricing of a pair of similar securities by buying the undervalued security and selling the overvalued security. As the cohort size increases, competition for these opportunities intensifies, and exploiting the mis-pricing becomes less profitable.

Table 4: Relation between cohort size and future fund performance (strategy breakdown)

Table 4 reports results on the relation between cohort size and returns within hedge fund sectors, based on the same panel regression as Table 3. Columns 1 and 2 report results with fund sector-adjusted return (SAR) as the dependent variable. Columns 3 and 4 report results with fund factor-adjusted return (FAR) as the dependent variable, estimated using the Fung and Hsieh (2004) seven-factor model. To save space, only the cohort size estimates are presented. As per Petersen (2009), standard errors are clustered by fund.

	SAR, %		FAR, %	
	(1)	(2)	(3)	(4)
Directional traders				
Cohort Size	−0.005 (0.165)	−0.008 (0.272)	−0.191*** (6.025)	−0.195*** (6.029)
Cohort Size SQ		0.020 (1.556)		0.005 (0.380)
Other				
Cohort Size	−0.204*** (2.964)	−0.137* (1.647)	−0.297*** (3.886)	−0.185** (2.062)
Cohort Size SQ		−0.055** (2.073)		−0.096*** (3.150)
Security selection				
Cohort Size	−0.016 (0.663)	−0.023 (0.903)	−0.210*** (7.622)	−0.215*** (7.466)
Cohort Size SQ		0.022** (2.263)		0.021* (1.653)
Macro				
Cohort Size	−0.013 (0.305)	0.025 (0.475)	−0.143*** (2.632)	−0.074 (1.176)
Cohort Size SQ		−0.027* (1.878)		−0.048*** (2.580)
Multi-process				
Cohort Size	−0.060*** (2.720)	−0.043** (2.128)	−0.143*** (6.289)	−0.112*** (5.708)
Cohort Size SQ		0.016* (1.847)		0.030*** (3.582)
Fixed income				
Cohort Size	−0.096*** (2.676)	−0.090** (2.511)	−0.215*** (6.251)	−0.210*** (6.194)
Cohort Size SQ		0.046*** (3.015)		0.037* (2.478)
Relative value				
Cohort Size	−0.182 (1.015)	−0.287 (0.994)	−0.414** (2.491)	−0.567** (2.292)
Cohort Size SQ		0.072 (0.785)		0.110 (1.471)
Absolute t statistics in parentheses				
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

The results for SAR differ slightly. Although the relation between cohort size and performance is negative within all seven sectors, it is only statistically significant for funds classified in the multi-process, fixed income, and other sectors. The less significant findings for SAR are to be expected for some sectors, such as directional traders and security selec-

tion. These sectors will contain a large number of funds with significantly different factor exposures. Without adjusting for factor exposures, *SAR* is likely to contain a significant amount of noise that is not present when analyzing *FAR*.

My results confirm the importance of considering total cohort size when analyzing capacity constraints. These findings also extend the work of [Hanson and Sunderam \(2014\)](#) on the limits to arbitrage. They conclude that, as more capital is allocated to momentum and value strategies, the performance of these strategies decreases. My finding that funds in cohorts with low AUM outperform funds in cohorts with high AUM provides further support for the limits to arbitrage theory.

My results contrast with several previous studies by not finding statistically significant negative relation between fund size and performance.²⁶ Indeed, I document a positive relation between fund AUM and performance after controlling for cohort size, which I posit is driven by diseconomies of cohort size coupled with economies of fund size. However, there is one case in which fund size can be used to examine capacity constraints, being where funds form their own cohort. In the case of single-fund cohorts, fund size represents the full cohort size, and would be expected to be associated with diseconomies of scale.

To test if diseconomies of fund size emerges for funds forming their own cohort, I introduce a dummy variable equal to one for single-fund cohorts, and zero otherwise. I then estimate a panel regression of equations [\(17\)](#) (linear relation) and [\(18\)](#) (quadratic relation):

$$\begin{aligned} Performance_{i,t} = & \alpha + \beta_1 Single\ Cohort_{i,t-1} + \beta_2 Fund\ Size_{i,t-1} + \\ & \beta_3 Single\ Cohort_{i,t-1} \times Fund\ Size_{i,t-1} + Controls_{i,t} + \epsilon_{i,t} \end{aligned} \quad (17)$$

$$\begin{aligned} Performance_{i,t} = & \alpha + \beta_1 Single\ Cohort_{i,t-1} + \beta_2 Fund\ Size_{i,t-1} + \\ & \beta_3 Fund\ Size_{i,t-1}^2 + \beta_4 Single\ Cohort_{i,t-1} \times Fund\ Size_{i,t-1} + \\ & \beta_5 Single\ Cohort_{i,t-1} \times Fund\ Size_{i,t-1}^2 + Controls_{i,t} + \epsilon_{i,t} \end{aligned} \quad (18)$$

Performance is either *FAR* or *SAR*, as defined in Section [3.4](#)

Single Cohort is a dummy equal to one if the fund is the only fund within its cohort reporting returns at time $t-1$

²⁶For example, see [Ammann and Moerth \(2005\)](#), [Ramadorai \(2013\)](#) and [Yin \(2016\)](#).

Fund Size is defined in equation (3)

Controls are control variables

Regression estimates of equations (17) and (18) are presented in Table 5. I find no relation between fund size and performance for funds not forming their own cohort. I also document a negative and significant coefficient for the interaction term between the single cohort dummy and fund size. Hence, it appears that funds forming their own cohort experience diseconomies of scale, but that the negative impact of fund size does not exist for funds in multi-fund cohorts.

The results presented in Table 5 provide additional insight into the impact of being the only fund within a cohort. In terms of *FAR* (although not *SAR*), funds in single-fund cohorts significantly outperform other funds. I posit that this result is consistent with previous research on the impact of strategy distinctiveness on performance. Being the only fund in a cohort is comparable to applying a unique trading strategy. These funds will experience less competition when buying and selling, and hence are more likely to be able to trade at an advantageous price. This result further contributes to the findings of Sun et al. (2012) in highlighting the advantages of applying a unique trading strategy.

4.3 Relation between past returns and future cohort flows

Berk and Green's (2004) model of capital flows and performance of mutual fund managers explains how fund flows in rational markets will respond to past performance if it is revealing of manager skill, with the consequence that alpha may not persist as it becomes eroded by additional AUM. If allocators to hedge funds also follow past performance when making investment decisions, it is expected that past fund performance will predict future flows. I investigate the extent to which this relation operates at the cohort rather than fund level. If a fund performs well, allocators may aim to invest either in the fund or in a close substitute. However, when a fund performs well, its cohort is also likely to have high performance in reflection of similarities in strategy. Hence, it is also possible that flows may be related to cohort performance.

Table 5: Relation between fund size and future fund performance

Table 5 reports results on the relation between fund size and return, and how this relation depends on whether the fund is forming its own cohort, estimated through the panel regressions of equations (17) and (18) using quarterly data. Single Cohort is a dummy equal to 1 if the fund forms its own cohort as of the previous quarter, Fund Size is defined by equation (3), Fund Size SQ is the squared fund size, Return₂₄₋₂ is the annualized fund return net of fees over the period $t-24$ to $t-2$, Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the Lock-up measured in number of months. Columns 1 and 2 report results with fund sector-adjusted return (*SAR*) as the dependent variable. Columns 3 and 4 report results with fund factor-adjusted return (*FAR*) as the dependent variable, estimated using the Fung and Hsieh (2004) seven-factor model. As per Petersen (2009), standard errors are clustered by fund.

	SAR, %		FAR, %	
	(1)	(2)	(3)	(4)
Intercept	-0.675*** (3.002)	-0.645*** (2.827)	-0.890*** (3.502)	-0.870*** (3.374)
Single Cohort	0.024 (0.358)	-0.095 (1.200)	0.571*** (7.665)	0.533*** (6.059)
Fund Size	0.012 (0.530)	0.023 (0.846)	0.021 (0.846)	0.030 (0.996)
Single Cohort * Fund Size	-0.135*** (2.987)	-0.175*** (3.454)	-0.123** (2.418)	-0.139** (2.364)
Fund Size SQ		-0.011 (0.936)		-0.009 (0.634)
Single Cohort * Fund Size SQ		0.067*** (2.961)		0.021 (0.779)
Return ₂₄₋₂	-0.004 (1.258)	-0.005 (1.270)	0.005 (1.302)	0.005 (1.292)
Fund Age	0.092** (2.179)	0.092** (2.174)	0.093* (1.908)	0.093* (1.924)
Performance Fee	0.007* (1.650)	0.007 (1.624)	0.011** (2.270)	0.011** (2.240)
Management Fee	0.042 (0.784)	0.040 (0.754)	-0.004 (0.069)	-0.005 (0.088)
Minimum Investment	0.022 (1.042)	0.022 (1.049)	0.089*** (3.905)	0.089*** (3.926)
Redemption Frequency	0.000 (0.299)	0.000 (0.269)	0.000 (0.908)	0.000 (0.934)
Redemption Notice Period	0.003** (2.101)	0.002** (2.033)	0.004*** (3.131)	0.004*** (3.110)
Subscription Frequency	0.000 (0.245)	0.000 (0.223)	0.002 (1.550)	0.002 (1.550)
Lock-up Period	0.013** (2.463)	0.013*** (2.462)	-0.001 (0.118)	-0.001 (0.124)
# of Obs	97531	97531	97531	97531
Adj. R^2	0.000	0.001	0.002	0.002

Absolute t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To determine if past cohort performance predicts cohort flows, I utilize the panel regression method outlined in Section 3.5, by estimating equation (19). I estimate the regression for both definitions of cohort flow outlined in Section 3.3, i.e. the cohort flow rate and cohort flow in USD. Since cohort flow is an estimate of aggregated flow to the funds within a cohort, I elect to represent the independent variables and control variables by averages across the

cohort.

$$Cohort\ Flow_{i,t}^{adj} = \alpha + \beta_1 Return_{24-2,i,t-1} + \beta_2 Cohort\ Size_{i,t-1} + Controls_{i,t} + \epsilon_{i,t} \quad (19)$$

$Cohort\ Flow_{i,t}^{adj}$ is the rate of cohort flow (equation (9)) or the cohort flow measured in USD (equation (8))

$Return_{24-2}$ is the average annualized fund return net of fees over the past two years, excluding the returns of the most recent two months, of all funds within the cohort

$Cohort\ Size$ is defined in equation (5)

$Controls$ are control variables, represented by the averages across the fund's cohort

Table 6 presents the coefficients from the regressions described by equation (19). The results reveal that lagged performance is significantly related to cohort flows, both in terms of flow rate and flow measured in USD. In terms of the flow rate, a 1% increase in annualized return over the previous two years results in a 0.102% increase in cohort flow over the following quarter.²⁷ Barberis and Shleifer (2003) assume that investors make investment decisions depending on the relative performance of different investment styles. Since different cohorts can be seen as different investment styles, the relation documented in Table 6 is consistent with Barberis and Shleifer's (2003) assumption.

4.4 Fund flows and influence of cohort structure

Sections 4.2 and 4.3 have mainly focused on the relation between size and performance, both in terms of how cohort and fund size are related to performance, and how cohort performance predicts future cohort flows. In this section, I focus on how a fund's propensity to accept assets differs depending on the structure of their cohort, and how cohort structure may impact the fund's performance-flow sensitivity.

²⁷I estimate the percentage impact through $(\exp(0.102/100)-1)*100$.

Table 6: Determinants of cohort flows

Table 6 reports results on the determinants of cohort flows, estimated through the panel regression of equation (19) using quarterly data. Return₂₄₋₂ is the average annualized fund return net of fees over the period $t-24$ to $t-2$ of all funds within the cohort, Cohort Size is defined by equation (5), Fund Age is the average of the natural logarithm of the number of months since fund inception of all funds within the cohort, Performance Fee is the average percentage performance fee of all funds within the cohort, Management Fee is the average percentage management fee of all funds within the cohort, Minimum Investment is the average natural logarithm of minimum investment measured in million USD of all funds within the cohort, Redemption Frequency is the average redemption frequency measured in number of days of all funds within the cohort, Redemption Notice Period is the average notice measured in number of days of all funds within the cohort, Subscription Frequency is the average subscription frequency measured in number of days of all funds within the cohort, and the Lock-up Period is the average Lock-up measured in number of months of all funds within the cohort. In Column 1, flow is the cohort flow rate, defined by equation (9). In Column 2, flow is the USD cohort flow, defined by equation (8). As per Petersen (2009), standard errors are clustered by fund.

	Cohort Flow (rate) ^{adj} (1)	Cohort Flow (USD) ^{adj} (2)
Intercept	13.900*** (18.235)	231.755*** (4.242)
Return ₂₄₋₂	0.102*** (16.677)	4.261*** (6.619)
Cohort Size	-0.189*** (6.273)	12.675** (2.391)
Fund Age	-2.889*** (23.183)	-73.103 (6.118)
Performance Fee	-0.153*** (7.730)	0.001 (0.001)
Management Fee	-0.362** (2.035)	25.405** (2.528)
Minimum Investment	0.393*** (4.112)	-4.218 (0.926)
Redemption Frequency	0.002 (0.986)	-0.281*** (2.627)
Redemption Notice Period	0.008 (1.599)	-0.057 (0.192)
Subscription Frequency	-0.016*** (3.148)	-0.185 (0.842)
Lock-up Period	-0.013 (0.608)	0.204 (0.186)
# of Obs	90401	90401
Adj. R ²	0.018	0.002
Absolute t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$		

Given the combination of a positive relation between past performance and future cohort flows, and a negative relation between cohort size and future performance, I propose that funds within multiple fund cohorts may be more incentivized to accept assets compared to funds forming their own cohort. Furthermore, cohorts comprising multiple funds provide investors more options, and this may attenuate the performance-flow relation for individual funds.

To test these propositions, I estimate a regression that relates fund flow to both its prior performance and the fund's cohort structure. I use two variables as indicators of the cohort structure, both of which are indicative of the level of competition from other

funds in the cohort. The first is the single cohort dummy variable presented in Section 4.2. The second is the ratio of fund AUM to cohort AUM. Negative coefficients on these variables would indicate that cohort competition impacts a fund's propensity to grow, *ceteris paribus*. I also introduce an interaction term between past performance and the indicators of cohort competition, in order to capture cohorts' effects on the sensitivity of flows to past performance. The estimation uses panel regressions as described by equations (20) to (23):

$$Fund\ Flow_{i,t}^{adj} = \alpha + \beta_1 Return_{24-2,i,t-1} + Controls_{i,t} + \epsilon_{i,t} \quad (20)$$

$$Fund\ Flow_{i,t}^{adj} = \alpha + \beta_1 Single\ Cohort_{i,t-1} + \beta_2 Return_{24-2,i,t-1} + \beta_3 Single\ Cohort_{i,t-1} \times Return_{24-2,i,t-1} + Controls_{i,t} + \epsilon_{i,t} \quad (21)$$

$$Fund\ Flow_{i,t}^{adj} = \alpha + \beta_1 Prop.\ of\ Cohort_{i,t-1} + \beta_2 Return_{24-2,i,t-1} + \beta_3 Prop.\ of\ Cohort_{i,t-1} \times Return_{24-2,i,t-1} + Controls_{i,t} + \epsilon_{i,t} \quad (22)$$

$$Fund\ Flow_{i,t}^{adj} = \alpha + \beta_1 Single\ Cohort_{i,t-1} + \beta_2 Prop\ of\ Cohort_{i,t-1} + \beta_3 Return_{24-2,i,t-1} + \beta_4 Single\ Cohort_{i,t-1} \times Return_{24-2,i,t-1} + \beta_5 Prop\ of\ Cohort_{i,t-1} \times Return_{24-2,i,t-1} + Controls_{i,t} + \epsilon_{i,t} \quad (23)$$

$Fund\ Flow^{adj}$ is defined in equation (10)

$Single\ Cohort$ is a dummy variable equal to one if the fund is the only fund within its cohort at time $t-1$

$Prop\ of\ Cohort$ is the proportion of the cohort which is represented by the fund, calculated as $Fund\ AUM / Cohort\ AUM$

$Return_{24-2}$ is the annualized fund return net of fees over the past two years, excluding the returns of the most recent two months

$Controls$ are control variables

The estimates of equation (20), which does not include measures of cohort structure, are presented in Column 1 of Table 7. The results indicate that fund flows are dependent on past fund returns, consistent with previous research (e.g. Fung et al. (2008) and Lim et al. (2015)).

Estimates of equation (21) are presented in Column 2 of Table 7. These findings indicate that funds forming their own cohort are less likely to accept new assets, consistent with this group of funds being more incentivized to manage capacity constraints. Furthermore, the interaction term indicates that single-cohort funds have a significantly higher performance-flow relation compared to other funds. Hence, it appears that funds in multi-fund cohorts are less rewarded for good performance compared to funds forming their own cohort.

Table 7: Determinants of fund flows

Table 7 reports results for the analysis of the determinants of Fund Flows, estimated through panel regressions of equations (20) through (23) using quarterly data. Return_{24-2} is the annualized fund return net of fees over the period $t-24$ to $t-2$, Single Cohort is a dummy equal to 1 if the fund was forming its own cohort as of the beginning of the quarter, Fund Size is defined by equation (3), Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the Lock-up measured in number of months. The dependent variable is the rate of fund flow, defined as per equation (10). Column 1, 2, 3 and 4 provide regression estimates of equations (20), (21), (22) and (23), respectively. As per Petersen (2009), standard errors are clustered by fund.

	Fund Flow (rate) ^{adj}			
	(1)	(2)	(3)	(4)
Intercept	5.432*** (6.366)	5.515*** (6.487)	5.741*** (6.735)	5.748*** (6.734)
Single Cohort		-0.732** (2.383)		0.837 (1.509)
Prop. of Cohort			-1.180*** (3.802)	-1.909*** (3.397)
Return_{24-2}	0.142*** (18.016)	0.120*** (14.901)	0.092*** (10.435)	0.090*** (10.033)
$\text{Return}_{24-2} * \text{Single Cohort}$		0.112*** (4.506)		-0.029 (0.776)
$\text{Return}_{24-2} * \text{Prop. of cohort}$			0.147*** (6.255)	0.171*** (5.146)
Fund Size	-1.096*** (13.729)	-1.085*** (13.611)	-1.107*** (13.931)	-1.082*** (13.362)
Fund Age	-1.335*** (8.500)	-1.301*** (8.288)	-1.285*** (8.187)	-1.280*** (8.157)
Performance Fee	-0.073*** (4.804)	-0.076*** (4.925)	-0.074*** (4.707)	-0.072*** (4.522)
Management Fee	-0.166 (1.023)	-0.172 (1.065)	-0.190 (1.151)	-0.187 (1.132)
Minimum Investment	0.568*** (7.341)	0.569*** (7.388)	0.572*** (7.434)	0.571*** (7.395)
Redemption Frequency	0.001 (1.083)	0.001 (1.063)	0.001* (0.880)	0.001 (0.871)
Redemption Notice Period	0.008** (2.084)	0.007* (1.857)	0.007* (1.747)	0.007* (1.732)
Subscription Frequency	-0.016*** (4.149)	-0.016*** (4.170)	-0.017*** (4.237)	-0.017*** (4.234)
Lock-up Period	-0.014 (0.972)	-0.012 (0.894)	-0.015 (1.041)	-0.015 (1.059)
# of Obs	89938	89938	89938	89938
Adj. R^2	0.015	0.016	0.017	0.017
Absolute t statistics in parentheses				
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

The estimates presented in Column 3 of Table 7 suggest that my findings remain consistent when fund Proportion of Cohort is used as a measure of relative competition in the cohort. Funds with high Proportion of Cohort have a lower propensity to increase in size and a stronger performance-flow relation. As the Proportion of Cohort approaches zero, the fund can increase its size without having much impact on the cohort size; hence, providing little incentive to reject assets. However, as the Proportion of Cohort approaches one, a percentage increase in fund AUM will approach the percentage increase in cohort AUM, and fund size becomes important for managing capacity constraints. The positive interaction term between the Proportion of Cohort and $Return_{24-2}$ indicates that hedge funds which make up a significant proportion of their cohort experience larger inflows (outflows) in times of outperformance (underperformance). This implies that the reward structure of funds differs depending on cohort competition.

