# Essays in Hedge Fund Performance

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# ABSTRACT

Over the last decade, hedge funds domiciled in the Asia Pacific has been one of the fastest growing sectors in the global hedge fund universe both in terms of the number of funds and assets under management (AUM).

The issue of the sustainability of hedge fund risk-adjusted performance (alpha) has become more relevant given the rapidly increasing inflows in hedge funds in this region. The first part of this thesis investigates the alpha generating of the hedge funds domiciled in the Asia Pacific based on a recent sample compiled from the Eurekahedge, TASS, and Morningstar databases covering both the up and down markets and including the latest financial crisis. I find a positive average alpha in the cross-section for the majority of strategies and a positive and significant alpha for roughly half of all funds. Moreover, the alpha of three-quarter of the strategy indices is positive and significant in the time series. A comparison of the stepwise regression factor model and the widely used factor model proposed by Fung and Hsieh (2004a) reveals that the estimated alpha is robust with respect to the choice of the factor model. In contrast to prior research I find little evidence of a decreasing hedge fund alpha over time except dedicated short bias strategy.

The second part of this thesis examines the issue of performance persistence in relation hedge funds domiciled in the Asia Pacific. Evidence of performance persistence indicates active selection is likely to enhance the expected return, particularly relevant for hedge fund investors. The second sub period that includes the global financial crisis of 2007 to 2010 result only weak evidence of performance. Over the full sample period, the results illustrate only weak evidence of persistence.

Lastly, the thesis relates the survival of hedge funds domiciled in the Asia Pacific to the hedge fund characteristics. Given certain hedge fund characteristics such as age, size, performance, standard deviation, leverage, management and performance fees, high water mark provisions, redemption frequency, lockup provisions, minimum investment requirements, and whether the fund is listed on an exchange, I question whether attrition of hedge funds can be predicted. The results show larger, better performing funds with lower redemption frequency has a higher likelihood of survival irrespective of the model used.

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Last but not the least, I would like to express my gratitude to my family: Tien Dung, Dad, my siblings and my two special children, Ethan and Alex. Alex was born in my first year of my PhD. They all provided unflinching support and encouragement to accomplish this thesis. I dedicate this thesis to my late mother Ye Ruidi, whose memories kindle my heart with peace and greatness of purpose.

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# CHAPTER ONE

# INTRODUCTION

## 1. Introduction

The hedge funds domiciled in the Asia Pacific has been expanding rapidly both in terms of the number of funds and AUM. Compared to mutual funds, hedge funds as alternative vehicles provide a number of advantages (Lowenstein, 2000). Hedge fund managers face fewer constraints when they choose their investment style, in taking both short and long positions, they can provide investors upside potential and limited downside. Additionally, various derivatives and leverage can be used to enhance the managers' investment returns. According to Stromqvist (2007), this freedom and flexibility in investment style will allow the hedge funds to handle the characteristics of emerging markets better.

The extraordinary growth of the hedge fund industry in recent years has generated a large body of academic literature. However, most extant academic studies analyse hedge funds that operate in the United States or Europe (Fung and Hsieh, 1997; Ackermann, McEnally and Ravenscraft, 1999; Lo, 2001). With the exception of Abugri and Dutta (2009), little attention has been devoted to the hedge funds that invest in Asia Pacific or other emerging markets.

The 2007 global financial crisis impacted the hedge fund industry heavily. Every type of asset in almost every market is adversely impacted, thus lowering the positive effects of the diversification provided by the hedge funds' portfolios (Stromqvist, 2007). The hedge fund industry in the Asia Pacific went through a period of large scale redemptions and closures after experiencing phenomenal growth in the first eight years of the twenty first century. As a result of lack of data for that period, most academic studies to date on hedge funds domiciled in Asia Pacific used time intervals that exclude the financial crisis of 2007. Therefore, the aim of this thesis is to investigate the performance of hedge funds domiciled in Asia Pacific that includes the financial crisis of 2007.

