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Insights from financial data — old and new

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Doctor of Philosophy

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DECLARATION

This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism.

Signature: _____ Date: _____

QUANG MINH NHI NGUYEN

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ABSTRACT

This thesis investigates financial data — the backbone of empirical research in finance — to provide insights into the importance of precisely interpreting existing data as well as the power of findings from new data. Specifically, the first study in this thesis examines the impact of event-day misspecification on the market reaction to FDA new drug approval announcements granted by NYSE listed firms. The second study uses an entirely new dataset of company filings from hedge fund management companies registered in the UK to investigate the true profitability of investment companies which manage hedge funds and to explain why it varies across firms over time. The last study utilizes the same new hedge fund manager filings dataset to investigate whether the hedge fund compensation contract effectively aligns managerial incentives with investor interests.

Previous research has offered the attention-grabbing hypothesis as a behavioural explanation for abnormal returns in the day after FDA approval announcements. The first empirical study shows that when the precise timing of announcements is properly identified (i.e. existing data is precisely interpreted), the market reaction is centred on the event day and the increase in firm value is driven by after-market-close approval announcements.

The second study shows that hedge fund management companies generated incredibly high profitability and revenue growth prior to 2008. With the onset of the global financial crisis, profitability and growth rates dropped. Analysis of cross-sectional variability in hedge fund management firm profitability finds that the key determinant is firm size. That is, larger firms generate significantly higher profitability and this relationship is particularly severe during the financial crisis period.

Existing evidence shows that the standard hedge fund compensation contract incentivises the manager to grow the fund assets they manage, even if it deteriorates investment performance. Facilitated by the novel hedge fund dataset in this thesis, firms which are entirely focused on hedge fund management are distinguished from diversified firms (which generate a relatively small proportion of compensation from hedge funds). The third empirical chapter in this study confirms that the actual compensation of hedge fund only firms increases as fund assets grow, despite the increased cost and performance diseconomies of scale. This result also holds for diversified firms, even though there is a weaker alignment between managerial incentives and fund performance within these firms. Hedge funds managed by diversified firms have a markedly lower performance.

Chapter 1 : Introduction

1. Introduction

“Data are the bedrock of empirical research in finance” (Ljungqvist et al., 2009)

1.1 Overview

The biggest advances in finance research often occur when researchers gain access to new data sources. The availability of a new data source opens the opportunity for researchers to investigate topics for the first time, as well as provide new insights into existing questions explored in the extant literature. Similar insights can be achieved when empiricists experimentally investigate existing research questions through a slightly different lens. Learning from the limitations of prior studies, researchers often utilise various innovative methodologies to test the accuracy of existing data sets. One of the common additional contributions of such studies stems from improvements in the data accuracy used to retest/verify results from existing data sets. In this way, more accurate datasets can often provide novel insights to advance the finance literature.

The history of financial research reflects the changing nature of financial data (Billio et al., 2009). That is, a new strand of the literature typically emerges when a new data source becomes available. For example, research on the equity markets in the 1970s was primarily conducted based on a monthly basis due to the available monthly stock returns from the CRSP database. Daily data for the traditional asset markets became more readily available in the 1980s, which allowed academic publications to focus on the distributional properties of stock returns (Billio et al., 2009). Similarly, financial research on market volatility has increased precipitously with the availability of intraday high-frequency data (Ma et al., 2018). Academics also attempt to offer new insights that were not observed in the existing literature by looking for various unique

data sources in new markets, new industries and new sample periods (e.g. Wu et al. (2005); Huyghebaert and Van de Gucht (2007); Nash (2017)).

The number and type of investment vehicles available to financial-market participants has increased significantly over the past half century, coinciding with the boom and bust of the internet bubble. In addition to conventional asset classes, wealthy individuals and institutional investors are increasingly allocating their capital to many new alternative investment entities (i.e. private equity, hedge funds, commodities etc.). As a result, the demand for rigorous research into these new asset management vehicles is increasing for both investors and regulators. The biggest difficulty facing researchers in those areas is that information, both qualitative and quantitative, is often unavailable to general market participants. The hedge fund industry is an obvious example. Although it is generally accepted that the first hedge fund was started by Alfred W. Jones in 1949 (Brown et al., 1999), due to data limitations, research on hedge funds, both professional and academic, only emerged at the end of the 1990s¹. Even though ongoing data limitations meant that these first studies only sampled a small number of funds, they paved the way for a brand-new strand of literature.

Since the turn of the century, the enormous growth of the hedge fund industry has precipitated a significant improvement both in number of data sources and number of funds covered in commercial hedge fund databases (e.g. Lipper TASS, HFR, CISDM). Unsurprisingly, academic publication has increased concomitantly. Indeed, Fung and Hsieh (2006) believe that, since the appearance of commercial hedge fund databases, academic papers on hedge funds have grown at an even faster rate than the hedge fund

¹ For example, Fung and Hsieh (1997); Schneeweis and Spurgin (1998); Ackermann et al. (1999); and Brown et al. (1999). See a survey in a study by Fung and Hsieh (2006).

industry itself. For example, prior to 2005, there were only 16 papers on hedge funds published in the top-four finance journals (e.g. JF, JFE, RFS and JFQA)² whereas there were 105 articles on hedge funds published from 2005 to 2015 (Agarwal et al., 2015). These publications, facilitated by the availability of data sources, have contributed to the building of a comprehensive literature on the hedge fund industry over that time.

Even when data are available, another difficulty facing researchers is the accuracy of information contained in existing databases. The extant literature has evolved to address the role of accurate financial data in providing important implications for empirical research (Guenther and Rosman, 1994, Ince and Porter, 2006, Kahle and Walkling, 1996, Lara et al., 2006). Researchers understand that incorrect/inaccurate data can seriously undermine the conclusions drawn from empirical results, such that research effort can be wasted. Also, to the extent that financial-market participants utilise academic research for trading purposes, they can lead to capital misallocation decisions.

Data inaccuracies can arise from collection methods of data providers. When there are questions about the accuracy of an available data source, previous literature has been careful to investigate possible measurement errors, data biases and/or unreliability (Bennin, 1980, Kern and Morris, 1994, Rosenberg and Houglet, 1974, San Miguel, 1977, Yang et al., 2003). Acknowledging these data-related issues, empiricists often attempt to make appropriate corrections to reduce the impact of these problems. Such corrections shed further light on conclusions from the extant literature. For example, when Davis (1996) mitigates the impact of survivorship bias in the Compustat data,

² Namely: *Journal of Finance* (JF), *Journal of Financial Economics* (JFE), *Review of Financial Studies* (RFS) and *Journal of Financial and Quantitative Analysis* (JFQA).

he concludes that the effectiveness of contrarian investment strategies observed in a previous paper by Lakonishok et al. (1994) might be overstated. Using a free-biased sample, Chou et al. (2009) contribute a stronger result and more robust evidence than previous studies to the literature on prospect theory.

On the other hand, data inaccuracy can also arise from the incorrect ways that users interpret data in practice. Therefore, researchers continue to put forward new methods to investigate existing issues in order to evaluate economic problems as accurately as possible. The development of new measures for existing variables, new models for old specifications, or new interpretations of data in traditional databases could make incremental and multi-faceted contributions to the existing literature. For instance, Grinblatt and Titman (1989) developed an alternative proxy with desirable properties for informed investors in evaluating performance, Ma et al. (2018) proposed a new model that obtains superior performance in forecasting volatility and gains higher economic values than the existing models in the literature, and Berkman and Truong (2009) introduced an adjustment which is proposed to provide a better interpretation of the value relevance of information about earnings announcements from existing databases (i.e. the Compustat or the I/B/E/S earnings announcement dates).

1.2 Research context and motivation

The evidence from previous studies has confirmed that there have always been data issues in general financial studies that are mainly due to the accuracy and the availability of empirical datasets. This study is concerned with these data issues in the contexts of event studies and hedge funds. Specifically, this study proposes to provide

new insights to the literature from i) correctly interpreting a conventional database widely used in event studies, and ii) new datasets for the hedge fund industry.

1.2.1 Event studies

The event study methodology is frequently used to measure the effects of a specific event (e.g. earnings, dividend announcements, stock splits, merger notifications) on firm value (MacKinlay, 1997). Even as a standardized methodology with a long history, researchers are still required to make decisions about several different options for some common elements when performing an event study. An obvious problem is the exact identification of the event and, hence, the correct specification of the event window (i.e. the period over which the security prices of the firms involved in this event should be investigated). Some survey papers on the event study methodology have recognized that it may be difficult to identify the exact event day (MacKinlay, 1997, McWilliams and Siegel, 1997, Peterson, 1989). This difficulty potentially results from the databases which collect announcement dates of financial events and which are widely used in many event studies. These data sources (e.g. the *Wall Street Journal*, Compustat, the I/B/E/S) often contain uncertain, incorrect or late reported dates after the true event dates (Peterson, 1989, Acker and Duck, 2009).

One possible way to handle this problem is that researchers who implement the event study methodology conduct some slight modifications in their research design. For instance, the event window needs to expand to multiple days (i.e. 2–3 days) rather than a one-day event. However, in practice, different researchers have made different event window choices in their research design (see details of the survey in Berkman and Truong (2009)), which potentially result in different findings for the same underlying

event being analysed. The different conclusions of these studies might be driven by the event date decision, rather than being a true reflection of the information contained in the new announcements. On the other hand, in some cases, even multiple event day windows cannot solve the problem if the report date is erroneously listed too far after the true event date (Acker and Duck, 2009).

There is also strong evidence of differences in stock market reaction to corporate announcements released to the public at different points of time within a day (Patell and Wolfson, 1982, Francis et al., 1992, Gennotte and Trueman, 1996). Researchers who have utilised event studies have begun to pay attention to the need to carefully account for the timing of the announcement when specifying the event date (Greene and Watts, 1996, Berkman and Truong, 2009). The latter authors suggest that researchers should conduct a small change in event study research design (i.e. due to after-close-market announcements, earnings announcement windows should include Compustat (or the I/B/E/S) event day +1 and examination of post-earnings announcement abnormal return should exclude the return on Compustat day +1) to clearly identify when the information content in firm announcements is available to the public.

The evidence from the previous literature on event studies and timing of announcements highlights the need to carefully identify the event date of new announcements from a reliable source. This is especially true for pharmaceutical companies because the risks related to innovation in that industry might be more serious than those related to business reporting for other rapid-changing, technology-intensive industries (i.e. telecommunications, biotechnology, software). That is, in the pharmaceutical industry, non-financial information is likely to be more value-relevant

than financial information (Amir and Lev, 1996). The pharmaceutical industry — an R&D intensive sector — is heavily impacted by product regulations from the US Food and Drug Administration (FDA); such companies therefore have attracted a lot of event studies examining the value effects of FDA non-financial notifications such as announcements associated with new product developments (Hamill et al., 2013, Bosch and Lee, 1994, Dedman et al., 2008, Hingorani et al., 1994, McNamara and Baden-Fuller, 2007, Sarkar and de Jong, 2006, Sharma and Lacey, 2004). The empirical results from such studies also provide interesting implications for financial-market participants. The finding of a significant positive stock market reaction to information on corporate innovations could lead to investment decisions in companies engaged in all phases of the development, production and application of pharmaceuticals.

There is also a specific type of hedge funds who specialise their investment strategies around the potential value relevance of new drug approvals in the pharmaceutical industry. Managers of such hedge funds, who maintain an excessive level of expertise, believe that they can earn benefits by owning portfolios of pharmaceutical securities because these companies can generate strong growth in revenue and profits from successfully developed drugs. Despite the fact that healthcare is a mature industry, analysts believe that hedge fund interest in this sector will continue to grow, as the number of new drugs increases. Indeed, the amount of money invested in specialty biotech hedge funds has already exhibited significant growth over time. For example, hedge fund ownership in the pharmaceutical industry was approximately \$105 billion

at the beginning of 2015, significantly more than the estimated \$5–10 billion total capital invested in 2006.³

However, in the pharmaceutical industry setting, it is often impractical or impossible to obtain a large sample of FDA announcements with the exact announcement times. All event studies in this sector assume that the date on FDA official announcements, which are easily compiled from the FDA website, is the event date, although there is potential of new information leakage before the announcements and/or the company releases new notification by itself prior to FDA official announcements. Indeed, the lack of accounting for the announcement times in empirical work could lead to the misspecification of the event date, which has been confirmed in the literature on earnings announcements (see Berkman and Truong (2009)). Therefore, the conclusions about this industry drawn from these empirical results might be seriously distorted. Such incorrect findings, in turn, possibly lead to resource misallocation by investors (i.e. hedge funds).

Motivated by the above reasons, this study focuses the analysis on an event study in the pharmaceutical industry with a new and more appropriate data interpretation (i.e. properly accounting for announcement times).

1.2.2 Hedge funds

Even though the availability of hedge fund data has improved significantly over the last few decades, there is an ongoing demand for new sources of hedge fund data for

³ “Hedge funds gain edge by doubling biotech investments”, Nature Biotechnology, April 2006 and “Healthcare is all the rage for hedge funds”, S&P Global Market Intelligence, June 22nd, 2015.

at least three reasons. First, the hedge fund industry is always of interest to investors and academics. Despite hedge funds having gained popularity in the last few decades⁴, due to the lack of regulation, the industry is still opaque and there is no required disclosure of information to the regulator. It is therefore imperative, wherever possible, to gather information on hedge funds. Second, although many researchers and other stakeholders have recently been calling for greater transparency, and regulators have been adopting more disclosure requirements for the hedge fund industry (i.e. the Dodd-Frank Act, the 13F Form filings), financial reporting in the industry is still mostly voluntary. As private investment entities, hedge fund managers can not only choose which databases to which to report, but also whether to report their funds' information in the first instance. Even for those managers who decide to report their characteristics to a commercial database, they often choose to report selectively and can also choose to stop reporting when and if they like. Although hedge funds have benefited from this privacy policy, it hurts researchers and investors who have to rely on third-party data. Many years of self-reporting to publicly available hedge fund databases, therefore, have resulted in a non-standardized, non-comprehensive data set (Edelman et al., 2013). Third, the existing commercial hedge fund databases potentially contain several data problems that are often observed in the literature. Liang (2000, 2003) is the first to question the accuracy of reported returns in available hedge fund data providers. His results identify significant data inconsistencies between two different snapshots from the same database and between

⁴ Hedge Fund Research (HFR) estimates that the total AUM of hedge funds have increased from \$39 million in 1990 to about \$972 million in 2004 (Agarwal and Naik, 2005). By the end of 2017, global hedge fund industry capital closed at \$3.21 trillion ("HFR Global Hedge Fund Industry Report – Year-End 2017 published", Hedge Fund Research, January 19th, 2018).

two major hedge fund databases of the same information (i.e. TASS database and US Offshore Fund Directory).

There are two main issues in available self-reporting commercial hedge fund databases. The first is the variety of biases (both natural and spurious) inherent in the data contained therein. Hedge fund managers have multiple arguments both for and against reporting their information to a public data vendor. However, the voluntary nature of these databases is the main cause of the biases — including selection bias, backfill bias and survivorship bias. These biases result in numbers that are strategically corrupted and interrupted (e.g. missing data because managers stop reporting information or average returns are pushed upwards due to survivorship bias). There is a well-developed literature that hedge fund inferences involving performance and risk are subject to a variety of biases (Ackermann et al., 1999, Agarwal et al., 2013, Aiken et al., 2013, Fung and Hsieh, 2000, Fung and Hsieh, 2009). There is also evidence that the conclusions about hedge funds made in earlier empirical research are affected by the biases in self-reported data (Bhardwaj et al., 2014). Given the fact that these biases will continue to exist until there is a mandatory requirement to disclose their information to the regulator, one challenge facing academic research on hedge funds is to carefully interpret empirical findings in light of these biases and/or attempt to apply some necessary steps to mitigate bias in their sample.

The second, and possibly more concerning data issue resulting from self-reporting, is the possibility of strategic reporting behaviour by hedge funds' managers. A large number of recent empirical studies on strategic misreporting, earnings smoothing, or delaying reporting, provide further evidence of challenges caused by hedge fund data inaccuracy (Agarwal et al., 2011, Aragon et al., 2013, Getmansky et al., 2004, Aragon

and Nanda, 2017, Cici et al., 2016, Liang and Qiu, 2015). For instance, Bollen and Pool (2009) observe that reported returns contain a significantly greater number of small gains than it should while the number of small losses is significantly lower. This suggests that managers smooth their returns by avoiding reporting losses. A recent study by Patton et al. (2015) provides additional evidence on the unreliability of voluntarily disclosed financial information by investigating the propensity of managers to revise that data. The finding of significantly lower performance by revising funds versus those that have never revised implies the possibility that the manager initially reported inaccurate and overinflated returns. These strands of literature have raised serious concerns about biased and possibly incorrect information in hedge fund databases, such that the need for new, bias-free, and more accurate hedge fund data sources has come in to focus.

1.3 Summary of findings

This thesis is motivated by data issues in empirical financial research, specifically the lack of event studies in the pharmaceutical industry focusing on the timing of new product approval announcements and the multiple problems posed by self-reporting in hedge fund databases. The study firstly focuses on event studies that examine the shareholder wealth effects of FDA new drug approval announcements granted to pharmaceutical firms listed on the NYSE. The analysis in this research makes an appropriate adjustment to properly account for announcement times, which causes the significant results observed in prior studies to disappear. The insignificant post-FDA new drug approval abnormal returns provide important implications for financial market participants. Whereas the evidence from earlier studies supports that investors

(i.e. hedge funds with a specialty in the healthcare industry) possibly capture abnormal returns by buying pharmaceutical stocks following new drug approvals; our new results show that it is not the case. This study provides an alternative explanation to the behavioural explanation offered in the prior literature to explain the observed post-announcement stock market reaction to new drug approval information.

The thesis then introduces a unique dataset from company filings by hedge fund management companies registered in the United Kingdom. This analysis is different from most existing papers which often conduct their research on a fund level basis. Unlike the US, virtually all hedge fund management companies in the UK are structured as private limited companies, and all private companies in the UK are required to file annual financial reports to Companies House each year. This filing requirement allows this thesis to create and analyse the first database of accounting information for companies that manage hedge funds. This approach also facilitates the avoidance of many well-known data issues inherent in current voluntary commercial hedge fund databases.

Using a hand-collected sample of company filings, this study provides new insights into the characteristics that determine the profitability of hedge fund management companies, as well as the effectiveness of the standard managerial contract in the hedge fund industry. Specifically, this study provides evidence on the actual financial performance of hedge fund management companies over time. The global financial crisis is identified in the sample period, which allows the study to present differences in firm characteristics of these firms between crisis and normal periods. In particular, their profitability and revenue growth were highest in the period prior to the crisis, before falling sharply during the crisis years. While this lower level of performance

has persisted in the period since the financial recession, it is interesting that, during this same period, these firms have steadily strengthened their balance sheets by increasing their liquidity and tangibility. Using actual profitability data of hedge fund management companies, this study confirms that size is the key determinant of profitability. Specifically, it shows that growth in company size leads to an 18 percent increase in profitability over the full period from 2004 through 2017. This relationship is more pronounced during the global financial crisis with an additional 5 percent increase in profitability when firm size grows.

The new dataset also allows the identification and comparison of firms who are entirely focused on hedge funds with diversified firms who generate their revenue from other sources in addition to hedge funds. As a result, this study shows that hedge funds managed by hedge fund only companies significantly outperform funds managed by diversified firms, and the outperformance is more severe for smaller firms over the sample period.

In addition, and for the first time, actual manager compensation is examined in this thesis. For hedge fund only firms, managers' compensation, consistent with estimated fee income in the literature, increases with assets under management (AUM) although the growth in fund size leads to an increase in firm operating expenses and a deterioration in fund performance. This evidence also holds for diversified companies, but the alignment between the investor and the fund manager is weaker in these firms because they only generate a relatively small proportion of their compensation from hedge fund management.

1.4 Key contributions

This study contributes to the literature on financial data in several ways. Firstly, it provides new insights into the importance of correctly interpreting financial data to carefully identify the timing of announcements in an event study. Properly accounting for when the information can be traded by investors has the potential to materially alter results and conclusions from event studies. Second, the study sheds further light on the stock market reaction to non-financial information; in this particular case, FDA new drug approval announcements. When the precise timing of announcements is accounted for, the attention-grabbing hypothesis no longer provides a behavioural explanation for post-event abnormal returns. Instead, the market's reaction is centred on the event day and is driven by after-market-close announcements. This result supports event-day misspecification as an alternative explanation for shareholder wealth effects after FDA approval information. Third, new data on hedge funds provide the opportunity for additional contributions to the literature. The new datasets developed in this study provide an alternative, more accurate, and more reliable source of hedge fund information. Fourth, by being the first to examine the financial performance of hedge fund management companies over time, an additional contribution is the provision of new evidence on the life cycle of the hedge fund industry and the effect of regulatory changes on performance. It provides direct evidence of the changes in the performance of hedge fund management companies during the financial crisis and non-crisis periods. Fifth, by identifying the determinants of hedge fund firm profitability, the study explains cross-sectional differences in profitability, both in the crisis and non-crisis periods, and also reports evidence supporting that performance in the hedge fund industry exhibits diseconomies of scale. Sixth, to the best of this author's knowledge, no previous study has identified actual

audited compensation earned by managers of hedge funds. By collecting data on compensation from management company filings, this research adds a new precise measure for managers' income to compare with that which can be estimated from voluntary commercial databases in the literature (Lim et al., 2016, Agarwal et al., 2009). Seventh, the new dataset also allows the research to distinguish between firms who are focused exclusively on hedge fund management and diversified firms (who manage other products in addition to hedge funds) and to document differences in their performance and other firm characteristics. In doing so, it makes a significant additional contribution to the existing literature on hedge fund management firms (Fung et al., 2017, Sun and Teo, 2019). Finally, the study also complements the literature on the effectiveness of the hedge fund managerial contract (Lim et al., 2016, Yin, 2016).

1.5 Thesis structure

The thesis is organised as follows:

Chapter 2: Literature review. This chapter reviews the relevant literature on financial data. It firstly summarizes the literature on the current state of financial databases in general. The chapter then explores the context of data interpretation in event studies in general and, specifically relevant to this study, the pharmaceutical industry. It next focuses on data issues in the hedge fund industry. In particular, it concentrates the review on the data biases that are well documented in the literature, the strategic behaviour in reporting data by managers and the emergence of alternative hedge fund data from recent SEC requirement filings. This chapter ends with a discussion on

several features which are drivers of hedge fund performance and the literature on hedge fund management companies.

Chapters 3, 4, and 5 are the empirical chapters. These three chapters present the contents which are exactly matched with the published article or the updated versions. Additional materials to the papers are included in an extra appendix at the end of each chapter.

Specifically, Chapter 3: *FDA approval announcements: Attention-grabbing or event-day misspecification?* This chapter investigates the importance of exact timing in event studies which examine the market reaction to FDA new drug approval announcements. The chapter also explores whether the attention-grabbing hypothesis provides a behavioural explanation for post-event abnormal returns offered in the literature. It also accounts for after-market-close announcements to further test whether increases in shareholder wealth in reaction to FDA approvals can be alternatively explained by event-day misspecification.

Chapter 4: *Just how profitable is it to manage a hedge fund? Insights from company filings.* This chapter introduces a novel dataset of audited filings from companies that manage hedge funds. By using this unique dataset of hedge funds, this chapter explores the financial performance of private hedge fund management companies (HMCs) registered in the United Kingdom over the period 2004 through 2017. The global financial crisis during this period allows this chapter to present the differences in firm characteristics between crisis and non-crisis periods. In addition, the study estimates a regression model of the drivers of profitability in different sub-sample periods. The cross-sectional analysis interacted with crisis dummy variables is also conducted to help explain variability in HMC profitability and its determinants over time.

Chapter 5: *Private hedge fund firm's incentives and performance: New evidence from audited company filings*. By using a new hedge fund database from audited company filings by hedge fund management companies, the chapter directly tests the effectiveness of standard hedge fund managerial contracts in aligning managerial incentives with investor interests. This chapter also tests for whether growth in fund assets affects fund performance. Besides performance, this chapter also compares the actual compensation earned by managers of firms who are exclusively focused on hedge funds, with diversified firms who generate income from other products in addition to hedge fund management.

Finally, Chapter 6: Conclusions. The chapter summarizes the contributions and outlines some directions for future investigation.

Chapter 2 : Literature Review

2. Literature review

2.1 Introduction

The appearance of many large secondary databases during the last few decades has solved the biggest data issues for finance academics — data inaccuracy and incompleteness. In the past, researchers were limited in their ability to analyse many interesting questions due to the unavailability of large and electronic databases of financial information. Since new data sources have become readily available, researchers can offer a greater insight on topics new (e.g. private equity, hedge funds) and old, as well as provide a better understanding of the implications of their findings for investors and regulators. In addition to the general data availability problem, researchers often face data accuracy issues in existing databases. The presence of potential data errors observed in the literature can lead to ongoing concerns about the spurious nature of results from empirical studies, and the distorted conclusions derived therefrom. The general suggestion is that researchers should fully understand and carefully interpret the data with which they work so as to properly account for this data issue.

The literature on the accuracy of data is centred on the existence of errors, biases, and unreliability which arise from the data collection methods of the data vendors. But data inaccuracy can also arise from the ways in which researchers empirically interpret the data in their studies. The event study methodology is particularly susceptible to this data issue due to the way in which such studies are designed. That is, despite it being a standardized method, researchers often face several options about how they interpret data at different points in the process. Among these, the event date specification is the most important choice because it is sometimes uncertain when new

information actually reaches the public. This difficulty can result in errors in findings because different researchers can make different decisions even though they use the same database. All of this can be further exacerbated by data providers which can potentially deliver erroneous information about the financial events in the first instance. There is also a well-documented literature on the need to properly account for the exact event time specification to carefully examine the value relevance of a specific financial announcement. However, although the event study methodology is extensively used to examine the stock market reaction to the events in the specific context of the pharmaceutical industry, this data issue has been virtually ignored in all studies.

Another data issue — data incompleteness — can be mitigated by the availability of new data sources. Indeed, by utilising novel data sources for new industries, new markets or new time periods, researchers can contribute numerous additional insights to the extant financial literature. The appearance of many voluntary commercial hedge fund databases is one such example that has facilitated significant research on various aspects of the hedge fund industry. This notwithstanding, the evidence from the research to date shows that virtually all available hedge fund data vendors suffer from many well-known data-related issues caused by data biases, managers' strategic self-reporting behaviour, and the unique characteristics of the hedge fund industry itself. In that regard, the literature on alternative data sources has emphasised the need to acquire additional datasets that avoid/counter many of these data issues in existing databases as well as to provide new information not previously available to studies in the existing literature on hedge funds.

This chapter explores the extant literature on financial data — specifically the event study methodology and the hedge fund industry — to identify gaps in the research. It is also designed to provide a background to and the context for the empirical studies carried out in the thesis. The chapter is structured as follows: Section 2.1 discusses the sources of data problems in several secondary databases and summarises the effects of data-related issues on empirical research in accounting and finance. Section 2.2 analyses the event study methodology and the vital role of event-day specification is addressed. The literature on the need to account for the timing of announcements is then discussed. This section also explains why the event-day misspecification is especially important in the specific context of the pharmaceutical industry and so, worthy of a specific investigation. Section 2.3 discusses several of the hedge fund data issues described in previous academic research. Specifically, this section details the data biases that stem from the voluntary reporting nature of hedge fund databases. The challenges posed by the strategic reporting of fund performance by managers for hedge fund data are also reviewed. Section 2.4 covers the recent literature utilising hedge fund information from SEC form filings and the drawbacks of these alternative sources of data. Section 2.5 examines the relationship between a number of hedge funds' features and fund performance, including the characteristics of managerial contracts and fund size. Section 2.6 reviews a new emerging strand of literature on hedge fund families or hedge fund management companies. Section 2.7 summarizes and concludes by identifying the significant research gaps in previous studies.

2.2 Financial data in general

Even in the most popular databases — which provide a whole range of data on stock prices, company information, or funds data — the existence of erroneous data is inevitable and well-documented in the extant literature (Kern and Morris, 1994, Yang et al., 2003, Rosenberg and Houglet, 1974, Bennin, 1980). Two of the largest and best-known databases, Compustat and the CRSP monthly return tapes, both contain a few large, infrequent and independent errors in reported stock prices that sharply affect to the nature of the data (Rosenberg and Houglet, 1974, Bennin, 1980). A lot of earlier papers have provided evidence of potential biases inherent in investigating CRSP data (Ball et al., 1995, Shumway, 1997, Canina et al., 1998, Shumway and Warther, 1999). The significant variations in reported figures between Compustat and The Value Line Investment Survey are also identified, which suggest inconsistency between these two accounting data providers. Researchers argue that the differences in data assimilation policies, the classification factors and the coverage issues among them are the main cause of these discrepancies (Kern and Morris, 1994, Yang et al., 2003). In addition to mistakes in company's financial statements and reported stock returns, a question has arisen in recent studies about whether or not two widely used mutual fund databases (those provided by CRSP and Morningstar) are free of errors. Specifically, there is an omission bias in the CRSP database such that their return data is biased upward. Moreover, their reported returns have significant differences when compared to Morningstar return data from 1994 to 2001, especially for older and smaller funds (Elton et al., 2001). Ljungqvist et al. (2009) have cast serious doubt on the accuracy of the I/B/E/S database — a major resource for researchers in the US — by documenting the considerable changes of match observations across seven different downloads this database across time.

The presence of errors in most of the well-known (and supposedly well-maintained) database vendors, suggests that researchers should be more concerned with the effects of these errors on their studies, which in turn have important implications for policymakers and investors. It is suggested that researchers should be careful in choosing databases when conducting a study since the conclusions drawn from empirical results can be seriously undermined based upon these choices (Kern and Morris, 1994) such that research effort can be wasted. For instance in a study using seven different databases (i.e. Datastream, Global Vantage, Company Analysis, Worldscope, Thomson Financial, Financials and BvD Osiris) to replicate a simple study, Lara et al. (2006) find that it leads to significant differences in empirical results, confirming that database choice matters. Kern and Morris (1994) believe that both Compustat and Value Line, which tend to cover large and well-known firms, might significantly affect those studies that examine the effects of firm size. Studies by Guenther and Rosman (1994) and Kahle and Walkling (1996) confirm that the differences in research results on monthly returns correlations and significance level of financial tests are down to which the database is chosen, irrespective of the underlying economic issues being analysed. Ince and Porter (2006) show that naïve use of Thomson Datastream might cause misleading economic inferences. In addition, to the extent that investors process academic research in the sphere of investing, the existence of erroneous data could lead to capital misallocation. Ljungqvist et al. (2009) provide evidence that significant changes in the I/B/E/S database over time have had a significant effect on data that are routinely used by academics and practitioners. They illustrate that these changes affect trading signal classification and the empirical analyst literature on the profitability of trading signals, the profitability of consensus recommendation changes, and the persistence in individual analyst performance.

In the finance and accounting literature, there are numerous studies that provide several suggestions to improve the quality of data used in empirical research. For instance, in order to verify the accuracy of the data, Rosenberg and Houglet (1974) and San Miguel (1977) suggest whenever multiple databases that contain the same information are available, the data should be matched. A comparison among databases is the most effective and least expensive way of screening for data errors in accounting (Yang et al., 2003). Researchers using Compustat tapes are suggested to include the delisted companies during the study period or at least attempt to evaluate the sensitivity of their results to these firms due to the presence of survivorship bias (McElreath Jr. and Wiggins, 1984, Davis, 1996). Ulbricht and Weiner (2005) believe that Worldscope should be the first choice for studies investigating firms after 1997 because of the significantly greater number of firms covered by this database (versus Compustat). Due to the different coverage size of various databases, multiple sources of data should be used whenever possible (Lara et al., 2006, Alves et al., 2007).

2.3 Data issues in event study methodology

2.3.1 Event study methodology in general

The event study methodology is a powerful tool in financial research which helps to assess the impact of a specific event on firm value. The event study is extensively applied in accounting and finance and is frequently used to measure the effects of specific corporate control changes or economy-wide events (e.g. mergers and acquisitions, earnings announcements, stock splits). The objective of this method is to determine whether there is any observed abnormal or excess stock price in reaction to some well-defined events over a relatively short time period (MacKinlay, 1997).