When I estimate equation (23), which includes the single cohort dummy variable as well as the Proportion of Cohort in the regression, only the coefficients on the latter variable are statistically significant. Hence, it appears that the level of competition with other funds in the cohort is more important than whether the fund forms its own cohort as a potential determinant of flows and the performance-flow relation.

The indirect incentives for accepting inflows is discussed by Lim et al. (2015), who find that future income through fund flows outweighs the direct income earned through performance fees. My findings have important implications for interpreting the results of Lim et al. (2015), and help to further understand incentives within the hedge fund industry. Funds making up a larger proportion of their cohort experience a higher reward for past performance. Accordingly, the nature of the cohort may have a significant impact on indirect incentives of hedge funds. Therefore, my findings show that the flow-performance relation may differ depending on the fund's competition with other funds in the cohort.

5 Robustness tests

I perform several robustness tests to control for potential data biases, different cohort definitions, and to examine if my findings are explained by similarities between cohort size and strategy distinctiveness.

5.1 Delisting bias

One important bias within hedge fund databases relates to delisting. The reporting of hedge fund information to databases is not regulated, and hedge funds have discretion over if they report. It is possible that funds may see the databases as a marketing tool, and stop reporting if they underperform. Agarwal et al. (2011) find that funds underperform after they delist from databases. If the negative impact of cohort size is driven by the delisting bias, I would expect that funds within small cohorts would be more likely to delist compared to funds within large cohorts, so that returns for small cohorts are more distorted by failure to observe negative post-delisting returns.

To investigate the possibility, I analyze how the likelihood of delisting is impacted by the cohort size and fund size using logit and probit regression models. The dependent variable is a delisting dummy (equal to one if the fund was delisted during the quarter, and zero otherwise), which is regressed against the same independent variables as Table 3. The logit and probit regressions are described by equation (24).²⁸

$$Delist_{i,t} = \alpha + \beta_1 Size_{i,t-1} + Controls_{i,t} + Sector_{i,t} + Year_{i,t} + \epsilon_{i,t} \quad (24)$$

Delist is a dummy equal to one if the fund was delisted during the quarter

Size refers to the fund size and cohort size

Controls are control variables

Sector are dummies to represent the fund's sector

²⁸In previous regressions I do not include sector and year dummies, since I already control for these by mean-adjusting the dependent variables across each sector for each cross-section. I am unable to mean-adjust the delisting variable, and hence include sector and year dummies in equation (24).

Year are dummies to represent the year

The results of the logit and probit regressions are presented in Table 8, and represent how the probability of delisting relates to the independent variables. The cohort size coefficient shows that funds in large cohorts are more prone to delist compared to funds in small cohorts. In light of the findings of Agarwal et al. (2011) that post-delisting returns are poor, it appears that the negative impact of cohort size presented in Table 3 could be understated. Consequently my findings do not appear to be driven by delisting bias, but rather may even be strengthened if I could account for post-delisting returns.

Table 8: Probability of delisting

Table 8 reports results for the analysis of the probability of delisting, estimated using the probit or logit regression of equation (24) using quarterly data. Delist is a dummy variable equal to one if the fund is delisted from the database in the quarter. Cohort Size is defined by equation (5), Fund Size is defined by equation (3), Return₂₄₋₂ is the annualized fund return net of fees over the period $t-24$ to $t-2$, Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the Lock-up measured in number of months. Column 1 reports results for the probit regression, and Column 2 report results for the logit regression.

	Probit regression (1)	Logit regression (2)
Cohort Size	0.016*** (4.545)	0.035*** (4.714)
Fund Size	-0.157*** (22.13)	-0.359*** (21.98)
Return ₂₄₋₂	-0.009*** (14.62)	-0.022*** (15.36)
Fund Age	-0.111*** (8.304)	-0.251*** (8.527)
Performance Fee	0.017*** (10.76)	0.040*** (10.82)
Management Fee	0.047*** (3.673)	0.102*** (3.887)
Minimum Investment	0.037*** (5.616)	0.084*** (5.684)
Redemption Frequency	0.000 (0.492)	0.000 (0.497)
Redemption Notice Period	0.000 (0.328)	0.000 (0.049)
Subscription Frequency	0.001* (1.776)	0.002* (1.942)
Lock-up Period	-0.002* (1.818)	-0.007** (2.235)
Sector Dummies	Yes	Yes
Year Dummies	Yes	Yes
# of Obs	93425	93425
Pseudo R^2	0.052	0.053
Log likelihood	-13539	-13526

Absolute t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Use of factor-adjusted returns to determine cohorts

Throughout Section 4, I determine if funds belong to the same cohort by estimating the correlation of net returns. It is possible that these returns mainly reflect exposures to different common factors, rather than to unique strategies. Consequently, I re-estimate the results presented in Table 3 while forming cohorts based on returns adjusted for factor exposure, as estimated through equation (12) (i.e. the model of Fung and Hsieh (2004)). The results presented in Table 10 suggest that cohort size continues to have a significant relation with future fund performance when factor-adjusted returns are used to assign funds to cohorts. The fact that the results remain significant after controlling for factor exposures indicates that a significant proportion of information in cohort size is explained by similarities in trading strategies which is unrelated to factor exposures, and confirms the robustness of my findings.

5.4 Sample used to identify cohorts

This section reports on analysis designed to gauge the sensitivity of results to the sample used to identify cohorts in two ways: use of only prior information, and sample length. The results reported earlier were based on assignment of funds to cohorts based on correlations estimated from all available monthly returns over the sample period. This uses information that was not available to investors at each point in time. Investors using available information to determine which funds belong to a certain cohort may not have made the same assignments. While I contend that it is appropriate to utilize the full dataset to determine cohorts given my research question (see Section 3.1), it is helpful to understand if the results are consistent after removing the forward-looking element. Accordingly, I introduce an alternative definition where an expanding window of returns is used to assign funds to cohorts.

A second related issue is the length of the sample used to identify cohorts. As explained in Section 3.1, I expect that cohorts are more likely to be accurately identified when based on a longer history of returns. Using the expanding window method to identify cohorts shortens the estimation period, especially earlier in the sample period. It is expected that cohorts will be more accurately identified later in the sample period once I use an expanding

Table 10: Relation between cohort size and future return when cohorts are identified using factor-adjusted returns

Table 10 re-examines the relation between cohort size and returns with cohorts identified using factor-adjusted returns, estimated through the panel regressions of equations (15) and (16) using quarterly data. Cohort Size is defined by equation (5), Cohort Size SQ is the squared cohort size, Fund Size is defined by equation (3), Fund Size SQ is the squared fund size, Return₂₄₋₂ is the annualized fund return net of fees over the period $t-24$ to $t-2$, Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the Lock-up measured in number of months. Columns 1 and 2 report results with fund sector-adjusted return (*SAR*) as the dependent variable. Columns 3 and 4 report results with fund factor-adjusted return (*FAR*) as the dependent variable, estimated using the Fung and Hsieh (2004) seven-factor model. As per Petersen (2009), standard errors are clustered by fund.

	SAR, %		FAR, %	
	(1)	(2)	(3)	(4)
Intercept	-0.493** (2.170)	-0.426* (1.848)	-0.503** (1.971)	-0.417 (1.601)
Cohort Size	-0.088*** (4.834)	-0.071*** (3.503)	-0.104*** (5.014)	-0.087*** (3.757)
Cohort Size SQ		-0.019*** (2.728)		-0.019** (2.430)
Fund Size	0.048** (2.033)	0.014 (0.475)	0.059** (2.156)	0.032 (0.913)
Fund Size SQ		0.019* (1.757)		0.011 (0.861)
Return ₂₄₋₂	-0.004 (1.247)	-0.005 (1.272)	0.005 (1.191)	0.004 (1.155)
Fund Age	0.076* (1.813)	0.07* (1.778)	0.051 (1.057)	0.051 (1.050)
Performance Fee	0.001 (0.315)	0.000 (0.045)	0.010* (1.816)	0.008 (1.471)
Management Fee	0.035 (0.659)	0.032 (0.598)	-0.023 (0.038)	-0.07 (0.113)
Minimum Investment	0.014 (0.643)	0.012 (0.580)	0.090*** (3.981)	0.090*** (3.941)
Redemption Frequency	0.000 (0.334)	0.000 (0.368)	-0.001 (1.384)	-0.001 (1.359)
Redemption Notice Period	0.003** (2.238)	0.003** (2.403)	0.004*** (3.092)	0.004*** (3.227)
Subscription Frequency	0.000 (0.325)	-0.001 (0.385)	0.002 (1.487)	0.002 (1.427)
Lock-up Period	0.013** (2.318)	0.013** (2.344)	-0.003 (0.497)	-0.003 (0.486)
# of Obs	97531	97531	97531	97531
Adj. R^2	0.001	0.001	0.001	0.001
Absolute t statistics in parentheses				
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

window. To understand if this is the case, I introduce a variable representing the average number of historical quarterly returns available at each point in time as defined by equation (25):

$$Avg\ Hist_t = \frac{\sum_{n=1}^N Fund\ Hist_{n,t}}{N} \quad (25)$$

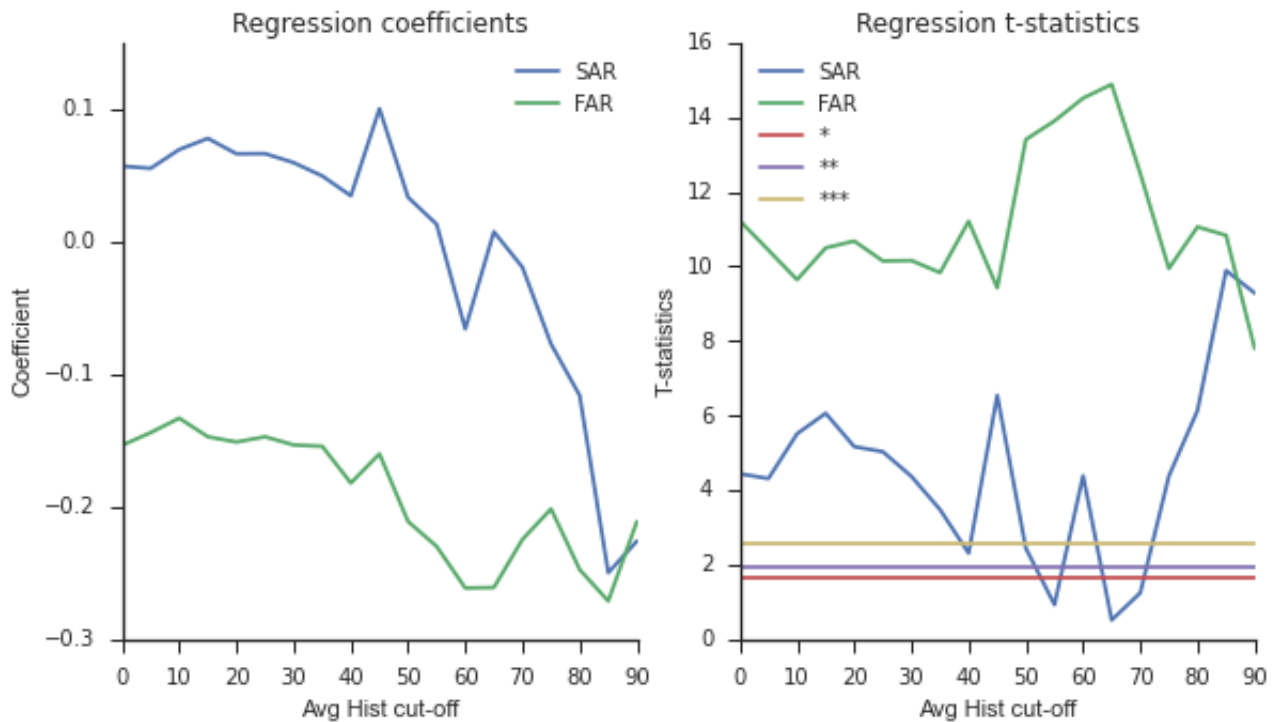
N is the number of funds reporting their returns at time t

$Fund\ Hist_{n,t}$ is the number of quarters of returns available for fund n at time t

I start by estimating panel regressions of equation (15) with cohorts identified using the expanding window method based on the full sample. I then progressively reduce the sample in increments of five percent by removing the quarters with lowest $Avg\ Hist$, until ten percent of the sample remains. The resulting coefficients on cohort size and t-statistics are reported in Figure 2. The trajectory of the coefficients is similar for both FAR and SAR , declining as the sample is restricted so that identification of cohorts becomes based on increasingly longer samples. This finding suggests that cohort identification is more reliable when based on longer sample periods, and may influence the strength of the results.

Figure 2: Relation between cohort size and future fund return when cohorts are identified using trailing returns

Figure 2 re-examines the relation between cohort size and returns with cohorts identified using an expanding-window approach, thus using data available at time t . The estimates are based on the same panel regression as Table 3. Cohort Size is defined by equation (5). The regression is estimated for different samples based on exclusion of quarters with lowest $Avg\ Hist$, with the cutoff being indicated on the x -axis. Cutoff of 0 means that the full sample is used, and a cutoff of 90 means that 90 percent of the sample is excluded. The dependent variable is illustrated by the labels in the figure. The blue line reports results with fund sector-adjusted returns (SAR) as the dependent variable. The green line reports results with fund factor-adjusted returns (FAR) as the dependent variable. The left graph reports the regression coefficient of cohort size, and the right graph reports the absolute t-statistics. The *, ** and *** lines represent the lower limit of $p < 0.1$, $p < 0.05$ and $p < 0.01$ respectively. To save space, I only report the coefficients on cohort size.



However, there are evident differences in the magnitude of the coefficients for the two measures of performance. For *FAR*, the coefficient on cohort size is negative and statistically significant regardless of *Avg Hist* sample reduction, consistent with previous sections. The results for *SAR* are less consistent. If quarters with short history available are included in the sample, the sign on cohort size is reversed to positive, implying that larger cohorts outperform their sectors. However, as I restrict the sample to include only quarters with a high *Avg Hist*, the results revert back to the original finding of diseconomies of cohort size.

Further analysis suggests that the driver of the different results for *FAR* and *SAR*, when the sample includes quarters with a low *Avg Hist*, is explained by a correlation between cohort size and factor exposures. First, I find a positive relation between cohort size and the fund's correlation to the return of its sector; and that the correlation to sector return is associated with higher future *SAR*. This relation is significantly stronger when cohorts are identified with the expanding window method, and also reduces in strength as the *Avg Hist* increases. This indicates that when cohorts are estimated over shorter periods, factor exposures drive the results rather than capacity effects. Meanwhile, I do not see the same results for *FAR* since it controls for exposure to the common factors included in the seven-factor model. Second, I find that when cohorts are identified with returns adjusted for factor exposure (as per Section 5.3) combined with the expanding window method, the negative coefficient on *SAR* emerges for the full expanding window sample.

Taken together, the results in this section indicate that it is important to base analysis of the relation between cohort size and *SAR* on longer sample periods, to reduce the impact of any correlation between cohort size and sector returns. This finding strengthens the case for the in-sample definition of cohorts. The alternative is to reduce the influence of any correlation by adjusting returns for factor exposures before identifying cohorts.

5.5 Control for strategy distinctiveness index

In this section, I include a control for similarities between cohort size and the strategy distinctiveness index (*SDI*) introduced by Sun et al. (2012). *SDI* is a measure of the uniqueness

of a fund's strategy, and is defined as follows:

$$SDI_i = 1 - \text{corr}(R_i, R_S) \quad (26)$$

R_i is the fund return over the previous 24 months

R_S is the return of the fund's sector, estimated as the average return of all funds within the sector

SDI is based on the returns over the previous 24 months, and ranges between 0 and 2, with a higher value for more distinctive strategies compared to the fund's sector. Since my definition of cohort size is relative to other cohorts in the fund's sector, I mean-adjust the SDI following equation (27):

$$SDI_{i,t}^{adj} = SDI_{i,t} - \overline{SDI}_t \quad (27)$$

\overline{SDI}_t is the mean of the SDI across all funds in the sector

There is a possibility that my findings for cohort size might be explained by the SDI . A fund belonging to a cohort containing several funds may have an undistinctive strategy and a large cohort size. Consequently, funds within single-fund cohorts are likely to have a highly distinctive strategy as well as a small cohort size. If the findings are explained by cohort size being negatively correlated with the distinctiveness of a fund's strategy, then I would expect the relation between cohort size and performance to disappear once SDI is included in the regression. I therefore include the SDI^{adj} in the panel regression. Since SDI^{adj} is based only on past returns, I apply the same definition of cohorts as in Section 5.4.

Columns 1 and 3 of Table 11 present the results of the panel regression to determine if SDI^{adj} predicts future fund performance with cohort size excluded from the regression. For FAR , my results are consistent with Sun et al. (2012) in that funds with more distinctive strategies outperform, with both economic and statistical significance. However, for SAR , the opposite results emerge for SDI^{adj} , with distinctive strategy funds underperforming other funds.

Results when including both cohort size and SDI^{adj} in the panel regression are presented in Columns 2 and 4 of Table 11. The negative impact of cohort size survives the inclusion of SDI^{adj} , and helps explain why the relation between cohort size and SAR is positive when quarters with short amount of available history are included in the sample in Figure 2. When both SDI^{adj} and cohort size are included in the regression with SAR as dependent variable, both have significantly negative coefficients. As discussed in Section 5.4, it appears that the positive coefficient on cohort size observed in Section 5.4 under the SAR regressions is driven by funds with a high correlation to their sector. In this case, the SDI appears to be controlling for this correlation, permitting the negative coefficient on cohort size to become apparent.