### 1.1 Research objective and key questions

There are three purposes of this thesis. Building on the academic studies of Ackermann et al., (1999), Stromqvist (2007), Fung, Hsieh, Naik and Ramadorai (2008), Eling and Faust (2010) and Xu, Liu and Loviscek (2010), multi factor models including both linear and non linear risk factors are used to examine the performance of hedge funds domiciled in the Asia Pacific. This study includes the 2007 global financial crisis period and analyses risk adjusted performance in cross-section, time series, for different strategies, different sub periods, different market environments and breaks (Eling and Faust, 2010). The impact of the crisis needs to be properly accounted for otherwise the accuracy of performance evaluations and empirical models that include the crisis period is questionable (Xu et al., 2010).

The second part of the thesis examines whether the returns exhibit performance persistence over time by concentrating on the returns of hedge funds domiciled in the Asia Pacific. The survivorship bias is measured and attrition rates during the time period studied is controlled for. From the perspective of the hedge fund investors, this is an important question as they face selection problems constantly when deciding on which hedge funds to invest.

The third part of the thesis investigates whether the hedge fund mortality can be predicted from certain hedge fund characteristics such as age, performance, standard deviation, size, leverage, lock-up period and management fee.  This issue of hedge fund survival and mortality patterns is relevant because if the probability of hedge fund death can be predicted based on certain characteristics, then the pure selection of them will increase future portfolio performance.

Consequently, the following research topics and research questions have been defined:

Research topic 1: Capacity constraints, fund flows and alpha

Research question 1.1: Do hedge funds domiciled in the Asia Pacific produced alpha in cross section and time series and for what strategies?

Research question 1.2: Do hedge funds domiciled in the Asia Pacific produce alpha over the period of global financial crisis and robust to the factor models used?

Research topic 2: Persistence of hedge fund performance

Research question 2.1: Is performance of hedge funds domiciled in Asia Pacific an outcome of managers' skill or simply luck?

Research topic 3: Hedge fund factors and survival analysis

Research question 3.1: What are the factors impacting on the survival of hedge funds domiciled in the Asia Pacific?

## 1.2 Results and contribution to the existing literature

This section outlines the main results of this thesis and its contribution to the existing literature. Section 1.2.1 summarizes the results of the first empirical study presented in Chapter 3 of hedge funds to produce risk adjusted performance (alpha) over the period under investigation. Section 1.2.2 presents the major results of second empirical study on hedge fund performance persistence, studied in Chapter 4. Lastly, section 1.2.3 summarizes the results of the Chapter 5 which analyses the probability of hedge fund survival relative to its idiosyncratic characteristics.

### 1.2.1 Do hedge funds domiciled in the Asia Pacific produce alpha in cross section and time series?

Using the Eurekahedge, TASS and Morningstar databases, the risk adjusted performance of hedge funds domiciled in the Asia Pacific is analysed in Chapter 3. Very few studies analyse the performance of hedge funds domiciled in the Asia Pacific in the academic literature most studies focus on US-centric and Europe-centric hedge funds. Using the two multi factor models that include both the linear and non-linear risk factors, this thesis fills the gap and analyses the performance of hedge funds domiciled in the Asia Pacific over the time period that includes the financial crisis of 2007. Using the Fung and Hsieh (2004a) model and the step wise regression model, results show positive average alpha in the cross-section for majority of strategies and a positive and significant alpha for roughly half of funds. A comparison of the stepwise regression factor model and the widely used factor model proposed by Fung and Hsieh (2004a) reveals the estimated alpha to be robust to the choice of the factor model. In contrast to prior research I find little evidence of a decreasing alpha over time.

### 1.2.2 Do hedge funds domiciled in the Asia Pacific display persistence in performance?

Using a horizon of 12 months and the Eurekahedge, TASS and Morningstar databases from January 2000 until December 2010, Chapter 4 visits the performance persistence of hedge funds domiciled in the Asia Pacific. This thesis examines the largest data sample of hedge funds domiciled in the Asia Pacific that includes both bullish and bearish market periods using parametric methodology rather than non-parametric methodology (Koh, Naik and Teo, 2007). I find only weak evidence of performance persistence in hedge funds domiciled in the Asia Pacific over the full sample period and only among medium and poor performers. For the second sub period that includes the global financial crisis of 2007, there is only weak evidence of performance persistence among middle performers. Since most of the performance persistence is found in the first, bullish sub period, results are similar to Capocci and Hubner (2005).