Using this method, the identification of the event of interest and the specification of the period over which the stock prices of the firms associated with the event are critical. This method is based on the assumption that if the event was clearly unanticipated and took place on the date identified, the appropriate window to observe the stock prices of the firms involved in the event should be one day. The literature also suggests that researchers should determine the event date with as much precision as possible when employing this methodology (MacKinlay, 1997, McWilliams and Siegel, 1997, Peterson, 1989).

However, it is sometimes difficult to identify the exact event date. In practice, the event window is therefore often expanded to multiple days, but different researchers have made different choices. As the event is often related to the release of announcements to market participants through the financial press (e.g. the *Wall Street Journal*) or via corporate press releases, Peterson (1989) argues that most new items are given to the paper on the day before they appear in print, such that new information on a given event may reach some investors the day prior to its public announcement. McWilliams and Siegel (1997) suggest a useful method for handling this uncertain event date problem is to expand the window for this event to two days to include the day of the event and the day prior to it (with an assumption that these are trading days). In a different view, MacKinlay (1997) recommends that the period of interest of value relevance of the event should include at least the day of the announcement and the day after the announcement in order to capture the price effects of announcements that occur after the stock market closes on the event day.

There is a large body of studies that perform event studies to examine the effects of firm's financial information, such as earnings or dividend announcements on stock

prices (Ayers et al., 2011, Ball and Shivakumar, 2008, Garfinkel and Sokobin, 2006, Hung et al., 2015, Livnat and Mendenhall, 2006, Zhang, 2012). Although virtually all studies utilise Compustat or I/B/E/S announcement dates, they investigate stock returns or volume measured over different event windows in their research design. Specifically, Berkman and Truong (2009) identify that 63 percent of research include the day after the Compustat or I/B/E/S earnings date in the event window. Therefore, the remaining 37 percent of studies do not do so and some of these measure abnormal returns on Compustat or I/B/E/S day +1 as post-announcement effects. It is clear that inconsistency in choosing the event window when performing event studies might lead to different results about how the stock market reacts, which in turn might change conclusions about the value relevance of corporate new announcements.

The database sources from which event dates are collected can also potentially contribute to difficulties for event studies. That is, there is evidence that has questioned the accuracy of source of announcement dates on the I/B/E/S database (Ljungqvist et al., 2009, Acker and Duck, 2009). Ljungqvist et al. (2009) document significant changes in the historical contents on the I/B/E/S database across seven different downloads across time. The changes are not random and can be forecasted by several characteristics such as analyst reputation, broker size and status. Acker and Duck (2009) detail the errors of this database when making comparisons on earnings announcements dates between Worldscope database and the I/B/E/S for UK and US companies and among two databases with manually collected dates from UK company reports from 1999 to 2006. They reveal that the I/B/E/S database reports 24 percent of earnings announcement dates are incorrect and most of them (97%) are dated after the true announcement dates. The authors also observe many differences between announcement dates reported to two databases and most of these discrepancies are due

to the correct date in Worldscope but a “mislabelled” date in I/B/E/S. Worldscope is found to have a lower rate of inaccurate earnings dates compared to the I/B/E/S, with 8% being incorrect dates and 74% being later date than the true ones. The nature and scale of the inaccuracies in the data might distort the results of accounting and finance research in general, and in event studies in particular due to a crucial role of event date specification in such studies. For instance, due to the large number of wrong and late reported dates, studies cannot find evidence of post-event drift even though it does exist and the estimated important parameter might be biased towards to zero (Acker and Duck, 2009). These authors also believe that the modifications in research by allowing a multiple (often 2 or 3) day event window cannot handle this problem as 72% of the I/B/E/S dates are out by more than three days. As a result of their findings, approximately 2 million records have to be reviewed and 50,000 of them are in the process of being corrected by Thomson Reuters, who provides the I/B/E/S.

2.3.2 Importance of announcement times

In the finance literature, there is a separate strand of studies that has evolved to address the important role of announcement times when examining stock market reaction surrounding a specific corporate event.

Patell and Wolfson (1982) were the first to study the timing of announcements, particularly for firms’ earnings and dividend announcements. They document differences in share value effects resulting from the different intraday timing of notifications. The authors find that 15 percent of announcements occur after the trading hours as well as the stock price reaction to announcements depends on the time when these disclosures are made. Using an endogenous stock price classification

method, Patell and Wolfson (1982) highlight that notifications occurred after the close of trading are more likely to be associated with negative stock price changes whereas those released during trading hours tend to contain positive price surprises. In other words, this study shows the potential impact of different announcement timings on daily stock price movements. They also imply that a misaligned disclosure date might decrease the significance of the research on stock price movements surrounding announcements and suggest that these investigations may be more precise by providing “a more detailed specification of the process by which accounting disclosure are actually released to market participants” (Patell and Wolfson, 1982, p. 526).

Subsequently, various studies have investigated the difference in market responses to earnings announcements at different times of the day (Francis et al., 1992, Gennotte and Trueman, 1996, Greene and Watts, 1996). For instance, Francis et al. (1992) argue that traders learn about and differently respond to information contained in an earnings release due to differences in the information dissemination processes during and after trading hours. Greene and Watts (1996) illustrate that stock price movements in reaction to quarterly earnings notifications are affected by both announcement timing and security market microstructure. However, the different stock price discovery in reaction to trading hours and non-trading hours earnings announcements is concentrated in the first post-announcement transaction. Similarly, research by Gennotte and Trueman (1996) implies that corporations strategically disclose mandatory announcements to take advantage of post-announcement value effects from different timing of earnings announcements. Specifically, managers are likely to release earnings with positive (negative) implications for firm value during (after) trading hours because the valuation effects are reflected in market prices better for trading-hours announcements rather than those occur after the closing of trading.

In a similar vein, Berkman and Truong (2009) draw attention to the need to account for the announcement times in event studies where researchers utilise the default Compustat or the I/B/E/S earnings announcement dates. The authors believe that the first opportunity for investors to respond to new information contained in after-hours earnings announcements is the next trading day. Default announcements dates, therefore, needs to be properly adjusted to accurately examine, *inter alia*, price changes in reaction to those announcements. Their results provide several important implications in an event study context. In particular, they suggest that the event window should include one trading day after Compustat (or the I/B/E/S) earnings date to capture the price effects of after-hours announcements. As well, an examination on stock price effects during the post-announcement period should exclude Compustat (or the I/B/E/S) date +1 because earnings announcements occur after the trading hours might cause a spurious effect on abnormal returns. The research implies that a misspecification of the event day zero, due to after-hour earnings announcements, could explain post-event abnormal returns. Therefore, no event study should be undertaken without properly accounting for after-hours announcements and making the appropriate adjustments.

2.3.3 Event studies in the pharmaceutical industry context

Besides more obviously value-relevant financial information such as earnings or dividend announcements (e.g. Beaver (1968); Oppong (1980); Aharony and Swary (1980); and Kane et al. (1984)), non-financial information is also found to have an incremental influence on firm value by grabbing investor attention. This is especially true for firms in rapidly-changing, technology-intensive industries (i.e.

telecommunications, biotechnology, software), where non-financial information is likely to be more important because risks related to innovation might be more serious than business reporting (Amir and Lev, 1996). Indeed, in the biotechnology context, Dedman et al. (2008) confirm that the effect of non-financial announcements, such as new drug development notifications, on stock price is more important than earnings-related announcements.

For this reason, the food and drug industry — an R&D intensive sector heavily impacted by product regulations from the FDA — has attracted a lot of attention examining the value effect of announcements associated with the new product development process. Previous studies have focused on evaluating how the market responds to the FDA product approvals, rejections, recalls and disciplinary decisions (Bosch and Lee, 1994, Hingorani et al., 1994, Torabzadeh et al., 1998, Sarkar and de Jong, 2006). In general, they report that shareholders' wealth increases after a drug approval and decreases after a rejection or recall decision. More recent research documents the relevance of product innovation news with stock price movements (Dedman et al., 2008, McNamara and Baden-Fuller, 2007, Pérez-Rodríguez and Valcarcel, 2012, Sharma and Lacey, 2004). However, these researchers find an asymmetric reaction at various stages of R&D, depending on firm size and types of announcements. Specifically, announcements relevant to later stage of new drug research outcomes are likely to be associated with larger stock price changes (Dedman et al., 2008, McNamara and Baden-Fuller, 2007). For firm size, McNamara and Baden-Fuller (2007) find that both exploration and exploitation announcements are seen as value indicators in large firms while investors' trading is driven only by exploration activities in small firms. Dedman et al. (2008) show that it is the ultimate stage announcements that are most important to dominant firms whereas their smaller

counterparts generate more significant stock return reaction to all types of announcements. Regarding types of news, stock prices are likely to have larger movements in response to negative as opposed to positive announcements (Torabzadeh et al., 1998, Sharma and Lacey, 2004, Pérez-Rodríguez and Valcarcel, 2012).

A study by Hamill et al. (2013) focuses on the value relevance of FDA notifications of completely new drugs and enhancements to existing drugs as well as examines the different impacts between application and approval announcements on shareholders' wealth in US and UK pharmaceutical companies. They find statistically significant positive abnormal returns in two days surrounding the event in both markets. They suggest that such post-event abnormal returns might be explained by the attention-grabbing hypothesis, which is proposed by Barber and Odean (2008). The attention-grabbing hypothesis highlights the importance of news items in driving individual investors' behaviour. The appearance of news, such as FDA approvals, will draw the attention of some investors and lead to an extreme one-day returns on the event day. Other investors are then attracted by the extreme returns/news after the market closes but they have no opportunity for reaction until the next trading day, which results in the increase in stock returns on the day after a major announcement. It is noted, however, that the details of how the event day is specified is not included in the Hamill et al. (2013) study.

A large body of research demonstrates the shareholder wealth effects of a variety of announcements released by the FDA. However, most of these studies do so without consideration of the announcement times (i.e. the hour and minute rather than day). Given the importance of announcement timings in employing event studies examining

earnings announcements, the conclusions on pharmaceutical companies drawn from empirical results could, therefore, be affected by notifications occurring after the market has closed. Previous studies assume the dates on the announcements are the event dates, which might lead to an event-day misspecification. The lack of event studies that include after-hours announcements in the choice of event window is possibly due to the lack of data sources to practically obtain a sufficiently large sample of FDA announcements with the exact times. This study primarily focuses on filling this gap in the event study literature in the specific context of the pharmaceutical industry.

2.4 Data issues in the hedge fund industry

Although recent industry reports indicate that hedge funds are likely to be maturing, the global industry capital continues to reach a new record at \$3.21 trillion as of the last quarter of 2017⁵. Hedge funds also hold an increasing proportion of the stock market over time. A study by Cao et al. (2014) found that at the end of 2012, hedge funds held an average 10% of outstanding shares for the typical firms listed on the US exchange. Given their increasingly important role in the financial markets, it has become even more imperative to gather and understand information on hedge funds. However, this task is challenging due mainly to data limitations, which result from the lightly regulated environment and the fact that hedge funds are not publicly traded. The lack of mandatory information disclosure to the market regulator is also contributing to the lack of transparency in the hedge fund industry. While hedge funds

⁵ “HFR Global Hedge Fund Industry Report – Year-End 2017 published”, Hedge Fund Research, January 19th, 2018.

have benefited from these loose regulations (insofar as they protect their proprietary trading strategies), they hamper academic studies in the area.

Virtually all recent empirical studies rely on the data provided by several voluntary reported commercial hedge fund databases. One of the most extensively used databases in academic research is the Lipper TASS (about 79% of published papers in top five frequently cited finance journal)⁶, which was initially founded in 1990. The HFR database — a production of Hedge Fund Research Incorporation and Barclayhedge — is also popularly used in hedge fund research. Another common database is Morningstar's hedge fund database that is the result of a combination of Morningstar and other databases including CISDM, MAR, Altvest and MSCI/Barra hedge fund database. EurekaHedge also provides hedge fund databases covering European and Asian funds. Two newly launched databases — eVestment and Preqin — are also commonly used by practitioners and, like other databases, obtain data from hedge fund managers which report voluntarily.

Most hedge fund databases started within small independent data vendors and their organizational structure has significantly changed over the years via several mergers and acquisitions, that in itself can/has induce(d) specific data issues (Joenväärä et al., 2019a). For example, the merger of Lipper and the TASS database from Tremont Capital to create the Lipper TASS database caused several spurious biases, according to Fung and Hsieh (2009) and Aggarwal and Jorion (2010a). In addition to the difficulties involved in merging historical databases, the amount of resources required to maintain a large database has also affected the data collection process (Ljungqvist

⁶ See Joenväärä et al. (2019a) for the survey on five frequently cited finance journals (e.g. JF, JFE, RFS, JFQA and FAJ) to investigate how hedge fund researchers use different commercial databases.

et al., 2009). Liang (2003) has investigated the data accuracy of hedge fund information across multiple databases from various providers and has concluded that there are significant discrepancies between them (and even across different versions of the same database from the same provider!). In finding that discrepancies are significantly lower for hedge funds with auditors, the author highlights the clearly effective and transparent impact of auditing on the accuracy of commercial databases.

Notwithstanding the quality of the data in commercial hedge fund databases, the challenges of data accuracy are compounded by the self-reporting nature of these databases and, specifically, the biases caused by strategic reporting behaviour of hedge fund managers. These biases are well-known and well-documented in the survey papers.

2.4.1 Database biases

As private investment vehicles, hedge funds protect their secrets around trading strategies by generally disclosing only limited information. On the other hand, because alternative investments are essentially prohibited from advertising, hedge funds voluntarily report their past performance and other fund characteristics to publicly available databases in order to market themselves to potential investors. Self-reporting of data to several commercial data vendors introduces a variety of biases to hedge fund databases (Bhardwaj et al., 2014). Indeed, Joenväärä et al. (2019a) emphasize the impact of these biases on the conclusions drawn from research on fund performance by comparing results from using seven different databases with those from utilising individual databases. Their paper argues that the effects of the data biases are mitigated in the aggregated database and so, in some cases, the results and conclusions drawn

therefrom are different. For instance, when they use the widest possible database, average performance is significantly lower but more persistent than those from a single database. Also, hedge funds do not deliver significant superior risk-adjusted net-of-fee returns on average while the gross-of-fee returns are significantly positive. The authors highlight the importance of researchers acknowledging the biases in the database with which they work. In a similar vein, Bhardwaj et al. (2014) document that several biases in databases result in an overstatement of the hedge fund performance, particularly for commodity trading advisors (CTAs), which can lead to incorrect inferences for investors and academics. They find that excess returns (i.e. net of fees) are insignificantly different from zero and no alpha delivery, while gross excess returns are 6.1% after correcting for the biases. Their research implies that CTAs are a kind of market failure but have persisted as an asset class for at least twenty years because their poor performance is not common knowledge for individual investors.

The way that hedge fund managers voluntarily report their performance causes systemic/natural biases, as well as idiosyncratic/spurious biases which stem from the choice of empirical design of researchers (Fung and Hsieh, 2000, 2009). Both types of biases are documented extensively and measured in the early literature; these include selection bias, survivorship bias and instant history (or backfill bias).

Selection bias arises from the fact that hedge funds choose whether or not to report to a data provider. Commercial databases can miss poor performing hedge funds because these funds have little incentive to report (Aiken et al., 2013). It is also possible that databases can miss the best-performing hedge funds because these funds often close to new investors and choose to stop reporting (Ackermann et al., 1999, Aiken et al.,

2013, Fung and Hsieh, 1997), such that it can be argued that every existing hedge fund database is incomplete (Joenväärä et al., 2019a). This notwithstanding, the latter authors find that most researchers only use a single database for their studies on hedge funds. Only a few authors construct a comprehensive database containing hedge fund information from several major data vendors, such that 21% of papers published in the top-five finance journals have used at least three of the databases. Although the selection bias may not invalidate the results of hedge fund research that use this data, the question of the generalizability of those results to the universe of hedge funds has been raised (Aiken et al., 2013). Moreover, because mainly well-performing funds are likely to choose to be included in a commercial database, the fund average returns are likely pushed upward (Fung and Hsieh, 2000).

Agarwal et al. (2013) compare returns from Form13F filings and use characteristic-based benchmarks to document that the returns of funds who self-report are higher than those that do not report. The authors also analyze the strategic reporting decision by a fund. That is, hedge funds tend to self-report following superior performance and delist when their return deteriorates. In a similar vein, Aiken et al. (2013) use quarterly holdings information filled by registered funds-of-funds to create a new dataset including hedge funds that have never been reported to a commercial database. Their new data allows them to compare returns between funds which are not included in a commercial database with those which are. The evidence shows that the average alpha of non-reporting funds (5 bps/quarter) is significantly lower than the alpha of database funds (120 bps/quarter), suggesting that there is significant selection bias in the commercial database.

Another major concern for researchers is the potential survivorship bias in available commercial databases, which occurs when database vendors only retain information for funds that are still operating. Because hedge funds voluntarily report their performance, both good and poor performing funds have reasons to leave the database. If funds become defunct (mainly following poor performance), then the survivorship bias causes upward bias on the average fund performance. Earlier studies have recognised this and have attempted to estimate the size of this bias by comparing returns of the surviving funds to the whole data set of returns (including funds that left the database during the sample period); the impact ranges from 2 to 3.6 percent per year (Brown et al., 1999, Fung and Hsieh, 2000, Liang, 2000). On the other hand, Ackermann et al. (1999) argue that, on average, the poor performance of funds that delisted due to liquidation or bankruptcy will offset with the good performance of funds that ceased reporting voluntarily. They find estimates of survivorship were small and insignificant, such that it is not obvious whether survivorship bias causes the average fund returns to be biased upward or downward.

Malkiel and Saha (2005) compare the annualized returns for the funds which are still reporting data to the database in their study with the whole data set of returns (with the defunct funds included). They report that the average difference between live funds and defunct funds is 442 bps over the period 1996–2003. This estimated survivorship bias is higher than the results of previous studies, but similar to recent research by Aggarwal and Jorion (2010a), Ibbotson et al. (2011), and Bhardwaj et al. (2014). Ibbotson et al. (2011) suggest that their estimate of survivorship bias of 5.13 percent is more accurate due to the lack of backfill bias. Bhardwaj et al. (2014) illustrate surviving funds increase the average performance of all funds in a CTA sample by 4.15%; Aggarwal and Jorion (2010a) arrive at the same conclusion. The authors also

recognize that there is a hidden source of survivorship bias in the TASS database stemming from this database merger (the Tremont database with survivorship problems). This hidden source causes earlier research to underestimate the effects of biases contained in the TASS database.

In a different view, Edelman et al. (2013) and Hodder et al. (2014) directly estimate the effect of delisting bias arising from funds that choose to stop reporting or do not participate in commercial databases. They find no evidence of significant differences in performance, both at fund level and mega hedge fund management companies. Hodder et al. (2014) find the returns of all exiting funds are insignificantly different from returns of live hedge funds. There is also no difference between the performance of non-reporting mega firms and the firms that report performance to databases (Edelman et al., 2013). On the other hand, Jorion and Schwarz (2014) use information from multiple databases to suggest a lower bound for the delisting bias of 35 basis points per year because they believe that funds often delist from one database but continue to report to another. The authors also argue that managers have incentives to stop reporting their funds before the end of the funds' lives. It is, therefore, possible that omissions of end-of-life observations push the average reported hedge funds returns upward.

A related bias that makes researchers worry when using self-reported hedge fund databases is backfill bias. Backfill bias, or instant history bias, arises because managers can decide to submit their performance records at the time of its entry into a database. Insofar as managers tend to report their good performance and avoid reporting funds with poor histories then the average reported returns prior to the date of entry are biased upward. Researchers have reported different estimates of backfill bias, ranging

from 1.2 to 5 percent (Fung and Hsieh, 2000, Edwards and Caglayan, 2001, Posthuma and Van der Sluis, 2003, Malkiel and Saha, 2005, Ibbotson et al., 2011). Bhardwaj et al. (2014) find that adjusting for backfill bias reduces the average annual CTA returns from 8.5 to 4.84 percent.

Although Ackermann et al. (1999) and Fung and Hsieh (2000) believe that survivorship bias and self-selection bias might offset each other, it is impossible to eliminate selection bias until the hedge fund industry has a regulatory requirement to disclose performance⁷. The evidence from a study by Edelman et al. (2013) suggests that selection bias might be offset by the missing returns of successful funds and the missing returns of liquidating funds. Results from Agarwal et al. (2013) imply that using multiple data providers might mitigate the effects of selection bias on data accuracy. Various techniques in practice are used to mitigate the effects of survivorship and backfill bias. Since 1994, the TASS database has maintained a graveyard file of nonsurviving funds. Researchers investigating hedge funds then conduct the sample period with 1994 as a common start date to include both live and dead funds in their sample.

Backfill bias can be mitigated by using only those funds whose inception date and database entry date are in proximity (Fung and Hsieh, 2009). However, this approach is very costly academically because the researcher will lose a lot of information content with obvious implications for sample size. Recent literature suggests that if the database vendor provides a flag of first reporting, researchers can use only the post-entry-date data in order to eliminate the backfill bias. If the first dates of reporting

⁷ Because mutual funds must publicly disclose their performance, selection bias does not exist in mutual fund databases (Fung and Hsieh, 2000).

are missing, the first 24 to 36 months of each return tape can be removed (Malkiel and Saha, 2005, Posthuma and Van der Sluis, 2003). However, this adjustment has drawbacks in that it may also exclude non-backfilled data.

2.4.2 Reporting behaviour issues

In addition to database-related biases, recent literature has also investigated the implications for data accuracy of the strategic behaviour of hedge fund managers in reporting their performance to publicly available databases.

Among the first, Asness et al. (2001) and Getmansky et al. (2004) identify a serial correlation problem in hedge fund returns that is mainly an outcome of the existence of illiquid securities in the fund. Due to the lack of a price for these illiquid securities, hedge funds have flexibility in how to value their investment positions and so are in a position to manage their reported monthly returns. This stale price bias results in lower estimates of volatility and correlation with traditional indices (Asness et al., 2001), such that the reported returns of funds containing illiquid securities are likely to be smoother than true economic returns (Getmansky et al., 2004). Such serial correlation leads to misleading implications not only for common performance statistics but also for wealth transfer between investors. Getmansky et al. (2004) also imply that some of the most successful types of funds tend to have more attractive performance characteristics because of the effects of smoothed returns. The authors argue that even though these smoothed returns are due to the valuation of the underlying assets, and not a result of managers' manipulation, the returns should be acknowledged to be inaccurate in empirical studies. Similarly, Cassar and Gerakos (2011) differentiate between asset illiquidity and misreporting-based explanations for the "anomalous"

properties of hedge fund returns. Their results support that the illiquidity of underlying assets explains much more of the variation in observed returns smoothing than does manager malfeasance. The authors find that managers with greater discretion in pricing investment positions are more likely to report smoother returns.

Bollen and Pool (2008) use conditional serial correlation to measure conditional return smoothing in a large sample of hedge funds. The authors argue that hedge fund managers have incentives to misreport returns in order to attract investors and, therefore, are more likely to smooth losses than gains. Their study also provides evidence that conditional serial correlation is a leading indicator of fraud. Via a different approach, Bollen and Pool (2009) observe the pooled distribution of monthly hedge fund returns and identify a significant discontinuity at zero. They document that the proportion of small gains significantly exceeds that of small losses, which suggests that the discontinuity is a result of avoidance behaviour by managers in reporting losses. In a more recent study, the same authors propose several performance flags as indicators of the potential fraudulent activity based on returns patterns (Bollen and Pool, 2012). That is, funds charged with misappropriation, overvaluation, misrepresentation, or Ponzi schemes are more likely to have a higher risk of fraud. Consistent with Bollen and Pool (2009), Cumming and Dai (2010) find strong evidence on misreported returns. Returns are much more likely to be positively reported than zero/marginally negative. The authors also identify a strong relationship between hedge fund regulation and misreporting. They find that the positive relation between wrappers and misreporting is exacerbated for funds without a lockup provision. In contrast, the study shows that misreporting monthly returns is infrequent among funds in jurisdictions with minimum capitalization requirements and restrictions on the location of key service providers (Cumming and Dai, 2010).

Tracking return revisions in historical performance recorded in available commercial databases, Patton et al. (2015) and Liang and Qiu (2015) analyse the reliability of voluntary information disclosures by hedge funds. Both studies document significant changes in returns, suggesting that funds often revise their previous reported returns to databases. Patton et al. (2015) identify that these revisions are not random and are predicted by some specific characteristics such as size, volatility, liquidity and the investment strategy of funds. The authors find evidence that funds who revise their returns significantly underperform relative to unrevised funds. Disagreeing with Patton et al. (2015), Liang and Qiu (2015) find that the performance of revising funds is higher. They argue that upward and downward revisions offset each other, implying only a small net effect on the accuracy of the performance records. In further downplaying the impact of return revisions in the future, the authors also find that the number and proportion of revisions has been decreasing as regulations have tightened for the hedge fund industry. Although they find no direct evidence of hedge fund managers manipulating historical returns, both Patton et al. (2015) and Liang and Qiu (2015) suggest that voluntary disclosures might be unreliable sources of information for investors.

Similar to the earnings management phenomenon in corporations, Agarwal et al. (2011) find evidence of returns management for hedge funds. The authors identify that hedge funds tend to manage their returns by strategically reporting upward returns in December compared to returns during the rest of the year. Funds with higher incentives (e.g. higher delta, more in-the-money options) and greater opportunities (e.g. higher volatility, lower liquid investments) are more likely to manage their returns. Their evidence shows that managers are incentivised to misreport returns in December in order to maximize fee rewards and to avoid capital withdrawal following

poor performance. Their paper also finds that funds often manage their returns by underreporting positive returns earlier in the year in order to create reverses for future use rather than borrowing from future returns in the following year.

Aragon and Nanda (2017) investigate the strategic behaviour of managers in delaying information disclosures. Using a TASS database (updated on a daily basis), their results suggest that managers strategically delay reporting bad news to the database for approximately two weeks (16 days). They find that these reporting lags are more prominent for funds with illiquid assets and a longer lockup period and redemption notice period. In addition, funds that are likely to have greater operational risk and smooth their returns also exhibit a slower reporting period. Although the manager has benefited from the delay in reporting poor performance, the study implies that investor flows are significantly lower following delays in disclosure.

Studying a sample of Confidential Form 13F filings, Aragon et al. (2013) examine the strategic behaviour of fund managers who request confidential treatment to delay the public disclosure of some or all of their holdings. The results highlight the benefits of allowing confidential treatments, i.e. a positive and significant abnormal return earned over the post-filing confidential period. Moreover, funds are more likely to seek confidentiality for illiquid securities in their holdings in order to avoid front-running costs. Although hedge fund managers avoid disclosure to protect their valuable proprietary information, these decisions contribute to the current policy debate on transparency in the hedge fund industry.

Recent research by Cici et al. (2016) also utilises Form 13F reports to compare the differences between hedge funds' reported valuations and standard valuations from equity prices in the CRSP stock database. The authors find that approximately 7% of

all equity positions are valued by hedge funds using prices that are different from those in CRSP and suggest that stock characteristics (i.e. highly illiquid and high intraday volatility) are the main reason for these valuation deviations. Their study documents that, particularly for those advisors who voluntarily report to commercial data vendors, funds with poor past performance are more likely to overestimate their equity positions. In addition, these funds with more valuation differences are also more likely to experience highly misreported returns such as a strong upward December spike (Agarwal et al., 2011), and stronger discontinuity in reported returns around zero (Bollen and Pool, 2009, 2012).

2.5 Alternative hedge fund source of data

Recently, there has been a new strand of research that has utilised an alternative source of data for hedge funds in order to mitigate the impact of several biases inherent in self-reported commercial databases. Another reason for the emergence of this literature is the appearance of various significant changes in regulatory filings requirements.

Specifically, in 2004 the SEC adopted a new regulatory rule, which required hedge fund managers to register as investment advisers by February 2006. Thereby, all funds were required to file Form ADV with the SEC, containing information about their operations, conflicts of interest, past legal history and other material facts. Although the US Court of Appeals vacated the rule changes a few months later, the Form ADV filings allow market participants to measure the operational risk of hedge fund investment managers. These filings also provide a much larger and less biased sample

of fund characteristics and fund managers (Brown et al., 2008b). However, large and sophisticated capital market participants may have already been aware of the information related to operational risks that are captured in commonly available databases. For these investors, therefore, the mandatory disclosure in Form ADV is effectively redundant. Dimmock and Gerken (2012) also utilise Form ADV to test the power of mandatory disclosures in investment fraud predictions. The authors document information on conflicts of interest, regulatory and legal violations history and monitoring to identify those firms with fraudulent behaviour. Their findings suggest that the 5% of firms with the highest predicted fraud risk are responsible for 29% of fraud cases and over 40% of the total dollar losses from fraud. In short, the Form ADV filings did provide information on ownership and key operational risk factors of hedge fund investment managers but did not provide detailed accounting information (Brown et al., 2008b). In addition, Dimmock and Gerken (2012) argue that though the public can access each investment adviser's current Form ADV filings, the panel of historical filings is not publicly available.

Starting from March of 2009, the SEC required the electronic filing of Form D by all hedge funds seeking to raise capital from US investors, allowing several empirical studies to further explore hedge fund behaviour. For instance, Jorion and Schwarz (2015) believe that information about the size of the industry gleaned from Form D provides a more complete picture of US hedge fund industry than that available from commercial databases. In fact, they find that approximately 22,800 hedge funds file Form D with the SEC over the period from 2009 to 2014, with total lifetime sales of over \$6 trillion whereas only 3,800 (with \$3.2 trillion) of these funds are reported to either HFR or the TASS database. The study also confirms the findings of Edelman et al. (2013) that commercial data vendors miss most large hedge funds and that the

coverage of private data providers is even lower for smaller funds. Based on the figures of historical total amount of the offerings sold and the number of investors, Jorion and Schwarz (2015) observe the changes in inflows, outflows and number of investors in the hedge fund industry. In addition, Form D also discloses the limited information on the name and address of the fund's board members. Clifford et al. (2018) take advantage of these filings to build a database containing 5,400 directors of 5,126 hedge funds over the 2009–2013 period. The authors are the first to provide an investigation on the governance role of boards of directors in hedge fund firms. Their evidence suggests that extremely busy independent directors play a vital monitoring role in hedge funds due to their more reputational capital, independence from management and better monitoring. Funds with these directors also are less likely to commit fraud, abuse discretionary liquidity restrictions, or engage in performance-based risk-shifting. As well, funds with better performance and fewer regulatory violations are more likely to hire busier independent directors who can certify fund quality for investors and attract outside investments.

There are a number of empirical studies that have documented new information in Form 13F filings to examine hedge fund performance (Agarwal et al., 2013, Aragon et al., 2013, Cici et al., 2016). Form 13F is required to be filed to the SEC by hedge funds who exercise investment discretion over certain size with their long portfolio holdings. Although Form 13F filings do not suffer from the selection issues inherent in commercial hedge fund databases, these filings are only mandatory for large funds (i.e. over \$100 million), such that smaller funds are not included. In addition to only quarterly snapshots of long equity-based positions disclosed at the level of hedge fund advisor rather than the fund level provided, the performance information extracted from these filings ignores the impacts of short-selling, illiquid securities, trading costs,

hedge funds fees and intra-quarter trading (Aiken et al., 2013, Agarwal et al., 2013). Another drawback of using 13F filings is that the strategic behavior of hedge funds to reduce the information content of their holdings to “front runners” and “copycats” potentially impact on the information supplied in Form 13F (Agarwal et al., 2013). In addition, while the data in Form 13F is publicly available, it provides no information on the financial performance of the investment management company.

Fung and Hsieh (2000) propose using track records of funds-of-funds (hedge funds that are invested in portfolios of other hedge funds) as they are almost free of the many biases contained in databases of individual funds. They believe that funds-of-funds returns represent a more accurate picture of the returns earned by hedge fund investors. Similarly, Aiken et al. (2013) avoid the issues that arise from using voluntary commercial databases and Form 13F filings by using registered funds-of-funds. Although their results indicate that their sample of database funds provides a similar representation of the population of funds reporting to databases over their sample period, they recognise that they could not control for the effects of any hedge funds that are both missing from a database and not held by a registered funds-of-funds on the inferences from their results (Aiken et al., 2013).