Table 11: Relation between cohort size and future fund return when controlling for SDI

Table 11 re-examines the relation between returns and cohort size (based on cohorts using expanding window approach), while also controlling for the Sun et al. (2012) SDI measure. The estimates are based on the same panel regression as Table 3. Cohort Size is defined by equation (5), Cohort Size SQ is the squared cohort size, Fund Size is defined by equation (3), Fund Size SQ is the squared fund size, SDI^{adj} is defined by equation (27). Columns 1 and 2 report results with fund sector-adjusted return (SAR) as the dependent variable. Columns 3 and 4 report results with fund factor-adjusted return (FAR) as the dependent variable, estimated using the Fung and Hsieh (2004) seven-factor model. In Panel A, I test for a linear relation between size and performance, and in Panel B I test for a quadratic relation. To save space, estimates for control variables are not reported. As per Petersen (2009), standard errors are clustered by fund.

	SAR, %		FAR, %	
	(1)	(2)	(3)	(4)
Panel A: Linear size relation				
SDI^{adj}	-0.828*** (8.238)	-0.953*** (7.408)	0.743*** (7.463)	0.134 (1.072)
Cohort Size		-0.029* (1.770)		-0.142*** (8.078)
Fund Size	-0.027 (1.347)	-0.013 (0.623)	-0.012 (0.523)	0.055** (2.361)
# of Obs	96335	96335	96335	96335
Adj. R^2	0.002	0.002	0.002	0.002
Panel B: Quadratic size relation				
SDI^{adj}	-0.828*** (8.241)	-0.948*** (7.365)	0.743*** (7.463)	0.141 (1.123)
Cohort Size		-0.033*** (2.000)		-0.146*** (8.288)
Cohort Size SQ		-0.009 (2.104)		-0.012 (2.399)
Fund Size	-0.031 (1.319)	-0.029 (1.119)	-0.008 (0.305)	0.044 (1.550)
Fund Size SQ	0.005 (0.487)	0.009 (0.890)	-0.004 (0.313)	0.002 (0.169)
# of Obs	96335	96335	96335	96335
Adj. R^2	0.002	0.002	0.002	0.002
Absolute t statistics in parentheses				
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

Finally, the results for FAR reveal that when the diseconomy of cohort size is accounted for, the predictive power of SDI^{adj} vanishes. Hence, when controlling for cohort size, the SDI^{adj} does not contain any additional information useful to predict future FAR , i.e. alpha. This suggests that SDI^{adj} is proxying for factor exposures, and is supplanted by the factors in the seven-factor model when the analysis is based on FAR . Finally, the coefficient on cohort size remains negative and highly significant when SDI^{adj} is included in the regression. This indicates that the relation between cohort size and FAR is not explained by SDI , thus confirming the robustness of my findings.

6 Conclusion

The literature has assessed capacity constraints within hedge funds by analyzing the impact of fund or sector size on fund performance. I investigate the importance of considering the total size of all funds applying similar strategies when analyzing the performance-size relation. To perform this analysis, I introduce the concept of ‘fund cohort’ in order to capture strategy similarities. I find a negative relation between cohort size and future fund performance, consistent with capacity constraints operating within hedge funds at the cohort rather than at the individual fund size level. Furthermore, I conclude that the relation between past performance and future asset flows operates in part at a cohort level. Assets flow to the cohorts of funds with high past performance, and are redeemed from cohorts of funds with poor past performance.

The combination of these two findings introduces a dilemma to funds deciding whether to accept or reject inflows. A fund may reject assets because of capacity constraints, with a view to preventing performance falling below a certain threshold. However, if the fund rejects the assets, the investors may re-allocate to other funds within the same cohort. In this case, fund performance will still be negatively impacted, thereby eliminating one of the motives for the fund to reject assets. Furthermore, if a fund makes up only a small proportion of cohort AUM, the fund can experience high percentage inflows before it impacts the cohort AUM. Consistent with this notion, I find that hedge funds that experience a higher level of competition from other funds in the cohort have a high propensity to increase size, compared

to funds that run unique strategies and form their own cohort, or manage a substantial portion of the AUM within their cohort.

My findings provide important insights for fund managers and allocators within the hedge fund industry. Hedge funds may wish to reconsider before launching a new product into an already crowded cohort, since within these cohorts it will be difficult to manage capacity. Meanwhile, allocators within the hedge fund industry may consider avoiding investment in cohorts which have already reached a significant size, since they are less likely to perform in the future.

While this study provides several novel insights into the importance of considering cohort size when assessing capacity constraints for hedge funds, it raises the question of whether diseconomies of cohort size exist within other segments of the fund management industry. The method presented in this paper might be applied to mutual funds, for instance. Additionally, a more detailed analysis of how capacity constraints are impacted by cohorts could potentially be achieved through analysis of detailed hedge fund holdings and trades, if such data were to become available. I leave these questions for further research.

Appendices

A Fund sector mapping

The following mapping is used to map database sectors to one of seven different sectors.

The list is based on the mapping by [Ramadorai \(2013\)](#), but is extended to the eVestment universe.

Sector information from data vendor	Mapped sector
Commodities - Agriculture Focus	Other
Commodities - Broad Sector Focus	Other
Commodities - Energy Focus	Other
Commodities - Metals Focus	Other
Commodities - Synthetic Strategy	Other
Equity Long Short - 100% Net Long Exposure	Directional traders
Equity Long Short - Activist	Security selection
Equity Long Short - Commodity - Energy	Directional traders
Equity Long Short - Discretionary Thematic	Security selection
Equity Long Short - Diversified	Security selection
Equity Long Short - Equity Market Neutral	Security selection
Equity Long Short - Fixed Income - Corporate	Security selection
Equity Long Short - Fundamental Growth	Security selection
Equity Long Short - Fundamental Value	Security selection
Equity Long Short - Long Only	Directional traders
Equity Long Short - Market Neutral	Security selection
Equity Long Short - Multi Strategy	Security selection
Equity Long Short - Multi-Strategy	Security selection
Equity Long Short - Quantitative Directional	Directional traders
Equity Long Short - Sector - Energy/Basic Materials	Directional traders
Equity Long Short - Sector - Technology/Healthcare	Directional traders
Equity Long Short - Sector Focus	Directional traders
Equity Long Short - Short Bias	Directional traders
Equity Long Short - Short Selling/Short Bias	Directional traders
Equity Long Short - Special Situations	Multi-process
Equity Long Short - Statistical Arbitrage	Relative value
Equity Long Short - Strategic	Security selection
Equity Long Short - Systematic Diversified	Security selection
Equity Long Short - Variable Net Exposure	Directional traders
Equity Long Short - Yield Alternatives - Energy Infrastructure	Security selection
Equity Long Short - Yield Alternatives - Real Estate	Security selection
Event Driven - Activist	Multi-process
Event Driven - Credit Arbitrage	Multi-process
Event Driven - Distressed/Restructuring	Multi-process
Event Driven - Fixed Income - Asset Backed	Multi-process
Event Driven - Fixed Income - Corporate	Multi-process
Event Driven - Merger Arbitrage	Multi-process
Event Driven - Multi Strategy	Multi-process
Event Driven - Multi-Strategy	Multi-process
Event Driven - Private Issue/Regulation D	Multi-process
Event Driven - Sector - Technology/Healthcare	Multi-process
Event Driven - Special Situations	Multi-process
Insurance - Catastrophe Bonds	Directional traders
Macro - Active Trading	Macro
Macro - Commodity - Agriculture	Macro
Macro - Commodity - Energy	Macro
Macro - Commodity - Metals	Macro
Macro - Commodity - Multi	Macro

Sector information from data vendor	Mapped sector
Macro - CTA/Managed Futures	Other
Macro - Currency - Discretionary	Macro
Macro - Currency - Systematic	Macro
Macro - Discretionary Macro	Macro
Macro - Discretionary Thematic	Macro
Macro - Foreign Exchange (FX)	Macro
Macro - Fundamental Growth	Macro
Macro - FX	Macro
Macro - Global Tactical Asset Allocation (GTAA)	Macro
Macro - Market Defensive	Directional traders
Macro - Multi-Strategy	Macro
Macro - Systematic Diversified	Macro
Macro - Systematic Macro	Macro
Macro - Yield Alternatives - Energy Infrastructure	Macro
Multi Strategy - Broad	Multi-process
Multi Strategy - Broad Sector Focus	Multi-process
Multi Strategy - Commodity - Energy	Multi-process
Multi Strategy - Concentrated	Multi-process
Multi Strategy - Conservative	Multi-process
Multi Strategy - Diversified	Multi-process
Multi Strategy - Market Defensive	Directional traders
Multi Strategy - Market Neutral	Multi-process
Multi Strategy - Strategic	Multi-process
Niche - Direct Lending	Other
Niche - Other	Other
Niche - Seeding/Emerging Managers	Other
Real Estate - Real Estate Arbitrage	Relative value
Relative Value - Conservative	Relative value
Relative Value - Credit Arbitrage	Relative value
Relative Value - Discretionary Thematic	Relative value
Relative Value - Fixed Income - Asset Backed	Fixed income
Relative Value - Fixed Income - Convertible Arbitrage	Fixed income
Relative Value - Fixed Income - Corporate	Fixed income
Relative Value - Fixed Income - Sovereign	Fixed income
Relative Value - Multi-Strategy	Multi-process
Relative Value - Sector - Energy/Basic Materials	Relative value
Relative Value - Volatility	Relative value
Relative Value - Yield Alternatives - Energy Infrastructure	Fixed income
Relative Value - Yield Alternatives - Real Estate	Fixed income
Volatility - Long Volatility	Directional traders
Volatility - Tail Risk Hedging	Directional traders
Volatility - Volatility Arbitrage	Relative value

Chapter 5

Relative hedge fund skill and the informativeness of cohort alpha

1 Introduction

The hedge fund industry has grown exponentially since its origin in 1949, and now comprises more than three trillion USD.¹ A number of aspects create difficulties in analyzing hedge fund performance. Hedge funds commonly provide limited information on their trading strategies, reflecting in part less regulation compared to more traditional managers such as mutual funds. Furthermore, hedge funds often apply strategies with significantly different payoff structures where the returns are not well-explained by recognized risk factors. Fung and Hsieh (1997) argue that models commonly used to analyze mutual fund performance, such as the Sharpe (1992) style factor decomposition, are insufficient when applied to hedge funds. These difficulties can translate into various complications and biases when assessing the performance of individual hedge funds. Further, Lehmann and Modest (1987) document the importance of factor choice when estimating fund alpha, and therefore the need to use appropriate benchmarks. Poor benchmark choices can give rise to biases in the analysis of fund performance, creating difficulties in the identification of skilled managers. An improved ability to identify hedge fund manager skill would be valuable to investors, as truly skilled managers may be expected to continue outperforming their peers. Knowledge of the most skilled managers that are trading on particular strategies can enhance manager selection, and assist in the construction of more optimal hedge fund-of-funds portfolios.

¹See Eichengreen and Mathieson (1999) and BarclayHedge (2017).

The literature has aimed to improve the evaluation of hedge fund performance – and hence identification of skilled managers – by introducing additional risk factors in the analysis of fund returns. This has entailed developing a different factor set to those typically utilized in studies of mutual funds. For instance, [Fung and Hsieh \(2004\)](#) and [Agarwal and Naik \(2004\)](#) present multi-factor models that also include factors with option-like payoffs. Nevertheless, the question remains as to whether the factor set is sufficient for the purpose. A key concern is omitted variables that may lead to biases in separating out the component of performance related to common factors associated with the strategy being applied. For example, [Bollen \(2013\)](#) finds evidence of omitted variables even when including factors with option-like payoffs in assessing performance. The evidence indicates that the complexity of hedge funds, and their widely differing strategies, make them difficult to analyze using common factor models – even with controls for non-linearity in returns.

The cohort model introduced in this paper provides an alternative method for evaluating hedge fund performance that addresses the omitted variable problem. In doing so, it offers a more effective method than factor models for separating the component of returns related to manager-specific skill from that arising from factor exposures associated with the strategy. The cohort model achieves this by not attempting to specify the risk factors to which funds are exposed. Instead, peer benchmarks are formed from the thousands of hedge funds reporting their returns to hedge fund databases. Return correlations are used to identify cohorts of managers that apply the same, or very similar, strategies. Peer benchmarks are then estimated based on the average return of other funds within the cohort. The extent to which a fund outperforms its cohort provides a measure of the manager's skill at applying the strategy employed within its cohort. The underlying assumption is that cohorts contain funds with highly similar strategies, and hence are exposed to the same factors. The cohort benchmark thus reflects the return on a portfolio of weighted factor exposures similar to the factor exposures of the fund itself. The factors in cohort returns include not only factors applied in traditional hedge fund factor models, but also any novel factors or exposures that are shared by funds trading on similar strategies, thus solving the issue with omitted variables. I demonstrate that the cohort model is a more effective method for identifying skilled

managers than a factor-based approach, and consequently can support the construction of hedge fund-of-funds portfolios that subsequently generate more significant outperformance.

To test the effectiveness of the cohort model, I first compare its ability to predict out-of-sample (i.e. future) hedge fund performance relative to the seven-factor model, with performance measured after adjusting for observed cohort and factor returns. The out-of-sample tests reveal the cohort model explains a higher proportion of hedge fund returns than the Fung and Hsieh (2004) model during 99% of periods, and for over 90% of funds. Average R^2 indicates a substantial gain of 31%-36% in the ability to explain the returns of individual funds. This is not to say that the Fung and Hsieh (2004) model is not useful. Factor models of this type still provide an understanding of the common factor exposures contained within portfolios of hedge funds. Further, the cohort model does not explicitly identify factor exposures. However, the cohort model is more effective in comparing individual funds to their peers and identifying skilled managers, as it removes as much as possible of the strategy specific return. This result is consistent with the cohort model suffering less from omitted variable bias, as compared to Fung and Hsieh (2004) and other similar models, where a limited set of factors must be explicitly selected. Essentially, factor models and the cohort model may be employed in tandem, with factor models used to understand common factor exposures within hedge fund portfolios, and the cohort model used to identify strategy peer-groups and the most skilled managers within each group.

Examination of performance persistence provides a further test of the effectiveness of the cohort model in identifying manager skill: if genuine skill exists, it should be revealed in greater persistence. Employing the cohort model, I find that hedge funds that outperform their cohort over the previous 24-month period continue to outperform for the following three years. In contrast, alpha persistence under the seven-factor model is both lower in magnitude and continues for less than one year, depending on regression specification. These results provide further evidence that the cohort model can more accurately identify manager skill by separating out performance that is related to the overall factor exposures of the fund's strategy.

Further analysis documents significant differences in fund characteristics that are related to seven-factor alpha and cohort-adjusted alpha, specifically with respect to fees. Funds

with higher seven-factor alpha commonly charge higher performance fees relative to other funds. Meanwhile, funds with higher cohort alpha tend to charge lower fees. A possible explanation is that funds generating higher alpha under the seven-factor model are doing so partly from omitted factor exposures, which in turn earns them higher performance fees. However, the cohort model controls not only for the gross returns on these omitted factors but also any related performance fees. This allows a negative relation between cohort alpha and fees to emerge. This finding suggests that the persistence in cohort alpha may be partly attributable to fee differences, and implies that lower fee funds should be preferred within cohorts.

To better understand the potential value for hedge fund investors, I estimate how selecting managers based on cohort alpha would have improved the performance of a fund-of-funds portfolio comprised of the 15 largest cohorts under realistic assumptions of reporting delay. Selecting the best funds within each cohort results in a significant alpha gain, ranging from 10-24 bps per month. My tests span the selection of the top-two and top-four funds within each cohort, two different rebalancing periods, and evaluation of performance using both the seven-factor model and direct comparison with other funds in the same cohort. This analysis indicates that using the cohort model to identify skilled managers can add substantial value to hedge fund-of-funds portfolios, leading to a significant increase in alpha while retaining similar exposure to the underlying strategies and factors.

This paper's main contribution relates to the proposal of a more effective method in identifying hedge fund manager skill. The cohort model breaks from the traditional approach of relying on explicit factor models, and expanding the range of factors included as the main strategy for improving the identification of alpha and skill. Since [Jensen \(1968\)](#) introduced the Jensen alpha for assessing the performance of actively managed mutual funds, researchers have used factor models to evaluate performance. Ongoing attempts to improve the evaluation models by including additional factors were inspired by the Arbitrage Pricing Theory (APT) of [Ross \(1976\)](#), with [Chang and Lewellen \(1985\)](#) and [Lehmann and Modest \(1987\)](#) applying the APT to actively managed portfolios by allowing the intercept of the regression to not pass through the origin. The three- and four-factor models of [Fama and](#)

French (1993) and Carhart (1997) have subsequently become the most common models used in the analysis of actively managed mutual funds.

However, the factor models applied to mutual funds proved insufficient for modeling hedge fund returns, which apply a wide range of strategies involving various asset classes and often non-linear payoffs. For instance, Fung and Hsieh (1997) find that the traditional Sharpe (1992) style factor model explains more than 50% of returns for 92% of the mutual funds examined, but explains less than 25% of returns for 48% of the hedge funds. This motivated the addition of new risk factors to support analysis of hedge fund returns, including controls for non-linearity in fund performance. Fung and Hsieh (2001) introduce lookback straddles, suitable for analysis of trend-following funds. These factors were later included in the Fung and Hsieh (2004) seven-factor model, which has become the most commonly applied factor model for examining hedge fund performance.² An alternative approach to the seven-factor model is the Agarwal and Naik (2004) multi-factor model, which controls for asset returns as well as returns on options on these assets. As a substitute to factor models, some studies have aimed to incorporate style benchmarks when assessing the performance of hedge funds. Barberis and Shleifer (2003) discuss the use of style benchmarks for institutional investors, and argue that these benchmarks are increasingly used to evaluate fund performance.³ Brown and Goetzmann (2003) classify hedge funds into eight different style groups to assess style-adjusted performance of individual funds. Jagannathan et al. (2010) utilize the return of 32 different hedge fund style indices to determine style-adjusted performance.⁴

Although factor models have been useful in describing average returns across portfolios of hedge funds, studies have found that they may be insufficient for analyzing individual funds. Titman and Tiu (2011) find that the average R^2 is as low as 26% when the seven-factor model is applied to individual funds. Bollen (2013) documents that one third of the hedge funds had an R^2 insignificantly different from zero, and further proposes that these

²Since the seven-factor model was introduced in Fung and Hsieh (2004), it has been utilized in several studies, including Kosowski et al. (2007); Boyson (2008); Fung et al. (2008); Jagannathan et al. (2010); Nohel et al. (2010); Sadka (2010); Teo (2011); Titman and Tiu (2011); Brown, Grundy, Lewis, and Verwijmeren (2012); Sun et al. (2012); Aiken et al. (2013); Bali et al. (2013); Buraschi et al. (2013); Ramadorai (2013); Brandon and Wang (2013); Yin (2016).

³Brown and Goetzmann (1997) and Hunter et al. (2014) utilize style benchmarks for the analysis of mutual funds.

⁴Jagannathan et al. (2010) introduce a model that adjusts hedge fund returns for the return of the market portfolio, the return of the self-reported hedge fund style, and the return of the model-selected hedge fund style. The self-reported style and the model-selected style are selected from a list of 32 HFR style indices.

zero- R^2 funds are likely to be exposed to omitted risk factors. These findings are consistent with Fung and Hsieh's (2004) proposition that the seven-factor model is more suitable for an analysis of a diversified fund-of-funds portfolio, rather than analysis of individual funds.