### 1.2.3 What are the factors impacting on the survival of hedge funds domiciled in the Asia Pacific?

Using the various hedge fund characteristics such as age, size, performance, standard deviation, leverage, management and performance fees, high water mark provisions, redemption frequency, lockup provisions, minimum investment requirements, and whether the fund is listed on the an exchange, Chapter 5 studies whether these hedge fund mortality can be predicted. Since the number of institutional investors who allocate part of their portfolio to hedge funds is growing, this issue of hedge fund attrition relative its fund characteristics are of significant practical relevance. No study has examined the issue of hedge fund survival in the context of hedge funds domiciled in the Asia Pacific to my knowledge. I use both the parametric probit regression and the semi parametric Cox proportional hazards analysis to look at the relationship between hedge fund characteristics and hedge fund survival. Larger, better performing funds with lower redemption frequencies have more chance to survive, consistent with previous studies. Higher standard deviation enhances the chances of hedge fund survival surprisingly. One possible explanation is the nature of the databases used in the study. Before the global financial crisis began in 2007, most of the hedge funds in the defunct group died. Consequently, the funds that were exposed to the market turmoil during the 2007 crisis or surviving funds have a higher standard deviation than the defunct fund group. I also find that the evidence of leverage on survival differs, depending on the statistical model used, and the incentive structure does not appear to impact on hedge funds domiciled in the Asia Pacific.

### 1.3 Research output from the thesis

Essay one, "Capacity Constraints, Fund Flows and Hedge Fund Alpha: Emerging Market Evidence", accepted or presented at

- World Finance Banking Symposium in Bangkok in December 2017
- Academy of Financial Services Meeting in Nashville in October 2017
- AFAANZ in Adelaide in July 2017
- 24th Multinational Finance Society Conference (MFS) in Bucharest, Romania in June 2017
- The 8th Financial Markets and Corporate Governance Conference (FMCG) at Victoria University of Wellington in Wellington in April 2017
- The 21st New Zealand Finance Colloquium at University of Auckland in Auckland in February 2017

- Accounting and Finance Association of Australia and New Zealand Association Conference (AFAANZ) in Gold Coast in July 2016
- 5th Auckland Finance Meeting (AFM) at Auckland University of Technology in Auckland in December 2015
- Inaugural SIRCA Pitching Research Symposium in Sydney in February 2015, FUNDED by SIRCA
- The 19th New Zealand Finance Colloquium at University of Waikato in Hamilton in February 2015
- Financial Management Association International Conference at Fudan University in Shanghai in April 2013
- The School of Economics and Finance Seminar at Massey University in September 2012

Essay two, “Persistence of Hedge Fund Performance”, accepted or presented at

- 7th Auckland Finance Meeting at Auckland Centre For Financial Research in Queenstown in December 2017
- Financial Management Association International Conference at Fudan University in Shanghai in April 2013

Essay three, “Survival Analysis of Hedge Funds”, accepted or presented at

- World Finance Conference in Mauritius in July 2018
- AFAANZ Conference in Auckland in July 2018
- 93rd Annual Conference, WEAI in Vancouver in June 2018

- 25$^{th}$ Annual Conference of the Multinational Finance Society in Budapest in June 2018
- CTBC Business School, INVITED and FUNDED by CTBC Business School in Tainan in May 2018
- The 22nd New Zealand Finance Colloquium at Massey University in Palmerston North in February 2018
- Western Economic Association International (WEAI) 14$^{th}$ International Conference at Newcastle Business School, University of Newcastle, Australia in January 2018
- 6$^{th}$ Annual Winter Conference of Multinational Finance Society, Caribe Hilton Hotel, San Juan, Puerto Rico, USA in January 2018
- The 2$^{nd}$ Vietnam Symposium in Banking and Finance by Association of Vietnamese Scientists and Experts in France (AVSE), International Society for the Advancement of Financial Economics (ISAFE) and Vietnam National University HCMC – International University in Ho Chi Minh in October 2017

## 1.4 Structure of the thesis

Chapter 2 presents the hedge fund industry in general. Detailed insight into the industry and categorization of hedge funds are provided. Next, the historical evolution of hedge funds is discussed. The first part of this chapter also visits the overviews of the global hedge fund industry and hedge fund industry domiciled in the Asia Pacific. Chapter 3 investigates the risk adjusted performance of hedge funds through different multi factor models in cross-section and time series. Chapter 4 examines the performance persistence of hedge funds domiciled in the Asia Pacific. Chapter 5 relates the hedge fund characteristics to the hedge fund attrition rates. Chapter 6 concludes the thesis.