2.6 Hedge fund features and performance

Hedge funds, with their unique characteristics such as managerial compensation contracts, flexibility, and their loose regulatory environments, have attracted a lot of attention from researchers. A large number of prior studies have examined the cross-sectional variation in hedge fund performance as well as managerial characteristics

that have effects on fund performance. This section reviews the related literature on the interactions among compensation contracts, fund size and fund performance.

2.6.1 Manager compensation and the relationship with fund performance

Hedge fund managers are often incentivised via management fees (which is a fixed percentage of AUM) and incentive fees (which are subject to fund performance). There is empirical evidence on the effects of special hedge fund compensation structures on fund performance. A general conclusion is that the standard managerial contract in the hedge fund industry is designed to align the interests of the manager and investor. That is, hedge fund managerial contracts incentivize managers to generate superior performance. Earlier studies by Liang (1999), Ackermann et al. (1999) and Edwards and Caglayan (2001) document significant results that funds with higher incentive fees, the inclusion of a high-water mark provision or higher lockup period are more likely to have better performance. Their finding of outperformance is consistent with the view that manager skill, rather than luck, can partly explain fund performance.

More recent studies have challenged the results of earlier research. Specifically, researchers have found that compensation contracts can also create agency problems. That is, managers are incentivized to increase fund assets even when it leads to the detriment of fund performance. Teo et al. (2003) find no significant evidence to support the conjecture that funds with higher fees (both management and incentive) are associated with higher fund returns. A cross-sectional analysis by Kouwenberg and Ziemba (2007) finds a negative relationship between performance fees and net-of-fee returns for individual funds, but shows an upward tendency for funds of funds

(FOFs). Yin (2016) considers the effectiveness of a standard compensation contract in resolving conflicts of interest between fund managers and fund investors. The author finds empirical evidence that managers' compensation increases when fund size grows even though diseconomies of scale exist in hedge funds. He concludes that managers choose the optimal fund asset size to maximize their own compensation even though this might not maximise fund performance for investors. Therefore, to avoid outflows, managers are motivated to close their funds to new investment to maintain style-average performance. A similar conclusion is also true for fund families. Fund management firms increase their total AUM, including their flagship funds to maximise their incentives, even at the expense of fund performance.

The direct and indirect managerial incentives of hedge fund managers have been analysed extensively and empirically in the literature. Goetzmann et al. (2003) develop a valuation model to estimate the costs and benefits of a high-water mark provision to investors. They find that a high-water mark provision in the compensation contract represents a claim on investor wealth, such that the total percentage of wealth claimed by the managers can be as high as 33 percent. The authors argue that performance fees are valuable for managers, but the high-water mark limits the value of the performance fees. Their evidence suggests that the existence of a high-water mark can be a signal to investors that the returns in the industry are diminishing in scale. The model developed in their study also provides a framework for valuation of a hedge fund management company.

In related research, Aragon and Nanda (2011) focus on the risk-shifting decision of hedge funds and investigate how such behaviour is related to the manager's incentive contract (i.e. the inclusion of a high-water mark provision), personal capital

investment and risk of fund closure. The authors argue that the high-water mark benchmark can induce a form of risk aversion in certain settings because incentives tied to a high-water mark may offset the managers' propensity to increase risk of poorly performing funds. They document that 65% of funds utilised a high-water mark and managers of these funds are less likely to increase risk following poor performance.

Agarwal et al. (2009) complement the model of Goetzmann et al. (2003) by being the first to empirically quantify the manager's call option-like incentives fee contract. The authors believe that their estimate of manager's option delta, which is the total expected dollar increase in the manager's compensation for a 1% increase in the fund's NAV, is a better measure of managerial incentives than the incentive fee percentage. They find that higher values of delta are associated with higher future returns, whereas the incentive fee rate by itself has no explanatory power for performance. Their results also suggest that funds with larger direct incentives (i.e. higher value of delta, higher level of managerial ownership, the existence of hurdle rate and high-water mark provision) and higher degree of managerial discretion (i.e. longer lockup and restriction periods) are more likely to have better performance.

In addition to direct incentives, others have focused on some of the indirect incentives of hedge fund managers. For example, Lim et al. (2016) use an extension of the models developed by Goetzmann et al. (2003) and Lan et al. (2013) to estimate indirect incentives, which are defined as the expected future fees that can be earned from an incremental percentage point of current returns. The authors argue that manager's indirect incentives come from the expectation that better current performance increases AUM, which leads to increased future fees. Their results suggest that indirect

incentives in the hedge fund industry account for the majority of manager's total incentives; specifically, that indirect incentives are at least 1.4 times as large as direct incentives. This ratio is even larger for younger and more scalable hedge funds due to their stronger flow-performance relationship. In addition, Lim et al. (2016) also estimate the direct incentives following the method used by Agarwal et al. (2009), and find that managers expect to earn \$331,000 for every one percentage increase in returns (an amount higher than the estimated \$188,000 in the previous paper). However, whereas Agarwal et al. (2009) provide strong evidence of the positive relationship between direct incentives and fund returns, Lim et al. (2016) do not provide direct evidence on the effects of indirect incentives on performance.

2.6.2 Relation between fund size, fund performance and optimal hedge fund size

Earlier studies document that fund assets are positively related to fund performance, suggesting economies of scale for performance in the hedge fund industry (Liang, 1999). Teo et al. (2003) show a positive relationship between holding firm size and fund returns. That is, funds managed by larger companies are more likely to outperform those managed by smaller holding firms. Brown et al. (2008a) find an opposite result between individual funds and FOFs. Their result shows that small hedge funds are associated with the highest annual returns while larger FOFs have statistically and economically significant greater performance than smaller FOFs due to their due diligence. The authors argue that large FOFs which can absorb the high cost of due diligence have a significant advantage over smaller counterparts, which leads to better performance.

Since then, researchers have documented the negative relationship between fund size and performance and suggest that managers are facing decreasing returns to scale in hedge funds (Fung et al., 2008, Agarwal et al., 2003, Edelman et al., 2012). These recent studies provide evidence in favour of an assumption underlying the model of Berk and Green (2004) which suggests that fund size is negatively related to performance.

Agarwal et al. (2003) and Teo (2009) find evidence of diseconomies of scale for individual funds but not for FOFs. Agarwal et al. (2003) argue that larger FOFs may benefit from diversification, due diligence, and well-performing managers that attract potential new investments, such that these FOFs, therefore, enjoy economies of scale. Teo (2009) shows that the risk-adjusted returns of small hedge funds are higher than those of large hedge funds by 3.65 percent per year whereas large FOFs outperform small FOFs with a smaller spread of 0.46 percent. He explains the outperformance of small funds as being due to capacity constraints. He argues that stronger capacity constraints are possibly explained by price impact, especially for funds engaged in illiquid securities. Teo (2009) also identifies hierarchy costs of larger funds, induced by competition among multiple principals, as a part of the explanation for capacity constraints.

A few studies examine fund performance under the effects of capacity constraints. Naik et al. (2007) investigate hedge funds absolute returns (alpha) and capacity constraints at the level of hedge fund strategies. The authors document that alphas have exhibited a significant decline over the 1995–2004 period and four of eight hedge fund strategies have experienced lower alphas followed by large capital inflows to the strategy. Their results imply negative movements in fund performance as a result of

increased fund size. The authors also find evidence for the tendency for hedge fund fees to increase over time, which supports the argument that managers are incentivised to increase fund size. Differently, Joenväärä et al. (2019b) detail the effects of numerous types of constraints at the investor level on investors' returns. Of eight types of investor constraints, the constraint labelled as the percentage of AUM has a large incremental effect on hedge fund performance persistence, that leads to portfolio returns falling by 1–2 percent per year. Their finding provides evidence of decreasing returns to scale in the hedge fund industry.

Getmansky (2004) documents a concave relationship between fund performance and AUM, suggesting that hedge funds suffer from diseconomies of scale. He also identifies the different functional form in the performance-size relationship across different fund strategies. In fact, illiquid fund categories with higher market impact and limited investment opportunities are more likely to exhibit a concave relationship between fund assets and performance, such that the optimal size can be obtained. The author proposes a model for attempting to calculate an optimal asset size by balancing out the effects of past returns, fund flows and market impact, competition and favourable positioning.

In addition to negative price impact and hierarchy costs explored in the literature, recent studies provide another possible and testable explanation for the decreasing returns to scale in the hedge fund industry, i.e. the ineffectiveness of standard compensation contracts in aligning managers' incentives with investors' interests. Lan et al. (2013) find that the present value of managers' future management fees is much higher than the present value of future incentive fees. In addition, Yin (2016) confirms that there is an optimal fund size for fund performance due to the existence of

diseconomies of scale in both individual funds and fund families. He also finds that management fees account for a large proportion of total compensation when fund assets increase, such that optimal size for fund performance might not match with the optimal size for managers' compensation. These studies suggest that diseconomies of scale may reflect that compensation rewards are more reliant on management fees than incentive fees when fund size grows, implying that the design of the standard compensation contract is ineffective.

In a similar vein, Fung et al. (2017) complement the results from previous papers when examining the growth strategies of hedge funds firms. Their finding suggests that fund management firms strategically leverage the successful performance of a first fund to launch new follow-on funds with higher fees and longer restriction periods. Although this strategy hurts investors (because multiple-product firms underperform those with single fund), fund managers benefit due to the increase in amount of fee income that they can harvest (Fung et al., 2017).

Differently from most previous empirical studies which document the relationship between fund size and performance using panel data, Gao et al. (2019) use an event time approach. Their results provide additional evidence on the diseconomies of scale in relation to fund age. In fact, they find that small hedge funds outperform the large group after a two to four years period from the start of fund performance and these small funds are more likely to maintain good performance during these years. Consistent with Yin (2016), Gao et al. (2019) also suggest a possible explanation for declining performance with size related to the compensation contract. That is, managers may have less incentives to improve fund performance when funds grow large because their compensation comes mainly from asset-based management fees

rather than from performance-based incentive fees. Their explanation implies that the standard compensation contract is not effective in minimising conflicts of interest between fund managers and investors.

2.7 Hedge fund management firms

There has been a developing strand of literature documenting hedge fund characteristics at the fund management firm or hedge fund family level, which builds on the well-established literature that has typically utilized individual hedge funds as the basic unit of analysis. The development of this literature has resulted from the growth in the number of funds launched by a given fund management company⁸. Boyson (2008) documents that the number of hedge fund families increased by 2,180% over the period from 1994–2007. The author is the first to examine hedge fund families and investigate the costs and benefits accruing to fund investors when families launch new funds. She reports a difference of 4.4 percent per year in risk-adjusted returns between single-fund families and larger families. However, neither family size nor the number of funds offered is a possible explanation for this outperformance. This study argues that fund families outperform because they concentrate on their core competencies. Moreover, the author also suggests that managers which expand their offerings in fewer style categories are more likely to enjoy higher market share and generate better performance for investors.

⁸ In this thesis, the terms of hedge fund management firms and hedge fund families are used interchangeably.

Ramadorai and Streatfield (2011) analyse hedge fund fees at fund-families level and document an increasing trend in management fees and a declining tendency in incentive fees for newly launched funds over time. Analysing the cross-section of funds, they find that larger management firms with better performance are more likely to start new funds with higher management and incentive fees. However, there is no evidence that funds with high management fees at launch have higher returns than those with lower management fees, suggesting that investors paid such higher fees for nothing. This notwithstanding, there is still a weak positive relationship between incentive fees and future performance on a raw return basis.

A number of recent papers document the growth strategies of hedge fund firms and examine their interaction with fund performance and the incentives of managers (Kolokolova, 2011, Yin, 2016, Fung et al., 2017). Kolokolova (2011) investigates the strategic behaviour of fund families on decisions to launch a new fund and to liquidate family-member funds. Her findings indicate that hedge fund families with past superior performance are more likely to attract new capital inflows. In addition, Kolokolova (2011) finds that the compensation in dollars earned by managers in multi-fund companies are higher than those in single-fund companies although hedge funds in the former deliver significantly lower returns than the latter, implying the presence of diseconomies of scale in hedge fund families.

Similarly, while Yin (2016) presents more evidence on hedge fund firms by focusing on the conflict of interests between managers and investors, Fung et al. (2017) shed light on firms' strategic behaviour by investigating the effects from successful first funds (which they term stellar funds) to follow-on funds on performance and fee revenues. Yin (2016) argues that managers are incentivised to grow individual fund

assets beyond that which is optimal for fund performance. This finding also holds for fund families where hedge fund management firms have incentives not only to launch more funds but also to increase more capital for each fund under management despite the expense of fund performance (Yin, 2016). Fung et al. (2017) also focus on the performance differential between first and follow-on funds. They find that firms take advantage of successful first funds to start new funds which charge higher fees and have longer redemption and notice periods but underperform the flagship funds. This growth strategy has benefited firm managers but has hurt investors.

Likewise Yin (2016) and Fung et al. (2017), Sun and Teo (2019) pay attention to the agency problem within an asset management firm. The latter paper focuses on the alignment between hedge fund managers and investors as well as the fund performance implications of the private to public transition process of fund management firms. Hedge funds managed by listed firms are likely to be more successful in raising capital inflows for existing funds, launching new funds and earning more fee revenues than those managed by unlisted firms. However, Sun and Teo (2019) provide empirical results that show, for hedge fund firms, the process of going public not only deteriorates fund performance by 2.89% per year but also weakens the alignment between ownership, control and investment capital, thereby heightening conflicts of interest between fund investor and manager.

Taking a different approach, a publication by Edelman et al. (2013) addresses concerns relating to a data gap that overshadows the extant literature on hedge funds. By using privately collected performance characteristics at hedge fund firm level, Edelman et al. (2013) attempt to bridge the gap caused by the missing performance data associated with firms which do not participate in commercial databases and the missing return

records from reporting hedge fund firms. They directly compare the performance characteristics among these firms and find that mega reporting firms behave similarly to their non-reporting counterparts during normal market conditions. The authors are also the first to estimate the net impact of delisting bias on the performance of the hedge fund industry.

2.8 Summary and conclusions

This chapter outlines the extant literature on the data issues in the general financial sector, in the event study methodology (specifically in the context of pharmaceutical companies) and in the hedge fund industry. The chapter also details the literature on several hedge fund characteristics and their interactions with fund performance as well as the literature studies conducted at the management firm level. This section explores the current state of the literature in these areas and identifies that significant shortcomings in the financial data presents opportunities for the investigations carried out in the following chapters.

The chapter starts with a focus on the current state of financial data in general. The existence of erroneous data in all well-known secondary databases has raised many challenges for researchers conducting empirical studies because there is evidence that inaccurate data distort their research results. In the presence of these data problems, it is suggested that researchers carefully interpret their empirical results and that investors use academic implications therefrom with caution.

There is evidence that the event-day specification plays a vital role in event studies. Despite the fact that it is difficult in practice to identify when new information content

reaches the public, previous studies have applied several modifications in research design to examine the market effects of the event. In the specific context of the pharmaceutical industry, there is a large existing literature which provides evidence of a significant increase in shareholders' wealth following an FDA approval. Hamill et al. (2013) suggest the attention-grabbing hypothesis as an explanation for the significant post-event abnormal returns reported in their study. Another observation from the well-developed literature on the value relevance of earnings announcements is that properly accounting for announcement times in event studies potentially provides an alternative explanation. The evidence explains post-event abnormal returns as the misspecification of the event day zero in event studies due to the existence of after-hours earnings announcements (Berkman and Truong, 2009). The explanatory power of event-day misspecification has been identified for firms' earnings announcements but its application to explain stock market reactions surrounding FDA approval announcements has not yet been explored. This study uses a different data interpretation (i.e. accounting for announcement timings) in order to examine the shareholder wealth effects of FDA approval announcements and to proffer an alternative explanation for post-announcement abnormal returns. In so doing, this study provides new insights from old financial data.

There is a large body of literature about data-related issues in the context of the hedge fund industry. The voluntary reporting of the hedge fund data included in publicly available commercial databases is problematic for several reasons. First, because the data is self-reported, firms who choose to report performance to commercial databases often do so selectively and do not need to report data for all of the hedge funds managed by their firms (Edelman et al., 2013). Even for those hedge funds whose monthly data records are available in commercial databases, their reported AUM

records are often missing. Second, the evidence suggests that the self-reported hedge fund databases suffer from several well-known biases, including selection bias, survivorship bias and backfill bias. These data biases are found to distort the empirical results and call the conclusions drawn therefrom into question. Third, there is strong evidence that managers which self-report to commercial data vendors do so strategically which further exacerbates the hedge fund data accuracy and reliability problem. Some papers have identified alternative data sources to mitigate the data issues inherent in voluntary reported databases (such as the SEC form filings or FOFs). However, these alternative data sources have their own drawbacks. This study provides insights from new sources of financial data, and in so doing proposes the use of alternative and more reliable data sources to corroborate/contradict findings in the extant literature.

This study also contributes to the extant literature on diseconomies of scale for fund performance in the hedge fund industry and the effectiveness of the standard managerial contract (Yin, 2016, Fung et al., 2017, Lim et al., 2016). Previous studies commonly assume that fee revenues (estimated from self-reported returns to hedge fund commercial data vendors) equals manager compensation. However, this assumption overlooks the fact that hedge funds are managed by firms which often have operating costs that increase as AUM grows and do not take into account those cases where revenues might be generated from business lines other than managing hedge funds. Another major assumption of many empirical studies is that managers' compensation contracts are set at inception and fixed over time. More recent studies provide evidence that this is not true. That is, the investors can renegotiate contracts with fund managers as a result of both changes in fund size and past performance (Agarwal and Ray, 2011, Deuskar et al., 2013, Schwarz, 2007). Estimated fee revenues

in previous studies could not update the changes in fund fees throughout time because there is no time series of annual management fees and performance fees records in voluntary hedge fund databases. Furthermore, the AUM information reported to the commercial databases, which are critical for the fees estimation process, are not available for all funds and, in many cases, are infrequently updated. None of the earlier studies examine real manager compensation from hedge funds' fees alone. By using a new and novel financial dataset from hedge fund companies, this study fills this research gap.

Due to the increase in the number of funds offered by a given management company, a new strand of research has emerged that considers fund families as their basis of analysis. However, excepting a study of Edelman et al. (2013), the samples in these studies are basically collected from self-reporting commercial data vendors, such that these studies suffer from the same data problems well-identified in the literature. In addition, mainly due to data limitations, there is no literature that specifically examines the financial performance and firm characteristics of investment firms that manage hedge funds over time. To fill this research gap, this study creates a new source of audited accounting data from firm financial statements to provide a better understanding of the industrial organisation of hedge fund management companies. This novel dataset also proposes to be able to avoid current data issues inherent in the existing hedge fund databases and so provides new insights from new financial data.

Chapter 3 : FDA Approval Announcements:

Attention-grabbing or Event-Day

Misspecification?

3. FDA Approval Announcements: Attention-grabbing or Event-day Misspecification?⁹

Highlights

- *The R&D sector is an important enabler of innovation to support growth.*
- *The attention-grabbing hypothesis provides a behavioural explanation for abnormal returns for FDA approval announcements for NYSE listed firms.*
- *We support event-day misspecification as an alternative explanation.*
- *Increases in shareholder wealth are driven by after-market-close announcements.*

Abstract

The attention-grabbing hypothesis has been offered as a behavioural explanation for post-event abnormal returns for FDA drug approval announcements for NYSE listed firms. We show that when event-day misspecification is accounted for, the market reaction is centred on the event-day and that the increase in firm value is driven by after-market-close approval announcements.

JEL classification: O31; G14; G18; L11

Keywords: Research and Development; FDA; Attention-Grabbing; Pharmaceuticals; Event study

⁹ This paper has been published in *Economics Letter* (2018), volume 170, page 171-174. The research reported in this paper has been presented at the following conferences: *Irish Accounting & Finance Association Annual Conference*, IAFA Limerick, 2018 and *Irish Academy of Management*, IAM Cork, 2018. With co-authors: Philip A. Hamill, Mark Hutchinson and Mark Mulcahy.

3.1 Introduction

The importance of R&D in driving innovation is well established in the endogenous growth literature (Coe and Helpman, 1995, Dungey and Volkov, 2018). Subsidies and patents are two of the main tools of R&D policy to support and protect the outputs from innovation (Perez-Sebastian, 2015). In this paper, we focus our analysis on shareholder wealth effects for pharmaceuticals firms listed on the New York (NYSE) who were granted Food and Drug Administration (FDA) approval for new drug applications. Specifically, this paper investigates the impact of determining the exact timing of the market's reaction to FDA approval announcements and explores whether the attention-grabbing hypothesis provides an explanation for post-event abnormal returns reported (Hamill et al., 2013).

An insight from the accounting literature, Berkman and Truong (2009) show that post-event abnormal returns accompanying earnings announcements can be explained by misspecification of the event day 0 as an increasing proportion of earnings were announced after-hours. Consequently, after-hours earnings-related volume and price changes were observed with a lag of 1-day which had significant implication for measures of post-earnings announcement abnormal returns reported in the accounting literature. Differently, this study focuses on non-financial announcements (i.e. FDA new drug approvals) which are viewed as a key value driver for biotech-pharma firms (Hamill et al., 2013). On the other hand, from an economic perspective, corporate disclosure has been categorized into mandatory regulated financial statements and voluntarily disclosed information to reduce the information asymmetry (Healy and Palepu, 2001). The complexity of the pharmaceutical industry exacerbates information gap between investors and entrepreneurs (Hamill et al., 2013). Gennnotte and

Trueman (1996) imply that corporations strategically disclose mandatory announcements in order to take advantage of post-announcement value effects from different timing of earnings announcements. However, the random nature of the timing of the FDA announcements is different to earnings announcements. The precisely event-day specification, therefore, is becoming more important in the specific case of FDA new drug approvals.

Barber and Odean (2008) examine the day following extreme returns to mitigate endogeneity. In an event study context, strict application of their model implies possible post-event abnormal returns on day +1. They point out that news items, such as FDA approvals, will catch the attention of some investors, while the extreme one-day returns — the previous day's big gainers and losers — will catch the attention of others. The result is that many investors may learn of the extreme returns/news after the market closes such that their first opportunity to respond is the next trading day. *Ex-ante*, adjusting for event day misspecification and observing a positive market reaction on day +1 supports the attention-grabbing hypothesis and should provide impetus to explore this issue further. In contrast, accounting for after-market-close announcements and observing a market reaction exclusively on day 0 provides clear evidence of the impact of event-day misspecification and the need to make this adjustment when seeking to understand valuation effects accompanying FDA approval announcements, and for event studies in general.

3.2 Data

We identify original new drug approvals — including New Drug Applications (NDAs) and biologic license applications (BLAs) — from January 2009 to December 2015

from the US Food and Drug Administration (FDA) website. We note that drug approvals for sale in the US can be traded to another pharmaceutical company. Because the FDA monthly drug database only shows **current** information for the products listed (i.e. at December 2016)¹⁰, we also match the drug approvals database with the applicant column in the “*CDER Drug and Biologic Calendar Year Approvals*” list provided every year to align the actual sponsor companies with the FDA drug announcements. In our sample, all companies are listed on the New York Stock Exchange. To be included in the sample, firms must have daily share price data available to conduct an event study from DataStream. We exclude any observations with contemporaneous news announcements +/- 3 days from the LexisNexis database. Table 3.1 provides a breakdown of the 233 approval announcements from 2009 to 2015.

We use PRNewswire and Business Wire to identify the announcement dates and timestamps from press releases issued by the firm being granted a new drug approval. In the FDA’s ‘*Policy and Procedures for Communicating Approval Information*’, the information dissemination process from the FDA to the firm requires the regulatory project manager to promptly inform the application company of the FDA’s decision before notifying the FDA Press Officer¹¹. Therefore, there is a possibility that a firm’s own announcement may precede an announcement on the FDA website and other online sources. To ensure the timing of a drug approval announcement is exact we also searched for press releases on the company’s website. When timings from alternative

¹⁰ Note from FDA website, consulted December 2016.

¹¹ See FDA’s Policy and Procedures about Communicating Approval Information, consulted April 2017.

<https://www.fda.gov/downloads/AboutFDA/CentersOffices/CDER/ManualofPoliciesProcedures/UCM082010.pdf>

sources conflicted, the earliest timestamp was used. We identified the precise timings for 168 approval announcements comprising 6 before market opening releases (which released before 9:30 ET of the FDA announcement dates), 41 during market hours (those announced from 9:30 to 16:00 ET) and 121 after-close announcements (which occurred after 16:00 ET of the announcement dates or a couple of days after the FDA announcement dates).

Table 3.1. FDA approvals for NYSE listed pharmaceutical firms from 2009 to 2015

Year	Before market open	During market hours	After market close	No time stamps	Total by year
2009	0	2	21	12	35
2010	0	2	16	11	29
2011	1	7	15	10	33
2012	2	5	13	8	28
2013	2	4	15	9	30
2014	1	8	19	8	36
2015	0	13	22	7	42
Total	6	41	121	65	233

Notes: Before the market open for announcements released before 9:30 ET of the FDA announcement dates; during market hours for those announced from 9:30 to 16:00 ET; after the market close for FDA notifications occurred after 16:00 ET of the announcement dates or a couple of days after the FDA announcement dates.

3.3 Methodology

An event study methodology is employed to estimate abnormal returns to FDA approval announcements for a 43-day test period from day –21 to +21 with the market model estimated from day –150 to –22 with the S&P 500 market index used as the

market proxy. In the event study methodology, the market model¹² is employed as following form:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (3.1)$$

where ε_{it} is the abnormal returns accruing to shareholders in firm i on day t relative to the day of the announcement, R_{it} is the log daily returns to stockholders adjusted for dividends and other capital changes, R_{mt} is the daily natural log returns on the S&P 500 Market Index.

Scholes and Williams (1977) procedure is adopted to adjust the beta to account for the possibility of asynchronous prices when calculating returns. Their adjusted beta estimate is as follows:

$$\hat{\beta}_i = \frac{(\sum_{+n=1}^{+N} \hat{\beta}_i^{+n} + \hat{\beta}_i^0 + \sum_{-n=1}^{-N} \hat{\beta}_i^{-n})}{1 + 2 \sum_{+n=1}^{+N} \hat{\rho}_{+n}} \quad (3.2)$$

where $+N$ is the number of leads in the estimator; $-N$ is the number of lags in the estimator; and ρ_{+n} is the autocorrelation coefficient of the market model; β_i^{+n} and β_i^{-n} are the lead and lagged security beta respectively.

The intercept coefficient for specific stock i is calculated as follows:

$$\hat{\alpha}_i = \bar{R}_i - \hat{\beta}_i \bar{R}_m \quad (3.3)$$

¹² The market model — an example of a one-factor model — which is an improvement on the constant mean return model since the variance of the abnormal return is decreased (MacKinlay, 1997). Brown and Warner (1985, p.3) argue that “a simple methodology based on the market model is both well-specified and relatively powerful under a wide variety of conditions, and in special cases even simpler methods also perform well”. Moreover, because of the gains to additional explanatory power, the marginal benefits of employing multifactor models in an event study are limited, the market model is appropriate (MacKinlay, 1997).

where $\bar{R}_i$ and $\bar{R}_m$ are the return averaged over the estimation period on firm i and the market, respectively.

According to Hamill et al. (2002), the maximum lags/leads are set to ± 2 to adjust for thin trading bias. This is also consistent with Scholes and Williams (1977) and Fowler and Rorke (1983) in the investigation of asynchronous trading adjustments.

The abnormal returns for the event period are calculated by the difference between predicted returns and the actual returns:

$$\varepsilon_{i\tau} = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau} \quad \tau = -21, -20, \dots, +20, +21 \quad (3.4)$$

Then, taking average abnormal returns for the period τ as follows:

$$AR_{\tau} = \frac{1}{N} \sum_{i=1}^N \varepsilon_{i\tau} \quad (3.5)$$

Cumulative average abnormal return for various periods around the event day, for example, the period from day τ_1 to day τ_2 , is the sum of average abnormal returns for this period, and is defined as:

$$CAR_{\tau_1, \tau_2} = \sum_{j=\tau_1}^{\tau_2} AR_j, \quad -21 \leq \tau_1 \leq \tau_2 \leq +21 \quad (3.6)$$

We use Ruback (1982) test to calculate the significance of cumulative abnormal returns over different holding periods. As the series of error terms ($\varepsilon_{i\tau}$) experience first-order autocorrelation, the series of abnormal returns are auto-correlated (Ruback, 1982). The variance of the cumulative abnormal returns is:

$$\text{Var}(CAR_{\tau_1, \tau_2}) = T * \text{Var}(AR_{\tau}) + 2 * (T - 1) * \text{cov}(AR_{\tau}, AR_{\tau+1}) \quad (3.7)$$

where $T = \tau_2 - \tau_1 + 1$

The t-statistics for the cumulative average abnormal returns over the period day τ_1 through day τ_2 as follows:

$$t = \frac{CAR(\tau_1, \tau_2)}{\sqrt{\text{Var}(CAR_{\tau_1, \tau_2})}} \quad (3.8)$$

Mean abnormal returns as a measure of central tendency are susceptible to the influence of outliers. To ameliorate their influences, and to corroborate the results for the parametric event study, Corrado (1989) non-parametric rank test is also employed as a robustness check. A problem with previous non-parametric tests, i.e. the signed rank and sign tests emphasized by Brown and Warner (1980, 1985) is the requirement of symmetrical distributions of excess returns distributions for correct test specification. On the other hand, Corrado (1989) offers a nonparametric rank test for abnormal returns in an event study nevertheless the skewness level of the cross-sectional distribution of excess returns. This test is less impacted by an event-day excess-return variance increase compared with the parametric tests. When abnormal performance exists, the rank test is more powerful than its parametric counterparts.

According to Corrado (1989), in order to implement the rank test, it is necessary to transform the time series of market-model abnormal returns into their respective ranks. The ranking procedure transforms the distribution of security excess returns into a uniform distribution across the possible rank values, regardless of any asymmetry in the original distribution. Under the null hypothesis, a day 0 excess-return rank is a drawing from a uniform distribution.

3.4 Results

Table 3.2 panel A columns 1 and 2 report the results for the unadjusted sample which simply takes the approval date announced by the FDA and ignores the time of the announcement — which could be before-market-close (BMC), or after-market-close (AMC). As would be expected, given insider trading restrictions, and consistent with the empirical literature, the pre-event mean abnormal returns on day -1 and CARs over the holding periods (-10:-1) and (-5:-1) are statistically insignificant. The market reaction on day 0 is also insignificant whereas the mean abnormal return of 0.44 of a percent on day 1 is significant with a t -statistic of 4.61. Ostensibly, this would support the attention-grabbing hypothesis. The economic importance of this economically and statistically significant day 1 mean abnormal return is evident from the post-event abnormal returns, i.e. the CAR holding periods (1:2) and (1:21) are also statistically significant but that for period (2:21) is insignificant.

Table 3.2. Shareholder wealth effects around FDA new drug approval announcements

	<i>Unadjusted</i>		<i>Event adjusted</i>		<i>Event and time stamp adjusted</i>	
	<i>AR/MR^a</i> <i>N = 233</i>	<i>t-stat</i>	<i>AR/MR^a</i> <i>N = 233</i>	<i>t-stat</i>	<i>AR/MR^a</i> <i>N = 168</i>	<i>t-stat</i>
<i>Panel A: Parametric tests</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
[-10, -1]	0.18	0.62	0.15	0.48	0.14	0.34
[-5, -1]	0.17	0.81	-0.08	-0.36	-0.19	-0.69
-1	-0.08	-0.89	0.06	0.57	0.05	0.40
0	-0.03	-0.36	0.42**	4.22	0.61**	4.90
1	0.44**	4.61	0.11	1.07	0.04	0.28
2	0.07	0.69	-0.06	-0.58	-0.09	-0.77
[1, 2]	0.50**	3.83	0.05	0.34	-0.06	-0.35
[1, 21]	0.97**	2.32	0.53	1.18	0.39	0.68
[2, 21]	0.53	1.30	0.43	0.97	0.35	0.63
<i>Panel B: Corrado's Non-Parametric tests</i>						
-1	-2.33	-0.68	2.42	0.73	2.03	0.49
0	-2.22	-0.64	2.13	0.64	4.54	1.11
1	6.58*	1.91	5.18	1.56	4.13	1.01

Notes: ^aAR is mean abnormal returns from the parametric events study, while MR is the mean rank from Corrado's (1989) non-parametric rank test. * denotes significant at the 5% level, ** denotes significance at the 1% level or less. N is the sample size.