Although the problem of omitted risk factors has been recognized, the literature is yet to propose a viable solution, other than further expanding the number of factors or including style benchmarks. These solutions create their own issues. Factor selection is difficult, and fraught with risks, such as the possibility of model mis-specification or the generation of spurious results if factors are introduced that are not relevant for the fund being evaluated. Style benchmarks, on the other hand, require a pre-specified number of hedge fund styles, which is problematic since the number of styles is unknown and may change over time. Unless styles are included that fit every fund, these models will also suffer of omitted variables. The cohort model takes a different direction that does not require identifying the 'right' set of factors or styles needed to evaluate hedge fund performance in order to identify manager skill. By relying on return correlations to identify peer groups of funds that are exposed to common factors, the cohort model avoids the need to explicitly nominate factors or to pre-specify the number of styles. It hence averts the omitted factor problem, but does so in a way that does not bring exposure to errors that might arise from introducing irrelevant factors.

Other key contributions of this paper relate to the practical benefit of the cohort model for hedge fund investors. Applying a cluster method to identifying cohorts provides a means for identifying peer groups of funds. This is of value in itself. Identifying fund cohorts can enhance the understanding of the range of strategies available within the hedge fund universe, as well as the performance of those strategies. It also facilitates the evaluation of fund performance relative to their closest peers. Combining the knowledge of strategy with a sharper identification of managers that are skilled in applying their chosen strategy can improve the construction of fund-of-fund portfolios. It can assist investors to both identify cohorts of funds trading on similar strategies across which they may want to diversify, and then assist with selection of preferred managers within each cohort.

I also contribute to the literature on hedge fund performance persistence. The effectiveness of the cohort model in identifying manager skill allows me to demonstrate that perfor-

mance persistence may be greater than otherwise detected by previous studies. Whereas a majority of researchers identify some degree of persistence, the evidence on the duration of that persistence is mixed. A common finding, most notably in the earlier literature, is that performance persists for around one quarter, but is less evident as the horizon increases. [Brown et al. \(1999\)](#) and [Brown and Goetzmann \(2003\)](#) find little evidence when testing for persistence over one-year. [Agarwal and Naik \(2004\)](#), [Baquero et al. \(2005\)](#), [Barès et al. \(2003\)](#) and [Harri and Brorsen \(2004\)](#) all find that past performance is informative of next quarter returns, but becomes inconsistent thereafter⁵. Similar results have been found by [Herzberg and Mozes \(2003\)](#) and [Barès et al. \(2003\)](#). Another group of studies find performance persistence over horizons from one year up to two years (see [Edwards and Caglayan \(2001\)](#); [Agarwal and Naik \(2000\)](#); [Kosowski et al. \(2007\)](#); [Horst and Verbeek \(2007\)](#); [Boyson \(2008\)](#)). Meanwhile, [Jagannathan et al. \(2010\)](#) conclude that funds outperforming over three years continue to outperform over the subsequent three-year period. However, it is not clear if the persistence they find reflects ongoing outperformance over the full three-years, or if the outperformance accrues over shorter sub-periods.

I extend these studies by examining persistence under the cohort model, thus focusing on persistence in the component of returns not driven by strategy performance and therefore unique to the fund itself. The persistence I detect is not only larger in magnitude and more extended than that detected under the seven-factor model, but the estimated duration of around three years or more is considerably longer than indicated by previous studies. These results further confirm the practical importance for investors of separating out the strategy-specific component in hedge fund returns to better identify manager skill. The finding that skilled managers identified under the cohort model are likely to continue outperforming their peers over multiple years underwrites the value of the model for enhancing manager selection and the formation of hedge fund-of-funds portfolios.

The remainder of the paper is organized as follows: Section [2](#) summarizes the data. Section [3](#) describes the method. Section [4](#) presents the empirical findings. Section [5](#) presents a performance comparison of a fund-of-funds portfolio. Section [6](#) discusses robustness tests. Section [7](#) concludes.

⁵[Eling \(2009\)](#) provides a literature review of hedge fund persistence, and document that more than half of previous studies are unable to find persistence at a one year horizon.

2 Data

The hedge fund data is sourced from Hedge Fund Research (HFR) and eVestment (EV). These databases contain information on fund returns, assets under management (AUM), and meta-data such as fee structure and notice periods. Consistent with previous hedge fund literature, I only keep funds in the sample that report their returns and assets in U.S. Dollars (USD), and also filter out funds not reporting their net-returns. Following Yin (2016) and Forsberg (2017a), I exclude very small funds by applying a filter of USD 10 million in AUM. I merge the databases using the method developed by Forsberg (2017a). First, I remove fund duplicates appearing in each database, identified by a return correlation exceeding 0.95 and managed by the same firm.⁶ After removing all but one duplicate in each database, I merge the databases by firm names, then repeat the correlation analysis to remove duplicates across the two databases.⁷ Since alpha relative to cohort is being estimated in this paper, I apply a final filter requiring at least one other fund in the cohort. This filter reduces the sample by 22% (4,469 compared to 5,739). After applying these filters, the total number of funds included in the study is 4,469, of which 43% are still active at the end of the sample period. While my tests focus on this sample of funds, I show in Section 6 that the cohort model remains robust when the 22% of non-matched funds are assigned to their closest available cohort.

Several studies have documented a backfill-bias in hedge fund databases caused by self-reporting, given that funds decide if they report their returns or not. It is common that funds do not report returns immediately at inception, but instead wait to see if performance is positive, and then subsequently backfill the returns since inception. Fung and Hsieh (2000) document that the average backfilled return is 1.4% higher compared to non-backfilled returns, and that the average backfill-period is 12 months per fund. To mitigate against this bias, I exclude all observations prior to the date when the fund was added to the database. In cases when this date is not available, I eliminate the first 24 months of reported returns.⁸

⁶This step is necessary since funds often exist through different classes.

⁷Since firm names often are reported with small differences across different databases, I allow for some contrast in the firm names when performing the matching. All the matches are then manually confirmed.

⁸There are a few cases within the EV database in which the date the fund was added to the database is reported incorrectly. In these cases, I remove the first 24 months of reported returns.

Table 1: Summary statistics

Table 1 provides summary statistics for the data, based on the period January 1997 until June 2016. Monthly Return is the percentage return net of fees. Performance Fee is the percentage performance fee charged by the fund. Management Fee is the percentage management fee charged by the fund, Minimum Investment is the minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the lock-up measured in number of months.

	Mean (1)	25th pct (2)	Median (3)	75th pct (4)	Std (5)
Monthly Return (%)	0.33	-1.10	0.48	1.91	4.21
Performance Fee (%)	16.76	15	20	20	6.81
Management Fee (%)	1.46	1.0	1.5	2.0	0.56
Minimum Investment (\$M)	1.29	0.25	1.00	1.00	3.26
Redemption Frequency (days)	64.90	30	30	90	73.17
Redemption Notice Period (days)	30.86	1	30	45	33.24
Subscription Frequency (days)	29.01	30	30	30	24.02
Lock-up Period (months)	3.84	0	0	12	6.77

Table 1 presents the summary statistics for the funds included in the study. Performance fee, management fee, minimum investment, redemption frequency, redemption notice period, subscription frequency, and lock-up period are all in line with what has been observed in studies such as those by Sun et al. (2012), Yin (2016) and Forsberg (2017a).⁹

3 Method

3.1 Fund alpha

3.1.1 Impact of omitted variables on estimated alpha

I discussed earlier the presence of omitted variables when using factor models to evaluate hedge fund performance. To understand how this issue impacts the estimation of fund alpha (α), I start by describing fund returns as a combination of fund skill (α) and returns to factor exposure. These factors can have any possible payoff structure, i.e. they can be linear or non-linear.

$$r_t = \alpha + \sum_{k=1}^K \beta_k^F F_{k,t} + \epsilon_t \quad (1)$$

⁹In cases when a fund has not reported one of these variables, I replace the missing value with the median presented in Table 1. The only exception is in Section 4.4, in which I drop funds not reporting one of the variables, since the variables in that case are the variables of interest rather than control variables.

r_t is the fund return net of fees

β_k^F is the fund's exposure to factor k

$F_{k,t}$ is the return on factor k

Assume that the factors (F) are uncorrelated and can be divided into two subsets of L known and M unknown factors. Equation (1) can then be rewritten as:

$$r_t = \alpha + \sum_{l=1}^L \beta_l^X X_{l,t} + \sum_{m=1}^M \beta_m^Z Z_{m,t} + \epsilon_t \quad (2)$$

β_l^X is the fund's exposure to *known* factor l

$X_{l,t}$ is the return on *known* factor l

β_m^Z is the fund's exposure to *unknown* factor m

$Z_{m,t}$ is the return on *unknown* factor m

As the unknown factors (Z) are not observed, the estimated alpha will be based only on returns adjusted for X :

$$r_t = \hat{\alpha} + \sum_{l=1}^L \beta_l^X X_{l,t} + \hat{\epsilon}_t \quad (3)$$

Since the unknown factors (Z) are uncorrelated to the known factors (X), β_l^X will be correctly estimated. However, the alpha and the error term will both have misspecification errors. These errors can be described by equations (4) and (5) respectively:

$$\hat{\alpha} = \alpha + \sum_{m=1}^M \beta_m^Z \overline{Z_m} \quad (4)$$

$\overline{Z_m}$ is the mean return on *unknown* factor m

$$\hat{\epsilon}_t = \epsilon_t + \sum_{m=1}^M \beta_m^Z (Z_{m,t} - \overline{Z_m}) \quad (5)$$

If a fund has positive exposure to omitted factors that on average yield a positive return, then the alpha will be overestimated compared to the true alpha ($\hat{\alpha} > \alpha$). Similarly, negative exposure to factors with an average return above zero will result in an underestimation of

alpha ($\hat{\alpha} < \alpha$). Depending on the average returns and exposures to the omitted factors, the misspecification may have a significant impact on the estimated alpha as a measure of skill.

3.1.2 Cohort benchmarks to account for omitted variables

The cohort method provides a way of controlling for omitted factors when evaluating hedge fund performance. The first step is to introduce a benchmark portfolio (λ) that invests in F factors. Assume that a fund has exposure to the benchmark equal to β^λ , and that the benchmark's weight in each factor is described by equation (6):

$$w_k^\lambda = \beta_k^F / \beta^\lambda \quad (6)$$

The return of the benchmark portfolio (λ) can be described by equation (7):

$$\begin{aligned} \lambda_t &= \sum_{k=1}^K w_k^\lambda F_{k,t} \\ &= \sum_{k=1}^K \frac{\beta_k^F}{\beta^\lambda} \times F_{k,t} \end{aligned} \quad (7)$$

Given this, equation (1) can be rewritten from a multi-factor model that includes all factors to which the fund is exposed, to a model including only the benchmark portfolio:

$$\begin{aligned} r_t &= \alpha + \sum_{k=1}^K \beta_k^F F_{k,t} + \epsilon_t \\ &= \alpha + \beta^\lambda \sum_{k=1}^K \frac{\beta_k^F}{\beta^\lambda} \times F_{k,t} + \epsilon_t \\ &= \alpha + \beta^\lambda \lambda_t + \epsilon_t \end{aligned} \quad (8)$$

β^λ is the fund's exposure to benchmark λ

λ_t is the return on benchmark λ

As long as it is possible to observe the benchmark λ , an unbiased estimate of α can be derived through equation (8). This is based on the assumption that the benchmark is exposed to the same factors as the fund. The next question is if λ can be observed, or if a reasonable approximation can be estimated. To form a proxy for λ , I apply a novel approach

of constructing benchmarks from within the universe of hedge funds. If two funds apply similar investment strategies, they should share similar factor exposure. Furthermore, [Fung and Hsieh \(1997\)](#) and [Forsberg \(2017a\)](#) argue that if two funds apply similar strategies, their returns will be highly correlated. Based on this argument, if I am able to identify at least one fund in the universe of hedge funds with highly correlated returns to the fund of interest, then this fund can be used as a proxy for benchmark λ .

To identify appropriate benchmarks from the sample of funds, I apply a correlation analysis similar to [Forsberg's \(2017a\)](#) cohort method.^{[10](#)} However, cohorts are defined here as clusters of funds that apply similar strategies. One of the difficulties when identifying these cohorts is that the number of unique strategies is unknown. For this purpose, I apply hierarchical cluster-analysis using the unweighted pair group method with arithmetic mean (UPGMA) linkage. This is an agglomerative clustering technique that has, to the best of my knowledge, not yet been applied to study hedge fund managers within the literature.^{[11](#)} The method constructs a dendrogram, joining funds together into clusters based on their similarity. Each fund is first treated as an individual cluster. The dendrogram is formed by constantly linking together the two clusters with the closest similarity into merged clusters. [Figure 1](#) provides an illustration of a dendrogram. As per the UPGMA algorithm, the distance between two clusters, A and B, is determined by equation [\(9\)](#).

$$d_{A,B} = \frac{1}{|A||B|} \sum_{i \in A} \sum_{j \in B} d_{i,j} \quad (9)$$

$d_{i,j}$ is the distance between fund i and j

¹⁰The methods differ in a few key aspects. First, [Forsberg \(2017a\)](#) define a unique cohort for each fund based on a correlation threshold of 0.75. This can result in cases where fund B and C belong to the cohort of fund A, but fund C does not belong to fund B's cohort. While this setting is preferable when diseconomies of cohort size is analyzed, it is not the preferred approach when the task is to compare fund performance. Therefore, in this paper I apply a method in which if fund B and C belong to the cohort of fund A, then fund C must belong to fund B's cohort. Second, [Forsberg \(2017a\)](#) generate cohorts based on all available information and keep the cohorts constant throughout time. However, when analyzing performance persistence it is important to not take into account information which would have been unknown at the time of assessment of past performance. Therefore, I update cohorts each month, as new return information becomes available.

¹¹There is some literature assigning funds to groups based on covariation in returns. [Brown and Goetzmann \(1997\)](#) classify mutual funds into eight different style groups based on past returns, and [Brown and Goetzmann \(2003\)](#) apply the same method to hedge funds. Under this classification method, the number of clusters is pre-defined. This imposes a cluster structure, and the similarity between funds in each cluster may vary over time. Under the cohort method, the 'similarity' cutoff is pre-defined, so that the number of clusters emerges from the analysis and may change over time.

$|A|$ and $|B|$ are the cardinality, or number of funds, in A and B respectively

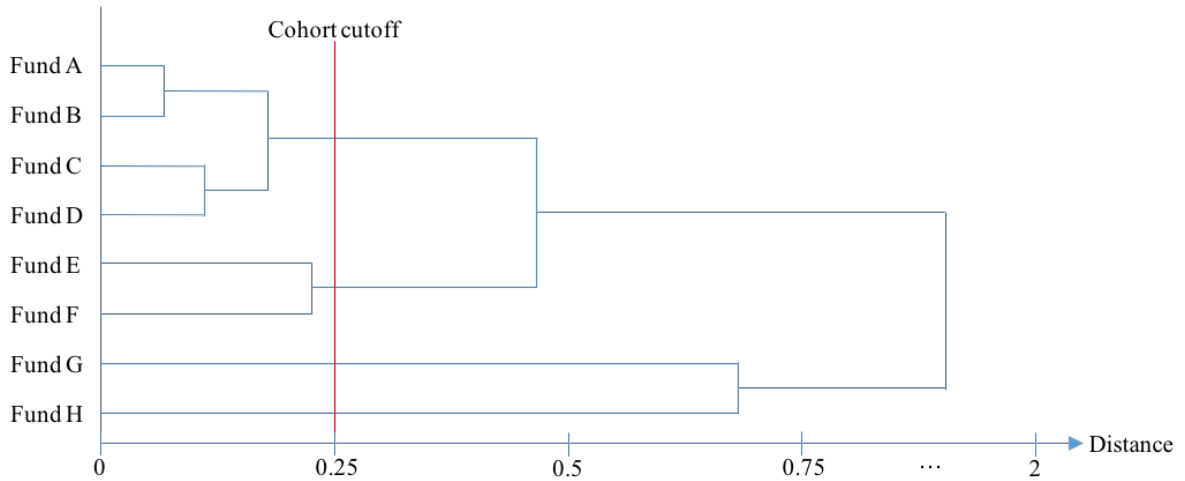
The advantage of hierarchical clustering is that there is no need to specify the final number of clusters. The only inputs are the distance matrix, and the maximum distance allowed for sub-clusters to be assigned to the same merged cluster. I define the distance between two funds as per equation (10). Hence, two funds applying similar strategies will have a distance closer to zero, whereas funds using opposite strategies will have a distance closer to two.

$$d_{i,j} = 1 - \rho_{i,j} \quad (10)$$

$\rho_{i,j}$ is the Pearson correlation between fund i and j

Figure 1: Fund clustering dendrogram

Figure 1 illustrates an example of a dendrogram based on the distance between funds. Funds joined together prior to the cohort cutoff are considered to belong to the same cohort. In the figure example, funds A, B, C, and D form one cohort, and funds E and F form a second cohort. Funds G and H do not belong to any cohort.



I use 0.25 as the maximum distance for assignment of sub-clusters to the same merged cluster. Therefore, clusters will continue to be joined until the average correlation between the funds in cluster A and B is less than 0.75. This cutoff resembles that used by Forsberg (2017a), who define cohorts based on a correlation threshold of 0.75. I illustrate the threshold and how it is used to determine final cohorts in Figure 1.