# CHAPTER TWO

# THE HEDGE FUND UNIVERSE

## 2.1 The evolution of the hedge fund industry

The term hedge fund was first coined by Carol Loomis while the first hedge fund was created by Alfred Winslow Jones in 1949. The fund was not subject to the regulation under the US Investment Company Act of 1940 as it was organized as general partnership. The fund had to restrict the number of investors to 100 prior to 1996 and later to investors defined as qualified investors to maintain the exemption (Anderson, Born and Schnusenberg, 2010). Jones added a 20% performance fee to the regular management fee based on the fund's net assets and in 1952, converted his fund to a limited partnership. Jones was the first to combine short selling, leverage and a compensation plan based on investment performance. He felt it would be inappropriate to be paid high incentive fees for risking only investors' money unless his own money is invested too. At the age of 82, he altered the fund's partnership agreement so it became fund of funds.

Hedge fund managers constructed hedged portfolios using both long and short techniques as they realised that using short sales to hedge a portfolio is an expensive, time consuming activity particularly in the bull market. Hedging long positions was very costly in the market downturns of 1969 to 1970 and 1973 to 1974, when most of the hedge fund industry lost the confidence of the investment community.

In 1986, interest re-emerged when the Institutional Investor magazine published an article on the Manager of the Tiger Fund. During the next six years of its existence, the Tiger Fund delivered an annual return of 43%. Relative to the 18.7% annual return from the S&P 500, this was regarded as an impressive achievement. This led to another wave of hedge fund formation with rapidly rising securities (Anderson et al., 2010).

Hedge funds lifted to new highs when the Quantum Fund managed by George Soros earned USD 1.8 billion simply by holding a long position on the Deutschmark and a short position on the British pound. The dramatic collapse of the Russian ruble in 1998 led to a USD 2 billion loss for the Quantum Fund (Anderson et al., 2010). Additionally, the default of the Russian ruble and the market events led to US $4 billion loss for the Long Term Capital Management (LTCM) hedge fund and its subsequent collapse in 1998. The Federal Reserve engineered the bailed out LTCM to avoid the market catastrophe. According to Lowenstein (2010), the correlation always goes to one during a crisis, sovereign countries do default and investors must not ignore these risks. In the eyes of the general public, the hedge fund industry was creating a bad reputation and this was reinforced by lack of information accessible to the public due to lack of reporting requirements (Anderson, et al., 2010).

Schaub and Schmid (2013) relate the effect of the lockup period and the financial crisis. Their results show that funds with share restrictions held more illiquid assets and achieved an illiquidity premium before the financial crisis. During the financial crises, however, these funds suffered lower returns and lower alphas. The study conclude that share restrictions are not enough to prevent funds from having an asset liability mismatch and the problem grows during crises. Billio et al. (2012) develop a measure of systematic risk by creating econometric measures of sector connectedness. They show significant dynamic and increasing linkages between banks, insurance companies, broker dealers and hedge funds. Other results show banks and insurance companies impact hedge funds but not vice versa and the significant number of connections greatly increased during the LTCM 1998 crisis and the financial crisis of 2007-2009. This suggests that hedge funds are impacted by systematic risk rather than trigger it.

### 2.2 Hedge fund characteristics

A commonly accepted definition of hedge fund does not exist even though there is strong interest from the public, regulators and academics. Hedge funds are unregulated, privately organized, professionally managed pools of capital that are not widely available to the public (Lhabitant, 2004). Most hedge funds will accept only individual or institutional investors that meet the requirements of the local regulatory agency such as the Securities and Exchange Commission (SEC) in the United States, and the Financial Services Authority (FSA) in the UK. Because they are not available to the general public, participation in the hedge funds is limited to high net worth individuals and institutional investors such as foundations, life insurance companies, endowments and investment banks (Gregoriou and Duffy, 2006). While the investment philosophy of the traditional money manager is to value performance relative to a market benchmark, hedge funds ultimate goal is to produce absolute positive returns by risk taking and simultaneously avoid losses and negative capital. As the performance, correlation, and volatility characteristics vary from those of other asset classes such as bonds, equities or commodities, hedge funds are often perceived as a distinct asset class (Buraschi, Kosowski, and Trojani, 2014).