Columns 3 and 4 report the results when the sample is event-adjusted to identify day 0 as the day investors are able to trade on the information. Table 3.1 highlights that, for the total sample of 233 announcements, 121 took place AMC. The adjusted sample treats these AMC announcements as if they occurred on event day 0 given that the stock price cannot reflect this information until the following day. When the dataset is thusly re-centred, day 0 has a positive market reaction of 0.42 of a per cent with a *t*-statistic of 4.22 and day +1 becomes insignificant. Columns 5 and 6 report the results from this re-centred excluding the 65 announcements where a timestamp could not be identified. The market reaction on day 0 remains statistically significant with a mean abnormal return of 0.61 of a percent and accompanying *t*-statistic of 4.90.

From a firm valuation perspective, these results support the hypothesis that FDA approval announcements are value-relevant and convey new information to the market. From a theoretical perspective, the value of firms in the pharmaceutical sector can be viewed as a portfolio of real options (Hartmann and Hassan, 2006) which recognises that R&D projects are a collection of bets with a low probability of paying off given the observed empirical probability of success for new drug discoveries¹³. Pharmaceutical investors hope that a small number of successful R&D projects will experience extremely large returns associated with blockbuster discoveries¹⁴. To evaluate the possibility that the market reaction reflects a few extreme observations, we use Corrado (1989) non-parametric rank test as a robustness check. The results in panel B of Table 3.2 show that, for the unadjusted sample, day +1 remains significant at the 5% level with a mean rank of 6.58. For both the event-adjusted sample and the event- and timestamp-adjusted sample, none of the days are statistically significant which indicates that the mean abnormal return of 0.61 of a percent reported in panel A is influenced significantly by a few large observations — an outcome consistent with the payoff from a portfolio of real options.

¹³ One estimate is that approximately 5 out of 5000 new chemical entities progress to human clinical trials with only 1 likely to be granted FDA approval (Dedman et al., 2008).

¹⁴ The FDA approval of the muscular dystrophy drug Eteplirsen 2016 increased the share price of Sarepta Therapeutics by 90%. “FDA Approves Sarepta’s Muscular Dystrophy Drug”, Wall Street Journal, September 19th, 2016.

Table 3.3. Before and after market close analysis

Days	<i>Before-market-close</i>		<i>After-market-close</i>	
	<i>AR/MR^a</i>		<i>AR/MR^a</i>	
	<i>N=47</i>	<i>t-stat</i>	<i>N=121</i>	<i>t-stat</i>
<i>Panel A: Parametric test</i>				
-1	0.27	1.31	-0.03	-0.23
0	-0.18	-0.89	0.92**	6.23
1	-0.06	-0.32	0.07	0.50
<i>Panel B: Corrado's Non-Parametric test</i>				
-1	13.76*	1.86	-2.52	-0.51
0	-10.03	-1.36	10.20*	2.08
1	11.55	1.57	1.25	0.26

Notes: ^aAR is mean abnormal returns from the parametric events study, while MR is the mean rank from Corrado's (1989) non-parametric rank test. * denotes significant at the 5% level, ** denotes significance at the 1% level or less. N is the sample size. The 47 BMC announcements comprise 6 before market open announcements and 41 during market hours.

Table 3.3 reports the results for the parametric event study and Corrado's nonparametric rank test for the BMC and AMC announcements. None of the BMC mean abnormal returns for days -1, 0 and +1 are statistically significant. Day -1 is significant at the 5% level for the rank test. The lack of consistency for the BMC sample provides strong support for an economically significant market reaction. In contrast, the AMC announcements are statistically significant for both tests with an economically significant market reaction of 0.92 of a percent that is significant at the 1% level. There is no evidence of market reaction on days -1 or + 1 for the parametric or non-parametric tests for the AMC sample.

To shed further light on companies who announce FDA approvals before the market closes and who release announcements after the market closes, we next examine several characteristics of firms belong to two subsamples. Specifically, to investigate difference in the firm-specific means and medians of each proxy of firm size (i.e.

market capitalization, EBIT, and net sales) between the BMC and AMC samples, a parametric t-test and a nonparametric Wilcoxon (Mann-Whitney) rank test are conducted.

Table 3.4. Firm characteristics for BMC and AMC samples

This table presents average firm market value, earnings before interest & tax (EBIT) and net sales for BMC and AMC samples. *Market value* is the market capitalization in \$US millions at approval date, *EBIT*, and *net sales* are collected at year end in \$US thousands. These firm characteristics are the average of all firms in each subsample. The *p*-value in column (4) is based on t-test that means of each proxy for firm size between BMC and AMC group are not significantly different. Similarly, the *p*-value in column (5) is based on a nonparametric Wilcoxon (Mann-Whitney) rank test that medians of two subsamples are not significantly different. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 level, respectively.

<i>Firm characteristics</i>	<i>BMC</i>	<i>AMC</i>	<i>Difference</i>	<i>p-value</i>	
				<i>H₀: $\mu_1 = \mu_2$</i>	<i>H₀: $\eta_1 = \eta_2$</i>
	(1)	(2)	(3)	(4)	(5)
Market value	134,089	103,951	30,138	0.01***	0.02**
EBIT	8,636,495	6,934,555	1,701,941	0.04**	0.07*
Net sales	41,600,000	32,800,000	8,876,833	0.02**	0.04**

Table 3.4 shows that BMC firms are larger and have more earnings and net sales than AMC firms. Column (4) reports that all these differences are significant at the 1% and 5% level. In addition, a nonparametric Wilcoxon (Mann-Whitney) rank test shows similar results for the different medians between the BMC and AMC groups. Both tests provide evidence that firms with announcements taking place before the close of trading are larger than those with notices making after the market close. Our evidence supports that firm size might cause the difference in price changes resulting from approval decisions between the two groups (i.e. BMC and AMC). Larger firms, which are more widely followed by analysts, would have greater information diffusion about

the expectation of a positive FDA announcement, whereas smaller firms which are less widely covered by analysts are more likely to have positive surprises.

3.5 Conclusion

Our results improve the understanding of the relationship between FDA drug approval announcements and shareholder wealth and imply the importance of properly aligning event day zero in the event study. We show that when an appropriate adjustment for timing is made, the positive market reaction to FDA approval announcements is centred on day 0 and is driven by after-market-close announcements. Our results are robust to the influence of outliers. Our findings show that the lagged abnormal return following an FDA announcement reported in prior studies may be due to incorrect identification of day zero. We find a significant extreme stock price change on the event day for the adjusted sample, demonstrating the effect of approval decisions on shareholders' value. However, different from Sarkar and de Jong (2006) and Hamill et al. (2013), this market reaction disappears the following day. This analysis supports event-day misspecification as opposed to the attention-grabbing hypothesis as an explanation for shareholder wealth effects. Second, by examining the differences in stock market reaction to FDA approval announcements that occurred before and after the market close, we also contribute to the extensive literature on interaction between announcement times and value-relevance of non-financial information (Patell and Wolfson, 1982, Francis et al., 1992, Gennotte and Trueman, 1996, Greene and Watts, 1996, Berkman and Truong, 2009).

Chapter 4 : Just How Profitable is it to Manage a Hedge Fund? Insights from Company Filings

4. Just How Profitable is it to Manage a Hedge Fund? Insights from Company Filings¹⁵

Abstract

We provide evidence on the profitability of the investment management companies which manage hedge funds, using a novel dataset. Using hand-collected private company information for hedge fund management companies (HMCs) registered in the United Kingdom, we show what the true profitability of HMCs has been over time, and why it varies across HMCs. Our results show that HMCs generated particularly high profitability (ROA of 46% per annum) and revenue growth (95% per annum) up to 2008. With the onset of the global financial crisis, profitability and revenue growth declined. Prior research shows that the standard hedge fund management contract incentivises the manager to grow the assets in the funds they manage, even if it leads to deteriorating fund performance. We find that size is the key determinant of cross-sectional variability in HMC profitability. Larger HMCs, benefiting from larger dollar management and performance fees income, generate significantly higher profitability. This difference is particularly acute during the financial crises.

JEL Classification: G23, G30, G01.

Keywords: Hedge funds; Private Companies; Firm profitability; Global financial crisis.

¹⁵ The research reported in this paper has been accepted to present at the following conferences: *Financial Management Association Annual Meeting*, FMA New Orleans 2019 and *FMA European Conference*, Glasgow 2019. The paper was withdrawn due to the novelty of the data. With co-authors: Philip A. Hamill, Mark Hutchinson and Mark Mulcahy.

“Hedge fund stars rake in billions for new funds” Financial Times, May 27th, 2018

4.1 Introduction

Worldwide close to \$3 trillion is invested in hedge funds. Each of these hedge funds is managed by an investment management company, paid fees for managing the fund. Extensive research has focused on the fee-based incentives for the investment manager for managing the fund, typically made up of an annual management fee and a performance fee (2 and 20), and the performance of the investments chosen by the investment management company. The hedge fund industry enjoyed tremendous growth in the early 2000s. While recent industry reports indicate that the industry may be maturing, with more hedge funds closing than opening, they continue to play an increasingly important role as financial intermediaries in diverse areas such as activist-investing and non-bank financing.¹⁶ Nevertheless, very little is known about the industrial organisation of the companies of investment managers who manage hedge funds, mainly due to data limitations. This paper seeks to fill that gap using a novel dataset of hedge fund management companies’ accounting data.

Unlike the US, where hedge fund management companies are registered as limited liability corporations (LLCs) or limited liability partnerships (LLPs) (typically in Delaware), virtually all hedge fund management companies in the UK are structured as private limited companies. Filing requirements for private limited companies in the United Kingdom are quite onerous, with all private companies (with the exception of very small entities) being required to file annual financial reports with Companies

¹⁶ In 2017, according to data from Hedge Fund Research, 784 funds went out of business compared with 735 that launched. “More hedge funds closed than started globally in 2017”, Reuters March 23rd, 2018.

House each year. This filing requirement allows us to create and analyse the first database of financial accounting information of companies which manage hedge funds.

We are not the first authors to consider the profits which accrue to the managers of hedge funds. The first paper on this topic was Goetzmann et al. (2003), who considered the valuation of hedge fund management companies using their forecast fee income, conditioned on AUM. Yin (2016) addresses similar issues, considering the size of a hedge fund which optimises the manager's compensation and extends the literature by showing that this result is sub-optimal returns to investors in the fund, due to diseconomies of scale. Due to data limitations, none of these papers address profitability of the hedge fund management company, instead assuming estimated fee income equates to compensation, nor do they use actual audited accounting information, instead relying on voluntary disclosure by the hedge fund management company to commercial hedge fund databases. Many of our most important conclusions are driven by the new insights which are drawn from the novel accounting data.

There has been a growth in regulation and institutional requirements post the global financial crisis, which has increased the costs of operating a hedge fund management company. Before 2008, it was possible to manage a hedge fund with a small team of less than ten professionals. With the requirement for new periodic regulatory filings in the US (Form PF and Form 13F to the SEC) and the growth of regulation in the EU (UCITs, MIFID), hedge fund management companies typically employ teams of

compliance officers.¹⁷ Cumming et al. (2017) show the negative effect on the performance of this regulation. For the first time, we are able to capture the effect of these changes in the industry on profitability; and assess which HMCs are best able to maintain profitability.

Our paper makes two key contributions to the hedge fund literature. We provide the first evidence on the financial performance of these companies, finding that the profitability and revenue growth of hedge fund management companies peaked in the period prior to the Global Financial Crisis, before falling sharply and remaining at these lower levels. Over time, our sample of firms have strengthened their balance sheets, increasing investments in fixed assets and improved their working capital management positions. These findings provide new evidence to support recent research on the life cycle of the hedge fund industry (Getmansky (2012) and Getmansky et al. (2015)) and the effect of regulatory changes on performance (Cumming et al., 2017).

Our second and the most important contribution is in relation to cross-sectional variation in profitability. It has been documented that despite of diseconomies of scale to investment performance, hedge funds typically continue to seek to grow assets, beyond optimal levels for investors, due to direct and indirect incentives around fees (Lim et al. (2016) and Yin (2016)). Our results confirm that size matters to profitability. Over the full sample, increasing the total size of the management company leads to an 18 percent increases in profitability. During the global financial crisis, size became even more important with an additional 5 percent increase in

¹⁷ “Hedge funds hunt for bank compliance officers looking to switch tracks”, Financial News London, January 4th, 2017.

profitability for increasing size. These findings confirm that for the manager of a hedge fund, given the structure of their compensation contract, it is rational to maximise fund size, even at the expense of performance (Yin, 2016).

The remainder of the paper is organized as follows. Section 4.2 provides a review of the relevant hedge fund literature. Section 4.3 describes our data. Section 4.4 reports our results. Section 4.5 presents our conclusions.

4.2 Institutional background and related literature

Hedge funds and their management companies have historically had minimal reporting obligations. Since 2012 in the US, management companies that have at least \$150 million in AUM are now required to report key operational and risk data periodically using Form PF to the Securities and Exchange Commission (SEC). However, the data submitted using Form PF is not publicly available. Hedge funds above a certain size are also required to file Form 13F with their long portfolio holdings to the SEC. This data is publicly available but provides no information on the investment management company.

Because hedge funds use proprietary intellectual property to generate their returns, they are consequently motivated to be opaque. However, this is offset by their motivation to raise more capital for the funds they manage. Hence, many funds voluntarily report their returns and fund characteristics to commercial hedge fund databases, such as BarclayHedge, HFR and TASS. However, there is no such motivation for hedge fund management companies to report the profitability of their own companies, so this data is not voluntarily disclosed to these database vendors.

The voluntary nature of hedge fund reporting to commercial database vendors leads to several challenges for researchers, which have been well documented in the literature. These include “survivorship bias” and “instant history” bias. Hedge funds also tend to avoid reporting small negative returns (Bollen and Pool, 2009), report inflated performance at year-end (Agarwal et al., 2011) and even strategically choose when to report returns to the databases (Aragon and Nanda, 2017) or to cease reporting. Aiken et al. (2013) confirm that the performance of funds that do not report or cease reporting to a database is much lower than reporting funds.

Prior to the introduction of Form PF, the SEC introduced a requirement to file Form ADV, a regulatory tool designed to allow market participants to measure operational risk of hedge fund investment managers, which was subsequently overturned in the judicial system. This filing did provide information on ownership and key operational risk factors but did not provide detailed accounting information (Brown et al., 2008b). Recent research has documented new information in Form 13F filings about hedge fund performance (see for example Aragon et al. (2013)) but no information is reported in these filings on hedge fund management company financial performance.

There is a large literature focused on direct and indirect managerial incentives of hedge fund managers. In general, research finds that large direct incentives and investor discretion are associated with better performance (Agarwal et al., 2009), but others have focused on some of the indirect incentives, which are less geared towards performance. Goetzmann et al. (2003) model performance fees as a claim on investor wealth, allowing them to develop a framework for valuing a hedge fund management company, which increases with AUM, while Lim et al. (2016) show that high current returns lead to increased AUM, which leads to increased future annual management

fees, which are larger than the current performance fees, particularly for younger funds. In related research, Aragon and Nanda (2011) focus on the extent of risk-shifting behaviour of hedge fund managers, conditioned on the current NAV of the fund relative to the high-water mark, to maximise incentive fees.

We hypothesise that when we examine the financial performance of hedge fund management companies, size will be the key determinant of HMC profitability. Research shows that managers appear to grow their fund beyond the optimal size for maximising investor returns (Teo (2009) and Getmansky (2012)). Once a fund gets too big, it becomes more difficult for the manager to generate high returns due to relatively limited investment opportunities, the negative price impact of large block trading, and the need to reduce overall fund volatility to satisfy large institutional investors (Yin, 2016). Fund performance begins to deteriorate. Given the performance fee that the hedge fund manager earns on the returns to the fund, it would appear sub-optimal for the hedge fund manager to grow the assets of their fund too big.¹⁸ However, given the hedge fund manager is incentivised to maximise the dollar amount of their fees, it may be optimal from the managers perspective to grow the assets of the fund, in order to have a larger dollar annual management fee and large dollar performance fee (though it may be lower in percentage terms). Yin (2016) show that managers' dollar fees can increase when fund assets grow, even when diseconomies of scale in fund performance exist.

¹⁸ Some managers close their funds to new investors in order to avoid diseconomies of scale. In an extreme case, Bluecrest Capital Management returned \$7 billion in outside capital to its investors, instead choosing to only invest with the Partners capital, due to diseconomies of scale. Subsequently, investment returns increased to 50% in 2016 and 54% in 2017. "Platt's BlueCrest Gains 54% in Blockbuster Year", Bloomberg, January 4th, 2018.

4.3 Data

In the United States, hedge fund management companies are either registered as limited liability corporations (LLCs) or limited liability partnerships (LLPs), typically in Delaware. Companies registered in the US are generally not required to file financial accounting data, so to-date it has not been possible to conduct research on the profitability of HMCs. However, the requirements for private companies to file financial accounting data vary across countries. In the United Kingdom, private limited liability companies are required to file their full accounts at Companies House.¹⁹

Due to this filing requirement, there is a large corporate finance literature examining private UK companies. The Bureau Van Dijk FAME database contains the most recent ten years of digitized accounting information filed by all UK and Ireland companies. In addition, it also contains all PDF copies of the actual filings made by the companies to Companies House since 2004.

In order to identify UK hedge fund management companies, we match management companies registered in the UK from the TASS database of hedge funds with the FAME database of UK companies. Our academic version of the TASS database does not include the HMC name, only including the web address, e-mail address, postal address and telephone number. Using the contact details from the TASS database, we use a web search to match the contact details with the HMC name. Next, using the HMC name and the contact details from TASS, we identify the HMC in the FAME database. We exclude HMCs which are dissolved prior to 2004 (6 companies), HMCs

¹⁹ With the exception of small and micro companies which are only required to file abridged accounts.

which are restructured via merger or acquisition (3 companies) or change their accounting policies (1 company). This leaves us with a sample of 483 UK private hedge fund management companies.²⁰

As FAME only keeps the most recent 10 years of accounting information in their database, having identified the HMCs in the FAME database, we are only able to download the most recent ten years of accounting data for each HMC up to the 2017 accounting year, or their final year of filing. For firms which cease trading before 2017, we are able to download the most recent ten years of accounting information up to and including the final filing year. As this excludes pre-2008 accounting information for all HMCs still alive at the end of 2017, we also hand collect accounting information for the years 2004 to 2007 using PDFs of company filings for the companies. We firstly download PDFs of company reports from year 2004 to 2007 which provide comprehensive accounting information for each company. We then collect all required accounting data for the calculation from these PDF reports, such as total assets, turnover, profit (loss) before/after tax, current assets, current liabilities, etc. Further, we find that some obvious outliers in the sample. For example, some companies report total assets as low as £1. Such noise potentially biases the analysis and make it difficult to measure firm performance accurately. To minimise the effect of outliers, all accounting data is constrained to be within the 1st and 99th percentile of the distribution²¹.

²⁰ We observe that firms classified on FAME as banks account for a significant proportion of our dataset (23% of total firms) and their total turnover represented around 79.5% of total sales. To ensure the results are not driven by sample selection bias, all regressions are re-run having removed these firms. All findings are consistent with reported results. This robustness test is presented in Appendix 4.A.

²¹ In order to test the robustness of the results, all tests are repeated using unwinsorised data to verify the findings are not affected by the winsorisation process. The results with unwinsorised data are shown in Appendix 4.A.

Our final sample covers a fourteen-year period, from 2004 to 2017 with a total of 4,843 firm-year observations. This sample covers a period of great change in the hedge fund industry and is ideal for analysis of hedge fund profitability. There is a period of tremendous growth for the hedge fund industry up to 2007, the global financial crisis from 2008 to 2010 and a seven-year period of post-global financial crisis performance.

4.4 Empirical findings and discussion

In order to assess the profitability and determinants of profitability of HMCs, we take two main approaches. We first calculate financial ratios and examine them in different sub-sample periods and by calendar year. Next, we estimate a regression model of the determinants of profitability, and then examine the effect of the global financial crisis on hedge fund profitability and its determinants.

To measure performance, we specify Return on Assets (ROA) as it is most commonly used in the private company literature (see for example Megginson et al. (1994)).²² We include four standard control variables in addition to size in our analysis to explain profitability: firm liquidity, firm growth, asset tangibility and leverage.

4.4.1 HMC financial ratios

We calculate financial ratios measuring profitability, size, leverage, liquidity, growth in turnover, and asset tangibility. We compare the mean values of these ratios for sub-

²² ROA is defined as profit before tax divided by total assets. As a robustness test, all tests are repeated with ROA calculated from profit after tax. Results that are reported in Appendix 4.A are unchanged.

samples covering the whole sample period, a period pre-Global Financial Crisis (2004 to 2007), the GFC period (2008 to 2010), and the most recent seven years post the recession (2011–2017) in Table 4.1.

Table 4.1. Firm characteristics of hedge fund management companies

This Table presents the mean values (standard deviations) collected from the FAME database of UK private companies, who manage hedge funds in the TASS database, from 2004 to 2017. This Table reports the number of observations, mean and standard deviation covering the whole sample period, before, during and after the global crisis used a number of ratios relating to firm profitability: return on assets (ROA) and firm characteristics: size (Natural logarithm of turnover); leverage ratio (Total liabilities/Total assets); liquidity ratio (Current assets/Current liabilities); tangibility (Fixed assets/Total assets); and growth in turnover.

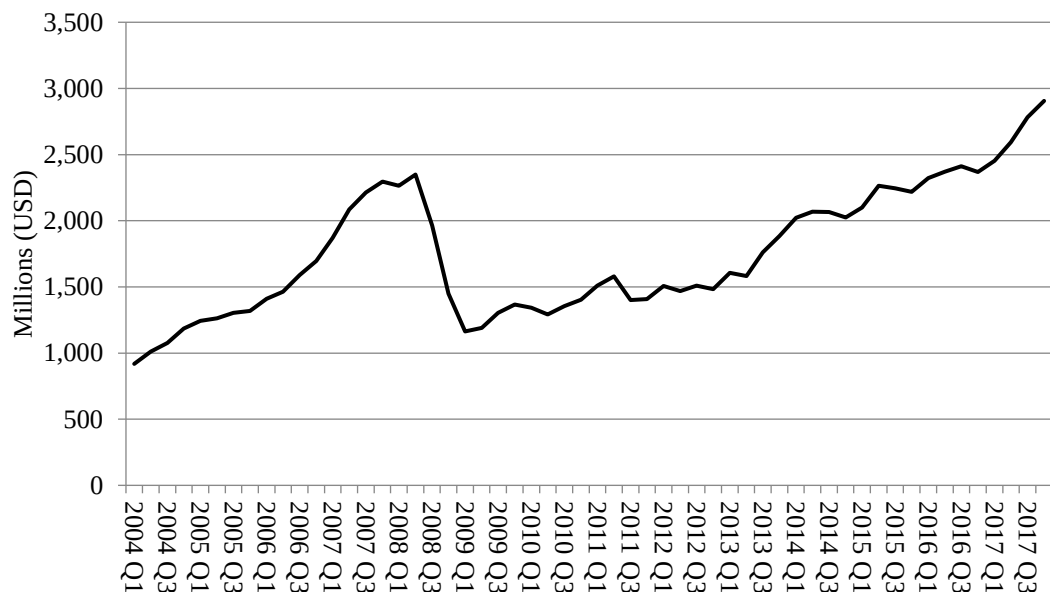
Variables	Full sample: 2004–2017		Pre-crisis period: 2004–2007		Crisis period: 2008–2010		Post-crisis period: 2011–2017	
	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Profitability (ROA)	4,361	36.80 (100.83)	1,186	46.80 (112.10)	1,065	38.73 (108.85)	2,110	30.20 (88.77)
Size	4,101	15.22 (2.30)	1,116	15.10 (2.26)	995	15.10 (2.28)	1,990	15.35 (2.33)
Leverage	4,790	48.02 (48.21)	1,260	50.71 (42.88)	1,156	45.09 (42.73)	2,374	48.01 (53.09)
Liquidity	4,685	13.41 (46.43)	1,223	9.73 (35.03)	1,131	12.00 (43.69)	2,331	16.03 (52.44)
Growth	3,564	39.34 (150.89)	767	94.71 (206.11)	895	31.43 (154.99)	1,902	20.73 (112.45)
Tangibility	3,638	18.28 (27.02)	947	16.06 (24.36)	882	17.38 (25.87)	1,809	19.88 (28.75)

The mean ROA and growth in turnover are higher in the pre-GFC period than in the other periods. We suggest that the period from 2004 to 2007 was a period of abnormal growth and profitability for HMCs. For illustration, we also report the estimated AUM

of the entire hedge fund industry by BarclayHedge in Figure 4.1. This shows a dramatic drop off in AUM post the GFC with AUM only recovering to pre-crisis levels in the second quarter of 2016. From 2008 onwards, the onset of the GFC has resulted in the returns to hedge funds being lower (Getmansky et al., 2015), lower performance fees, and consequently fewer opportunities for HMCs to generate high income growth and profitability.

Figure 4.1. Hedge fund industry AUM

This Figure displays the AUM of the hedge fund industry from the period 2004 to 2017. Source: BarclayHedge.



In contrast, the mean liquidity and tangibility of HMCs has increased post the pre-crisis period. With the onset of the GFC, it became necessary for HMCs to reduce exposure to short term liabilities, holding higher current assets (including cash) relative to current liabilities, due to the reduction in short term financing available. Likewise, it became necessary for HMCs to hold a higher proportion of fixed assets.

With respect to size and leverage, both stayed relatively constant across time, though there was a small decline in leverage during the GFC. The size data is reported as the natural log of annual turnover, so this equates to mean turnover of approximately £4.5 million per annum.

Table 4.2. Firm characteristics of hedge fund management companies in each accounting year

The Table presents the mean data for UK private hedge fund management firms for each accounting year in the period 2004–2017 used a number of ratios relating to firm profitability: return on assets (ROA) and firm characteristics: size (Natural logarithm of turnover); leverage ratio (Total liabilities/Total assets); liquidity ratio (Current assets/Current liabilities); tangibility (Fixed assets/Total assets); and growth in turnover.

Year	Profitability	Size	Leverage	Liquidity	Growth	Tangibility
2004	19.07	14.75	54.65	8.67	-	16.98
2005	40.88	14.95	53.48	8.68	129.19	15.86
2006	58.79	15.22	49.90	10.03	103.11	15.52
2007	58.62	15.35	46.45	11.02	63.86	16.19
2008	50.36	15.25	45.50	12.27	40.58	15.84
2009	29.81	14.97	42.59	11.29	14.00	17.40
2010	35.81	15.09	47.05	12.42	38.94	18.82
2011	31.18	15.27	45.55	15.26	25.85	19.33
2012	23.64	15.18	43.20	13.21	9.76	18.80
2013	22.92	15.33	47.34	14.42	32.03	19.65
2014	36.85	15.44	48.95	16.29	28.30	20.31
2015	28.09	15.50	52.49	19.20	22.89	20.77
2016	31.76	15.50	51.43	18.03	7.29	20.67
2017	72.81	14.83	46.23	16.83	5.73	19.51

The annual trends in the above ratios are shown for each accounting year in Table 4.2. Over the periods, profitability steadily increased from 2004 to 2008, before declining markedly in 2009 and remaining at this low level until 2016. Notably, profitability has

jumped in 2017. Growth in turnover was extremely high in 2005 and 2006 (with mean turnover doubling in each year) before declining to a growth rate of 14 percent in 2009. Subsequently, turnover has grown at between 5.7 and 32 percent, never matching the pre-GFC years. The average size of the HMCs is notable in that they have stayed relatively constant for the full 14 years as has leverage. Both liquidity and tangibility have steadily increased, with the ratio of current assets to current liabilities doubling between 2004 and 2017. Again, these findings are consistent with improved working capital control and balance sheet strength, being required by HMCs subsequent to the onset of the global financial crisis.

4.4.2 Determinants of HMC profitability

The evidence from existing literatures regarding to determinants of firm profitability is mixed (Booth et al., 2001, Lee, 2009, Deloof, 2003, Greiner, 1972). However, these studies often employ sample of listed firms due to lack of data accessibility (Booth et al., 2001, Lee, 2009) or exclude financial industry from their sample because of the specific nature of their activities (Deloof, 2003, Goddard et al., 2005, Pattitoni et al., 2014). Other studies that examine factors affecting firm profitability and efficiency only focus on banking industry (Bourke, 1989, Molyneux and Thornton, 1992, García-Herrero et al., 2009, Sufian, 2009, Berger and Bouwman, 2013).

The economies of scale theory states that larger firms which have more market power tend to have higher profit rates than their smaller counterparts (Baumol, 1959, Hall and Weiss, 1967, Lee, 2009); therefore a positive relationship between firm size and profitability is expected.

The agency cost model developed by Myers (1977) and Jensen (1986) in which debt is likely to mitigate overinvestment problem but worsen the underinvestment problem. Highly geared firms have to face cash constraints which may require them to give up some profitable investment opportunity (Rajan and Zingales, 1995, Booth et al., 2001, Graham, 2000, Capon et al., 1990); therefore, a negative correlation between leverage and profitability is expected. On the other hand, the trade-off theory supposes that although debts might increase the risk of bankruptcy undertaken by firms, debts still benefit shareholders if profit exceeds borrowing costs. Thus, a positive/negative relationship is expected between firm leverage and performance.

Firms with high liquidity might reduce the risk of being unable to repay short-term financial liabilities and flexibly react to sudden adverse changes in its environment, implying a beneficial effect on profitability (Goddard et al., 2005); therefore, we expect that firm liquidity is positively correlated with company performance. Employees in company with higher investment and growth opportunities are likely to have more working motivation, increase their productivity, and therefore improve firm profitability (Greiner, 1972, Capon et al, 1990). Firms that have higher tangibility are expected to have less profitability because high liquid firms are easier to access to long-term investment opportunities (Griliches and Lichtenberg, 1984, Deloof, 2003); therefore, a negative relationship between tangibility and performance is expected.

We next estimate a regression model of the determinants of HMC profitability, where profits (ROA) are defined as a function of a number of firm-level variables specified in the prior literature: Size, Leverage, Liquidity, Growth in Turnover and Tangibility.

All variable definitions and selected empirical studies on the determinants of firm profitability are summarized in Table 4.3.

Table 4.3. Variable definitions

This Table describes the dependent and independent variables and selected literature on the determinants of firm profitability.

Variable	Acronym	Author(s) (year of publication)	Description	Expected effect
<i>Profitability</i>				
Return on Assets	ROA		Profit before tax divided by total assets (%)	n.a.
<i>Explanatory Variable</i>				
Size	SIZE	Goetzmann et al. (2003), Lim et al. (2016) and Yin (2016)	The natural logarithm of turnover	+
<i>Control Variables</i>				
Leverage	LEV	Capon et al. (1990); Rajan and Zingales (1995); Booth et al. (2001); Maury and Pajuste (2005); Huang et al. (2015)	Total liabilities divided by total assets (%)	+/-
Liquidity	LIQ	Maury and Pajuste (2005); Faulkender and Wang (2006); Bates et al. (2009); Kieschnick et al. (2013); Capon et al. (1990); Huang et al. (2015)	Current assets divided by current liabilities	+
Growth	GROW	Capon et al. (1990); Maury and Pajuste (2005); Huang et al. (2015)	The annualized growth rate of sales (%)	+
Tangibility	TANG	Capon et al. (1990); Maury and Pajuste (2005)	Fixed assets divided by total assets (%)	-
<i>Dummy Variables</i>				
Crisis Dummy	CRIS		A dummy variable set equal to 1 for years during the financial crisis, and zero otherwise	-
No-Crisis 1	NC1		A dummy variable set equal to 1 for years prior to the financial crisis, and zero otherwise	+
No-Crisis 2	NC2		A dummy variable set equal to 1 for years after the financial crisis, and zero otherwise	+

We employ two panel estimation methods for our regression model: Firm Fixed Effects (FFE) and Firm & Year Fixed Effects (a specification we label FYFE). Robust standard errors are clustered at the firm level.