3.1.3 Cohort alpha

The return on the benchmark approximation ($\hat{\lambda}$) for a given fund is constructed based on the equal-weighted returns of other funds in its cohort. Excluding the return of the fund for which the benchmark is being constructed avoids the bias that may occur when estimating peer-adjusted returns (see Section 3.2).

$$\hat{\lambda}_{i,t} = \frac{\sum_{j \in A \setminus \{i\}} R_{j,t}}{|A| - 1} \quad (11)$$

A is a set containing the funds belonging to fund i 's cohort

$|A|$ is the number of funds in set A

$R_{j,t}$ is the return of fund j

Throughout the analysis, I re-estimate the fund alpha each month based on the cohort as identified at time t . The cohort alpha (α^c) as described by equation (8) is estimated using equation (12), based on a time series regression using returns from the previous 24-months:

$$r_t = \alpha^c + \beta^{\hat{\lambda}} \hat{\lambda}_t + \epsilon_t \quad (12)$$

$\beta^{\hat{\lambda}}$ is the estimate of the fund's exposure to benchmark $\hat{\lambda}$

$\hat{\lambda}_t$ is the estimated return on the benchmark

3.1.4 Seven-factor alpha

To enable a comparison between the cohort alpha and a more traditional measure of alpha, I also estimate the Fung and Hsieh (2004) seven-factor alpha (α^{FH}). The seven-factor model includes the following factors: the equity market factor (represented by the S&P 500 return), the size spread factor (represented by the difference between Russell 2000 return and S&P 500 return), the bond market factor (represented by the change in 10-year constant maturity yield), the credit spread factor (represented by the change in the Moody's Baa yield less 10-year treasury constant maturity yield) and the three trend-following factors introduced in

Fung and Hsieh (2001).¹² I re-estimate the seven-factor alpha of each fund each month using the time series regression described by equation (13). Given the cohort alpha, I use the return of the previous 24-month period when estimating the seven-factor alpha.

$$r_t = \alpha^{FH} + \sum_{j=1}^7 \beta_j^G G_{j,t} + \epsilon_t \quad (13)$$

β_j^G is the fund's exposure to factor j

$G_{j,t}$ is the return on factor j within the Fung and Hsieh (2004) seven-factor model

3.2 Measures of performance

To support the investigation of performance persistence, I develop estimates of both cohort-adjusted performance and factor-adjusted performance. In both instances, I draw on estimates of fund exposure and factor returns under the cohort model and seven-factor model formed using equations (12) and (13). Hedge fund returns in the subsequent period are adjusted by returns to the factor and cohort exposures to form peer-adjusted return (PAR)¹³ and factor-adjusted return (FAR) respectively, following equations (14) and (15):

$$PAR_t = r_t - \beta_{t-1}^{\hat{\lambda}} \hat{\lambda}_t \quad (14)$$

$$FAR_t = r_t - \sum_{j=1}^7 \beta_{j,t-1}^G G_{j,t} \quad (15)$$

3.3 Measure of fund flow

In Section 4.5, I analyze the relation between alpha and future fund flow. I estimate fund flow using equation (16):

$$Flow_{i,t} = 100 \times \ln\left(\frac{Fund\ AUM_{i,t}}{Fund\ AUM_{i,t-1} \times r_{i,t}}\right) \quad (16)$$

$r_{i,t}$ is the fund return net of fees

¹²Available to download: <http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls>

¹³I use the acronym PAR (peer-adjusted return) rather than cohort-adjusted return or CAR , to avoid confusion with the use of CAR to represent cumulative adjusted return elsewhere in the finance literature.

$Fund AUM_{i,t}$ is the fund's assets under management

4 Empirical results

4.1 Summary of alpha and performance measures

Table 2 provides summary statistics of the estimates of seven-factor alpha and cohort alpha using the method of Section 3. Summary statistics show that the seven-factor alpha has the higher mean, with the average monthly seven-factor alpha of 0.31% (3.78% per annum) comparing with cohort alpha of 0.03% (0.36% per annum). Seven-factor alpha also has a higher standard deviation at 0.96% per month (about 3.3% per annum), versus 0.59% (2.0% per annum) for cohort alpha. The same relation exists for the seven-factor-adjusted return (FAR) and the peer-adjusted return (PAR). Hence, it appears that the cohort model leaves a smaller proportion of returns as fund-unique, compared to the seven-factor model. This is consistent with what would be expected if there existed omitted factor exposures with positive returns under the seven-factor model, as described in Section 3.1. Furthermore, both measures of adjusted returns have a lower mean compared to average total net return of 0.33% (see Table 1), indicating that the funds on average have earned positive returns from their factor exposures.

Table 2: Summary of alpha and performance measures

Table 2 provides summary statistics for the alpha and adjusted performance estimates. Seven-factor alpha is the fund alpha in percentage per month, defined by the Fung and Hsieh (2004) seven-factor model (see equation (13)). Cohort alpha is the fund alpha in percentage per month, estimated through a regression of fund returns on average return of the other funds in the cohort (see equation (12)). FAR is the factor-adjusted return in percentage per month, estimated using the Fung and Hsieh (2004) seven-factor model (see equation (15)). PAR is the peer-adjusted returns in percentage per month, estimated using the cohort model (see equation (14)).

	Mean (1)	25th pct (2)	Median (3)	75th pct (4)	Std (5)
Seven-factor alpha (%)	0.31	-0.13	0.28	0.74	0.96
Cohort alpha (%)	0.03	-0.20	0.04	0.31	0.59
FAR (%)	0.07	-1.34	0.19	1.54	3.93
PAR (%)	0.00	-0.81	0.02	0.86	2.50

4.2 Model accuracy

The cohort model aims to utilize returns of other hedge funds to address the omitted variables problem. In this section, I compare the accuracy of the cohort model and the seven-factor model in explaining or ‘predicting’ returns, in order to gauge whether the cohort model suffers less from omitted variables. Following Tashman (2000), I elect to assess model accuracy using an out-of-sample analysis with rolling origin, window and recalibration. The advantage of rolling origin and rolling recalibration is that the estimation does not suffer from potential biases caused by an arbitrarily selected origin. Furthermore, Swanson and White (1997) argue that a rolling window is preferable to an expanding window for multi-period model accuracy estimation. The model accuracy estimation is undertaken through the following process at each period t :

1. Estimate α and β s through an OLS regression for both the cohort model and the seven-factor model, based on returns between $t - 25$ and $t - 1$.
2. Estimate predicted returns for period t , as the sum of α and the product of β s estimated under step 1 and the observed benchmark (i.e. cohort) or factor returns at time t .
3. Compare the predicted return of each fund under the model to the actual fund return.

For robustness, I use two approaches for establishing model accuracy. The first refers to cross-sectional regressions between predicted and actual returns. The second approach is based on fund-by-fund time series regressions. In both instances, the dependent variable is the actual fund return, and the independent variable is the forecast. My measures of model accuracy include regression R^2 and slopes: R^2 reveals the percentage of return variation explained, while slope provides a measure of forecast bias. A more accurate model should have a higher R^2 and a slope that is closer to unity.

The cross-sectional analysis is undertaken by running regressions at each time t . The results are presented in Figure 2 and in Panel A of Table 3. The cohort model has higher accuracy compared to the seven-factor model. The average R^2 for the cohort model of 0.45 compares with 0.14 for the seven-factor model, which equates to an average R^2 gain of about 31% (0.45 vs 0.14). Further, the cohort model has higher R^2 in 99% of months.

The regression slopes confirm the higher accuracy of the cohort model. On average, the slope differs from the expected value of 1 by 0.22 for the cohort model, and 0.62 for the seven-factor model. The cohort model outperforms the seven-factor model on this measure in 92% of months.

Table 3: Model accuracy

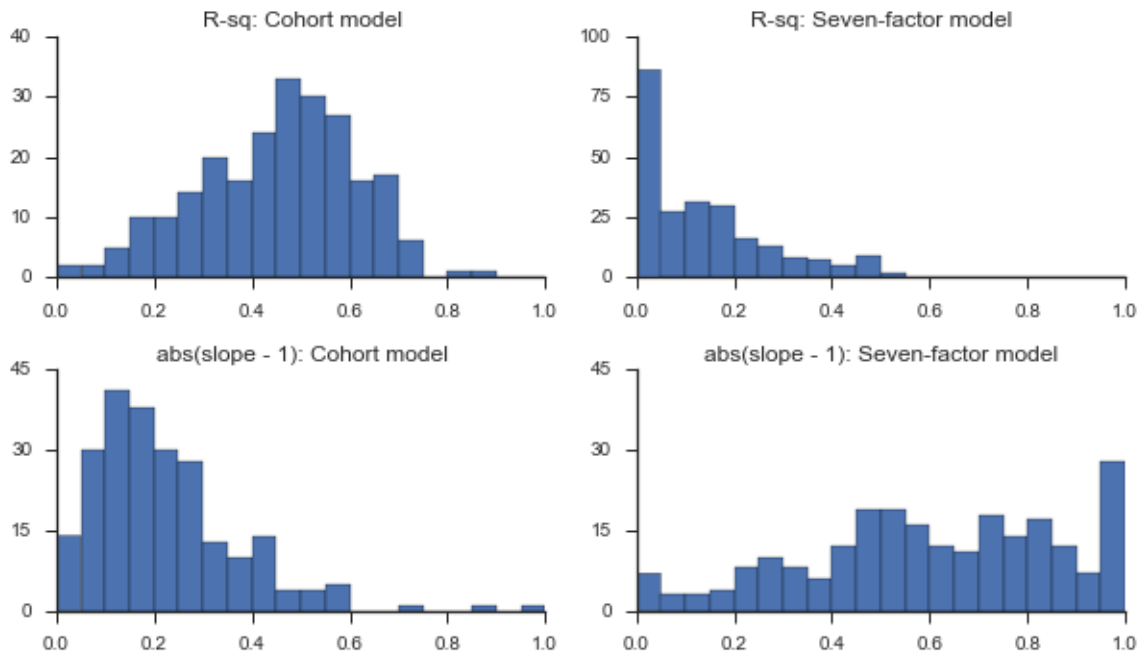
Table 3 provides summary statistics from model accuracy estimations. Panel A summarizes results for cross-sectional regressions, and Panel B summarizes results for fund-by-fund time-series regressions. The dependent variable is fund returns, and the independent variable is model-predicted returns. The model-predicted fund return is estimated in two steps. First, the fund's α and β are estimated at time t using the cohort model or seven-factor model, based on the previous 24 months. Second, the model-predicted return is calculated as the α plus the product of the β and the factor, or cohort, return at time t . In Panel B, only the funds with at least two years of predicted returns are included in the analysis. In Columns 1 and 2, I present statistics for the regression R^2 s. In Columns 3 and 4, I present statistics for the regression slopes' absolute distance from 1. The highest accuracy statistics represents the proportion of observations in which the model has the highest accuracy.

	R^2 statistics		$ 1 - slope $ statistics	
	Seven-factor model (1)	Cohort model (2)	Seven-factor model (3)	Cohort model (4)
Panel A: Cross-sectional regressions				
Mean	0.14	0.45	0.62	0.22
Std	0.13	0.16	0.28	0.15
25th pct	0.02	0.35	0.44	0.12
50th pct	0.11	0.47	0.61	0.19
75th pct	0.20	0.56	0.82	0.29
Highest accuracy	0.01	0.99	0.08	0.92
# of Obs	234	234	234	234
Panel B: Fund-by-fund time-series regressions				
Mean	0.25	0.61	0.49	0.17
Std	0.20	0.22	0.26	0.22
25th pct	0.08	0.47	0.30	0.05
50th pct	0.22	0.65	0.48	0.10
75th pct	0.39	0.78	0.67	0.23
Highest accuracy	0.08	0.92	0.10	0.90
# of Obs	2244	2244	2244	2244

The fund-by-fund time series regression analysis involves running regressions with the actual return as dependent variable and the forecast as independent variable for each fund with at least two years of return forecasts. The results are presented in Figure 3 and Panel B of Table 3, and are consistent with those from the cross-sectional correlation analysis. The average R^2 is 0.61 for the cohort model compared to 0.25 for the seven-factor model, a gain in explanatory power of 36%. Furthermore, R^2 is higher under the cohort model as compared to the seven-factor model for 90% of the funds. Analysis of the regression slopes confirms the higher accuracy of the cohort model. On average, the slope differs from the expected value of 1 by 0.17 for the cohort model, versus 0.49 for the seven-factor model.

Figure 2: Histograms of cross-sectional model accuracy

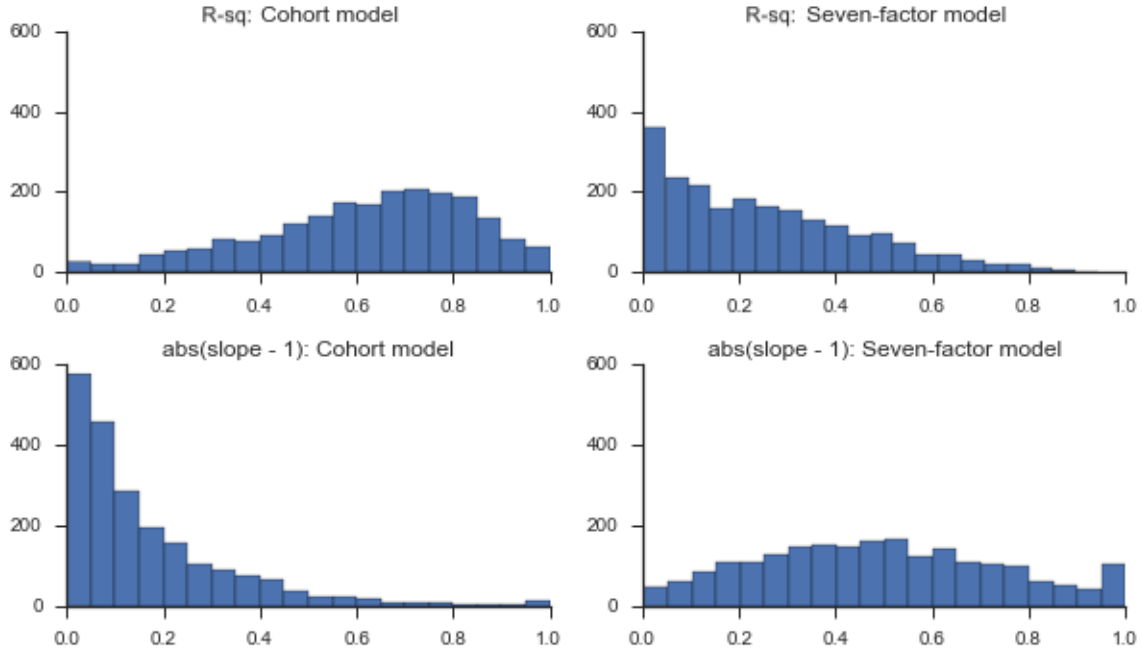
Figure 2 presents histograms of model accuracy estimated for each month. For each cross-section, I estimate OLS regressions with actual fund return as dependent variable and the model predicted fund return as independent variable. The top-left (top-right) histogram represents the distribution of regression R^2 for the cohort model (seven-factor model). The bottom-left (bottom-right) histogram represents the distribution of the absolute difference of the estimated regression slope and 1 under the cohort model (seven-factor model), with a forced maximum value of 1. The model-predicted fund return is estimated in two steps. First, the fund's α and β are estimated at time t using the cohort model or seven-factor model, based on the previous 24 months. Second, the model-predicted return is calculated as the α plus the product of the β and the factor, or cohort, return at time t .



These results reveal several important findings. The relatively low accuracy of the seven-factor indicates that it is unable to explain a substantial component of returns for individual hedge funds. This is consistent with [Titman and Tiu's \(2011\)](#) and [Bollen's \(2013\)](#) findings of low average in-sample R^2 when applying the seven-factor model to individual funds. [Bollen \(2013\)](#) suggests that the low R^2 is related to omitted variables. These results are also consistent with [Fung and Hsieh's \(2004\)](#) conclusion that the seven-factor model is not suitable for an analysis of funds with niche strategies where returns cannot be explained by the seven factors included in the model. They argue that, whereas the seven-factor model is suitable to describe well-diversified portfolios of hedge funds, one should construct customized models for individual funds. My findings not only support these arguments, but also suggest that the cohort model provides a superior method for creating custom benchmarks for individual funds. The increase in model accuracy under the cohort model indicates that it is helping to address any omitted variable bias. The increase in model accuracy of the cohort model

Figure 3: Histograms of fund-level model accuracy

Figure 3 presents histograms of model accuracy estimated per fund. For each fund, I estimate OLS regressions with actual fund return as dependent variable and the model predicted fund return as independent variable. The top-left (top right) histogram represents the distribution of regression R^2 for the cohort model (seven-factor model). The bottom-left (bottom-right) histogram represents the distribution of the absolute difference of the estimated regression slope and 1 under the cohort model (seven-factor model), with a forced maximum value of 1. The model-predicted fund return is estimated in two steps. First, the fund's α and β are estimated at time t using the cohort model or seven-factor model, based on the previous 24 months. Second, the model-predicted return is calculated as the α plus the product of the β and the factor, or cohort, return at time t .



relative to the seven-factor model can also be compared to the results of Jagannathan et al. (2010). They document that their style model increases R^2 by around 19% compared to the seven-factor model, whereas I document a relative increase of 31%-36%. This indicates that the Jagannathan et al. (2010) style model treats some of the omitted variable bias of the seven-factor model, but not as much as the cohort model. Further, since the analysis is out-of-sample, the results show that cohorts formed using correlation of past returns are viable for predicting future returns. In sum, these results suggest that the cohort approach improves the ability to identify the common sources of hedge fund returns, and hence support a more accurate quantification of manager skill.

4.3 Alpha persistence

Estimation of hedge fund alpha is of particular interest to investors if it can be used to predict future relative fund performance, preferably over long horizons. By removing as much of the factor exposure as possible from past performance, I hypothesize that this will be able to better identify fund-unique skill. If such skill is genuine, it is expected that it would persist. Hence if the cohort model improves the prediction of future performance, this is not only useful in its own right, but it would also provide confirmatory evidence that the cohort model offers a superior approach for identifying manager skill.

I focus on persistence over expanding horizons. One common approach is to construct a measure of past performance, and then analyze how this measure predicts future fund performance as the holding period increases. However, this approach introduces a problem. As the holding period is expanded, it is impossible to determine whether the performance is still persistent towards the end of the horizon. For instance, methods used in the literature to analyze persistence over a two-year period often do not distinguish between persistence driven purely by high persistence in the first few months, or if the persistence is significant throughout the two years. Two-year persistence purely driven by the first quarter is, in fact, only persistence over a quarterly horizon. It is important to understand the distribution of the persistence over time.

My approach analyses 16 performance-examination periods, each representing a quarter during the four years following the initial estimation of alpha. The approach is illustrated in Figure 4, and allows me to analyze the time horizon over which performance persistence remains significant. To analyze and compare persistence, I use *PAR* and the *FAR* as estimates of cohort alpha and seven-factor alpha respectively. I use quarterly examination periods with monthly values for *PAR* and *FAR* accumulated to quarterly values.¹⁴ To control for the differences in the mean alphas¹⁵ between the cohort model and the seven-factor model (see Table 2), as well as time effects, I mean-adjust the alphas and the return estimates during each cross-section following equation (17). Performance persistence is evaluated using three

¹⁴To convert monthly adjusted returns (*AR*) to quarterly values, I use the following transformation: $(1 + AR_1)(1 + AR_2)(1 + AR_3) - 1$.

¹⁵Recall that some of the ‘alpha’ identified under the seven-factor model may relate to omitted factors, and hence may not be indicative of unique manager skill.

methods: panel regressions, Fama-MacBeth regressions, and quartile portfolio analysis.

$$x_{i,t}^{adj} = x_{i,t} - \bar{x}_t \quad (17)$$

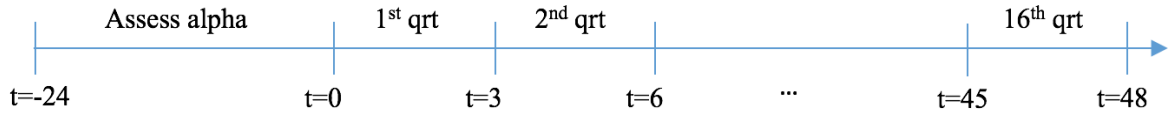
$x_{i,t}^{adj}$ is the mean-adjusted value

$x_{i,t}$ is the variable to mean-adjust

\bar{x}_t is the mean of x at time t

Figure 4: Performance persistence time-line

Figure 4 illustrates the time-line I use for examination of performance persistence. Fund alpha is estimated based on returns between time $t=-24$ and $t=0$. Performance persistence is then analyzed over quarterly frequency for the next four years, with exposure to factors and cohorts being re-estimated each month.