In chasing absolute returns, hedge fund managers have the flexibility to engage in both long and short positions, they are able to borrow and make widespread use of derivatives. To avoid the regulations that affect the mutual fund industry under the US Investment Company Act, hedge funds must abide by certain regulatory requirements. The number of investors is limited and investment services cannot be offered to the general public. The regulators do not need to regulate these hedge funds as long as the general public has no access to these private pools of capital.

There are some common characteristics even though hedge funds are far from homogenous. Hedge funds can pursue any type of investment strategy in contrast to the mutual funds that are highly regulated and have a limited array of investment strategies. They can employ leverage, use derivatives or short selling techniques and invest in illiquid or unlisted securities. Hedge fund managers pursue absolute returns while mutual fund managers pursue returns greater than certain benchmarks. Hedge funds are perceived as market neutral investment vehicles that provide returns regardless of whether the market rises or falls. In reducing the sensitivity to broad market factors, hedge funds are beneficial for investors seeking diversification.

Several studies examine hedge funds relative to other asset classes. Hasanhodzic and Lo (2007) found that more than 70% of total performance for many hedge fund strategies mirrors closely tradable market indices. Stulz (2007) finds that incentives of hedge fund managers differ significantly from those of mutual fund managers. Firstly, the incentive compensation must be symmetrical as the mutual fund managers' compensation is restricted by regulation. In other words, positive performance should have positive effects on compensation and vice versa. Ackermann et al. (1999) note that most hedge fund managers are guaranteed a substantial proportion (usually 20%) of the profits they generate due to the asymmetric compensation contracts. If investors experience high returns, these asymmetric compensation contracts' will enable hedge fund managers to earn extremely high levels of compensation (Stulz, 2007).

Secondly, high hedge fund fees can attract managers with poorly established and executed strategies resulting in large losses for investors (Lhabitant, 2004). Hence in compensation contracts, a high water mark is embedded. This means that managers can only claim performance fees after they recover any losses incurred. Without this clause, managers can take advantage of all the successful trades without suffering potential little losses. Stulz (2007) observes high water marks should reduce the risk taking of hedge fund managers. Nevertheless, this misaligned interest is not completely eliminated. The hedge fund manager might choose to close the fund if it incurs a major loss. In Stulz (2007), he uses an example of the trader who was responsible for most of the US $6 billion loss that brought down the Amaranth fund in September 2006. Reportedly, the trader received between US $80 million and US $100 million in 2005. The trader did not need to return his past compensation to the fund and he was able to set up his own hedge fund even after the Amaranth debacle.

As such, managers are required to invest a significant proportion of their personal wealth in the fund like other investors (Lhabitant, 2004; Lim, Sensoy and Weisbach, 2015). Many hedge funds invest in illiquid securities whereby they are not actively traded and market prices are not always immediately available (Asness, Krail, and Liew, 2001; Getmansky, Lo, and Makarov, 2004). The liquidity constraints impose by hedge funds such as lock up periods, that guarantee long term capital commitments and minimum notice times for redemptions allow flexibility for managers to follow their investment ideas through. Instead of focusing on liquidity management, hedge fund managers can focus on investments and performance.

### 2.3 Hedge fund strategies and investment styles

Though hedge fund is used universally, a wide array of hedge fund strategies and investment styles exist, each of which have very different approaches and objectives. No universally accepted convention on how to classify various hedge fund strategies exists as each data provider, investor, or consultant may use a different classification system. Between certain hedge fund strategies, there is always a degree of overlap.

Equity long/short funds are the largest strategy, accounting for over 57% of all hedge funds domiciled in the Asia Pacific. This strategy looks at purchasing equities with superior return characteristics and selling short equities with inferior return characteristics (Fung and Hsieh, 2004a).

Relative value hedge funds or arbitrage or market neutral funds try to gain from relative discrepancies in prices between equities, debt, options, and futures at the same time trying to avoid exposure to market wide movements. Betting that market prices of two related securities will converge over time is the most common trading strategy. Managers often employ leverage to obtain reasonable profitability by this strategy.