Initially, we consider the correlation matrix amongst variables in Table 4.4 in order to point out the correlation among variables as well as to test whether multicollinearity does exist in the model, before estimating the regression model for the full sample period. Hardy and Bryman (2004) recommend that the correlation value in the range of 0.7 to 0.9 as being high. Table 4.4 shows that there is no high correlation value between two independent variables, confirming that there is no multicollinearity in our model.

$$ROA_{it} = \alpha + \beta_1 SIZE_{it} + \beta_2 LEV_{it} + \beta_3 GROW_{it} + \beta_4 LIQ_{it} + \beta_5 TANG_{it} + \sum_{j=1}^m \gamma_{ij} ROA_{it-j} + \varepsilon_{it} \quad (4.1)$$

In these models, we include the lag of ROA (prior year(s) profitability) as an explanatory variable to incorporate past performance using lags of one and two years, alternately²³. The inclusion of the one or two lagged values of the dependent variable indicates the speed at which competitive forces cause above- or below-average profitability in one year to dissipate subsequently (Goddard et al., 2005). A significant positive lag of ROA indicates that profitability tends to persist from year to year and the forces of competition are not sufficiently strong to cause all abnormal profit to dissipate within a one-year time span. The existence of dynamic effects (up to lag 2) in profitability is empirically documented in the literature and suggests the presence of barriers to entry and/or exit in the market (McGahan and Porter, 2003, Geroski and

²³ The regression results without the lagged terms are remained unchanged.

Jacquemin, 1988, Goddard and Wilson, 1996). Further, the term of ROA_{it-2} is required in order to avoid a positive diagnosis of second-order autocorrelation in the residuals (Goddard et al., 2005, Callen and Morel, 2001).

The results are reported in Table 4.5 for the full sample and different sub-periods and the models appear well specified.

Table 4.4. Correlation matrix

The Table shows the correlation between selected variables. The definitions of all variables are in Table 4.3. The analyses cover the whole period of the study (2004–2017).

	ROA	SIZE	LEV	LIQ	GROW	TANG
ROA	1.00					
SIZE	0.27	1.00				
LEV	-0.01	0.18	1.00			
LIQ	0.05	-0.07	-0.20	1.00		
GROW	0.15	0.00	0.01	-0.01	1.00	
TANG	-0.12	-0.01	-0.10	0.08	-0.05	1.00

Table 4.5. Determinants of hedge fund management company profitability

This Table presents empirical regression results of the relationship between firm-level characteristics and firm profitability. The analyses cover the full sample period 2004 to 2017, the period before the financial crisis (2004 to 2007), the financial crisis period (2008 to 2010), and the period after the financial recession (2011 to 2017). Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Full sample: 2004–2017		Pre-crisis period: 2004–2007		Crisis period: 2008–2010		Post-crisis period: 2011–2017	
	FFE	FYFE	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel A: Include ROA_{it-1}</i>								
ROA _{it-1}	0.27*** (0.07)	0.26*** (0.07)	-0.19** (0.08)	-0.19** (0.08)	-0.31*** (0.09)	-0.33*** (0.09)	0.23*** (0.06)	0.23*** (0.06)
SIZE	18.59*** (3.22)	18.14*** (3.21)	32.73*** (4.79)	35.85*** (5.71)	47.82*** (14.35)	44.43*** (14.27)	21.59*** (4.58)	21.28*** (4.53)
LEV	-0.18* (0.09)	-0.19** (0.09)	-0.26*** (0.10)	-0.28** (0.11)	-0.50 (0.34)	-0.50 (0.34)	-0.29*** (0.10)	-0.29*** (0.10)
LIQ	-0.01 (0.04)	-0.00 (0.04)	0.04 (0.03)	0.03 (0.03)	-0.58 (0.57)	-0.56 (0.58)	-0.02 (0.03)	-0.02 (0.03)
GROW	0.09*** (0.02)	0.08*** (0.02)	-0.01 (0.01)	-0.02 (0.01)	0.00 (0.03)	-0.00 (0.03)	0.07*** (0.03)	0.07*** (0.03)
TANG	-0.47** (0.23)	-0.43* (0.23)	-0.45** (0.21)	-0.43** (0.22)	0.16 (0.37)	0.17 (0.35)	-0.16 (0.12)	-0.16 (0.12)
Constant	-251.91*** (49.27)	-239.28*** (49.54)	-439.67*** (73.16)	-484.40*** (86.05)	-664.07*** (219.76)	-601.89*** (219.57)	-297.40*** (72.01)	-293.87*** (72.08)
N	2,661	2,661	583	583	674	674	1,404	1,404
R-squared	0.27	0.28	0.23	0.24	0.30	0.31	0.28	0.29
No. of firms	384	384	245	245	275	275	307	307

(Continued)

Table 4.5. Continued

Variables	Full sample: 2004–2017		Pre-crisis period: 2004–2007		Crisis period: 2008–2010		Post-crisis period: 2011–2017	
	FFE	FYFE	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel B: Include ROA_{it-1} & ROA_{it-2}</i>								
ROA _{it-1}	0.31*** (0.08)	0.30*** (0.08)	-0.56*** (0.21)	-0.56*** (0.21)	-0.27*** (0.08)	-0.29*** (0.08)	0.26*** (0.07)	0.26*** (0.07)
ROA _{it-2}	0.02 (0.05)	0.02 (0.05)	-0.17** (0.09)	-0.17* (0.09)	-0.12 (0.15)	-0.12 (0.15)	-0.07 (0.05)	-0.07 (0.05)
SIZE	17.01*** (3.28)	16.46*** (3.24)	31.38*** (7.04)	31.03*** (7.29)	46.42*** (15.53)	42.83*** (15.50)	19.79*** (4.45)	19.54*** (4.40)
LEV	-0.19* (0.10)	-0.21** (0.10)	-0.39* (0.23)	-0.39 (0.24)	-0.41 (0.37)	-0.42 (0.38)	-0.28*** (0.10)	-0.28*** (0.10)
LIQ	-0.02 (0.03)	-0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	-0.34 (0.64)	-0.35 (0.65)	-0.03 (0.04)	-0.03 (0.04)
GROW	0.11*** (0.02)	0.11*** (0.02)	-0.03 (0.03)	-0.03 (0.03)	-0.01 (0.04)	-0.01 (0.03)	0.09** (0.04)	0.09** (0.04)
TANG	-0.38** (0.17)	-0.37** (0.17)	-0.75*** (0.29)	-0.75** (0.29)	0.26 (0.41)	0.25 (0.39)	-0.15 (0.11)	-0.15 (0.11)
Constant	-231.54*** (50.70)	-213.24*** (50.95)	-391.65*** (108.62)	-386.58*** (113.05)	-648.85*** (236.53)	-583.17** (237.58)	-269.50*** (71.11)	-266.84*** (71.43)
N	2,329	2,329	360	360	620	620	1,349	1,349
R-squared	0.28	0.29	0.39	0.39	0.26	0.28	0.29	0.29
No. of firms	355	355	217	217	249	249	295	295

As expected, size is the key determinant of ROA, with larger firms generating higher profitability. Also as expected, growth in turnover is positively related to ROA. This result is consistent with findings of Pattitoni et al. (2004) and Capon et al. (1990) which suggests that the company growth increases firm productivity, the profitability therefore is higher. Similar to previous papers (e.g. Rajan and Zingales, 1995, Graham, 2000, Deloof, 2003, Griliches and Lichtenberg, 1984), both leverage and tangibility of assets are negatively related to profitability, confirming that highly leveraged and more tangible firms are less profitable. Looking at the sub-samples, we can see differences emerging. For all three periods, size is positively related to ROA, though the coefficients are larger in the Crisis period. For the pre-crisis and crisis periods, lagged ROA is negatively related to current year profitability. Leverage is negatively related to ROA in all periods, but not statistically significant in the Crisis period. Growth is positively related to ROA only for the period 2011 to 2017, whereas Tangibility of assets is negatively related to ROA, only in the pre-crisis period of 2004 to 2007.

4.4.3 HMC profitability and the global financial crisis

Our expectation is that the size of the fund management company will become particularly important during periods of the financial crisis. Typically returns of the average hedge fund are lower in these periods, and hence they become more reliant upon annual management fees. Our expectation is that overall size will become more positively related to financial performance. In order to directly test this, in Table 4.6 we extend the model to include a crisis dummy, which we interact with the determinants of HMC profitability. As anticipated in crisis periods, size becomes more

positively related to ROA. In crisis periods, lagged ROA becomes less positively related to profitability.

Table 4.6. Determinants of HMC profitability interacted with crisis dummy

This Table presents the empirical regression results of the determinants of firm profitability included a dummy variable for the financial crisis years and its interaction with firm-level characteristics. Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, and Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

(see following page)

Variables	<i>Panel A: Include ROA_{it-1}</i>		<i>Panel B: Include ROA_{it-1} & ROA_{it-2}</i>	
	FFE	FYFE	FFE	FYFE
CRIS	-72.00*** (21.62)	-74.57*** (21.28)	-73.20*** (22.61)	-79.01*** (22.33)
ROA _{it-1}	0.29*** (0.07)	0.28*** (0.07)	0.40*** (0.08)	0.40*** (0.08)
CRIS*ROA _{it-1}	-0.05 (0.06)	-0.05 (0.06)	-0.27** (0.11)	-0.26** (0.11)
ROA _{it-2}			-0.09** (0.04)	-0.08** (0.04)
CRIS*ROA _{it-2}			0.31*** (0.09)	0.31*** (0.09)
SIZE	17.36*** (3.02)	17.02*** (3.03)	15.79*** (2.99)	15.28*** (2.95)
LEV	-0.16* (0.09)	-0.17* (0.10)	-0.20** (0.10)	-0.21** (0.10)
LIQ	-0.00 (0.03)	0.00 (0.03)	-0.01 (0.03)	-0.01 (0.03)
GROW	0.09*** (0.02)	0.08*** (0.02)	0.11*** (0.03)	0.11*** (0.03)
TANG	-0.48* (0.25)	-0.44* (0.25)	-0.38** (0.19)	-0.37** (0.19)
CRIS*SIZE	5.27*** (1.64)	5.00*** (1.61)	4.80*** (1.59)	4.58*** (1.56)
CRIS*LEV	-0.15 (0.12)	-0.15 (0.13)	-0.07 (0.12)	-0.08 (0.12)
CRIS*LIQ	-0.05 (0.07)	-0.05 (0.07)	-0.07 (0.07)	-0.07 (0.07)
CRIS*GROW	0.00 (0.03)	0.00 (0.03)	-0.03 (0.04)	-0.03 (0.04)
CRIS*TANG	0.03 (0.17)	0.03 (0.17)	0.03 (0.15)	0.03 (0.15)
Constant	-234.27*** (46.75)	-222.66*** (47.43)	-212.22*** (46.41)	-196.07*** (47.09)
N	2,661	2,661	2,329	2,329
R-squared	0.27	0.29	0.32	0.33
No. of firms	384	384	355	355

Finally, in Table 4.7 we extend the model to include two no-crisis dummy variables, to reflect the two sub-periods on either side of the GFC. In no-crisis period, one prior-year ROA is more positively related to profitability. In both no-crisis periods, firm size becomes less positively related to profitability. Size of the HMC really matters during the financial crisis.

Table 4.7. Determinants of HMC profitability interacted with no-crisis periods dummy variables

This Table presents the empirical regression results of the determinants of firm profitability included dummy variables for non-crisis periods and their interaction with firm-level characteristics. Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, and Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

(see following page)

Variables	<i>Panel A: Include ROA_{it-1}</i>		<i>Panel B: Include ROA_{it-1} & ROA_{it-2}</i>	
	FFE	FYFE	FFE	FYFE
NC1	61.02** (23.65)	58.41** (23.07)	66.90*** (22.02)	71.00*** (21.75)
NC2	71.14*** (24.69)	67.47*** (24.44)	72.23*** (24.54)	70.83*** (24.75)
ROA _{it-1}	0.23*** (0.08)	0.23*** (0.08)	0.13 (0.10)	0.12 (0.10)
NC1*ROA _{it-1}	0.16** (0.07)	0.16** (0.08)	0.44*** (0.13)	0.45*** (0.13)
NC2*ROA _{it-1}	-0.02 (0.08)	-0.02 (0.09)	0.19* (0.11)	0.19* (0.11)
ROA _{it-2}			0.23** (0.11)	0.23** (0.11)
NC1*ROA _{it-2}			-0.29*** (0.11)	-0.29*** (0.11)
NC2*ROA _{it-2}			-0.33*** (0.09)	-0.33*** (0.09)
SIZE	23.31*** (3.86)	22.75*** (3.81)	21.48*** (3.99)	20.92*** (3.90)
LEV	-0.29** (0.14)	-0.31** (0.14)	-0.25* (0.14)	-0.27* (0.15)
LIQ	-0.06 (0.09)	-0.05 (0.09)	-0.08 (0.08)	-0.08 (0.08)
GROW	0.09*** (0.02)	0.08*** (0.02)	0.08*** (0.02)	0.07*** (0.02)
TANG	-0.38*** (0.12)	-0.37*** (0.12)	-0.28** (0.13)	-0.27** (0.12)
NC1*SIZE	-4.61*** (1.70)	-4.45*** (1.67)	-4.69*** (1.64)	-4.66*** (1.61)
NC2*SIZE	-5.17*** (1.78)	-4.97*** (1.75)	-4.62*** (1.69)	-4.43*** (1.66)
NC1*LEV	0.24** (0.12)	0.25** (0.12)	0.12 (0.13)	0.14 (0.13)
NC2*LEV	0.10 (0.14)	0.11 (0.15)	0.05 (0.14)	0.06 (0.14)
NC1*LIQ	0.07 (0.10)	0.07 (0.10)	0.07 (0.08)	0.06 (0.08)
NC2*LIQ	0.05 (0.07)	0.04 (0.07)	0.07 (0.08)	0.07 (0.08)
NC1*GROW	-0.00 (0.03)	0.00 (0.03)	0.03 (0.04)	0.03 (0.04)
NC2*GROW	-0.01 (0.04)	-0.01 (0.04)	0.02 (0.05)	0.03 (0.05)
NC1*TANG	-0.08 (0.13)	-0.08 (0.13)	-0.04 (0.13)	-0.05 (0.13)
NC2*TANG	-0.01 (0.21)	-0.01 (0.20)	-0.02 (0.17)	-0.03 (0.17)
Constant	-317.22*** (57.40)	-309.38*** (56.00)	-300.07*** (60.76)	-292.74*** (59.05)
N	2,661	2,661	2,329	2,329
R-squared	0.29	0.30	0.34	0.34
No. of firms	384	384	355	355

4.5 Conclusion

In this paper, we have examined a novel database of hedge fund management companies' accounting information over the period leading up to and including the global financial crisis, and a long period post the financial crisis. Our entirely new datasets provide an alternative, more accurate and more reliable source of hedge fund information. New data on hedge funds then provides the opportunity for additional contributions to the literature on hedge funds. Many commentators associate the hedge fund industry with abnormal profits and compensation to the manager. They conjecture that due to the relatively high fees in the standard hedge fund contract (2% annual management fee and 20% performance fee), the industry must be incredibly profitable. By examining the financial performance of hedge fund management companies, our results provide new evidence on the life cycle of the hedge fund industry (Getmansky, 2012, Getmansky et al., 2017) and the effect of regulatory changes on performance (Cumming et al. 2017).

We find that the global financial crisis has a severe negative effect on hedge fund management company profitability. Prior to the crisis, the annual income of an HMC grew at an astonishing 94 percent per annum on average, doubling income each year, and these companies generated ROA of 46 percent. Since the onset of the crisis, growth rates of annual income have slowed to 20 percent on average, with ROA decline to 30 percent. We also show increases in liquidity and strengthening of the firms' balance sheets post the financial crisis. This result provides additional understanding of hedge fund management firms to the existing literature on hedge fund industry (Fung et al., 2017, Sun and Teo, 2019).

At the same time, there is a growing literature which examines the direct and indirect incentives of hedge fund managers, due to the structure of this compensation contract. This literature shows an incentive for managers to grow the assets in their fund, even if it leads to deterioration in fund performance (Lim et al., 2016, Yin, 2016).

For the first time using data on actual HMC profitability, not just fee income, we are able to show that size is the key determinant of HMC profitability. Increasing the size of the HMC leads to an 18% increase in ROA and this grows to a 23% increase in ROA relative to smaller funds during financial crisis periods. This evidence is consistent with hedge fund managers being incentivised to grow their AUM, irrespective of its effect on fund performance. Our results then contribute to the extant literature on diseconomies of scale for fund performance in the hedge fund industry (Teo, 2009, Getmansky, 2012, Yin, 2016).

4.A Appendix: Robustness tests

In order to verify the findings presented earlier in this chapter, this section presents three robustness tests i) using unwinsorised data, ii) excluding banks, and iii) using an alternative proxy of firm profitability.

Firstly, a robustness test to examine the relationship between firm-level characteristics and the profitability of HMCs using unwinsorised data is conducted in order to verify that all of the findings reported so far are not affected by the winsorisation process. Secondly, banks have accounted for a large proportion of the dataset (23% of total firms) and their total turnover has made up around 79.5% of total sales. To make sure that the results are not driven by this sample selection bias, these banks are excluded and then all regressions are re-estimated. Finally, in order to further test the robustness of the findings, an alternative specification for *profitability* is considered. This section uses the *ROA_after* instead of *ROA* for firm profitability ratio. The *ROA_after* keeps total assets in the denominator and considers profit after tax instead of income before tax in the numerator.

Table 4.8 summarises regression results of model 4.1 over the full period from 2004 to 2017 with adjustments for unwinsorised data, excluding banks and using *ROA_after* as an alternative profitability measure.

Table 4.8. Determinants of hedge fund management company profitability: Robustness tests

This Table presents robustness tests of the relationship between firm-level characteristics and firm profitability using unwinsorised data, excluding banks, and using an alternative proxy of profitability. The analyses cover the full sample period 2004 to 2017. Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Unwinsorised data		Excluding banks		Alternative profitability proxy	
	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel A: Include ROA_{it-1}</i>						
ROA _{it-1}	0.40** (0.19)	0.40** (0.19)	0.28*** (0.07)	0.27*** (0.07)	0.26*** (0.07)	0.26*** (0.08)
SIZE	23.19*** (4.07)	22.34*** (3.99)	21.41*** (3.97)	20.79*** (3.96)	17.10*** (3.15)	16.69*** (3.14)
LEV	-0.52*** (0.06)	-0.53*** (0.06)	-0.17 (0.11)	-0.19* (0.11)	-0.19** (0.09)	-0.20** (0.09)
LIQ	0.01 (0.02)	0.01 (0.02)	-0.03 (0.04)	-0.02 (0.04)	-0.00 (0.04)	0.00 (0.04)
GROW	0.00 (0.00)	0.00 (0.00)	0.10*** (0.02)	0.09*** (0.02)	0.08*** (0.02)	0.08*** (0.02)
TANG	-1.39 (0.94)	-1.32 (0.92)	-0.45* (0.27)	-0.40 (0.27)	-0.43* (0.23)	-0.40* (0.23)
Constant	-295.34*** (60.62)	-265.11*** (61.72)	-287.91*** (59.71)	-271.79*** (59.65)	-230.61*** (48.49)	-219.82*** (48.64)
N	2,661	2,661	1,976	1,976	2,694	2,694
R-squared	0.33	0.34	0.29	0.30	0.25	0.26
No. of firms	384	384	293	293	385	385

(Continued)

Table 4.8. Continued

Variables	Unwinsorised data		Excluding banks		Alternative profitability proxy	
	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel B: Includes ROA_{it-1} & ROA_{it-2}</i>						
ROA_{it-1}	0.57** (0.25)	0.57** (0.25)	0.32*** (0.08)	0.31*** (0.08)	0.30*** (0.08)	0.30*** (0.08)
ROA_{it-2}	-0.08 (0.19)	-0.08 (0.19)	0.02 (0.06)	0.02 (0.06)	0.03 (0.06)	0.03 (0.06)
SIZE	22.95*** (3.94)	22.16*** (3.92)	19.71*** (4.09)	19.03*** (4.02)	15.70*** (3.20)	15.27*** (3.16)
LEV	-1.19*** (0.34)	-1.21*** (0.34)	-0.18 (0.12)	-0.19 (0.12)	-0.20** (0.10)	-0.21** (0.10)
LIQ	-0.02 (0.02)	-0.01 (0.02)	-0.01 (0.04)	-0.02 (0.04)	-0.01 (0.03)	-0.01 (0.03)
GROW	0.03** (0.02)	0.03* (0.02)	0.12*** (0.03)	0.11*** (0.03)	0.11*** (0.02)	0.10*** (0.02)
TANG	-1.29 (0.80)	-1.27 (0.79)	-0.36* (0.20)	-0.34* (0.20)	-0.35** (0.16)	-0.34** (0.16)
Constant	-268.32*** (56.09)	-229.46*** (55.02)	-267.35*** (62.03)	-246.58*** (62.21)	-213.35*** (49.65)	-198.98*** (49.96)
N	2,329	2,329	1,716	1,716	2,366	2,366
R-squared	0.41	0.42	0.31	0.32	0.27	0.28
No. of firms	355	355	270	270	358	358

Table 4.8 indicates that the results in three robustness tests are essentially the same such that the conclusions regarding the firm-level determinants of HMC profitability, i.e. firms with larger size, higher growth opportunities, a lower leverage ratio and less tangibility are likely to be more profitable. The evidence implies that increasing the total size of the management company leads to an increase of about 20 percent in profitability. As before, size is the key determinant of HMC profitability.

This section next considers the relationship between firm-level characteristics and profitability during the global financial crisis by including a dummy variable for the financial crisis period and its interaction with firm determinants. To save the space, Table 4.9 only presents the coefficients on the dummy variable, firm size and lagged of profitability. The results from all three robustness checks are consistent with the baseline results in Table 4.6. Specifically, the coefficient on the dummy variable *CRISIS* is significantly negative, implying that HMCs are likely to be less profitable during crisis years. The evidence on firm determinants supports that the positive relationship between size and profitability is particularly exacerbated during the financial crisis period.

Table 4.9. Determinants of HMC profitability interacted with crisis dummy: Robustness tests

This Table presents robustness tests of the determinants of firm profitability included a dummy variable for the financial crisis years and its interaction with firm-level characteristics using unwinsorised data, excluding banks and using an alternative proxy of profitability. Control variables are the same as Table 4.6 (i.e. LEV, GROW, LIQ, TANG and their interactions with dummy variable) but not reported for brevity. Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, and Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Unwinsorised data		Excluding banks		Alternative profitability proxy	
	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel A: Includes ROA_{it-1}</i>						
CRIS	-98.01*** (37.82)	-106.73*** (40.44)	-97.60*** (33.57)	-99.84*** (32.56)	-68.73*** (20.93)	-71.37*** (20.48)
ROA _{it-1}	0.48* (0.28)	0.48* (0.28)	0.30*** (0.07)	0.29*** (0.07)	0.28*** (0.07)	0.28*** (0.08)
CRIS*ROA _{it-1}	-0.21 (0.22)	-0.21 (0.22)	-0.07 (0.07)	-0.07 (0.07)	-0.05 (0.07)	-0.05 (0.07)
SIZE	20.92*** (4.36)	20.25*** (4.23)	19.50*** (3.68)	19.04*** (3.68)	15.93*** (2.95)	15.62*** (2.95)
CRIS*SIZE	6.59** (3.04)	6.33** (3.07)	7.08*** (2.53)	6.64*** (2.48)	4.95*** (1.57)	4.73*** (1.54)
Constant	-261.12*** (63.68)	-234.55*** (65.00)	-260.89*** (56.04)	-246.71*** (56.70)	-213.72*** (45.89)	-203.65*** (46.41)
N	2,661	2,661	1,976	1,976	2,694	2,694
R-squared	0.35	0.36	0.30	0.31	0.26	0.27
No. of firms	384	384	293	293	385	385
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 4.9. Continued

Variables	Unwinsorised data		Excluding banks		Alternative profitability proxy	
	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel B: Includes ROA_{it-1} & ROA_{it-2}</i>						
CRIS	-102.11*** (35.79)	-122.65*** (39.48)	-91.65*** (33.84)	-97.40*** (33.37)	-68.01*** (21.70)	-72.82*** (21.41)
ROA_{it-1}	0.74*** (0.27)	0.74*** (0.27)	0.41*** (0.08)	0.41*** (0.08)	0.40*** (0.08)	0.40*** (0.08)
CRIS* ROA_{it-1}	-0.70** (0.27)	-0.70** (0.27)	-0.28** (0.12)	-0.27** (0.12)	-0.28** (0.11)	-0.27** (0.11)
ROA_{it-2}	-0.12 (0.11)	-0.11 (0.11)	-0.09** (0.04)	-0.08* (0.04)	-0.08** (0.04)	-0.08* (0.04)
CRIS* ROA_{it-2}	0.44*** (0.14)	0.42*** (0.14)	0.32*** (0.10)	0.32*** (0.10)	0.33*** (0.10)	0.33*** (0.10)
SIZE	19.16*** (3.58)	18.47*** (3.54)	17.55*** (3.69)	16.91*** (3.62)	14.44*** (2.91)	14.03*** (2.87)
CRIS*SIZE	5.55** (2.58)	5.51** (2.60)	5.98** (0.17)	5.67** (0.16)	4.38*** (0.13)	4.22*** (0.13)
Constant	-205.81*** (53.61)	-170.96*** (55.34)	-234.60*** (56.08)	-216.13*** (56.95)	-193.23*** (45.29)	-180.88*** (46.01)
N	2,329	2,329	1,716	1,716	2,366	2,366
R-squared	0.48	0.49	0.34	0.35	0.31	0.31
No. of firms	355	355	270	270	358	358
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Finally, Table 4.10 represents the robustness checks of the extended model to include two no-crisis dummy variables. As before, the positive coefficients on both no-crisis dummies reflect that HMCs are more profitable during the two sub-periods on either side of the global financial crisis, excepting the period before the global crisis period for unwinsorised data. In addition, size becomes less positively related to profitability in both no-crisis periods, results that are consistent with table 4.7. However, when using unwinsorised data, we only find significant evidence in the post-crisis period in both panels.

Table 4.10. Determinants of HMC profitability interacted with no-crisis periods dummy variables: Robustness tests

This Table presents the robustness tests of the determinants of firm profitability included dummy variables for non-crisis periods and their interaction with firm-level characteristics using unwinsorised data, excluding banks and using an alternative proxy of profitability. Control variables are the same as Table 4.7 (i.e. LEV, GROW, LIQ, TANG and their interactions with dummy variable) but not reported for brevity. Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, and Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

(see following pages)

Variables	Unwinsorised data		Excluding banks		Alternative profitability proxy	
	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel A. Includes ROA_{it-1}</i>						
NC1	56.18 (46.98)	55.26 (49.37)	74.54** (36.81)	71.09** (35.44)	58.48** (22.91)	57.26** (22.19)
NC2	77.48** (34.49)	61.40** (31.03)	99.25*** (36.41)	91.64*** (34.96)	67.89*** (23.70)	63.83*** (23.31)
ROA _{it-1}	0.26*** (0.06)	0.26*** (0.06)	0.22** (0.09)	0.22** (0.09)	0.23*** (0.09)	0.23*** (0.09)
NC1*ROA _{it-1}	0.34 (0.25)	0.35 (0.25)	0.19** (0.08)	0.19** (0.08)	0.16** (0.08)	0.16** (0.08)
NC2*ROA _{it-1}	-0.14* (0.07)	-0.13* (0.07)	-0.00 (0.09)	-0.00 (0.09)	-0.03 (0.09)	-0.02 (0.09)
SIZE	27.33*** (4.74)	27.22*** (4.83)	27.38*** (4.96)	26.58*** (4.89)	21.55*** (3.77)	21.09*** (3.72)
NC1*SIZE	-3.03 (3.30)	-2.82 (3.27)	-5.87** (2.63)	-5.56** (2.60)	-4.44*** (1.63)	-4.30*** (1.61)
NC2*SIZE	-5.55** (2.54)	-5.42** (2.53)	-7.11*** (2.67)	-6.76** (2.61)	-4.82*** (1.70)	-4.65*** (1.67)
Constant	-361.52*** (68.04)	-356.94*** (67.63)	-371.61*** (72.29)	-361.47*** (70.25)	-293.38*** (56.21)	-287.20*** (54.87)
N	2,661	2,661	1,976	1,976	2,694	2,694
R-squared	0.40	0.41	0.32	0.32	0.27	0.28
No. of firms	384	384	293	293	385	385
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 4.10. Continued.

Variables	Unwinsorised data		Excluding banks		Alternative profitability proxy	
	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel B. Includes ROA_{it-1} & ROA_{it-2}</i>						
NC1	74.46 (63.94)	98.69* (56.72)	87.67** (36.66)	91.28** (36.62)	60.41*** (20.92)	64.87*** (20.71)
NC2	75.49** (30.80)	66.38** (30.11)	86.16** (35.56)	81.80** (35.50)	67.76*** (23.31)	65.55*** (23.53)
ROA _{it-1}	0.05 (0.09)	0.05 (0.09)	0.12 (0.11)	0.12 (0.11)	0.11 (0.11)	0.11 (0.11)
NC1*ROA _{it-1}	1.06*** (0.23)	1.06*** (0.22)	0.47*** (0.14)	0.48*** (0.14)	0.47*** (0.14)	0.47*** (0.14)
NC2*ROA _{it-1}	0.15 (0.11)	0.15 (0.11)	0.19 (0.12)	0.19 (0.12)	0.20* (0.12)	0.20* (0.12)
ROA _{it-2}	0.31*** (0.09)	0.30*** (0.09)	0.24** (0.12)	0.24** (0.12)	0.25** (0.11)	0.25** (0.11)
NC1*ROA _{it-2}	-0.67* (0.39)	-0.65* (0.38)	-0.31** (0.13)	-0.31** (0.12)	-0.32*** (0.11)	-0.32*** (0.11)
NC2*ROA _{it-2}	-0.34*** (0.08)	-0.33*** (0.08)	-0.34*** (0.11)	-0.34*** (0.11)	-0.34*** (0.10)	-0.34*** (0.10)
SIZE	25.88*** (4.64)	25.90*** (4.72)	24.76*** (5.13)	23.99*** (5.01)	19.72*** (3.86)	19.27*** (3.78)
NC1*SIZE	-1.17 (4.52)	-1.53 (4.38)	-6.21** (2.56)	-6.06** (2.53)	-4.25*** (1.54)	-4.21*** (1.52)
NC2*SIZE	-5.00** (2.22)	-4.92** (2.22)	-5.40** (2.49)	-5.12** (2.45)	-4.22*** (1.60)	-4.07** (1.57)
Constant	-342.20*** (69.12)	-339.34*** (68.82)	-346.42*** (76.62)	-336.71*** (74.15)	-276.19*** (58.98)	-270.68*** (57.43)
N	2,329	2,329	1,716	1,716	2,366	2,366
R-squared	0.62	0.62	0.36	0.37	0.33	0.33
No. of firms	355	355	270	270	358	358
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

4.B Appendix: Supplementary analysis

4.B.1 Additional HMC financial ratios

This section extends the analysis of HMC financial ratios reported earlier in section 4.4.1. Table 4.11 reports the full descriptive statistics for the whole sample, a period leading up to the global financial crisis, the financial crisis period and the most recent years after the crisis.

Table 4.11. Full descriptive statistics

This Table summarizes the descriptive statistics for hedge fund management companies from FAME database. This Table reports a number of ratios relating to firm profitability: ROA and firm characteristics: SIZE, LEV, LIQ, TANG and GROW for the whole sample (from 2004 to 2017) in panel A, pre-crisis period in panel B, the financial crisis period in panel C and post-crisis period in panel D. The definitions of all variables are in Table 4.3.