4.3.1 Panel regressions

For each of the forecasting periods illustrated in Figure 4, I estimate a panel regression with either PAR^{adj} or FAR^{adj} as the dependent variable, and either cohort alpha or seven-factor alpha as the independent variable.¹⁶ I also include control variables in the regression:¹⁷

$$PAR_{i,t+x}^{adj} = intercept + \beta_1 \alpha_{i,t-1}^{c,adj} + Controls_{i,t-1} + \epsilon_{i,t} \quad (18)$$

$$FAR_{i,t+x}^{adj} = intercept + \beta_1 \alpha_{i,t-1}^{FH,adj} + Controls_{i,t-1} + \epsilon_{i,t} \quad (19)$$

The results presented in Figure 5 provide several insights. For seven-factor alphas, I document persistence that remains statistically significant for two quarters. This is broadly consistent with the quarterly to annually persistence documented by Agarwal and Naik (2000), Baquero et al. (2005), Kosowski et al. (2007) and Horst and Verbeek (2007). However, it is substantially shorter than the results reported by Boyson (2008) and Jagannathan

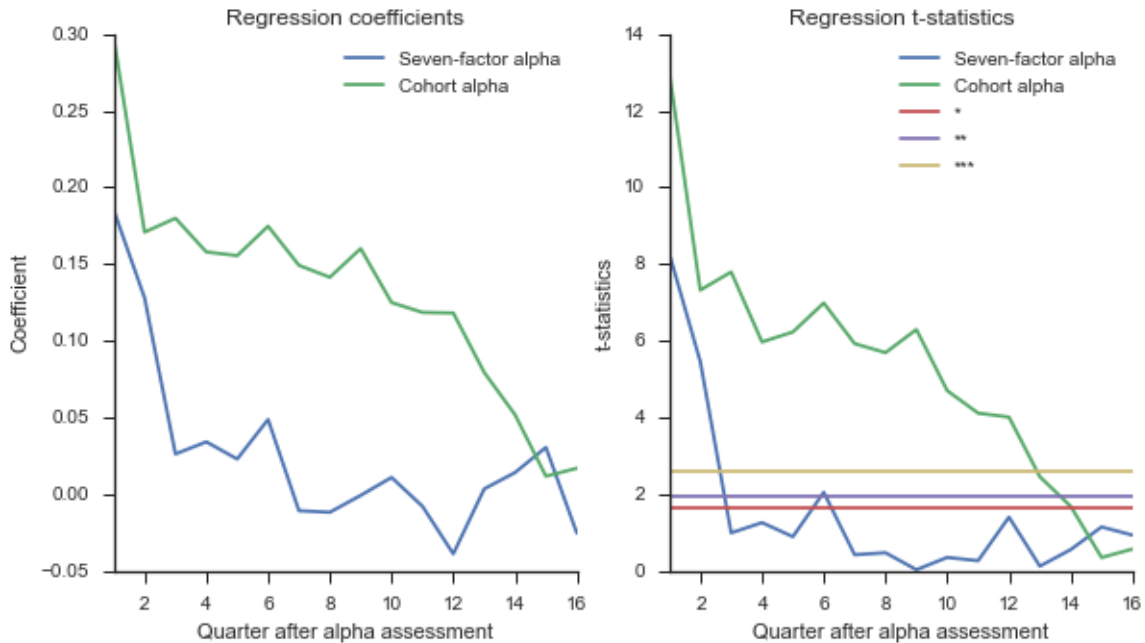
¹⁶Throughout this section, I utilise winsorization to ensure that a subset of extreme outliers are not driving the results. In the instances winsorization is used, I have validated that the conclusions remain even if the outliers are not cleaned.

¹⁷The control variables are performance fee, management fee, natural logarithm of minimum investment, redemption frequency, redemption notice period, subscription frequency, lock-up period, natural logarithm of fund age, and the natural logarithm of fund size.

et al. (2010). Meanwhile, I document a much higher degree of persistence for cohort alpha. Quarterly cohort alphas are significant at a 1% level for 12 quarters (3 years); and are still significant at the 5% level in quarter 13 and at the 10% level in quarter 14. Furthermore, the magnitude of the slope coefficients and hence economic significance is greater for the cohort model than the seven-factor model, even over short horizons.

Figure 5: Panel regression results - performance persistence

Figure 5 presents the panel-regression results from the performance persistence analysis. The left plot provides the estimated regression coefficients, and the right plot provides the estimated t-statistics. The *, ** and *** lines represent the lower limit of $p < 0.1$, $p < 0.05$ and $p < 0.01$ respectively. The x-axis represents quarters after alpha estimation. The dependent variable when seven-factor alpha is analyzed is FAR and the dependent variable when cohort alpha is analyzed is PAR . The alphas and the dependent variables are measured as percentage per quarter, winsorized at the 1st and 99th percentile, and mean-adjusted across each cross-section following equation (17). The panel regression also includes the following control variables: performance fee, management fees, minimum investment, redemption frequency, redemption notice period, subscription frequency, lock-up period, natural logarithm of fund age, and the natural logarithm of fund size. As per Petersen (2009), standard errors are clustered by fund.



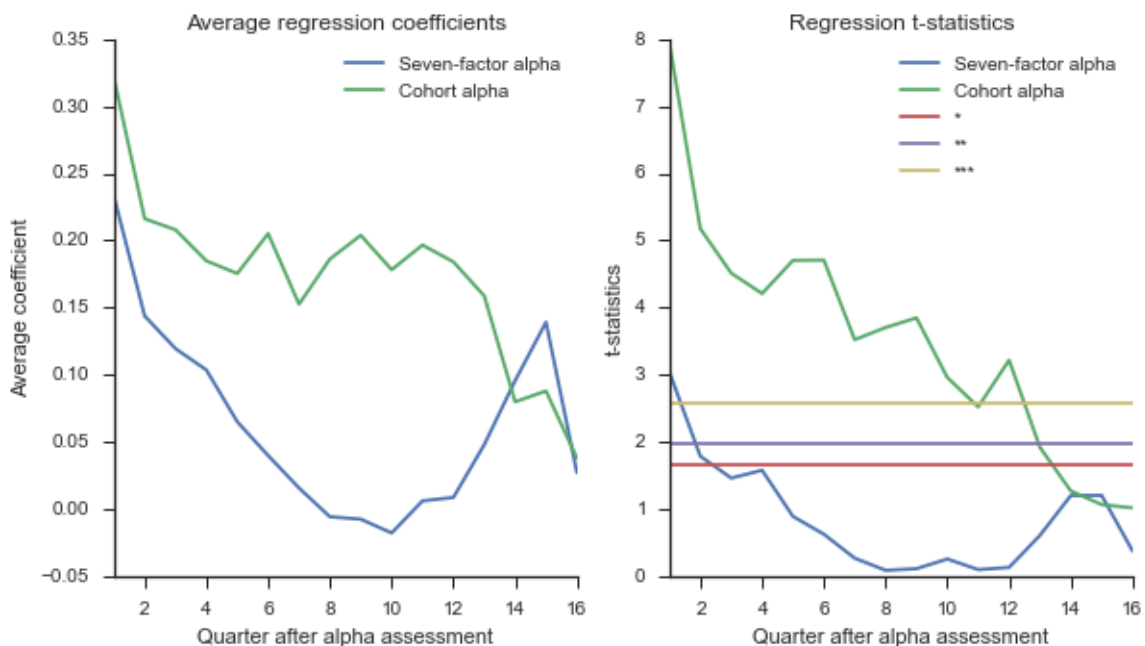
4.3.2 Fama-MacBeth regressions

The Fama and MacBeth (1973) approach is conducted by estimating cross-sectional regressions in each quarter, and then averaging the estimated coefficients to generate one coefficient per independent variable. I estimate Fama-MacBeth regressions in the form of equations (18) and (19), and present the results in Figure 6. Under this method, the persistence in seven-factor alpha extends for two quarters, with the result for the second quarter only significant

at a 10% level. Cohort alpha persists again over much longer horizons, with statistical significance at a 1% level for 11 out of the 12 quarters after alpha estimation (and 5% level for quarter 11); and significance at a 10% level for the 13th quarter. The regression coefficients again reveal greater economic significance under the cohort model, including at short horizons. These results are consistent with those for the panel regressions.

Figure 6: Fama-MacBeth regression results - performance persistence

Figure 6 presents results from the Fama-MacBeth style regression from the performance persistence analysis. The left plot provides the average estimated regression coefficients, and the right plot provides the estimated t-statistics. The *, ** and *** lines represent the lower limit of $p < 0.1$, $p < 0.05$ and $p < 0.01$ respectively. The x-axis represents quarters after alpha estimation. The dependent variable when seven-factor alpha is analyzed is FAR and the dependent variable when cohort alpha is analyzed is PAR . The alphas and the dependent variables are measured as percentage per quarter, winsorized at the 1st and 99th percentile, and mean-adjusted across each cross-section following equation (17). The regression also includes the following control variables: performance fee, management fees, minimum investment, redemption frequency, redemption notice period, subscription frequency, lock-up period, natural logarithm of fund age, and the natural logarithm of fund size. Standard errors are estimated using Newey-West adjustments.



4.3.3 Quartile analysis

The panel and Fama-MacBeth regressions examine persistence in the form of a linear relation, by regressing alphas in each quarterly review period on alpha as estimated at the base period $t=0$. As it is not possible to short-sell hedge funds, it has been argued that persistence for outperforming funds is more important than persistence for underperforming funds.¹⁸ To

¹⁸See e.g. Jagannathan et al. (2010).

investigate the distribution of persistence, I divide the funds into four alpha quartiles. I then estimate equally-weighted performance, measured as either PAR^{adj} or FAR^{adj} , within each of the groups over the 16 quarters following alpha estimation. This provides insight into whether performance persistence is driven by poor performers, good performers, or by both.

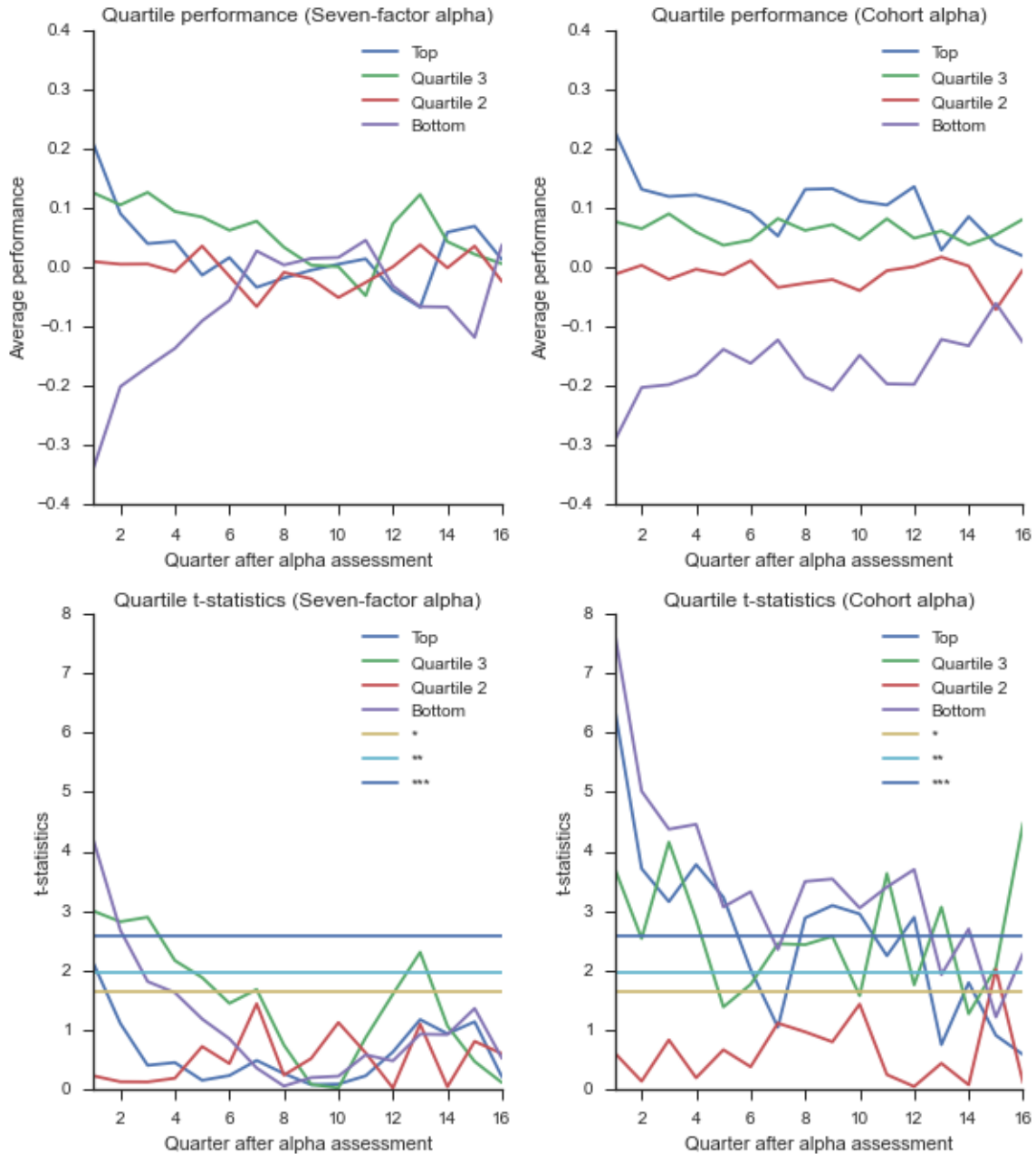
The results are presented in Figure 7. Over shorter horizons, persistence exists for both previous outperformers and underperformers under both the seven-factor model and the cohort model. Again, the persistence is not long-lasting for the seven-factor model. Even though the top two seven-factor alpha quartiles continue to provide higher average returns than the remaining funds for six quarters, the top-portfolio (bottom-portfolio) only provide returns significantly different from zero at a 5% level during the first quarter (two quarters). Hence it appears that persistence under the seven-factor model exists both for top and bottom performing funds, but is only barely significant for a short period.

Cohort alpha, on the other hand, shows persistence over a longer horizon for both outperforming and underperforming funds. The top quartile generates positive alpha that is at least 5% significant in 11 out of the first 12 quarters. The bottom quartile continues to underperform with at least 5% significance for 14 out of the 16 quarters. Although it appears that persistence is strongest for underperforming funds, it is clear that cohort alpha is still useful to predict funds that will outperform over the next three years. Furthermore, the persistently poor performance of funds with low cohort alpha is valuable information for fund investors, since it indicates which funds to avoid.

The results presented in this section align with those presented in Section 4.2. The cohort model appears to be better able to isolate fund unique performance not associated with factor returns than traditional factor models. This in turn translates into greater persistence in alpha in both magnitude and duration, consistent with more effective identification of skill. I also observe that alpha persistence decays over time. This is to be expected, and may be due to turnover of managers, or new technologies which potentially shift relative fund skill. However, alpha-decay occurs to a much lesser extent when skill is identified using the cohort model.

Figure 7: Quartile analysis - performance persistence

Figure 7 presents the quartile analysis of performance persistence. Each quarter, quartile portfolios are formed based on fund alpha. The top-left (top-right) plot provides the average performance using the seven-factor (cohort) model. The bottom-left (bottom-right) plot provides the absolute t-statistics using the seven-factor (cohort) model. The *, ** and *** lines represent the lower limit of $p < 0.1$, $p < 0.05$ and $p < 0.01$ respectively. The x-axis represents quarters after alpha estimation. The dependent variable when seven-factor alpha is analyzed is FAR and the dependent variable when cohort alpha is analyzed is PAR . The alphas and the dependent variables are measured as percentage per quarter, winsorized at the 1st and 99th percentile, and mean-adjusted across each cross-section following equation (17).



4.4 Determinants of cohort alpha

The results reported above indicate that the cohort model more accurately predicts future fund returns, while generating estimates of fund alpha that improve identification of man-

ager skill that is associated with performance persistence. I now examine whether fund characteristics can help explain why certain funds have higher alphas. Such analysis can provide insights into the drivers of alpha, including whether it relates to identifiable fund characteristics or the personal skills of the manager. When estimating the determinants of seven-factor alpha, I apply the cross-sectional mean adjustment to all characteristics as well as the alpha following equation (17), so that comparisons are relative to all other funds appearing in the sample at each point in time. Similarly, in examining the determinants of cohort alpha, I mean-adjust the fund characteristics and alphas within each cohort at each point in time, described by equation (20):

$$x_{i,t}^{c\ adj} = x_{i,t} - \mu_t^c \quad (20)$$

$x_{i,t}$ is the variable to mean-adjust

μ_t^c is the average of x across the cross-section of all funds in fund i 's cohort

I estimate panel regressions with alpha as the dependent variable and fund characteristics as independent variables, as described by equations (21) and (22). Variables in the panel regression include: the natural logarithm of fund age, performance fee, management fee, natural logarithm of minimum investment, redemption frequency, redemption notice period, subscription frequency, and lock-up period. To control for autocorrelation in fund alpha, I cluster by funds when estimating the standard errors.

$$\alpha_{i,t}^{c,\ adj} = \text{intercept} + \text{Controls}_{i,t-1}^{c,\ adj} + \epsilon_{i,t} \quad (21)$$

$$\alpha_{i,t}^{FH,\ adj} = \text{intercept} + \text{Controls}_{i,t-1}^{\ adj} + \epsilon_{i,t} \quad (22)$$

The results are reported in Table 4. Regressions estimates appear in Columns 1 and 2, and the difference between the coefficients in Column 3. The difference in coefficients is especially striking for performance fees. The relation between alpha and performance fees is positive for the seven-factor model, but negative for the cohort model. It appears that funds with positive performance after controlling for commonly recognized factors charge higher performance fees compared to other funds. Meanwhile, funds with low performance fees

relative to their close competitors are likely to outperform their cohort. These results suggest that differences in performance fees may be one of the drivers of the persistence in cohort alpha. I find similar results for management fees, but with lower statistical significance. For the remaining characteristics, the drivers for seven-factor and cohort alphas are similar. Younger funds generally have a higher alpha, and redemption notice periods are positively related to high alphas. The finding that fund age has an impact on performance is consistent with [Brown, Goetzmann, and Park \(2001\)](#) and [Agarwal et al. \(2009b\)](#).

Table 4: Determinants of fund alpha

Table 4 provides information on the determinants of seven-factor alpha and cohort alpha. The results are estimated through panel regressions with fund alpha as dependent variable and fund information as independent variables, using monthly data. Seven-factor alpha is the fund alpha in percentage per month, defined by the [Fung and Hsieh \(2004\)](#) seven-factor model (see equation (13)), Cohort alpha is the fund alpha estimated through a regression of fund returns on average return of the other funds in the cohort (see equation (12)), Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the lock-up Period is the lock-up measured in number of months. All variables are adjusted by the mean within the full fund universe (within the cohort) when estimating the determinants of seven-factor alpha (cohort alpha), following equation (17) ((20)). The fund alphas are measured as basis points per month and are winsorized at the 1st and 99th percentile. Columns 1 and 2 present the determinants of seven-factor alpha and cohort alpha respectively. Column 3 presents the difference between the coefficients estimated in Columns 1 and 2, including a Z-test of the difference presented in parentheses, following [Clogg et al. \(1995\)](#) and [Paternoster et al. \(1998\)](#). The standard errors are clustered by fund.

	Seven-factor alpha (1)	Cohort alpha (2)	Difference (3)
Intercept	0.556 (0.513)	-0.224 (0.314)	0.780 (0.601)
Fund Age	-7.787*** (4.521)	-5.366*** (3.972)	-2.420 (1.106)
Performance Fee	0.437*** (2.831)	-0.309*** (2.431)	0.746*** (3.736)
Management Fee	2.798 (1.195)	-0.527 (0.299)	4.982* (1.651)
Minimum Investment	2.566*** (3.321)	2.543*** (4.841)	0.024 (0.026)
Redemption Frequency	-0.012 (0.777)	0.004 (0.318)	-0.015 (0.789)
Redemption Notice Period	0.109*** (3.107)	0.050* (1.811)	0.059 (1.337)
Subscription Frequency	0.022 (0.448)	-0.019 (0.496)	0.041 (0.656)
Lock-up Period	0.105 (0.552)	-0.054 (0.341)	0.159 (0.643)
# of Obs	119525	119525	
Adj. R^2	0.010	0.006	
Absolute t statistics in parentheses in Columns 1 and 2			
Absolute z statistics in parentheses in Column 3			
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$			

A possible explanation for the differential relation between alpha and fees under the seven-factor model versus the cohort model relates to the link between fee determination and the respective performance measures. It appears that funds applying strategies which generate a high return after adjusting for commonly recognized factor exposures are able to charge higher fees, explaining the positive relation between seven-factor alpha and fees. This may occur as a consequence of being rewarded with higher fees for exposure to factors with positive returns that are omitted from the seven-factor model.¹⁹ However, the cohort model controls not only for the gross returns on these omitted factors, but also extracts out the average performance fee arising from these factors as earned by the cohort. After controlling for the factor-related gross return and fee effects, what remains is a direct, inverse relation between fees and relative net performance of funds within the same cohort. That is, for funds trading on similar strategies, those that charge lower fees generate higher after-fee performance. This appears in a negative relation between fees and cohort alpha as reported in Table 4. The implication is that funds charging lower fees might be preferred within each cohort as they generate higher cohort alpha, and this alpha is more likely to persist.

Lastly, the adjusted R^2 of 1% or less in the panel regressions, for both the seven-factor alpha and the cohort alpha, indicates that fund characteristics explain only a small proportion of the variance in fund alpha. In combination with the long-term persistence in cohort alpha, this suggests that the cohort model is largely isolating manager-specific skill in applying a particular investment strategy, rather than readily observed fund characteristics.

4.5 Alpha as determinant of future fund flows

A common finding of hedge fund studies is that past performance is a strong predictor of future fund flows.²⁰ I investigate if this relation holds between cohort alpha and subsequent cohort-adjusted fund flows. I estimate a panel regression with quarterly fund flow as the dependent variable, and cohort alpha as estimated at the start of the quarter as the independent variable. I mean-adjust the variables included in the regression within each cohort, following equation (20). By doing so, I am estimating how fund flow is predicted by in-

¹⁹The significant coefficient on performance fees under the seven-factor alpha regression reported in Column 1 of Table 4 is consistent with this interpretation.

²⁰See e.g. Fung et al. (2008); Lim et al. (2015); Forsberg (2017a).

dependent variables expressed relative to other funds in the same cohort. Results for the relation between seven-factor alpha and subsequent fund flows are also reported, in which case I adjust all values by the cross-sectional mean following equation (17). The regressions are outlined by equations (23) and (24):

$$Flow_{i,t}^{c\ adj} = intercept + \beta_1 \alpha_{i,t-1}^{c,c\ adj} + Controls_{i,t-1}^{c\ adj} + \epsilon_{i,t} \quad (23)$$

$$Flow_{i,t}^{adj} = intercept + \beta_1 \alpha_{i,t-1}^{FH,adj} + Controls_{i,t-1}^{adj} + \epsilon_{i,t} \quad (24)$$

Regression coefficients along with their t -statistics are presented in Table 5. Consistent with previous findings, past performance is a strong predictor of future fund flows. Both the seven-factor alpha and the cohort alpha are positively related with future flows, with t -statistics of 16.7 and 21.3 respectively. Cohort alpha appears to have a more economically significant impact on fund flows compared to seven-factor alpha. A one percent higher cohort alpha (per month, as generated over the preceding 24-months) is associated with three percent higher fund flow over the next quarter. This compares to a two percent higher fund flow following a one percent higher seven-factor alpha. Both regressions document higher flows for younger funds, and funds with longer lock-up periods and redemption frequencies.

The fact that high-performing funds within a cohort generate higher fund inflows is an important finding. It means that funds are rewarded not only for their performance after traditional factor-adjustment, but also for performance relative to their peers – perhaps more so. Lim et al. (2015) find that fund flows comprise a significant component of the reward structure for hedge funds. Since funds within the same cohort are likely to receive similar income through performance fees at the same time given their returns are highly correlated, outperforming funds will receive even greater rewards through higher fund flows.

5 Fund-of-funds portfolio analysis

This section investigates the value of cohort alpha using an analysis of simulated fund-of-funds portfolios. The analysis employs realistic assumptions of data availability and manager rebalancing. As hedge funds commonly report their returns with a one- or two-month de-

Table 5: Determinants of fund flow

Table 5 provides information on the determinants of fund flows. The results are estimated through panel regressions with fund flow as dependent variable and fund alpha as independent variable, using quarterly data. The regression also includes control variables. Fund flow is the flow to the fund defined by equation (16), Seven-factor alpha is the fund alpha defined by the Fung and Hsieh (2004) seven-factor model (see equation (13)), Cohort alpha is the fund alpha estimated through a regression of fund returns on average return of the other funds in the cohort (see equation (12)), Fund Size is the natural logarithm of fund AUM, Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the Lock-up measured in number of months. All variables are adjusted by the mean within the full fund universe (within the cohort) when estimating the determinants of flow in Column 1 (2), following equation (17) ((20)). The fund alphas are measured as percentage per month and are winsorized at the 1st and 99th percentile. Fund flows are measured per quarter and are winsorized at the 1st and 99th percentile. The standard errors are clustered by fund.

	Fund flow (1)	Fund flow (2)
Intercept	−0.049 (0.518)	−0.042 (0.581)
Seven-factor alpha	1.972*** (16.734)	
Cohort alpha		2.949*** (21.261)
Fund Size	−0.060 (0.903)	−0.193*** (2.793)
Fund Age	−0.462*** (2.740)	−0.469*** (2.826)
Performance Fee	−0.046*** (3.340)	−0.018 (1.142)
Management Fee	−0.208 (1.065)	−0.212 (0.963)
Minimum Investment	0.205*** (2.939)	0.123* (1.747)
Redemption Frequency	0.004*** (3.450)	0.004*** (3.506)
Redemption Notice Period	0.004 (1.337)	0.008** (2.578)
Subscription Frequency	−0.004 (1.060)	−0.008** (2.025)
Lock-up Period	0.028* (1.886)	0.031** (2.070)
# of Obs	45879	45879
Adj. R^2	0.014	0.019
Absolute t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$		

lay, I base manager selection on estimated cohort alpha lagged by one quarter. My analysis applies both quarterly or annual rebalancing of portfolios. Returns are after fees. The performance of the fund-of-funds portfolios is evaluated against peer funds within the same cohorts not included in the portfolio, using both the seven-factor model and direct comparison via regression analysis.

Portfolios are formed by selecting funds from the 15 cohorts with the highest number of funds at each point in time. These cohorts represent the 15 most common strategies, and hence are likely to be of greatest relevance to most fund-of-funds. Fifteen cohorts are chosen as the midpoint of what previous research indicates is needed to achieve sufficient diversification within a fund-of-fund portfolio. For instance, [Henker \(1998\)](#) concludes that at least 10 funds suffice to achieve sufficient diversification; whereas [Park and Staum \(1998\)](#) document that 20 funds are needed. [Brown, Gregoriou, and Pascalau \(2011\)](#) conclude that the optimal number of funds lies in the range of 10-20 funds. I construct portfolios containing the top-two and top-four funds within each of the 15 largest cohorts (top portfolios). Performance is then compared with portfolios formed from the remaining funds within each of the 15 cohorts (non-top portfolios). Cohorts are equally weighted in the portfolios, and individual funds are equally weighted within each cohort.

Results are reported in Table [6](#). Columns 1 and 2 present the estimated coefficients for the [Fung and Hsieh \(2004\)](#) seven-factor model for the top-two and the associated non-top portfolio. Column 3 reports the results from regressing returns for the top portfolio on returns for non-top portfolio. Columns 4 through 6 report the equivalent results for the top-four funds. The factor exposures are similar across the portfolios, with most significant exposure being to the return of the S&P 500. The R^2 is close to 0.7 for each of the portfolios.^{[21](#)} Meanwhile, the regression intercepts reveal meaningful differences in alpha between the top and non-top portfolios. Only the top portfolios have a positive and statistically significant seven-factor alpha, regardless of rebalancing frequency. The differences in seven-factor alpha between top and non-top portfolios ranges from about 10 bps per month (top-two, yearly rebalancing), and 22 bps per month (top-two, quarterly rebalancing). The intercepts from regressing top portfolio on non-top portfolio returns as reported in columns 3 and 6 confirm that selecting the top funds within each cohort adds significant value. The R^2 of the regressions are approximately 0.95, consistent with the portfolios investing in a similar combination of fund strategies containing similar factor exposures. All intercepts are positive and statistically significant, ranging from 10 bps to 24 bps per month. These estimates are comparable to the differences in seven-factor alpha between the top and non-top portfolios. In summary,

²¹These R^2 values are in line with e.g. [Fung and Hsieh's \(2004\)](#) analysis of hedge fund indices.

selecting the top funds from the 15 most common cohorts would have significantly enhanced performance – by around 1.2% to 2.9% per annum – without impacting the broader strategy and hence factor exposure. These findings confirm the substantial potential value to investors of using the cohort model to identify skilled managers.

Columns 1, 2, 4 and 5 of Table 6 also provide insights concerning the factor exposures. The estimated portfolio exposures mostly have the same signs as the exposures reported by Fung and Hsieh (2004) in their analysis of fund-of-funds and hedge fund indices. The main exception is exposure to the commodities trend-following factor for a subset of the portfolios. There is also high similarity in statistical significance. Hence, by investing in only 15 cohorts, a fund investor can achieve returns similar to broader hedge fund indices, indicating that using the cohort model with 15 cohorts provides sufficient diversification. The high R^2 s imply that the seven-factor model does a reasonable job in explaining common return factors within fund-of-funds portfolios, even though it may not be so effective in explaining returns for individual funds, consistent with the discussion in Fung and Hsieh (2004).

6 Robustness tests

This section considers the robustness of the cohort model. It reports on tests to assess the robustness to delisting bias and the approach to cohort identification. The assessment of funds without close peers is also investigated.

6.1 Probability of delisting

The first robustness test addresses delisting bias, and the potential impact it may have on the persistence in cohort alpha. Hedge fund delisting from databases, and its impact on the study of performance, has been considered by several authors. Agarwal et al. (2011) document that funds underperform as they delist from databases, and that the observed average performance of funds in hedge fund databases is therefore likely overstated. Subsequently, variables related to the probability of delisting could cause a potential upward or downward bias when employed as predictor of fund performance. For instance, if I document a positive

relation between fund alpha and future performance, as well as a positive relation between alpha and probability of delisting, then it becomes possible that the observed persistence in performance is driven by the delisting bias, at least in part.

I perform an analysis of the relation between alpha and probability of delisting through a logit regression, as described by equations (25) and (26). The dependent variable is a delisting dummy variable (*Delist*), with fund alpha and characteristics as independent variables. The independent variables are adjusted by the mean within each cohort for the analysis based on cohort alpha, and by means for the full universe for the seven-factor alpha analysis, following equation (20) and equation (17) respectively.

$$Delist_{i,t} = intercept + \beta_1 \alpha_{i,t-1}^{c,adj} + Controls_{i,t-1}^{c,adj} + \epsilon_{i,t} \quad (25)$$

$$Delist_{i,t} = intercept + \beta_1 \alpha_{i,t-1}^{FH,adj} + Controls_{i,t-1}^{adj} + \epsilon_{i,t} \quad (26)$$

$Delist_{i,t}$ is a dummy variable where 1 indicates that fund i delisted at time t , zero otherwise

The logit regression results as reported in Table 7 indicate a significant negative relation between the probability of delisting and both seven-factor alpha and cohort alpha. Hence, it appears that funds with poor past performance are more likely to delist from the database, consistent with Horst and Verbeek (2007). Furthermore, Horst and Verbeek (2007) find that persistence in hedge fund performance increases after controlling for the delisting bias. Therefore, it seems unlikely that the strong persistence in cohort alpha over multiple years is driven by delisting bias. Instead, by taking into consideration the findings in Horst and Verbeek (2007), the fact that poor performing funds tend to delist from the database may cause the positive relation between alpha and future performance to be understated. Further, cohort alpha appears to have a stronger effect on the probability of delisting, with a coefficient of -0.525, compared to the coefficient of -0.340 on seven-factor alpha. This indicates that funds that underperform relative to peers in their cohort are more likely to delist, as compared to funds that underperform relative to the full hedge fund sample in terms of seven-factor-adjusted performance.

Table 7: Probability of delisting

Table 7 provides information on the probability of delisting. The results are estimated using logit regressions with fund flow as dependent variable and fund alpha with a delisting-dummy as dependent variable, and fund alpha as independent variable, using monthly data. The regression also includes control variables. Delisting is a dummy equal to one if the fund is delisted, Seven-factor alpha is the fund alpha defined by the Fung and Hsieh (2004) seven-factor model (see equation (13)), Cohort alpha is the fund alpha estimated through a regression of fund returns on average return of the other funds in the cohort (see equation (12)), Fund Size is the natural logarithm of fund AUM, Fund Age is the natural logarithm of the number of months since fund inception, Performance Fee is the percentage performance fee charged by the fund, Management Fee is the percentage management fee charged by the fund, Minimum Investment is the natural logarithm of minimum investment measured in million USD, Redemption Frequency is the redemption frequency measured in number of days, Redemption Notice Period is the notice measured in number of days, Subscription Frequency is the subscription frequency measured in number of days, and the Lock-up Period is the lock-up measured in number of months. All variables are adjusted by the mean within the full fund universe (within the cohort) when estimating the probability of delisting in Column 1 (2), following equation (17) ((20)). The fund alphas are measured as percentage per month and are winsorized at the 1st and 99th percentile.

	Delisting (1)	Delisting (2)
Intercept	−4.892*** (140.065)	−4.679*** (158.440)
Seven-factor alpha	−0.340*** (13.557)	
Cohort alpha		−0.525*** (14.029)
Fund Size	−0.567*** (23.704)	−0.399*** (16.172)
Fund Age	−0.202*** (4.519)	−0.143*** (2.617)
Performance Fee	0.035*** (8.175)	0.021*** (4.270)
Management Fee	0.128*** (2.935)	0.159*** (2.897)
Minimum Investment	0.141*** (7.131)	0.131*** (5.694)
Redemption Frequency	0.000 (0.076)	0.000 (0.769)
Redemption Notice Period	−0.002*** (2.223)	−0.004*** (3.429)
Subscription Frequency	−0.002 (1.525)	−0.002 (1.290)
Lock-up Period	−0.009** (2.124)	−0.008 (1.603)
# of Obs	143281	143281
Pseudo R^2	0.067	0.037
Absolute t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$		

6.2 Alternative cohort identification methods

I conduct three tests to ascertain whether persistence in cohort-adjusted performance might be impacted by differing cohort identification methods. First, I test sensitivity to the threshold for the minimum number of funds per cohort. Throughout the paper, this threshold is set at two funds, meaning that a subset of funds may be compared only to one other fund

within their cohort. Setting the threshold to five funds, I find the results remain consistent, even though cohorts containing a low number of funds are removed from the sample. Second, I test if the results are sensitive to the method used to estimate return correlations between funds. Throughout the paper, correlations are estimated using equally weighted calculations that give the same weight to all returns over the estimation period. Pozzi, Di Matteo, and Aste (2012) argue that more recent data may be more descriptive of the near future. Hence I re-identify cohorts using exponentially weighted correlations with a half-life of two years. Again, my results remain consistent. Third, I test the sensitivity to the maximum distance for assignment of sub-clusters to merged clusters. Throughout the paper, the cohorts are based on the maximum distance of 0.25 (see Section 3.1.2). I re-estimate the results with a more stringent maximum distance (0.2), and with a more lenient maximum distance (0.3). The findings also remain consistent. The high persistence in cohort-adjusted performance does not appear to be sensitive to the cohort identification method.

6.3 Funds without close peers

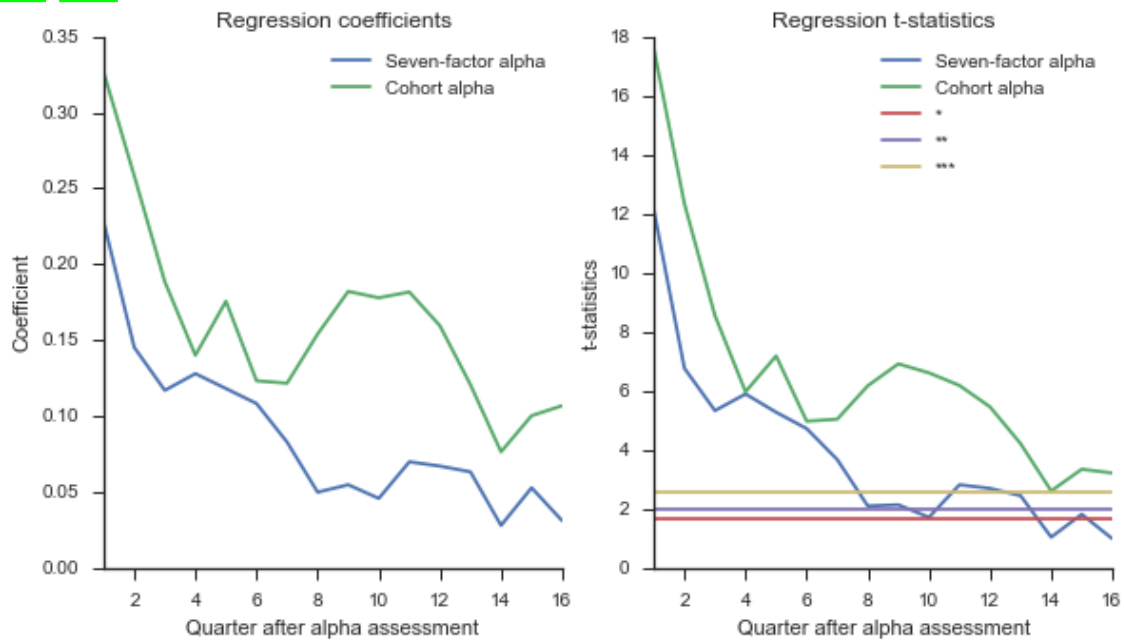
One shortcoming of the cohort model as applied so far is that it does not allow for performance evaluation of funds applying unique strategies. Peers were unable to be identified for 22% of the hedge funds in my sample based on the 25% distance measure. In this section, I introduce a variation on the original clustering method to ensure each fund is assigned to a cohort. In a first step, cohorts are generated exactly as described in Section 3.1.2. In a second step, each fund not matched to a cohort during step one is assigned to an existing cohort. This is done by estimating the return correlation between each non-matched fund and all funds within each of the formed cohorts. Each non-matched fund is then assigned to the cohort with which it has highest average correlation.²² Through this extra step, all funds are allocated to a cohort.