Variables	N	Mean	Standard deviation	25%	Median	75%
<i>Panel A. Full sample (2004–2017)</i>						
ROA	4,361	36.80	100.83	0.13	14.03	52.34
SIZE	4,101	15.22	2.30	13.70	15.21	16.81
LEV	4,790	48.02	48.21	16.37	40.06	67.79
LIQ	4,685	13.41	46.43	1.52	2.76	6.60
TANG	3,638	18.28	27.02	1.29	5.18	22.16
GROW	3,564	39.34	150.89	-22.74	4.34	43.92
<i>Panel B. Before the financial crisis (2004–2007)</i>						
ROA	1,186	46.80	112.10	1.74	18.08	57.84
SIZE	1,116	15.10	2.26	13.66	14.97	16.65
LEV	1,260	50.71	42.88	21.84	46.67	70.88
LIQ	1,223	9.73	35.03	1.47	2.39	4.73
TANG	947	16.06	24.36	1.55	5.04	18.13
GROW	767	94.71	206.11	0.57	32.07	100.22

(Continued)

Table 4.11. Continued

Variables	N	Mean	Standard deviation	25%	Median	75%
<i>Panel C. During the financial crisis (2008–2010)</i>						
ROA	1,065	38.73	108.85	0.08	14.68	51.67
SIZE	995	15.10	2.28	13.53	15.10	16.70
LEV	1,156	45.09	42.73	15.45	38.02	64.93
LIQ	1,131	12.00	43.69	1.54	2.67	6.05
TANG	882	17.38	25.87	1.45	5.37	19.81
GROW	895	31.43	154.99	-36.03	-5.44	38.15
<i>Panel D: After the financial crisis (2011–2017)</i>						
ROA	2,110	30.20	88.77	-0.33	11.51	48.15
SIZE	1,990	15.35	2.33	13.83	15.43	16.94
LEV	2,374	48.01	53.09	14.70	37.49	67.42
LIQ	2,331	16.03	52.44	1.53	3.14	7.97
TANG	1,809	19.88	28.75	1.07	5.16	25.08
GROW	1,902	20.73	112.45	-22.98	0.89	28.13

4.B.2 HMC profitability and turnover comparison over time

In the very first approach, to examine the relationship between the profitability of HMCs and firm size over time, companies are divided into four groups every year based on their turnover. We then calculate the average return on assets (ROA) for each group each year to observe the difference in ROA between the smallest group and the largest group. The mean values of profitability (i.e. ROA) and Turnover for each group are presented in Table 4.12. Figure 4.2 plots the results.

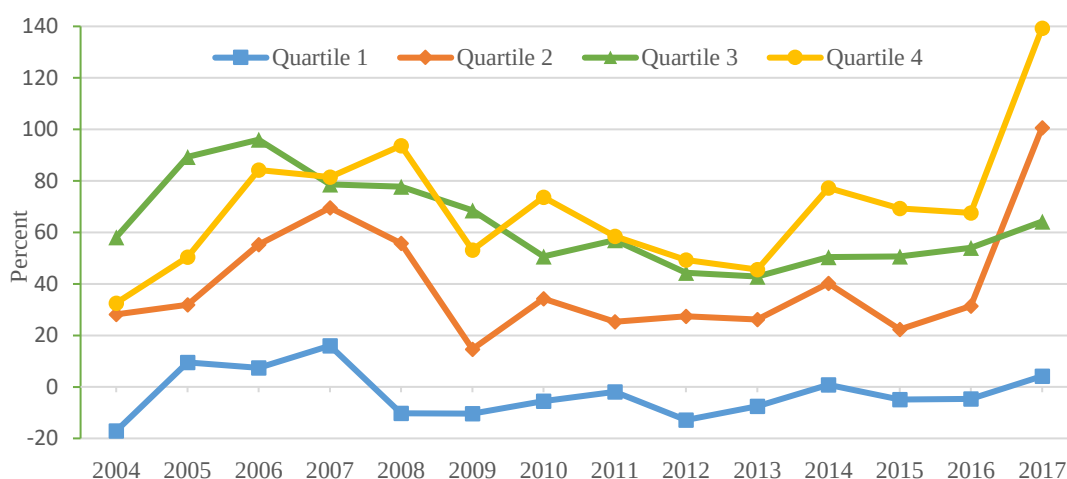
Table 4.12. HMC profitability and turnover comparison over time

This Table presents a profitability and turnover comparison of different HMC size quartiles for each accounting year. Each year, companies are ranked into four groups based on their turnover. Panel A reports the average of profitability (return on assets) of all companies in each size group for each year. Panel B presents the average of turnover of all companies in each size group for each year.

Size group	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
<i>Panel A. Profitability (%)</i>														
1 (smallest)	-17.12	9.56	7.43	15.99	-10.23	-10.37	-5.56	-1.88	-12.80	-7.50	0.83	-4.87	-4.63	4.13
2	28.20	31.86	55.20	69.53	55.74	14.66	34.20	25.24	27.37	26.13	40.19	22.37	31.35	100.69
3	58.12	89.28	96.00	78.62	77.78	68.55	50.70	57.01	44.27	42.86	50.44	50.71	54.06	64.25
4 (largest)	32.58	50.42	84.18	81.48	93.71	53.13	73.67	58.51	49.34	45.60	77.21	69.31	67.61	139.30
Diff. (1)-(4)	-49.69	-40.85	-76.74	-65.49	-103.93	-63.50	-79.24	-60.39	-62.14	-53.09	-76.38	-74.17	-72.23	-135.18
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
<i>Panel B. Turnover (£ millions)</i>														
1 (smallest)	0.19	0.29	0.42	0.55	0.39	0.25	0.31	0.38	0.31	0.39	0.44	0.45	0.41	0.17
2	1.19	1.42	2.03	2.23	2.12	1.74	1.87	2.35	2.11	2.51	2.91	2.81	2.73	1.77
3	6.79	7.12	9.16	10.60	10.00	8.32	8.92	10.30	10.30	11.40	13.60	14.20	15.90	8.12
4 (largest)	327.00	268.00	289.00	408.00	413.00	430.00	471.00	521.00	373.00	429.00	140.00	155.00	176.00	112.00

Figure 4.2. Hedge fund management company profitability comparison over time

This Figure displays the firm profitability of hedge fund management companies for each size quartile throughout the period from 2004 to 2017. Every year, firms are divided into four groups based on their turnover. Company profitability is the average return on assets for all companies in each size group.



The last two rows of Table 4.12 panel A show that firm performance increases as firm size increases. The profitability difference between the smallest group and the largest group is negative and statistically significant for all years.

Figure 4.2 suggests that over time, the profitability experienced an increasing trend during pre-crisis period, followed by a decrease during the global financial crisis years and remained at this level until 2016 for all four size groups. In addition, overall, the graph for four size groups indicates that the average profitability of larger companies is likely to be higher than their smaller counterparts although there are several exceptions. Figure 4.2 suggests that there might be a positive relationship between HMC profitability and firm size.

4.B.3 Non-linear models

The Porter (1985) “stuck in the middle” hypothesis suggests that the firm size-profit relationship is nonlinear. This hypothesis is also empirically supported by Amato and Amato (2004); Athanasoglou et al. (2008); and Lee (2009), such that this section extends equation 4.1 by including a squared term of the size variable to further explore the relationship between firm size and the profitability of hedge fund management firms. The model is specified as follows:

$$ROA_{it} = \alpha + \beta_1 SIZE_{it} + \beta_2 SIZE_{it}^2 + \beta_3 LEV_{it} + \beta_4 GROW_{it} + \beta_5 LIQ_{it} + \beta_6 TANG_{it} + \sum_{j=1}^m \gamma_{ij} ROA_{it-j} + \varepsilon_{it} \quad (4.2)$$

Table 4.13 shows the empirical results of the model in equation 4.2. The size coefficient is negative and size squared is positive and both are statistically significant for full sample. This implies that the relationship between size and profitability is convex. We do not find strong evidence for this non-linear relationship for three subsamples. Therefore, although there are some results of the non-linear effects of firm size on firm profits in the literature, we cannot find strong evidence support this relationship in the specific case of UK private hedge fund management companies. The inconsistent results for the non-linear model implies that the size-profitability relationship should be linear.

Table 4.13. Determinants of hedge fund management company profitability: Non-linear model

This Table presents the empirical results of the non-linear relationship between firm-level characteristics and firm profitability, following equation (4.2). The analyses cover the full sample period (2004 to 2017), the period before the financial crisis (2004 to 2007), the financial crisis period (2008 to 2010), and the period after the financial recession (2011 to 2017). Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

(see following pages)

Variables	Full sample: 2004–2017		Pre-crisis period: 2004–2007		Crisis period: 2008–2010		Post-crisis period: 2011–2017	
	FFE	FYFE	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel A: Include ROA_{it-1}</i>								
ROA _{it-1}	0.26*** (0.06)	0.25*** (0.06)	-0.19** (0.08)	-0.19** (0.08)	-0.31*** (0.08)	-0.33*** (0.08)	0.23*** (0.06)	0.23*** (0.06)
SIZE	-40.46 (24.83)	-46.04* (25.25)	43.61 (36.04)	44.11 (36.75)	-51.86 (56.61)	-55.21 (55.44)	-25.35 (38.75)	-24.13 (38.53)
SIZE ²	2.03** (0.88)	2.21** (0.90)	-0.36 (1.19)	-0.27 (1.24)	3.50* (1.95)	3.50* (1.92)	1.60 (1.37)	1.55 (1.36)
LEV	-0.20** (0.09)	-0.22*** (0.09)	-0.26*** (0.10)	-0.28** (0.11)	-0.48 (0.33)	-0.48 (0.33)	-0.31*** (0.10)	-0.31*** (0.10)
LIQ	-0.02 (0.04)	-0.01 (0.04)	0.04 (0.03)	0.03 (0.03)	-0.55 (0.58)	-0.53 (0.59)	-0.03 (0.03)	-0.04 (0.03)
GROW	0.09*** (0.02)	0.08*** (0.02)	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.03)	-0.01 (0.03)	0.08*** (0.03)	0.08*** (0.03)
TANG	-0.44** (0.21)	-0.39* (0.21)	-0.45** (0.21)	-0.43** (0.22)	0.21 (0.35)	0.23 (0.33)	-0.16 (0.12)	-0.16 (0.12)
Constant	167.57 (171.80)	217.96 (175.70)	-521.49* (274.23)	-546.37** (276.34)	24.90 (427.42)	85.82 (416.68)	39.70 (268.34)	32.29 (266.87)
N	2,661	2,661	583	583	674	674	1,404	1,404
R-squared	0.28	0.29	0.23	0.24	0.31	0.33	0.29	0.29
No. of firms	384	384	245	245	275	275	307	307

(Continued)

Table 4.13. Continued

Variables	Full sample: 2004–2017		Pre-crisis period: 2004–2007		Crisis period: 2008–2010		Post-crisis period: 2011–2017	
	FFE	FYFE	FFE	FYFE	FFE	FYFE	FFE	FYFE
<i>Panel B: Include ROA_{it-1} & ROA_{it-2}</i>								
ROA_{it-1}	0.30*** (0.07)	0.29*** (0.07)	-0.56*** (0.21)	-0.56*** (0.21)	-0.28*** (0.07)	-0.30*** (0.08)	0.26*** (0.07)	0.26*** (0.07)
ROA_{it-2}	0.01 (0.05)	0.01 (0.05)	-0.17* (0.09)	-0.17* (0.09)	-0.11 (0.15)	-0.11 (0.14)	-0.07 (0.04)	-0.07 (0.05)
SIZE	-45.74* (24.46)	-49.51** (24.55)	74.37 (47.40)	74.68 (46.58)	-55.14 (58.89)	-59.67 (57.20)	-35.30 (38.53)	-34.28 (38.41)
SIZE²	2.17** (0.87)	2.28*** (0.87)	-1.38 (1.55)	-1.40 (1.51)	3.58* (2.04)	3.61* (2.00)	1.88 (1.38)	1.84 (1.37)
LEV	-0.24** (0.09)	-0.25*** (0.09)	-0.37 (0.23)	-0.36 (0.24)	-0.41 (0.37)	-0.42 (0.37)	-0.31*** (0.10)	-0.31*** (0.10)
LIQ	-0.04 (0.03)	-0.04 (0.03)	0.02 (0.03)	0.02 (0.03)	-0.37 (0.68)	-0.39 (0.69)	-0.05 (0.04)	-0.05 (0.04)
GROW	0.11*** (0.02)	0.10*** (0.02)	-0.03 (0.03)	-0.03 (0.03)	-0.03 (0.04)	-0.03 (0.03)	0.09*** (0.04)	0.09*** (0.04)
TANG	-0.36** (0.16)	-0.34** (0.16)	-0.75*** (0.29)	-0.76** (0.29)	0.32 (0.38)	0.31 (0.36)	-0.15 (0.11)	-0.16 (0.11)
Constant	212.53 (167.60)	255.07 (168.78)	-723.06** (365.64)	-721.71** (362.25)	50.12 (441.94)	121.91 (427.10)	125.43 (262.28)	119.04 (261.72)
N	2,329	2,329	360	360	620	620	1,349	1,349
R-squared	0.30	0.31	0.40	0.40	0.28	0.29	0.30	0.31
No. of firms	355	355	217	217	249	249	295	295

Table 4.14 reports the analysis of non-linear relationship between HMCs profitability and size in interaction with a crisis dummy variable. The results show that the relationship between size and profitability is convex and we cannot find evidence of whether this relationship is more pronounced or attenuated during the global financial crisis. The coefficient on the dummy variable *CRISIS* is not significant. The negative sign, however, implies that HMCs experience a lower profitability in the financial recession period.

Table 4.14. Determinants of HMC profitability interacted with crisis dummy: Non-linear model

This Table presents the empirical regression results of the non-linear relationship between firm characteristics and profitability included a dummy variable for the financial crisis years and its interaction with firm-level characteristics. Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, and Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

(see following pages)

Variables	<i>Panel A: Include ROA_{it-1}</i>		<i>Panel B: Include ROA_{it-1} & ROA_{it-2}</i>	
	FFE	FYFE	FFE	FYFE
CRIS	-138.54 (110.50)	-156.96 (110.74)	-171.07 (104.71)	-179.85* (104.55)
ROA _{it-1}	0.28*** (0.06)	0.27*** (0.06)	0.39*** (0.07)	0.38*** (0.07)
CRIS*ROA _{it-1}	-0.06 (0.06)	-0.05 (0.06)	-0.26** (0.11)	-0.26** (0.11)
ROA _{it-2}			-0.09*** (0.04)	-0.09** (0.04)
CRIS*ROA _{it-2}			0.30*** (0.09)	0.30*** (0.09)
SIZE	-42.93* (24.54)	-48.52* (24.96)	-45.93** (22.93)	-49.18** (23.08)
SIZE²	2.07** (0.87)	2.25** (0.89)	2.13*** (0.82)	2.22*** (0.82)
LEV	-0.19** (0.09)	-0.21** (0.09)	-0.24*** (0.09)	-0.25*** (0.09)
LIQ	-0.01 (0.04)	-0.00 (0.04)	-0.03 (0.03)	-0.02 (0.03)
GROW	0.09*** (0.02)	0.08*** (0.02)	0.12*** (0.03)	0.11*** (0.03)
TANG	-0.44* (0.23)	-0.40* (0.23)	-0.35** (0.17)	-0.33** (0.17)
CRIS*SIZE	14.35 (14.49)	15.87 (14.37)	18.16 (13.38)	18.05 (13.26)
CRIS*SIZE²	-0.30 (0.48)	-0.36 (0.47)	-0.44 (0.42)	-0.45 (0.42)
CRIS*LEV	-0.13 (0.12)	-0.13 (0.12)	-0.05 (0.12)	-0.05 (0.12)
CRIS*LIQ	-0.03 (0.07)	-0.03 (0.07)	-0.05 (0.08)	-0.05 (0.07)
CRIS*GROW	-0.00 (0.03)	-0.00 (0.03)	-0.04 (0.04)	-0.04 (0.04)
CRIS*TANG	0.02 (0.15)	0.02 (0.15)	0.00 (0.13)	0.01 (0.13)
Constant	194.20 (169.05)	244.71 (172.85)	225.15 (156.64)	262.45* (157.89)
N	2,661	2,661	2,329	2,329
R-squared	0.29	0.30	0.33	0.34
No. of firms	384	384	355	355

When we examine the relationship between firm-level determinants and firm profitability using two no-crisis dummy variables, only the coefficients on the quadratic size term are significant. In addition, the results (reported in Table 4.15) do not provide significant evidence that size is less positively related to profitability in both no-crisis periods although the coefficients on interaction variables are negative.

Table 4.15. Determinants of HMC profitability interacted with no-crisis period dummy variables: Non-linear model

This Table presents the empirical regression results of the non-linear relationship between firm characteristics and profitability included dummy variables for non-crisis periods and their interaction with firm-level characteristics. Two model approaches are adopted: Panel A presents the results for the dynamic model that includes one lag of the dependent variable, and Panel B reports the results for the dynamic model that includes two lags of the dependent variable. Robust standard errors clustered at the firm-level are reported in parentheses. “FFE” labelled firm fixed effects model and “FYFE” labelled both firm fixed effects and year fixed effects. N is the number of observations. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	<i>Panel A: Include ROA_{it-1}</i>		<i>Panel B: Include ROA_{it-1} & ROA_{it-2}</i>	
	FFE	FYFE	FFE	FYFE
NC1	125.48 (105.04)	127.78 (104.49)	137.95 (109.70)	149.00 (108.76)
NC2	157.63 (135.13)	149.96 (133.83)	167.24 (124.02)	158.82 (122.10)
ROA _{it-1}	0.22*** (0.08)	0.22*** (0.08)	0.12 (0.10)	0.11 (0.10)
NC1*ROA _{it-1}	0.16** (0.07)	0.16** (0.08)	0.43*** (0.13)	0.43*** (0.13)
NC2*ROA _{it-1}	-0.02 (0.08)	-0.01 (0.08)	0.19* (0.11)	0.19* (0.11)
ROA _{it-2}			0.21** (0.10)	0.21** (0.10)
NC1*ROA _{it-2}			-0.27*** (0.10)	-0.27*** (0.10)
NC2*ROA _{it-2}			-0.32*** (0.09)	-0.32*** (0.09)

(Continued)

Table 4.15. Continued

SIZE	-29.64 (29.15)	-30.14 (28.83)	-27.04 (25.68)	-27.78 (25.32)
SIZE ²	1.83* (1.02)	1.83* (1.02)	1.68* (0.90)	1.69* (0.88)
LEV	-0.30** (0.13)	-0.32** (0.14)	-0.27* (0.14)	-0.29** (0.14)
LIQ	-0.05 (0.10)	-0.05 (0.10)	-0.09 (0.09)	-0.08 (0.08)
GROW	0.08*** (0.02)	0.08*** (0.02)	0.07*** (0.02)	0.07*** (0.02)
TANG	-0.36*** (0.12)	-0.35*** (0.12)	-0.28** (0.13)	-0.28** (0.12)
NC1*SIZE	-12.42 (13.72)	-12.76 (13.61)	-13.20 (14.02)	-13.89 (13.85)
NC2*SIZE	-17.36 (17.82)	-16.82 (17.47)	-18.07 (16.13)	-17.14 (15.85)
NC1*SIZE ²	0.24 (0.44)	0.25 (0.44)	0.26 (0.45)	0.28 (0.44)
NC2*SIZE ²	0.41 (0.58)	0.40 (0.57)	0.46 (0.51)	0.43 (0.50)
NC1*LEV	0.22* (0.11)	0.23** (0.12)	0.09 (0.13)	0.10 (0.13)
NC2*LEV	0.07 (0.14)	0.08 (0.14)	0.02 (0.14)	0.03 (0.14)
NC1*LIQ	0.07 (0.10)	0.06 (0.10)	0.07 (0.09)	0.06 (0.09)
NC2*LIQ	0.03 (0.08)	0.03 (0.08)	0.06 (0.08)	0.05 (0.08)
NC1*GROW	0.00 (0.03)	0.01 (0.03)	0.04 (0.04)	0.04 (0.04)
NC2*GROW	-0.00 (0.04)	0.00 (0.04)	0.03 (0.05)	0.03 (0.05)
NC1*TANG	-0.08 (0.13)	-0.08 (0.12)	-0.03 (0.13)	-0.04 (0.13)
NC2*TANG	0.02 (0.19)	0.01 (0.18)	0.02 (0.16)	0.01 (0.15)
Constant	57.88 (205.04)	64.27 (202.99)	42.84 (181.30)	50.69 (178.82)
N	2,661	2,661	2,329	2,329
R-squared	0.30	0.31	0.35	0.36
No. of firms	384	384	355	355

**Chapter 5 : Private Hedge Fund Firms' Incentives
and Performance: New evidence from Audited
Company Filings**

5. Private Hedge Fund Firms' Incentives and Performance: New evidence from Audited Company Filings²⁴

Abstract

Using an entirely new dataset of company filings from firms that manage hedge funds, this study examines whether the hedge fund compensation contract aligns managerial incentives and investor interests. Our novel dataset allows us to distinguish between firms which are focused exclusively on hedge fund management and diversified firms offering products in addition to hedge funds. Our results for compensation data of hedge fund only management firms confirm that compensation increases as AUM increase, despite increased costs and performance diseconomies of scale. Hedge funds managed by diversified firms have far lower performance. A relatively small proportion of the compensation from these firms is generated from hedge funds. The results are consistent with diversified hedge fund firms having weaker alignment between managerial incentives and investment performance.

²⁴ With co-authors: Mark Hutchinson and Mark Mulcahy.

“Hedge funds vary widely in investment style and performance but fees are
invariably high”

Financial Times, May 26th, 2015

5.1 Introduction

The hedge fund compensation contract is designed to incentivise performance, with the manager receiving a performance-based fee, in addition to their annual management fee. The aim of this contract design is to mitigate the motivation for the manager to increase fund assets to maximise annual management fees at the cost of reduced performance, due to diseconomies of scale. Existing evidence suggests that the effectiveness of the managerial contract may be limited. To date, due to data limitations, the literature uniformly assumes that fee income, estimated from self-reported returns to hedge fund data vendors, equates to manager compensation. Existing studies of hedge fund managerial incentives do not consider cases where not all compensation is generated from hedge funds.

This study directly tests the effectiveness of the managerial contract by using a novel database of actual audited company filings by firms who manage hedge funds. Addressing these shortcomings in the literature is important for three reasons. First, the hedge fund databases are self-reported unaudited data, which exhibit several biases. Second, assuming estimated fee income equates to compensation overlooks the fact that hedge funds are managed by firms which often have very significant costs that increase as AUM increase.²⁵ Third, if managers generate a large proportion of

²⁵ Yin (2016) recognises the important role that high costs (for example, risk management, trading software and investments in research) will play in explaining the non-linear performance-size relationship for hedge funds.

their compensation from sources other than hedge funds, then the incentives to perform may be weaker.

Estimating fee income from hedge fund databases is problematic for several reasons. First, there is no time series of annual management fees and performance fees, so if the fund fee changes over time it is not captured in the database. Second, the AUM reported to the databases are not reported for all funds and are in many cases infrequently updated. Third, there are well-known biases in the returns data, which suffer from backfill bias and survivorship bias. Fourth, as the data is self-reported, there is no information provided on fee discounts offered to investors, which anecdotal evidence suggests are offered for large investment allocations.²⁶ By using company filings, we are able to overcome all of these issues because the firms report their actual income as accounting turnover in the filings.

Using audited company filings has a second major advantage in allowing us to control for operating costs. In our sample, the firms which manage hedge funds exhibit large cross-sectional and time-series variability in costs, with, on average, compensation equating to only one-third of fee income. Using employee numbers as a proxy for size, while the median firm exclusively managing hedge funds in our sample employs only eleven people, the largest hedge fund only company has over three hundred employees. By using actual audited compensation, we are able to test the compensation-size relationship, controlling for costs.

We are motivated to distinguish between firms who are entirely focused on hedge funds and diversified firms (with diverse compensation sources) by the findings of

²⁶ “Hedge funds fees take a trim”, Financial Times, December 22nd, 2016.

Sun and Teo (2019) who show that hedge funds managed by listed firms underperform funds managed by unlisted firms. These large asset management firms tend to raise more capital and launch new funds. Our new dataset of hedge fund compensation data allows us to directly test whether having diverse compensation sources weakens the alignment between hedge fund managers and investors.

Our methodology is primarily motivated by the pioneering paper of Yin (2016) who recognised the shortcomings in the hedge fund management contract, developed and tested a model for the optimal size of a hedge fund. The results reveal significant conflicts of interest between hedge fund managers and their investors, with the manager being motivated to grow the fund beyond the optimal size for performance. Using our sample of hedge fund management firms and data from TASS, we first test whether growth in fund assets affects performance. Consistent with the theoretical model of Berk and Green (2004) and the evidence in Yin (2016), we find strong evidence of diseconomies of scale, particularly for hedge fund only firms. There is an optimal size for a hedge fund to maximise performance for the investor, beyond which performance declines. We also find strong evidence showing large differences in performance between hedge fund only firms and firms with diverse compensation streams.

Next, we test for the optimal hedge fund size to maximise compensation for the hedge fund manager. Using audited reported compensation to the employees, directors and owners of the company, we find that consistent with Yin (2016), despite the substantial costs associated with managing a larger fund and our evidence on diseconomies of scale, compensation increases as fund assets grow.

The key contribution of our paper is the specification of our new dataset of hedge fund company filings to test the efficacy of the hedge fund management contract. For the first time, we are able to identify actual compensation earned by the managers of these funds using audited data. Our study is closest to Brown et al. (2008b) who use data from the Form ADV filing which provides information on ownership and key operational risk factors (but not detailed compensation information) to provide new insights on risk.²⁷ Recent research has documented new information in 13F filings about hedge fund performance (see for example Aragon et al. (2013)) but, again, no information is reported in these filings on hedge fund management firm compensation.

While not focused on hedge fund size, there is a large literature focused on direct and indirect managerial incentives of hedge fund managers. In general, research finds that large direct incentives and investor discretion are associated with better performance (Agarwal et al., 2009), but others have focused on some of the indirect incentives, which are less geared towards performance. Goetzmann et al. (2003) model performance fees as a claim on investor wealth to develop a framework for valuing a hedge fund management company, which increases with AUM, while Lim et al. (2016) show that high current returns lead to increased AUM, which leads to increased future annual management fees, particularly for younger funds. In related research, Aragon and Nanda (2011) focus on the extent of risk-shifting behaviour of hedge fund managers, conditioned on the current NAV of the fund relative to the high-water mark, to maximise incentive fees. Our findings on the under-performance of managers with diverse compensation streams is consistent with Nohel et al. (2010) who show that

²⁷ Prior to the introduction of Form PF, the SEC introduced a requirement to file Form ADV, a regulatory tool designed to allow market participants to measure operational risk of hedge fund investment managers, which was subsequently overturned in the judicial system.

mutual fund managers who manage side-by-side hedge funds tend to have, at best, comparable performance to their hedge fund only peers.

The remainder of the paper is organized as follows. Section 5.2 describes our data. Section 5.3 reports results on the size-performance relationship, while section 5.4 discusses results on the compensation-size relationship. Section 5.5 presents our conclusions.

5.2 Data

5.2.1 Databases

We specify two databases for this study. We first use data collected from the Lipper TASS Database to identify hedge fund management firms located in the United Kingdom, and the performance and characteristics of the hedge funds managed by these firms. We then combine this with accounting data from the Bureau Van Dijk FAME database of United Kingdom private company filings.

In the United States, hedge fund management firms are either registered as limited liability corporations (LLCs) or limited liability partnerships (LLPs), typically in Delaware. Firms registered in the US are generally not required to file financial accounting data, so to-date it has not been possible to conduct research on the filings of private hedge fund firms. However, the requirements for private firms to file financial accounting data vary across countries. In the United Kingdom, private limited liability companies are required to file their full accounts at Companies House. Due to this filing requirement, there is a large corporate finance literature examining private UK firms. The Bureau Van Dijk FAME database contains the most recent ten

years of digitized accounting information filed by all UK private firms. In addition, it also contains all PDF copies of the actual filings made by the firms to Companies House since 2004.

In order to identify UK hedge fund management firms, we match management firms registered in the UK from the TASS database of live and dead hedge funds with the FAME database of UK company filings. Using the contact details from the TASS database we identify the hedge fund management firm in the FAME database. Within TASS, there is an initial sample of 483 UK private hedge fund management firms. We exclude firms which manage hedge funds which are dissolved prior to 2004, firms which are restructured via merger or acquisition or change their accounting policies. We also exclude firms which only manage funds from the dedicated short bias, options strategy and fund-of-funds styles. In addition, firms with funds for which TASS does not contain information on returns, AUM or investment styles are also deleted.

As is well documented in the literature, the voluntarily reported hedge fund performance in commercial databases suffers from backfill bias. To mitigate this problem, we follow Yin (2016) and remove data preceding the date when funds first report to the TASS database. If the add-dates are unavailable, the first 18-months of observations are removed. In addition, Aggarwal and Jorion (2010b) point out that the same fund might appear multiple times as duplicate share classes in the database. In order to eliminate duplicate funds, we calculate the return correlation between each pair of funds within the same management firm. If the returns are 0.99 correlated and more, we keep the oldest fund or the fund with longest return record or the larger of the two funds by AUM. Finally, because our paper focuses on the hedge fund management firms in the UK, for data reported to TASS in currencies other than the

UK pound, we convert to UK pounds, using end-of-month exchange rates from the IMF website.

As Bureau Van Dijk FAME only keeps the most recent ten years of accounting information in their database, having identified the firms in the FAME database, we are only able to download the most recent ten years of accounting data for each firm up to the 2017 accounting year, or their final year of filing. For firms which cease trading before 2017, we are able to download the most recent ten years of accounting information up to and including the final filing year. As this excludes pre-2008 accounting information for all firms still alive at the end of 2017, we also hand collect accounting information for the years 2004 to 2007 from PDFs of company filings for these firms.

Finally, to mitigate the effect of micro funds, we set a minimum threshold for AUM of £10 million. To minimize the effect of outliers and reporting errors, we also restrict our sample to funds with at least one year of TASS data available during the sample period and winsorize fund returns at the 0.1% level.

These steps leave us with a final the sample of total 133 UK private management firms corresponding with 358 hedge funds covering a twelve-year period from 2004 to 2015.

5.2.2 Measuring hedge fund manager compensation

We measure hedge fund manager compensation in two ways. First, following Yin (2016), we estimate fees using self-reported data to the TASS database, where fees are estimated as a function of management fee, AUM, performance fee and current period performance. Where funds have no high-water mark, performance fees are estimated

as a function of the period return and AUM. Where funds have a high-water mark, performance fees are estimated as a function of the period return, when the year-end NAV is in excess of the maximum historical NAV and AUM.

Our second measure is audited compensation from company filings, where compensation is equal to Turnover less all non-compensation related expenses.

$$\begin{aligned} \text{Compensation}_{it} = & \text{Turnover}_{it} - \text{Operating Expenses}_{it} - \\ & \text{Financing Expenses}_{it} - \text{Tax}_{it} + \text{Directors' Fees}_{it} + \text{Salaries}_{it} \end{aligned} \quad (5.1)$$

5.2.3 Hedge fund only firms and Diversified Firms

With our company filing data, we are able to divide our firm sample into those which are concentrated only on hedge fund management and those with diversified compensation sources. This sub-sample analysis allows us to test the effectiveness of the managerial contract in aligning managerial and investor interests for these two firm types. If manager compensation is less aligned with investment performance for firms with diversified compensation sources, we anticipate that the funds managed by these firms would generate lower returns, and the link between fund size and total compensation will be weaker.

As estimated fee income (TASS data) is the upper bound for income from managing TASS hedge funds (given it does not take into account discounts given to large investors), we can compare it to accounting turnover (FAME data) each year to classify firms. Firms which have accounting turnover greater than estimated fee income are generating compensation from other sources outside of the TASS hedge funds and are classified as “*Diversified firms*”. Likewise, firms with accounting

turnover less than or equal to estimated fee income are classified as “*Hedge fund only firms*”. Within our sample, seventy percent of firm years are classified as Diversified firm years, with the remaining thirty percent classified as Hedge fund only firm years.