To assess if the cohort model remains informative of future fund returns when initially non-matched funds are allocated to cohorts, I re-estimate the panel regressions of Section 4.3 for the sub-sample of funds assigned to a cohort during step two. The results are presented

²²Initially non-classified funds are allocated to cohorts with which they have an average correlation of 0.57 during step two.

Figure 8: Performance persistence for funds without close peers

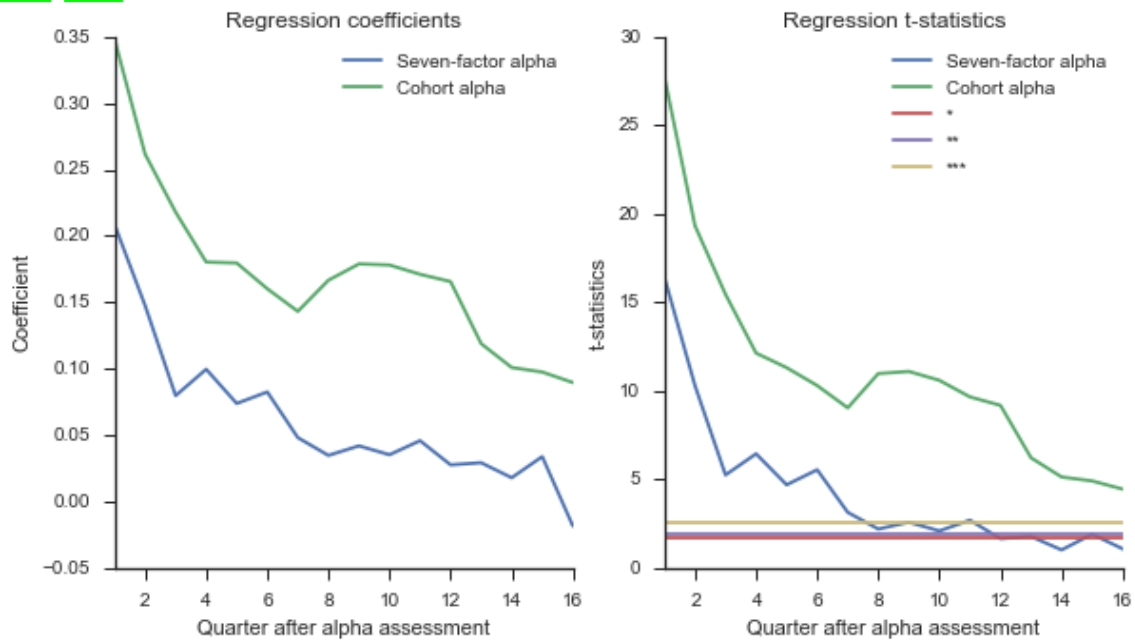
Figure 8 presents the panel-regression results from the performance persistence analysis, restricted to funds that are not matched to a cohort under the original cohort model. The left plot provides the estimated regression coefficients, and the right plot provides the estimated t-statistics. The *, ** and *** lines represent the lower limit of $p < 0.1$, $p < 0.05$ and $p < 0.01$ respectively. The x-axis represents quarters after alpha estimation. The dependent variable when seven-factor alpha is analyzed is FAR and the dependent variable when cohort alpha is analyzed is PAR . The alphas and the dependent variables are measured as percentage per quarter, winsorized at the 1st and 99th percentile, and mean-adjusted across each cross-section following equation (17). The panel regression also includes the following control variables: performance fee, management fees, minimum investment, redemption frequency, redemption notice period, subscription frequency, lock-up period, natural logarithm of fund age, and the natural logarithm of fund size. As per Petersen (2009), standard errors are clustered by fund.



in Figure 8. The cohort model again shows higher predictive power compared to the seven-factor model, regardless of horizon. Furthermore, cohort alpha shows persistence throughout all four years, longer than the three years of persistence in the matched sample (see Section 4.3). However, the persistence in the seven-factor alpha is also stronger for the sample of funds assigned during the second step, and the gap between the cohort model and seven-factor model appears to have decreased. Hence, there appears to be two counteracting effects impacting on the persistence in cohort alpha of initially non-matched funds. On one hand, the sub-sample of initially non-matched funds generally appears to have higher performance persistence, as reflected in higher persistence in seven-factor alpha. On the other hand, the funds in this sub-sample are not assigned to cohorts with the same precision as the funds matched during step one, meaning that benchmarking errors may creep in. This attenuates the ability to identify skill, causing the observed persistence in cohort alpha to decrease.

Figure 9: Performance persistence for complete sample of funds

Figure 9 presents the panel-regression results from the performance persistence analysis for the complete sample of funds, i.e. both the funds with and without close peers. The left plot provides the estimated regression coefficients, and the right plot provides the estimated t-statistics. The *, ** and *** lines represent the lower limit of $p < 0.1$, $p < 0.05$ and $p < 0.01$ respectively. The x-axis represents quarters after alpha estimation. The dependent variable when seven-factor alpha is analyzed is FAR and the dependent variable when cohort alpha is analyzed is PAR . The alphas and the dependent variables are measured as percentage per quarter, winsorized at the 1st and 99th percentile, and mean-adjusted across each cross-section following equation (17). The panel regression also includes the following control variables: performance fee, management fees, minimum investment, redemption frequency, redemption notice period, subscription frequency, lock-up period, natural logarithm of fund age, and the natural logarithm of fund size. As per Petersen (2009), standard errors are clustered by fund.



I also re-estimate the panel regression for the complete sample of funds, including funds assigned to cohorts during both step one and step two. The results are shown in Figure 9. Consistent with the previous results, the cohort model is more informative of future returns compared to the seven-factor model. Furthermore, the cohort alpha persists with high significance throughout the four examined years.

The results presented in Figure 8 and Figure 9 suggest that the cohort model can be applied across the full sample of funds, while still remaining more effective at identifying manager skill than the seven-factor model. Importantly, the cohort model appears superior for evaluating skill for funds that are initially not matched to any peers. This suggests that the cohort model can be universally applied by first identifying a menu of cohorts using a specified maximum distance, then drawing from this cohort menu in evaluating any non-matched funds by identifying their closest available cohort and using it for a benchmark.

7 Conclusion

Traditional factor models, such as the Fung and Hsieh (2004) seven-factor model, are useful tools when analyzing the performance of broader hedge fund indices or fund-of-funds. However, in explaining returns of individual hedge funds, traditional models suffer from the fact that hedge funds commonly apply specific strategies with return patterns that often cannot be readily explained with pre-defined factors. Furthermore, the relatively unregulated nature of the industry, and the fact that hedge funds commonly only provide limited information regarding their strategy, increase the difficulty of creating custom benchmarks for individual funds. I introduce a cohort model to deal with such issues. Instead of nominating factors based on the returns of different assets, I compile benchmarks from within the thousands of hedge funds. These benchmarks are created by locating funds that in the past have applied similar strategies, as revealed by returns that are highly correlated. The average returns of these fund cohorts are then used as benchmarks to separate out the component of individual fund performance arising from manager skill, from that related to the strategy and associated factor exposures.

I provide strong evidence that the cohort model is superior for benchmarking individual hedge funds, and hence identifying unique managerial skill. A comparison of realized fund returns versus predicted fund returns reveals that the cohort model explains a substantially higher proportion of individual hedge fund returns out-of-sample than does the seven-factor model. Furthermore, I document higher persistence in cohort-adjusted performance compared to persistence in seven-factor-adjusted performance. This is consistent with the cohort model being better able to identify hedge fund skill in applying their chosen strategy. These findings are consistent with the cohort model being an important tool for analysis of hedge funds, largely because it helps address the omitted variable problems that can arise under traditional factor models.

The cohort model can be applied for several different tasks. First, the high persistence in cohort-adjusted performance suggests that the model can be used to improve hedge fund selection. Through a fund-of-funds analysis, I conclude that selecting the top-two or top-four funds with the greatest cohort alpha from each of the 15 largest cohorts results in a

significant improvement of portfolio performance. Further, the cohort model could be used to highlight potential alternative funds of interest to investors. For instance, if an investor is considering investing in fund A, but the cohort model indicates that fund B belongs to the same cohort and has a higher cohort alpha, then investment in fund B may be preferable. Second, the cohort model could be used by hedge funds to identify their true peers, thereby supporting a more meaningful assessment of relative fund performance. Lastly, I argue that the cohort model could be useful for diversification purposes. By identifying clusters of funds, the cohort model is separating funds into the groups that apply similar strategies. This information could be used to help manage the strategy exposures within fund-of-funds portfolios, thus ensuring the portfolio remains adequately diversified.

Chapter 6

Conclusions and further research directions

1 Summary

Following hedge funds' fast growth, and therefore increasing importance to the financial market, they have recently attracted significant attention in the literature. Although many studies of hedge funds have emerged over the past years, there are unanswered questions surrounding the industry. In this dissertation, I present a literature review and three studies which relate to the performance of hedge funds. The first study seeks to determine which institutional investor type is the most informed. In the second study, I propose a new method to the analysis of capacity constraints in hedge funds. In the third study, I introduce a new model for analysis of relative hedge fund performance. The three studies improve understanding of hedge funds, and also provide analytical tools which will prove useful for further studies and for industry practitioners.

In Chapter [3](#), for the first study, I present the article “Which institutional investor types are the most informed?” In this study, I aim to determine if hedge funds, mutual funds, pension funds, or private banking firms on average are able to most accurately predict stock returns. For a fair comparison, it is important that the research design, dataset, and examination period is consistent regardless of institutional type. I argue that if one of these points differs depending on institutional type, conclusions regarding which type is most informed

cannot be drawn. The analysis presented in the article is, to the best of my knowledge, the first to achieve symmetry across each of these dimensions. The results indicate that hedge funds, on average, are superior to other institutional investor types. Stocks held by hedge funds significantly outperform their underweight positions. Furthermore, through a decomposition of holdings and stock returns, I show that hedge funds are superior to other institutional investors at picking stocks as well as industries, and that they are able to forecast returns both on a short-term and long-term basis. I investigate potential drivers of the results. I conclude that, although hedge funds tend to enter positions in smaller stocks compared to other institutional types, the superior performance of hedge funds is not driven by them earning a liquidity or small-cap premium. In fact, the informativeness of hedge funds holdings is higher compared to the holdings of other institutional investors regardless of whether the analysis is restricted to the ability to pick large-cap stocks, small-cap stocks, micro-cap stocks, liquid stocks, or illiquid stocks.

The findings presented in Chapter 3 have important consequences that influence content in Chapter 4 and Chapter 5. Being the institutional investor type with the highest ability to pick positively performing stocks makes hedge funds an extra interesting case for studies of capacity constraints. If fund managers are not skilled at picking securities, it raises the question whether diminishing returns with size would exist. For example, as soon as a fund starts impacting prices in the security in which it is trading, it can switch to another stock, thereby reducing execution costs through lower price impact. If the fund is skilled at predicting future returns, this switch is expected to increase opportunity cost. However, if the fund is uninformed, the expected opportunity cost of switching is zero. Thereby, skilled funds can be expected to experience capacity constraints to a wider degree compared to unskilled funds. Furthermore, hedge funds being skilled, on average, also makes them an interesting case for studies of performance persistence. If the funds are not skilled, past performance will be driven by noise, and hence no persistence is expected. Since hedge funds are skilled, on average, the likelihood of persistence increases.

Chapter 4, for the second study, consists of the article “Capacity constraints in hedge funds: The impact of cohort size on fund performance”. Previous studies of capacity constraints in hedge funds have analysed diseconomies of either fund size or sector size. Through

the article presented in Chapter 4, I analyse how hedge funds applying the same, or very similar, strategies may impact capacity constraints. To do this, I introduce fund cohorts, capturing funds that apply similar strategies based on correlation in returns. The analysis reveals a statistically significant negative relation between cohort size and future fund performance. Furthermore, when the negative relation between cohort size and performance is controlled for, I do not find any negative relation between fund size and cohort size. In this chapter, I also present findings that improve the understanding of fund flows. Hedge funds with high past performance experience significant inflows to its cohort. Furthermore, hedge funds that experience higher competition from other funds in their cohort show a higher propensity to increase in size, and encounter a weaker relation between past performance and future fund flows.

The findings presented in Chapter 4 highlight the importance of considering total assets allocated to similar strategies when assessing capacity constraints of funds, and are of importance to both fund managers and allocators. Hedge fund firms may want to consider the size of the cohort into which it is launching a fund, to avoid launching into ‘crowded’ spaces. Cohort size may also help hedge fund managers understand why certain strategies cease to generate significant returns in cases when a strategy’s poor performance coincides with a high inflow to the cohort. Allocators within the hedge fund industry may also consider the size of cohorts, and the impact it could have on fund performance, before making investment decisions.

For the third study, in Chapter 5 I take the foundation of the cohort concept introduced in Chapter 4 and develop the cohort model. In this chapter, I present the article “Relative hedge fund skill and the informativeness of cohort alpha”. I first form fund cohorts through a hierarchical clustering method. The cohort model then utilises these cohorts to create peer-benchmarks. Since the funds sharing cohorts are applying the same, or very similar, strategies, they are likely to be exposed to the same factors. Hence, the cohort model is a useful tool in performance analysis of hedge funds. The cohort model has several advantages over traditional multi-factor models commonly used to analyse the performance of hedge funds. Multi-factor models require a set of known and pre-defined factors, making the models prone to omitted variable biases when used to analyse a range of individual funds

which apply different strategies. The cohort model, on the other hand, does not suffer from this issue. By controlling for the return of funds applying similar strategies, the cohort model indirectly controls for the return of the factors to which the strategy is exposed. To understand if the theoretical advantages of the cohort model translates into reality, I compare the model-predicted returns of the cohort model and the Fung and Hsieh (2004) seven-factor model to the realised fund return. I find the cohort model to predict a higher proportion of hedge fund returns, consistent with the model suffering less from omitted variables. Since the cohort model is better at extracting factor returns from fund returns compared to multi-factor models, it can be expected that it is also able to more accurately estimate the fund's skill in applying the cohort's strategy. In support of this, I find persistence in cohort-adjusted performance lasting for three years, which is substantially longer compared to the persistence I document in seven-factor-adjusted performance.

The cohort model has several useful attributes. Following the persistence in performance, the most obvious one is in identification of skilled managers who are likely to continue outperforming. For instance, a hedge fund investor may have decided to invest in a certain strategy, and have located fund A as one of the funds applying the strategy. The investor is now looking for the hedge fund that is best at implementing the strategy, and the cohort model can be applied for this purpose. Another use of the cohort model is as a diversification tool. In identifying clusters of funds, the model is able to divide funds into groups of funds that utilise similar strategies. Hence, it can be used by fund-of-funds, to manage their diversification, and avoid putting too much weight in one cohort.

2 Further research directions

Each of the articles presented in Chapters 3, 4 and 5 highlight potential areas of further research. Throughout each of the studies presented, I mainly focus on the U.S. market. For instance, in Chapter 3 the database of institutional holdings is restricted to U.S. stocks, and in Chapter 4 and Chapter 5, I focus on funds reporting their returns and AUM in USD. The reason for this focus is the quality and the amount of data available for U.S. funds. Furthermore, a majority of the hedge fund literature uses U.S. data; therefore, making the

articles presented in this dissertation more comparable to past research. Nonetheless, if data becomes available that allows for the three studies to be replicated across other countries, this could provide evidence as to whether the insights provided in this dissertation are related to a global phenomenon or restricted to the U.S. market.

One potential knowledge gap in the first study, “Which institutional investors are the most informed?”, lies in the reporting frequency of the holdings. The article utilises quarterly holdings of institutional investors to assess the average informativeness of different types of institutions. Of course, the institutions will sometimes have changed their holdings between the quarterly observations. If a similar database becomes available which reports holdings at a higher frequency, a more accurate assessment of the informativeness of institutional investors could be made. Additionally, the holdings data utilised only contains institutions with more than USD 100 million invested in U.S. securities. If a dataset becomes available without this restriction, an improved understanding of the informativeness of smaller institutions may be reached.

The second study, “Capacity constraints in hedge funds: The impact of cohort size on fund performance”, introduces hedge fund cohorts, and utilises them to analyse capacity constraint. To improve the understanding of fund cohorts and how they impact the trading behaviour of hedge funds, it would be of interest to analyse detailed portfolio holdings and trades of the funds. To the best of my knowledge, this kind of data is not yet available for hedge funds. Furthermore, although capacity constraints are more likely to be experienced by hedge funds, future research may want to analyse if diminishing returns with cohort size is a phenomenon existing within other types of active funds, such as mutual funds. The advantage of using cohorts to analyse capacity constraints, is that the method only requires past returns and AUM of the funds.

Expanding the use of fund cohorts to other fund types may also be of interest in regards to the cohort model introduced in Chapter 5. In the final study, “Relative hedge fund skill and the informativeness of cohort alpha”, I develop the cohort model to account for the omitted variable bias present in multi-factor models. The main advantage of the cohort model lies in the analysis of funds of which traditional factor models suffer of omitted variables. Although models such as the Fama and French (1993) three-factor model and the Carhart (1997) four-

factor model, have proven sufficient in analysis of a significant proportion of mutual funds, the cohort model may be able to improve the analysis of the subset of mutual funds for which these existing models are insufficient.

3 Concluding remarks

With this dissertation, I aim to improve the understanding of hedge funds. The comparison of the informativeness of hedge funds and other institutional investor types, isolates hedge funds as the most informed type of institutional investor. The analysis of capacity constraints in hedge funds, provides novel insights into the impact hedge funds applying similar strategies have on capacity constraints. Through the cohort model, I develop a novel approach for improved analysis of hedge fund performance. The cohort model improves the ability to identify skilled managers compared to traditional multi-factor models. The content presented in these studies helps to improve academic understanding of hedge funds in particular, but also of the active funds management industry in general. The findings presented in these chapters also provide information that may be of significant use to industry practitioners, especially for fund-of-funds and for hedge fund managers.

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