5.2.4 Summary of data

Table 5.1 reports sample summary statistics. Panel A provides a description of fund characteristics for all hedge funds reporting to TASS. Within our sample, hedge funds generate mean monthly returns of 1.40%. These funds manage on average £196 million of assets across the funds, with the largest managing £5.6 billion. Hedge funds charge a management fee of between 1% and 2%, and an incentive fee of 20%. High-water marks are widely used in hedge funds within our sample, with three-quarters of funds having this provision. Panel B reports fund family information, including the number of investment styles used by the company and the number of hedge funds in the fund family, managed by the same company. On average, the management firms in our sample manage two hedge funds within their fund family and typically implement the same investment strategy for their hedge funds.

Panel C provides a description of company characteristics for all firms, who manage at least one hedge fund reported to the TASS database. Looking at the audited accounting data from FAME, the firms employ on average 73 staff, and report total income of £74.9 million per annum, of which £23.3 million (31 percent) is paid out to staff and firm owners as compensation.

Table 5.1. Summary statistics

Panel A reports summary statistics of fund characteristics at the individual fund level. *Rate of return* is the after-fee raw return as reported to TASS database. *Management fee* is the percentage of fund assets that investors pay to fund managers. *Incentive fee* is the percentage of fund returns that investors pay to fund managers. *High-water mark* equals one if a fund uses a high-water mark provision, and zero otherwise. Panel B reports the *number of styles* used by a management firm and the *number of funds* under management at the fund-family level. Panel C reports summary statistics of firm characteristics at the management firm level. *Compensation* equals Turnover less all non-compensation related expenses.

Variables	Mean	p25	Median	p75
<i>Panel A: Individual fund level</i>				
Rate of return (%)	1.40	-1.57	1.41	4.74
Fund AUM (£ millions)	195.80	31.33	79.20	206.10
Management fee (%)	1.63	1.50	1.50	2.00
Incentive fee (%)	18.75	20.00	20.00	20.00
High-water mark (dummy)	0.76	1.00	1.00	1.00
<i>Panel B: Fund-family level</i>				
Number of styles	1.31	1.00	1.00	1.00
Number of funds	1.90	1.00	1.00	2.00
<i>Panel C: Management firm level</i>				
Number of Employees	73.48	6.00	11.00	34.00
Total Assets (£ millions)	72.83	1.67	5.14	27.30
Turnover (£ millions)	74.94	1.97	6.22	28.28
Compensation (£ millions)	23.26	0.96	4.06	20.84

5.3 Performance-size relationship

The theoretical and empirical evidence for mutual funds shows that when managers have too much capital, they must invest more than is optimal, or find investment opportunities outside of their area of expertise in order to deploy the increased capital. Even when the manager has some skill, Berk and Green (2004) show that this has a consequent negative effect on fund performance and is known as diseconomies of

scale. More recently, Yin (2016) presents evidence of diseconomies of scale to hedge funds.

We first aggregate monthly returns into quarterly returns for each fund. Following Yin (2016), we use style-adjusted returns which are defined as the difference between individual fund quarterly returns and the average return of all funds in the same investment style²⁸. As our unit of observation is hedge fund firms, rather than hedge funds, where a firm manages more than one fund, we use the average return across all of the funds managed by that firm to measure performance in that quarter. In this study, we use both equal-weighted average returns and asset-weighted average returns for measures of performance.

5.3.1 Performance comparison: Hedge fund only and Diversified firms

We first divide hedge fund management firms into size quintiles each quarter and compare the average performance of equal-weighted and asset-weighted size quintiles.²⁹ If we compare the performance of the size quintiles, we see that the smallest hedge fund management firms generate the highest returns.

²⁸ Following Yin (2016), when all analyses are repeated with an alternative performance measure: net-of-fee raw returns, the results are consistent. Results are reported in Appendix 5.B.2.

²⁹ Due to concerns about the size of our sample, all analyses are repeated with firms sorted into size based terciles and quartiles. Findings are consistent with the quintile-based results. Results are reported in Appendix 5.B.1.

Table 5.2. Performance comparison of different firms' funds

This Table presents a performance comparison of different size quintiles, for all firms, hedge fund only management firms and diversified management firms. Each quarter, firms are divided into quintiles based on their lagged family fund size. Family fund size is the sum of the assets of funds managed by the same management firm. Firm performance is the average style-adjusted returns of funds managed by the firm. These are reported both equal-weighted and asset-weighted. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Size group	Equal-Weighted Performance				Asset-Weighted Performance			
	All firms	Hedge fund only firms	Diversified firms	Difference	All firms	Hedge fund only firms	Diversified firms	Difference
1	1.23	2.44	0.33	2.11**	1.28	2.53	0.34	2.19**
2	1.05	3.19	-0.88	4.07***	0.99	3.05	-0.88	3.92***
3	0.51	1.73	-0.63	2.36***	0.59	1.84	-0.59	2.43***
4	-0.12	0.33	-0.58	0.91*	-0.02	0.46	-0.50	0.96*
5	0.42	0.90	-0.04	0.94**	0.47	0.84	0.11	0.73*
Diff. (1) -(5)	0.81	1.54	0.37		0.81	1.69	0.23	
p-value	0.07*	0.07*	0.24		0.07*	0.06*	0.33	

Our accounting data allows us to sub-classify our sample into two distinct types of hedge fund management firms: (1) hedge fund only firms, which generate all of their compensation from hedge funds, and (2) diversified firms, which generate their compensation from other sources in addition to hedge funds. This provides a unique opportunity to test whether the performance incentives are weaker when managers have more diverse compensation streams.

Figure 5.1. Hedge Fund Only Firm versus Diversified Firm fund performance

Cumulative style-adjusted returns of hedge funds managed by hedge fund only firms versus hedge funds managed by diversified firms. Equal-weighted portfolios of hedge funds are constructed by sorting funds based on whether they are managed by a hedge fund only firms.

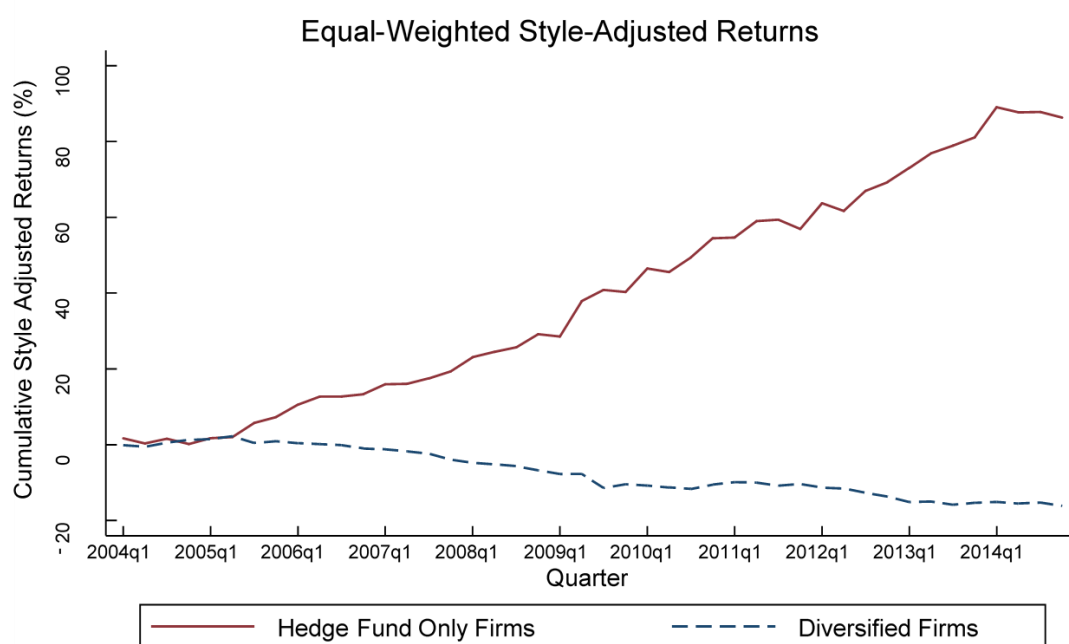


Figure 5.1 plots the cumulative style-adjusted returns of hedge funds managed by hedge fund only firms versus hedge funds managed by diversified firms. The difference in performance is striking. Funds managed by hedge fund only firms

generate average cumulative style-adjusted returns of 80 percent (outperformance of their peer group hedge funds), while the funds managed by diversified firms underperform other funds in their style classification by –15 percent over the sample period.

The outperformance of the smallest hedge fund management firms is particularly prevalent for firms who manage hedge funds only. Performance is markedly lower for firms who also generate compensation from sources other than hedge funds, highlighting the weaker performance incentives for this category of manager. Looking at the difference in performance between the two categories of firms, it is apparent that the outperformance is concentrated in the smaller quintiles. The outperformance is smaller when diseconomies of scale kick in for the largest hedge fund only firms.

The last two rows of Table 5.2 show that performance decreases as firm size increases. The performance difference between the smallest size group and the largest size group is positive and significant for all firms and for hedge fund only management firms.

5.3.2 Regression results

Using firm fund returns, we then test whether diseconomies of scale exist in fund performance using the following panel regressions:

$$\begin{aligned} \text{Company Return}_t & \hspace{15em} (5.2) \\ &= \beta_0 + \beta_1 \times \ln(\text{CompanyAUM}_{t-1}) + \text{Control Variables} \end{aligned}$$

$$\text{Company Return}_t = \beta_0 + \beta_1 \times \ln(\text{CompanyAUM}_{t-1}) + \beta_2 \times [\ln(\text{CompanyAUM}_{t-1})]^2 + \text{Control Variables} \quad (5.3)$$

$$\text{Company Return}_t = \beta_0 + \beta_1 \times \ln(\text{CompanyAUM}_{t-1}) + \beta_2 \times [\ln(\text{CompanyAUM}_{t-1})]^2 + \beta_3 \times [\ln(\text{CompanyAUM}_{t-1})]^3 + \text{Control Variables} \quad (5.4)$$

Where model (5.2) tests whether the relationship between firm fund size and performance is linear, model (5.3) tests whether the relationship is quadratic and model (5.4) tests whether it is cubic. We cluster standard errors by firm following Petersen (2009) and all models include year fixed effects and control variables. Petersen (2009) believe that when both a firm and a time effect are present in the data, researchers can address one parametrically (e.g. by including time dummies) and then estimate standard errors clustered on the other dimension. The standard errors clustered by firm are therefore unbiased and sized confidence intervals are produced correctly whether the firm effect is permanent or temporary³⁰.

Following Yin (2016), increasing the number of funds managed under the same company would not hurt the performance if the hedge fund management firm launches new funds and keeping each fund at its optimal capacity. However, if the fund family utilises the same investment style, the capacity constraints of the strategy could lead to deterioration in family performance. Therefore, in our model, we control for both

³⁰ As a robustness test, we re-run the analysis with firm fixed effects singularly and with year fixed effects in Appendix 5.B.3.

the number of funds under the management and the number of investment strategies used by the management firm.

Table 5.3. Performance–size relationship

This Table reports regression results of the performance-size relationship. The dependent variable is the average style-adjusted returns of the funds managed by the firm, both equal-weighted and asset-weighted. The independent variable is the natural log of lagged fund family assets. Control variables include the number of funds under the management and the number of styles used by the management firm. Panel A reports the performance-size regression results for hedge fund only management firms which generate all their compensation from hedge funds. Panel B presents the regression results for diversified management firms which generate their compensation from other sources in addition to hedge funds. Standard errors are clustered by firm and t-statistics are reported in parentheses. Model I tests for a linear relationship, model II tests for a quadratic relationship and model III tests for a cubic relationship. All models control for year fixed effects. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel A: Hedge fund only firms</i>						
Intercept	12.01** (2.17)	54.33 (0.67)	537.39 (0.47)	12.11** (2.17)	58.16 (0.71)	375.40 (0.33)
Log Lagged Family Assets	-0.65** (-2.31)	-5.11 (-0.60)	-81.96 (-0.46)	-0.68** (-2.39)	-5.54 (-0.65)	-56.00 (-0.31)
Square of Log Lagged Family Assets		0.12 (0.53)	4.178 (0.45)		0.13 (0.57)	2.80 (0.30)
Cubic of Log Lagged Family Assets			-0.07 (-0.44)			-0.05 (-0.29)
Number of Funds	-0.28 (-1.50)	-0.30 (-1.58)	-0.30 (-1.59)	-0.30 (-1.30)	-0.31 (-1.36)	-0.31 (-1.36)
Number of Styles	0.02 (0.05)	0.09 (0.19)	0.00 (0.00)	0.28 (0.53)	0.35 (0.62)	0.30 (0.55)
Observations	574	574	574	574	574	574
R-squared	0.03	0.03	0.03	0.04	0.04	0.04
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 5.3. Continued

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel B: Diversified firms</i>						
Intercept	4.15 (1.57)	70.39*** (2.77)	572.69** (2.33)	3.41 (1.26)	78.23*** (3.06)	591.52** (2.35)
Log Lagged Family Assets	-0.21 (-1.45)	-7.32*** (-2.75)	-86.62** (-2.27)	-0.18 (-1.19)	-8.20*** (-3.07)	-89.24** (-2.28)
Square of Log Lagged Family Assets		0.19*** (2.73)	4.35** (2.21)		0.21*** (3.08)	4.46** (2.22)
Cubic of Log Lagged Family Assets			-0.07** (-2.15)			-0.07** (-2.14)
Number of Funds	0.08 (0.66)	-0.09 (-0.72)	-0.00 (-0.03)	0.06 (0.39)	-0.13 (-0.97)	-0.05 (-0.32)
Number of Styles	0.26 (0.88)	0.46 (1.46)	0.33 (1.13)	0.44 (1.16)	0.67* (1.70)	0.54 (1.44)
Observations	1,249	1,249	1,249	1,249	1,249	1,249
R-squared	0.01	0.02	0.02	0.01	0.02	0.02
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

The regression results in panel A show a significant linear relationship for hedge fund only management firms. The negative coefficient on the linear term indicates that increasing fund assets has a negative effect on fund performance. We do not find evidence of a non-linear relationship between size and performance for these firms. On the other hand, a different story emerges for management firms that generate compensation from sources in addition to hedge funds. Panel B shows that the coefficients are significant for all lagged firm assets in the cubic equation, but the relationship is non-linear. The negative coefficient on lagged firm assets shows that as AUM increase, performance decreases. The positive coefficient on the quadratic term means that as you move away from the average of AUM, the performance of larger funds increases and smaller funds decreases, whereas the negative coefficients on the cubic term means that as you move to AUM extremes, the performance of the

smallest funds increases and the largest funds decrease. Consistent with Yin (2016), both panels suggest that hedge fund management firms suffer from diseconomies of scale.

5.4 Compensation-size relationship

Having established that diseconomies of scale exist for the firms in our sample and there is a negative relationship between firm fund performance and firm AUM, we next look at the incentives for a hedge fund management firm to increase its AUM beyond the optimal point for performance, using compensation data from our novel dataset. In particular, we wish to see whether the findings of Yin (2016) of a strong positive relationship between AUM and compensation hold up using actual compensation data (controlling for the increased costs of operating a large hedge fund), rather than using estimated fee income to proxy for compensation.

Given the terms of the hedge fund compensation contract, we expect that as AUM increase, the annual management fee will also increase. Consequently, the observed diseconomies of scale will have a negative effect on performance fees, but this will to an extent be offset by larger AUM. Yin (2016) finds that the larger AUM more than offset the diseconomies of scale to performance. However, our study extends Yin (2016) by also accounting for the larger costs associated with managing larger AUM. We anticipate that these should decrease the magnitude of the relationship between size and compensation.

5.4.1 Compensation comparison: Hedge fund only and Diversified Companies

To examine the compensation and size relationship, we first sort all hedge fund management firms into size quintiles each year and compare the average compensation of different size quintiles. For comparison, we also report the average of estimated fee income for each size quintile.

Table 5.4. Compensation and Estimated Fees comparison of different firms

This Table presents a compensation and estimated fee comparison of different size quintiles, for all firms, hedge fund only management firms and diversified management firms. Each year firms are divided into quintiles based on their lagged family fund size. Family fund size is the sum of the assets of funds managed by the same management firm. Compensation and Estimated Fee is the average of compensation and estimated fees of funds managed by the firm. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Size group	Compensation				Estimated Fees			
	All firms	Hedge fund only firms	Diversified firms	Difference	All firms	Hedge fund only firms	Diversified firms	Difference
1	6.95	0.76	11.29	-10.53**	1.62	2.38	1.08	1.30***
2	9.61	1.81	16.64	-14.82***	4.57	7.17	2.23	4.94***
3	12.39	3.55	20.35	-16.81***	7.69	11.04	4.68	6.36***
4	26.99	4.95	49.03	-44.08**	14.47	20.28	8.65	11.63***
5	65.03	18.60	111.46	-92.86***	49.84	51.79	47.89	3.89
Diff. (1) -(5)	-58.07	-17.84	-100.16		-48.22	-49.41	-46.81	
p-value	0.00***	0.00***	0.00***		0.00***	0.00***	0.00***	

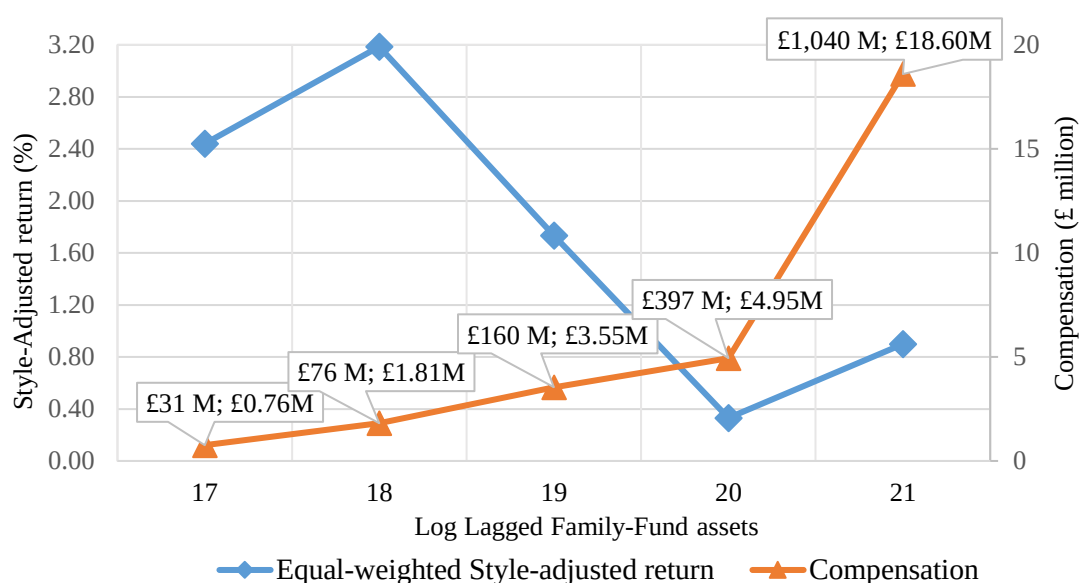
The results in Table 5.4 show that compensation and estimated fee income increase monotonically with AUM. The compensation and fee income of the largest size quintile is much larger than that of the other four groups. The difference between the smallest and largest group is negative and statistically significant for all management firms. When we look at hedge fund only and management firms whose compensation from hedge fund management only account for a small proportion of their total compensation, compensation and estimated fees increase when fund AUM increases.

Looking at the difference between the compensation between hedge fund only management firms and diversified firms, it is negative and statistically significant. This is due to the diversified firms generating compensation from sources outside of hedge funds. In contrast, comparing estimated fee income of hedge fund only management firms and diversified firms, the fee income of hedge fund only management firms are higher, due to the incentive fees earned from superior performance.

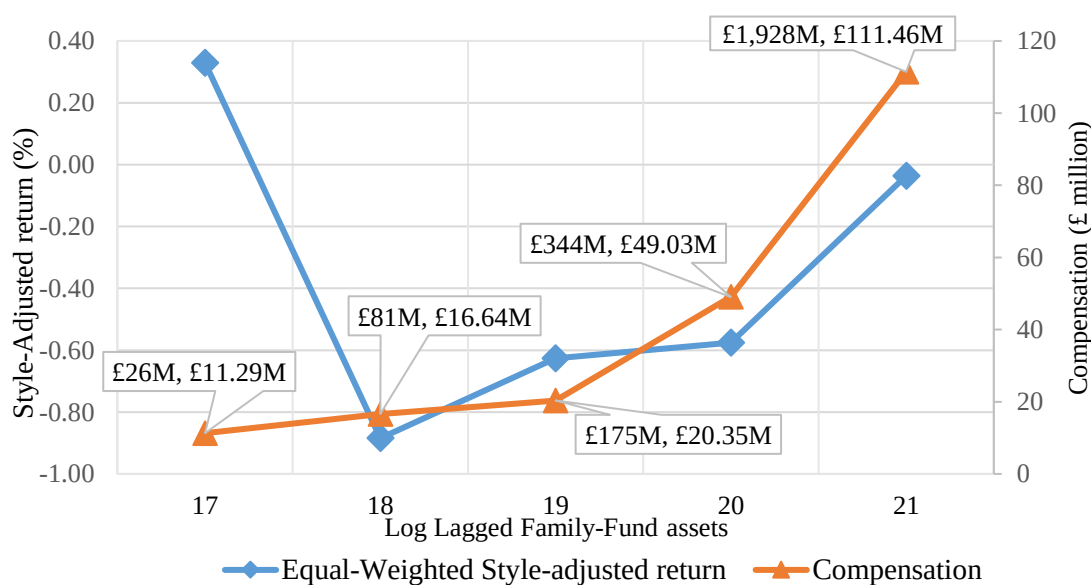
Figure 5.2. Managerial compensation

Fund family returns are ranked into five groups based on their lagged fund assets. The average managerial compensation for each group is calculated over time. The average lagged fund assets (in £millions) and average compensation (in £millions) for each size group are shown in the callouts. The average lagged fund assets (in £millions) and average style adjusted return (in %) for each size group are shown. Panel A shows hedge fund only firms. Panel B shows diversified firms.

Panel A: Hedge Fund Only Firms



Panel B: Diversified Firms



The relationship between fund assets, compensation and fund family returns is reported in Figure 5.2. The average lagged fund assets (in £millions), average compensation (in £millions) and average style-adjusted return (in %) for each size group are shown. Looking first at Panel A for hedge fund only firms, we can see that style-adjusted returns are highest for the bottom two quintiles, before gradually declining in the third and fourth quintile and then showing a slight increase for the largest firms. Compensation increases steadily as the size of the funds managed by the firm increase, before increasing quite dramatically for the largest funds. Panel B shows the same analysis for diversified firms. The relatively weak performance is reported on the primary axis, with only the smallest funds generating positive style-adjusted returns. However, compensation increases steadily before accelerating for the firms' managing the largest fund families.

5.4.2 Regression results

Next, using audited compensation data, we test the relationship between firm AUM and compensation using the following panel regressions:

$$\text{Compensation}_t = \beta_0 + \beta_1 \times \text{CompanyAUM}_{t-1} + \text{Control Variables} \quad (5.5)$$

$$\begin{aligned} \text{Compensation}_t = \beta_0 + \beta_1 \times \text{CompanyAUM}_{t-1} + \beta_2 \times [\text{CompanyAUM}_{t-1}]^2 + \\ \text{Control Variables} \end{aligned} \quad (5.6)$$

Table 5.5. Compensation-size relationship

This Table represents the regression results of the compensation-size relationship. The dependent variables are Compensation and Estimated fee income. The independent variable is lagged fund family assets. Both independent variables and dependent variables are in millions of pounds. Control variables include the number of funds under management and the number of styles used by the management firm. Standard errors are clustered by firm and t-statistics are reported in parentheses. All models control for year fixed effects. Panel A reports the compensation-size regression results for hedge fund only management firms which generate all their compensation from hedge funds. Panel B presents the regression results for diversified management firms which generate their compensation from other sources in addition to hedge funds. Model I tests for a linear relationship, model II tests for a quadratic relationship. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Compensation		Estimated Fee Income	
	I	II	I	II
<i>Panel A: Hedge fund only firms</i>				
Intercept	2.83 (0.49)	1.01 (0.20)	13.73** (2.38)	14.54** (2.65)
Lagged Family Assets	0.02*** (4.20)	0.05** (2.56)	0.05*** (7.59)	0.04*** (2.97)
Square of Lagged Family Assets		-0.00 (-1.45)		0.00 (1.05)
Number of Funds	-4.65*** (-4.78)	-5.13*** (-5.34)	-1.04 (-1.28)	-0.82 (-1.02)
Number of Styles	6.07*** (2.80)	4.16* (1.68)	-4.05 (-1.30)	-3.19 (-1.06)
Observations	129	129	129	129
Adjusted R-squared	0.37	0.43	0.66	0.66
Year FE	Yes	Yes	Yes	Yes

(Continued)

Table 5.5. Continued

Variables	Compensation		Estimated Fee Income	
	I	II	I	II
<i>Panel B: Diversified firms</i>				
Intercept	35.20*	33.50*	-4.66	-4.95
	(1.71)	(1.74)	(-0.89)	(-0.93)
Lagged Family Assets	0.01	0.04**	0.02***	0.02**
	(0.84)	(2.28)	(9.81)	(2.40)
Square of Lagged Family Assets		-0.00		-0.00
		(-1.28)		(-0.52)
Number of Funds	26.29	25.99	2.64	2.59
	(1.39)	(1.42)	(1.47)	(1.59)
Number of Styles	-39.16	-41.18	3.20	2.86
	(-1.19)	(-1.23)	(1.01)	(0.95)
Observations	299	299	299	299
Adjusted R-squared	0.26	0.28	0.63	0.63
Year FE	Yes	Yes	Yes	Yes

Table 5.5 presents results on the compensation-size relationship using audited compensation data, net of all costs. For comparison purposes, results are also reported using estimated fees. Looking first at hedge fund only firms in Panel A, we find a strong positive association between firm AUM and compensation.

In Panel B, when we report the results for diversified firms who generate their compensation from sources in addition to hedge funds, we see that, while there is a strong relationship between estimated fee income and size, the relationship between total compensation and fund size is much weaker. This is due to diversified firms (despite having weaker performance and lower estimated fee income) having much higher compensation. By generating compensation from other sources, the managers' compensation is less sensitive to the performance of their funds, leading to weaker alignment between the investors in the funds of these firms and their managers.

5.5 Conclusions

The contract between hedge fund manager and investor is designed to incentivise performance, with the manager receiving a performance-based fee in addition to their annual management fee. Existing evidence suggests that, despite this incentive, the manager is still motivated to grow the AUM of the fund, despite performance diseconomies to scale. Due to a paucity of data, to date, all of this evidence has relied upon the assumption that fees estimated from the hedge fund databases closely approximate the actual compensation earned by the hedge fund manager. This is problematic because hedge fund databases are well recognised to contain several biases, and the hedge fund managers will have very significant costs, varying across firms and time, which need to be accounted for to properly measure compensation.

Using our novel dataset of hedge fund manager filings, we are able to use audited compensation data to provide new evidence on the conflicts of interest between hedge fund managers and their investors. Our evidence is largely consistent with Yin (2016). We find significant evidence of diseconomies of scale — as AUM increase, performance deteriorates. Nonetheless, our evidence suggests that managers have an incentive to grow assets at the cost of performance, because their compensation, after accounting for all costs, increases with AUM. This result provides a more robust evidence that supports the extant literature on diseconomies of scale for fund performance in the hedge fund industry and the effectiveness of the standard managerial contract (Yin, 2016, Fung et al., 2017, Lim et al., 2016). In addition, our study also adds a new precise measure for managers' income to compare with that which can be estimated from current voluntary commercial databases in the literature (Lim et al., 2016, Agarwal et al., 2009).

Within our sample, we have two main types of hedge fund management firms. The first (hedge fund only firms) generate compensation entirely from hedge funds, while the second (diversified firms) generate a relatively small proportion of compensation from hedge funds. The funds managed by these two classifications of hedge fund firms have vastly different performance. Hedge fund only firms outperform by 80 percent relative to their peers, whereas diversified firms underperform by 15 percent. This result makes a significant additional contribution to the existing literature on hedge fund management firms (Fung et al., 2017, Sun and Teo, 2019).

We see a large variation in the compensation of these two classifications of hedge fund firms. Our results show that the incentives to grow assets are strong for hedge fund only firms because their compensation is tightly linked to AUM. Even when firms generate a relatively small proportion of their compensation from hedge fund management, managers are still motivated to maximize fund size, but the relationship is weaker due to their total compensation being less sensitive to fund size. This finding suggests that the effectiveness of standard hedge fund compensation contract is limited (Yin, 2016).

These results have an important implication for investors. Even accounting for the large cost base of firms who manage bigger funds, managers have strong incentives to grow AUM to maximise their own compensation. Investors should be particularly attentive to diversified firms who manage hedge funds because managerial incentives in these firms are less closely aligned with the interests of their investors.

5.A Appendix: Details of the sample construction process

As this paper considers the hedge fund management company as the unit of the analysis, the samples for investigating the performance-size relationship and compensation-size relationship are constructed by combining the Lipper TASS hedge fund database with the Bureau Van Dijk FAME company database. The TASS database tracks information on monthly rate of returns, AUM, management and performance fee percentage and other fund characteristics of individual funds. The FAME database provides comprehensive accounting information for each company on annual revenue, total assets, number of employees, salaries, etc. Since the sample for analysing the performance and size relationship is conducted based on quarterly frequency (and those for evaluating the compensation and size relationship is conducted based on annual frequency), the matching procedure between two databases is quite complicated. Figure 5.3 below illustrates the combining procedure to construct the samples used for the previous analyses.

This study first creates an individual hedge fund sample at quarterly frequency from TASS database. That is, monthly returns are aggregated into quarterly returns and fund size is measured by using assets reported at the end of each quarter. Similarly, for the individual hedge fund sample at annual frequency, monthly returns are aggregated into annual returns and fund size is measured by using assets reported at the end of each year.

This research then creates quarterly and annual samples at the management company level. That is, performance is measured as the average returns of all funds under the same management firm, both equal-weighted and asset-weighted, size is given as the

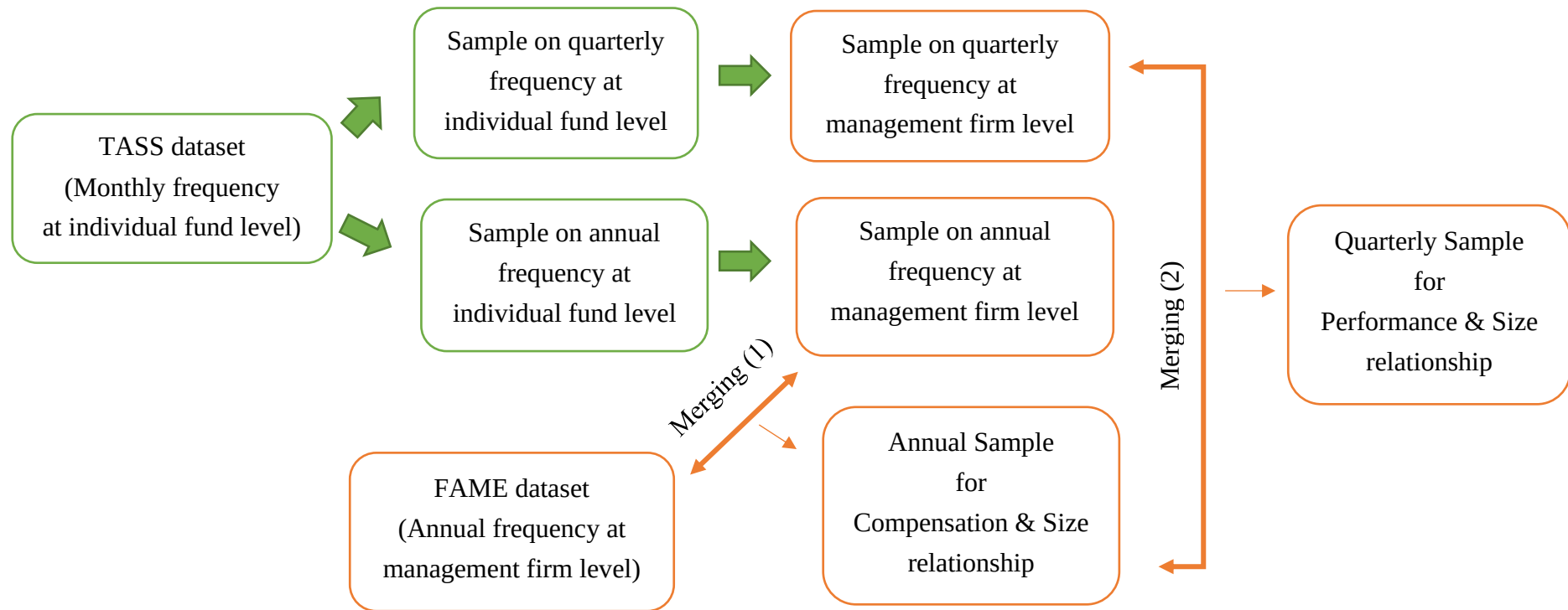
sum of the assets of all funds under management, and estimated fee income is the sum of the fees of all funds under the same management company.

To construct the sample for the analysis of the performance-size relationship and compensation-size relationship, this study performs two merging procedures. The first merging procedure (procedure (1) in Figure 5.3) for creating an annual sample for analysing the compensation and size relationship. Specifically, we merge the annual hedge fund TASS dataset and FAME accounting dataset by management company id and year and then look for the matches. Final annual sample for compensation and size relationship at the firm level only keeps the company id and years which appear in both databases.

The second merging procedure is for creating final quarterly sample for performance and size relationship analysis (procedure (2) in Figure 5.3) and for making sure that the study analyses the same sample for both relationships. From the annual sample for the compensation and size relationship, we create a list of unique management company names whose accounting data is available in FAME, and then look for the matches in quarterly hedge fund sample. The final quarterly sample for the performance-size relationship at the management firm level only keeps hedge funds managed by the companies which appear in FAME database.

Figure 5.3. Sample construction process

This Figure displays the details of the process how the samples are created by combining the Lipper TASS hedge fund database and the Bureau Van Dijk FAME accounting database of United Kingdom private company filings.



Notes: : Sample at the individual fund level
 : Sample at the management firm level

Merging (1): To create an annual sample for the compensation and size relationship, we merge the annual hedge fund TASS dataset and FAME accounting dataset by company id and year and then look for the matches.

Merging (2): From the annual sample for the compensation and size relationship, we create a list of unique management company names whose accounting data are available in FAME, and then look for the matches in quarterly hedge fund sample. The final quarterly sample for the performance-size relationship only keep hedge funds managed by the companies which appear in FAME database.

5.B Appendix: Robustness checks

5.B.1 Quartiles and Terciles comparison

Due to concerns about the size of our sample, this section repeats the performance and compensation comparison of different firms when hedge fund management firms are sorted into quartiles and terciles based on firm size. Findings presented in Table 5.6 and Table 5.7 are consistent with the quintile-based results reported earlier in Tables 5.2 and Table 5.4, respectively.

Table 5.6. Performance comparison with size quartiles and terciles

This Table presents a performance comparison of different size groups, for all firms, hedge fund only management firms and diversified firms. Panel A presents a performance comparison with size quartiles. Each quarter, firms are divided into quartiles based on their lagged family fund size. Panel B presents a performance comparison with size terciles. Each quarter, firms are divided into terciles based on their lagged family fund size. Family fund size is the sum of the assets of all funds managed by the same management firm. Firm performance is the average style-adjusted returns of all funds managed by the same firm, both equal-weighted and asset-weighted. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Size group	Equal-Weighted Performance				Asset-Weighted Performance			
	All firms	Hedge fund only firms	Diversified firms	Difference	All firms	Hedge fund only firms	Diversified firms	Difference
<i>Panel A: Quartiles analysis</i>								
1	1.09	2.38	0.04	2.34***	1.11	2.42	0.05	2.37***
2	0.76	2.45	-0.93	3.38***	0.75	2.42	-0.91	3.33***
3	0.24	1.08	-0.57	1.65***	0.32	1.16	-0.50	1.66***
4	0.15	0.47	-0.17	0.64*	0.22	0.46	-0.01	0.46
Diff. (1) -(4)	0.94	1.91	0.20		0.89	1.96	0.05	
p-value	0.03**	0.02**	0.32		0.03**	0.02**	0.45	
<i>Panel B: Terciles analysis</i>								
1	1.05	2.42	-0.19	2.61***	1.03	2.37	-0.18	2.56***
2	0.41	1.58	-0.77	2.35***	0.44	1.62	-0.74	2.37***
3	0.15	0.57	-0.26	0.83**	0.21	0.56	-0.13	0.69**
Diff. (1) - (3)	0.90	1.85	0.07		0.82	1.81	-0.06	
p-value	0.02**	0.01**	0.43		0.03**	0.01**	0.56	

Table 5.7. Compensation and Estimated Fees comparison with size quartiles and terciles

This Table presents a compensation and estimated fee comparison of different size groups, for all firms, hedge fund only management firms and diversified firms. Panel A presents Compensation and Estimated Fees comparison with size quartiles. Each year, firms are divided into quartiles based on their lagged family fund size. Panel B presents Compensation and Estimated Fees comparison with size terciles. Each year, firms are divided into terciles based on their lagged family fund size. Family fund size is the sum of the assets of all funds managed by the same management firm. Compensation and Estimated Fee is the average of compensation and estimated fees of funds managed by the firm. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Size group	Compensation				Estimated Fees			
	All firms	Hedge fund only firms	Diversified firms	Difference	All firms	Hedge fund only firms	Diversified firms	Difference
<i>Panel A: Quartiles analysis</i>								
1	7.16	1.12	11.99	-10.87***	2.64	4.34	1.27	3.07**
2	10.65	2.40	18.08	-15.68***	5.45	8.07	3.10	4.97***
3	21.78	4.59	38.98	-34.39***	11.53	16.46	6.59	9.87***
4	59.75	15.96	103.55	-87.59***	43.25	43.28	43.23	0.05
Diff. (1) -(4)	-52.60	-14.84	-91.57		-40.62	-38.94	-41.96	
p-value	0.00***	0.00***	0.00***		0.00***	0.00***	0.00***	
<i>Panel B: Terciles analysis</i>								
1	7.56	1.57	12.95	-11.38***	3.35	5.46	1.46	4.00***
2	14.57	3.39	25.74	-22.36***	8.09	11.38	4.79	6.59***
3	52.32	14.26	90.38	-76.12***	36.10	38.70	33.49	5.21
Diff. (1) -(3)	-44.77	-12.70	-77.43		-32.74	-33.24	-32.03	
p-value	0.00***	0.00***	0.00***		0.00***	0.00***	0.00***	

5.B.2 Different performance measure

As a robustness check, this section examines whether the performance and size relationship remains unchanged when using an alternative performance measure other than style-adjusted returns. Following Yin (2016), to measure family performance net-of-fee raw returns (which are as reported to TASS database) are used as the alternative performance proxy. Monthly returns are firstly aggregated into quarterly returns for each fund and then this section employs both equal-weighted and asset-weighted average returns across all of the funds managed by the same company as a measure of company performance.

In the first approach, companies are ranked into size quintiles each quarter and then we calculate the average of company performance over time for each size quintile. Table 5.8 compares company performance between hedge fund only firms and diversified firms for each size group. Looking at hedge fund firm performance across the size quintiles, it is evident that smaller companies have better performance. The performance difference between the smallest group and the largest group is positive but insignificant. Moreover, results show that hedge fund only companies (which generate all their revenue from hedge funds) outperform the diversified companies.

Table 5.8. Performance comparison of different companies' funds: A different performance measure

This Table presents a performance comparison of different size quintiles, for all companies, hedge fund only management companies and diversified companies used an alternative performance measure (i.e. net-of-fee raw returns). Every quarter, companies are divided into quintiles based on their lagged family fund size. Family fund size is the sum of the assets of funds managed by the same management company. Firm performance is the average net-of-fee raw returns of all the funds managed by a company, both equal-weighted and asset-weighted. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Size group	Equal-Weighted				Asset-Weighted			
	All firms	Hedge fund only firms	Diversified firms	Difference	All firms	Hedge fund only firms	Diversified firms	Difference
1	2.87	4.08	1.97	2.12*	2.91	4.16	1.97	2.18*
2	2.56	4.76	0.58	4.18***	2.49	4.62	0.57	4.05***
3	2.09	3.28	0.97	2.31***	2.11	3.33	0.98	2.35***
4	1.51	2.31	0.71	1.59**	1.55	2.39	0.72	1.66**
5	2.28	3.46	1.15	2.31**	2.31	3.42	1.25	2.16**
Diff. (1) - (5)	0.59	0.62	0.82		0.60	0.74	0.72	
p-value	0.24	0.34	0.18		0.24	0.32	0.21	

This section then tests whether hedge fund management firms suffer diseconomies of scale in fund performance using another different performance measure. Table 5.9 presents the regression results for hedge fund only firms which generate all their revenue from hedge funds and diversified firms who generate their revenue from other sources in addition to hedge funds, respectively.

For hedge fund only companies, Panel A reports a negative linear relationship when using raw returns as the performance proxy. Differently, the relationship between performance and size is convex for firms which generate a small proportion of their income from hedge fund management. Although the shape of the performance-size relationship differs slightly, all results indicate that the diseconomies of scale in performance persists in hedge fund management firms.

Table 5.9. Performance-Size relationship: A different performance measure

This Table reports regression results of the performance-size relationship used an alternative performance measure. The dependent variable is the average net-of-fee raw returns of the hedge funds managed by the firm, both equal-weighted and asset-weighted. The independent variable is the natural log of lagged fund family assets. Control variables include the number of funds under the management and the number of styles used by the management firms. Panel A reports the performance-size regression results for hedge fund only firms which generate all their revenue from hedge funds. Panel B presents the regression results for diversified firms which generate their revenue from other sources in addition to hedge funds. Standard errors are clustered by the company and t-statistics are reported in parentheses. All models control for year fixed effects. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel A: Hedge fund only firms</i>						
Intercept	13.23*	91.45	1,859.12	13.11*	95.82	1,749.27
	(1.90)	(0.92)	(1.31)	(1.85)	(0.95)	(1.24)
Log Lagged Family Assets	-0.60*	-8.85	-290.06	-0.61*	-9.33	-272.37
	(-1.68)	(-0.85)	(-1.30)	(-1.67)	(-0.89)	(-1.23)
Square of Log Lagged Family Assets		0.22	15.08		0.23	14.13
		(0.81)	(1.30)		(0.85)	(1.23)
Cubic of Log Lagged Family Assets			-0.26			-0.24
			(-1.30)			(-1.22)
Number of Funds	-0.43*	-0.45*	-0.45*	-0.45	-0.47	-0.47
	(-1.76)	(-1.85)	(-1.89)	(-1.52)	(-1.59)	(-1.62)
Number of Styles	0.17	0.29	-0.03	0.29	0.42	0.12
	(0.34)	(0.55)	(-0.05)	(0.51)	(0.70)	(0.20)
Observations	574	574	574	574	574	574
R-squared	0.08	0.09	0.09	0.09	0.09	0.09
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 5.9. Continued

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel B: Diversified firms</i>						
Intercept	5.85* (1.92)	68.32** (2.56)	380.61 (1.30)	5.70* (1.86)	72.14*** (2.67)	407.85 (1.35)
Log Lagged Family Assets	-0.21 (-1.23)	-6.91** (-2.47)	-56.22 (-1.23)	-0.20 (-1.20)	-7.33** (-2.59)	-60.33 (-1.29)
Square of Log Lagged Family Assets		0.18** (2.46)	2.76 (1.17)		0.19** (2.58)	2.97 (1.23)
Cubic of Log Lagged Family Assets			-0.05 (-1.11)			-0.05 (-1.16)
Number of Funds	0.07 (0.42)	-0.09 (-0.55)	-0.04 (-0.22)	0.09 (0.49)	-0.09 (-0.51)	-0.03 (-0.16)
Number of Styles	0.19 (0.49)	0.37 (0.90)	0.30 (0.72)	0.27 (0.58)	0.46 (0.96)	0.38 (0.80)
Observations	1,249	1,249	1,249	1,249	1,249	1,249
R-squared	0.09	0.09	0.09	0.08	0.09	0.09
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

5.B.3 Firm fixed effects and Year fixed effects

In order to verify the findings presented earlier in this chapter, this section presents the analysis of performance and size relationship with firm fixed effects singularly and with year fixed effects. Although the shape of the performance-size relationship differs slightly, all results indicate the existence of the diseconomies of scale for fund performance in all hedge fund management firms.

Table 5.10 Performance-Size relationship: With Firm fixed effects

This table represents regression results of the performance-size relationship included firm fixed effects singularly. The dependent variable is the average style-adjusted returns of the hedge funds managed by the firm, both equal-weighted and asset-weighted. The independent variable is the natural log of lagged fund family assets. Control variables include the number of funds under the management and the number of styles used by the management firm. Panel A reports the performance-size regression results for hedge fund only firms which generate all their revenue from hedge funds. Panel B presents the regression results for diversified firms which generate their revenue from other sources in addition to hedge funds. Robust standard errors are reported in parentheses. All models control for firm fixed effects. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel A: Hedge fund only firms</i>						
Intercept	40.43*** (4.26)	254.16* (1.98)	1,867.60 (1.26)	41.75*** (4.64)	245.18* (1.95)	1,829.59 (1.21)
Log Lagged Family Assets	-2.04*** (-4.04)	-24.62* (-1.83)	-280.78 (-1.21)	-2.16*** (-4.49)	-23.65* (-1.81)	-275.20 (-1.16)
Square of Log Lagged Family Assets		0.59* (1.70)	14.11 (1.17)		0.57 (1.66)	13.84 (1.13)
Cubic of Log Lagged Family Assets			-0.24 (-1.14)			-0.23 (-1.10)
Number of Funds	-0.33 (-0.85)	-0.36 (-0.88)	-0.35 (-0.93)	-0.43 (-0.92)	-0.46 (-0.92)	-0.45 (-0.96)
Number of Styles	0.45 (0.45)	0.52 (0.50)	0.32 (0.32)	1.24 (1.11)	1.31 (1.11)	1.12 (0.98)
Observations	574	574	574	574	574	574
R-squared	0.03	0.04	0.04	0.03	0.04	0.04
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 5.10. Continued

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel B: Diversified firms</i>						
Intercept	13.75*** (3.49)	45.75 (1.49)	497.90** (2.02)	13.41*** (3.44)	41.10 (1.31)	504.63* (1.98)
Log Lagged Family Assets	-0.77*** (-3.50)	-4.21 (-1.32)	-75.64* (-1.96)	-0.77*** (-3.48)	-3.74 (-1.15)	-76.97* (-1.93)
Square of Log Lagged Family Assets		0.09 (1.13)	3.84* (1.91)		0.08 (0.95)	3.92* (1.90)
Cubic of Log Lagged Family Assets			-0.07* (-1.88)			-0.07* (-1.88)
Number of Funds	0.04 (0.27)	-0.04 (-0.27)	0.03 (0.19)	0.03 (0.21)	-0.03 (-0.21)	0.03 (0.19)
Number of Styles	0.19 (0.48)	0.28 (0.68)	0.12 (0.28)	0.42 (1.01)	0.50 (1.14)	0.33 (0.72)
Observations	1,249	1,249	1,249	1,249	1,249	1,249
R-squared	0.01	0.01	0.01	0.01	0.01	0.01
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5.11 Performance-Size relationship: With Firm fixed effects and Year fixed effects

This table represents regression results of the performance-size relationship included firm fixed effects singularly. The dependent variable is the average style-adjusted returns of the hedge funds managed by the firm, both equal-weighted and asset-weighted. The independent variable is the natural log of lagged fund family assets. Control variables include the number of funds under the management and the number of styles used by the management firm. Panel A reports the performance-size regression results for hedge fund only firms which generate all their revenue from hedge funds. Panel B presents the regression results for diversified firms which generate their revenue from other sources in addition to hedge funds. Robust standard errors are reported in parentheses. All models control for firm fixed effects and year fixed effects. *, ** and *** denote significance at the 0.1, 0.05 and 0.01 level, respectively.

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel A: Hedge fund only firms</i>						
Intercept	38.81*** (3.27)	246.41* (1.83)	2,177.85* (1.71)	39.81*** (3.70)	233.44* (1.80)	2,200.16* (1.74)
Log Lagged Family Assets	-2.21*** (-3.34)	-24.16* (-1.69)	-331.12* (-1.67)	-2.31*** (-3.87)	-22.79 (-1.66)	-335.36* (-1.70)
Square of Log Lagged Family Assets		0.58 (1.52)	16.79 (1.64)		0.54 (1.48)	17.05 (1.67)
Cubic of Log Lagged Family Assets			-0.28 (-1.62)			-0.29 (-1.65)
Number of Funds	-0.43 (-1.12)	-0.42 (-1.00)	-0.46 (-1.17)	-0.56 (-1.28)	-0.55 (-1.13)	-0.59 (-1.27)
Number of Styles	0.38 (0.38)	0.35 (0.33)	0.18 (0.18)	1.22 (1.21)	1.19 (1.11)	1.02 (0.99)
Observations	574	574	574	574	574	574
R-squared	0.06	0.07	0.07	0.07	0.07	0.08
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 5.11. Continued

Variables	Equal-Weighted			Asset-Weighted		
	I	II	III	I	II	III
<i>Panel B: Diversified firms</i>						
Intercept	14.12*** (3.71)	46.97 (1.39)	467.44* (1.93)	13.82*** (3.61)	45.22 (1.32)	455.88* (1.84)
Log Lagged Family Assets	-0.81*** (-3.74)	-4.33 (-1.23)	-70.78* (-1.87)	-0.80*** (-3.65)	-4.16 (-1.17)	-69.07* (-1.79)
Square of Log Lagged Family Assets		0.09 (1.03)	3.58* (1.82)		0.09 (0.97)	3.49* (1.74)
Cubic of Log Lagged Family Assets			-0.06* (-1.78)			-0.06* (-1.71)
Number of Funds	-0.00 (-0.02)	-0.07 (-0.52)	-0.01 (-0.04)	-0.01 (-0.05)	-0.07 (-0.46)	-0.01 (-0.06)
Number of Styles	0.25 (0.66)	0.33 (0.82)	0.18 (0.42)	0.48 (1.16)	0.56 (1.28)	0.41 (0.87)
Observations	1,249	1,249	1,249	1,249	1,249	1,249
R-squared	0.01	0.01	0.01	0.01	0.01	0.01
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 6 : Conclusions

6. Conclusions

6.1 Introduction

The theme of this thesis is data — the lynchpin of empirical research in finance — with a key focus on the insights derived from a new dataset as well as a new interpretation of an old dataset. Specifically, this thesis provides insights from the availability of a new and novel data set for hedge funds and the appropriate interpretation of an event-day adjustment for event studies in the pharmaceutical industry to advance the finance literature.

Previous chapters presented i) a literature review on financial data, ii) an event study of the effect of determining the exact timing on the market reaction to FDA new drug approvals, iii) an examination of the financial performance of investment companies that manage hedge funds, and iv) an investigation of the effectiveness of the hedge fund compensation contract. This chapter draws together the conclusions from the three data related empirical studies that comprise this thesis. The first study demonstrates the implications of a more correct event-day specification of an event study (i.e. a new interpretation of existing data), in the specific context of the US pharmaceutical companies granted FDA approvals for their new drug applications. The following two empirical studies involve a novel dataset hand-collected from audited company filings by hedge fund management companies. The first of these two studies provides new time-series evidence of the actual profitability of investment companies who manage hedge funds and a discussion of the key characteristics determining the profitability of these firms. This is followed in the second by a direct test of the effectiveness of the hedge fund compensation contract as a managerial mechanism to reduce the conflicts of interest between fund managers and their

investors. This also includes significant evidence of a large variation in the performance and manager compensation between the two different types of hedge fund management companies.

The remainder of this chapter is organized as follows. Section 6.2 summarizes the key contributions that are generated by the empirical research presented in this thesis. Section 6.3 highlights areas for future research. This chapter ends with conclusions in section 6.4.

6.2 Summary of contributions

The extant literature on event studies highlights that event day zero needs to be carefully calibrated to clearly identify when the information content in firm announcements is available to the public (see for example Berkman and Truong (2009)). Although the event study methodology is widespread in academic research on the value relevance of announcement information in the pharmaceutical industry such studies have, due to data limitations, almost universally failed to account for the precise timing of the announcement in the specification of the event day. The first empirical study in this thesis, therefore, suggests that data needs to be carefully interpreted to correctly identify the event day in order to investigate the true stock market reaction to new announcements. In so doing, this chapter provides additional insights by interpreting existing data in a new and more appropriate way.

In terms of hedge funds, the emergence of numerous commercial hedge fund data vendors has offered opportunities for researchers to initially investigate new research questions and to publish on this alternative investment entity. These papers, which use

voluntarily reported hedge fund data, have resulted in a comprehensive literature on the hedge fund industry in a short period time. The existing evidence suggests that many of the conclusions on hedge funds drawn from these earlier empirical studies are potentially seriously affected by well-known data issues (i.e. data biases and the strategic reporting behaviour of hedge funds' managers) inherent in current commercial hedge fund databases. This, combined with the lack of regulation and no required mandatory information disclosures, has led to an ongoing demand for new sources of hedge fund data in order to gather more information on hedge funds and to generate further insights. With this in mind, the second and the third empirical chapters in this thesis contribute a new hedge fund data source that provides accounting information for hedge fund management companies and so avoids the data issues inherent in the data supplied by voluntary hedge fund data providers. In so doing, these chapters provide additional insights by sourcing a new dataset to more appropriately investigate open research questions.

The contributions of this thesis are achieved via sourcing new data and more precisely interpreting existing data. The key contributions are arranged under the following three areas: i) event-day specification for the event study; ii) new dataset for hedge funds and financial performance of hedge fund management companies; and iii) effectiveness of the standard hedge fund compensation contracts.

6.2.1 Event-day specification for the event study

The extant literature has agreed that the event-day identification plays a vital role in the event study methodology. That is, misspecification of the day zero (due to the lack of accounting for when new information reaches the public) has the potential to alter

the results and conclusions from event studies. However, a large body of event studies that demonstrate the shareholder wealth effects of a variety of FDA announcements do not consider the exact timings of announcements. By carefully identifying the event day, this study, therefore, makes a unique contribution to the event studies in general. Specifically, analysis of the case of FDA approval announcements in this study shows that when event-day misspecification is accounted for, the results are different to those observed in the prior literature. That is, the stock market reaction to a new drug approval is centred on the event day only, i.e. the significant post-event abnormal returns observed in prior studies disappear. Whereas previous studies have offered the attention-grabbing hypothesis as a behavioural explanation for post-event abnormal returns for FDA drug approval announcements granted by NYSE listed firms (Hamill et al., 2013), this study shows that the increase in firm value in the date after an FDA announcement observed in these prior studies is, in fact, the result of after-market-close notifications being inappropriately specified.

This finding emphasizes the important impact of determining the exact announcement timings in the event-day alignment when an event study is employed. When the precise identification of the event day is included, this study attributes the results of significant post-event abnormal returns obtained in previous studies to the incorrect data interpretation of researchers (i.e. no consideration of exact announcement timings). This result is robust to the influence of a few outliers — an outcome consistent with the payoff from a portfolio of real options.

6.2.2 New hedge fund data source and the financial performance of hedge fund management companies

Since the turn of the century, the availability of voluntary commercial hedge fund databases has contributed to the significant store of hedge fund information. However, many years of self-reporting to publicly available data vendors have resulted in non-standardized, non-comprehensive and biased hedge fund datasets. Indeed, the evidence from the extant literature shows that the conclusions about hedge funds drawn from empirical studies are subject to a variety of well-known data issues inherent in the commercial hedge fund databases. By using audited company filings from hedge fund management companies registered in the United Kingdom, this thesis, therefore, contributes a novel database for hedge fund information with which to test hypotheses to the finance literature. This unique dataset of accounting information, which is more reliable and more accurate than self-reported data or information extrapolated from self-reported data, has provided a better understanding of the investment companies that manage hedge funds by avoiding a variety of data problems inherent in current available hedge fund databases.

In both industry and academic research, it is commonly believed that the hedge fund industry (with abnormal profits and the high fees in the standard managerial contract, i.e. 2% annual management fee and 20% performance fee), is highly profitable. Analysis of the novel database of the accounting information of hedge fund management companies over the period from 2004–2017 shows that the profitability of these firms varies across time and firms. This research also establishes a link between the profitability of hedge fund management firms and the global financial crisis (2008–2010).

While these investment companies were incredibly profitable during the period leading to the global financial crisis, the onset of the crisis significantly reduced their profitability. Prior to 2008, hedge fund management companies generated revenue growth of 95 percent and profitability of 46 percent per annum. Since the crisis, growth rates of annual revenue dropped to 20 percent on average and profitability declined to 30 percent. It is noticeable that while these growth and profitability figures have remained at these lower levels across the long period post the financial recession, hedge fund management firms have increased their liquidity and strengthened firm's balance sheets at the same time. To the best of the author's knowledge, this is the first time that the actual profitability of companies which manage hedge funds has been analysed over time and so the results represent a significant and novel contribution to understanding the life cycle of the hedge fund industry.

At the same time, it has been documented that, due to the structure of the standard compensation contract, there are large direct and indirect incentives around fees of hedge fund managers. The evidence from previous studies also shows that managers are incentivised to grow the assets in their funds despite the existence of diseconomies of scale in hedge funds. A further insight into this relationship is obtained by investigating cross-sectional variations in profitability of hedge fund management companies, in both crisis and non-crisis periods. Using the novel data set of actual profitability, rather than fee income, this research finds that size is the key determinant of profitability. Over the full sample, larger firms are significantly more profitable, with an 18 percent increase in profitability relative to smaller companies. The difference is even larger during the financial crisis period, with an additional 5 percent increase when firm size grows. This result is consistent across two sub-periods on either side of the global financial crisis. These two tests strengthen the conclusion that

size really matters in determining the firm profitability. The results are robust to the influences of the winsorisation process, the large proportion of banks included in the original sample, and the measure of profitability. The evidence in this research supports the previous conclusions that, given the structure of their compensation contract, the manager of a hedge fund is rational to maximise fund size even when it leads to deterioration in fund performance.

6.2.3 Effectiveness of the standard hedge fund managerial contract

The compensation contract in the hedge fund industry is designed to align managerial incentives and investor interests, with the manager receiving a performance-based fee in addition to their annual management fee. That is, the manager is incentivised to generate higher fund performance, rather than increasing fund assets to maximise annual management fees. However, the evidence from prior studies and that from this thesis (detailed above) suggests that, despite this incentive, the manager is still motivated to grow the assets under their funds at the expense of investment performance. This finding indicates that the effectiveness of the compensation contract may be limited.

In all of the previous evidence to date, there is a common assumption (mainly due to the data limitation to be able to conclude otherwise) that fees estimated from the commercial hedge fund databases closely equate to the actual compensation earned by the manager. Insofar as this assumption is not true then the results from hedge fund studies that use hedge fund commercial databases to infer estimated compensation are called into question. This study avoids those problems by using the novel dataset of management company filings. This new and precise measure for audited reported

manager compensation provides new direct evidence on the alignment of interests between hedge fund managers and investors. The evidence on this actual manager income largely confirms that the standard hedge fund managerial contract is ineffective. Hedge fund managers typically continue to seek to increase assets beyond optimal levels for investors in order to maximise their incentives at the cost of fund performance.

Moreover, assuming that estimated fees closely approximate actual compensation ignores the substantial operating costs associated with managing hedge funds of investment companies (and the fact that these might both vary across firms and time and increase as fund assets grow). Failure to properly include these expenses in this assumption can make conclusions based on estimated fees unreliable. In particular, under-estimating costs can lead to erroneous conclusions of hedge fund manager incentives. Consequently, results on actual manager compensation presented in this research are net of all costs. Whereas there is significant evidence of diseconomies of scale in all hedge fund management companies, managers are still motivated to maximise fund assets because their compensation, after all costs are accounted for, increases with fund size.

A link between manager incentives and fund performance is further demonstrated in this research. If an investment company generates a large proportion of their revenues from sources other than managing hedge funds, then the managers' compensation is less sensitive to the performance of their funds. The novel dataset allows this study to distinguish between two different types of hedge fund management firms. While hedge fund only firms exclusively earn compensation from hedge funds, diversified firms generate a relatively small proportion of revenue from hedge funds. Managers

in these two classifications generate vastly different compensation and fee income. That is, managers in hedge fund only firms have stronger incentives to maximise assets under their management due to their compensation being tightly linked to fund assets. Because the relationship between their managers' compensation and fund assets is weaker, relative to hedge fund only firms, managerial incentives in diversified firms are less closely aligned with the interests of their investors. Indeed, there is a large variation in the performance of funds managed by these two classifications of hedge fund firms. That is, funds managed by diversified firms markedly underperform those managed by hedge fund only companies and the underperformance is concentrated in the smaller firms.

Taken together, these results confirm the limited effectiveness of standard hedge fund managerial contracts in reducing the conflicts between the investor and the manager. The results also represent a significant additional contribution to the literature on hedge fund management firms.

6.3 Avenues for future research

6.3.1 Event-day specification of other event studies

This study presents strong evidence of event-day misspecification (as opposed to the attention-grabbing hypothesis) as an explanation for the significant post-event abnormal returns reported in the extant literature. This research has suggested that the announcements occurring after the market hours need to be carefully adjusted for in order to precisely identify the event day when employing the event study. This result indicates that the correct alignment of day zero can be extended to other event studies

which seek to understand the firm value effects of a variety of financial and non-financial announcements (e.g. dividends, stock splits, M&A information, etc.). The significant results in this research also call into question any event studies which do not properly account for when new information can be traded by investors. As the exact timing of corporate announcements becomes available in the future, the replication of earlier event studies with after-market-close announcements included and properly adjusted for, would verify/retest existing results and provide further insights into the stock market reaction to new information.

6.3.2 Other finance topics with novel hedge fund datasets

Facilitated by a new source of hedge fund information, this research can be extended to explore the interface of many other topics in finance with hedge funds. There is a well-developed literature focused on the important role of corporate governance on corporate finance. Due to data limitations, to date no study has investigated either the corporate governance characteristics or the role of governance mechanisms in investment companies that manage hedge funds. Our novel dataset, collected from audited company filings, provides a full description of accounting information for private hedge fund management companies. This unique database, therefore, can be utilised to examine this topic and so provide additional understanding of this type of company. An investigation on whether the variations in internal governance relate to managers' compensation potentially offers a new and interesting area for future research.

6.4 Conclusions

The advancements in finance research over the last 30 years have been largely driven by access to more and new financial data. On the one hand, researchers have utilised (and continue to utilise) numerous innovative methods to interpret existing data in order to provide incremental and multi-faceted insights to the extant literature. On the other hand, newly accessible databases provide a great opportunity for researchers to offer novel contributions to the financial literature. The results in the empirical chapters of this thesis provide significant additional insights to the finance literature spanning both areas, facilitated by the correct interpretation of old, existing data on the one hand and the availability of brand-new datasets on the other.

The significant result in the first study concludes that the timing of announcements has important implications for research design when conducting event studies that has the potential to materially alter results and the conclusions drawn therefrom. In the specific context of FDA approval announcements, the research supports that when the precise timing of announcements is accounted for, event-day misspecification (as opposed to the attention-grabbing hypothesis) as an explanation for shareholder wealth effects. In combination, the results in the two other empirical chapters represent a significant and unique contribution to both the hedge fund management firm and incentives of hedge funds manager literatures. Synthesising elements of the findings shows the presence of a large variation in the profitability of hedge fund management firms over time and that size is a key driver of cross-sectional differences in this profitability. In addition to the evidence of the limited effectiveness of the standard hedge fund managerial contract in aligning the interests between the manager and the

investor, this research also provides a new measure of hedge fund managers' incentives from audited accounting information.

In conclusion, this study, which is focused both on a slightly different interpretation of existing data as well as the collection and examination of a novel data source, advances the literature by providing insights from financial data — old and new.

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