Event drive strategies revolve on equity or debt from companies in specific stages of their lifecycles as mergers and acquisitions, spin offs, reorganizations, bankruptcies, re capitalization or share buybacks. Being a popular strategy, merger arbitrage involves buying shares of a targeted company and the short selling of the shares of the acquiring company (Fung and Hsieh, 2004a).

Macro hedge funds rely on a top down approach whereby investment decisions are based on fundamental economic, political and market factors. To profit from investments in respective markets, macro hedge funds establish both long and short positions in an asset class as equities, bonds, currency, or derivatives.

Directional hedge funds try to predict movements in global equity, bond commodity and currency markets by putting unhedged bets on the respective assets. Directional funds take a directional view of the market they invest in despite employing an absolute return strategy.

Fixed income hedge funds take positions: long, short or both in different fixed income securities as interest rate swaps, mortgage back securities, and credit default swaps etc

(Fung and Hsieh, 2004a). These hedge funds also invest in distressed debt securities (securities issued at discounts by near bankrupt companies or turn arounds). Managed futures or commodity trading advisor (CTA) funds follow a set of systematic strategies to invest in futures, options or foreign exchange contracts.

Lastly, there are the others that contain multi strategy hedge funds domiciled in the Asia Pacific where they diversify their asset allocation by investing in more than one of the strategies.

Another hedge fund strategy not discussed in this thesis is funds of hedge funds (FOHF). FOHFs allow investors to gain diversification and access a variety of managers through a single investment vehicle. Some investors find it appealing to group several individual hedge funds in a portfolio as all the strategies have different risk return parameters like FOHFs.

### 2.4 The global hedge fund industry today

Hundreds of millions of dollars have been moved to hedge funds as a growing number of investors globally chase higher returns through alternative asset classes (Jovenvaara, Kosowski and Tolonen, 2014b; Chakravarty and Sovan Deb, 2013; Fung et al. 2014). Many new funds are appearing to satisfy the growing demand associated with the strong growth in the hedge fund industry. Referring to Fung, Hsieh, Naik and Ramadorai (2008), largely the growth was driven by institutional investors and high net worth individuals who allocated funds to hedge funds with the hope of obtaining high returns and portfolio diversification benefits. Hedge funds can lever themselves to unprecedented levels and put power in global financial markets as interest rates were kept at historical lows and capital was abundant.

Agarwal and Naik (2005) document the change in the structure of the hedge fund industry when analysing the academic research on hedge funds. The equity hedge strategy had the largest market share in 2004 while the macro strategy dominated the industry in 1990. While today the typical investor is an institutional investor, in 1990 the typical investor in a hedge fund was a high net worth individual (Agarwal and Naik, 2005).

Hedge funds are only obliged to report to their investors and not subject to the requirements imposed on traditional money managers. In this sense, it is difficult to estimate the true size of the industry. Recently, an increasing number of hedge funds have reported their results to one the hedge fund databases such as Hedge Fund Research (HFR), TASS, Centre for International Securities and Derivatives Markets (CISDM) or Eurekahedge. The results reporting to one of the databases is crucial in terms of visibility as hedge funds are not required to advertise to the general public (Lu et al. 2015; Aragon and Nanda, 2017).

Various databases provide different estimates in terms of AUM for the size of the industry. The global hedge fund industry experienced continuous expansion both AUM and the number of funds till middle of 2008. Based on the estimates from HFR, global

AUM grew at a compounded annual growth of 14 % or from US$ 491 billion in 2000 to peak of US$1.9 trillion. The global hedge fund population grew from about 2200 funds in 2000 to a peak of more than 12000 in 2007 (Heidrick and Struggles, 2010).

The hedge fund industry is still small relative to other asset classes. The global financial crisis of 2007 adversely impacted the hedge fund industry. As liquidity dried up in the markets, investors chose cash and other safe assets and hundreds of hedge funds were closed. The number of funds fell to approximately 8400 by the middle of 2010 and AUM drop drastically from the peak in June 2008 to US $1.3 trillion in June 2009. The positive effects of the diversification of hedge fund portfolios were reduced as during the financial crisis, almost every type of asset in every market of the world was impacted (Lowenstein, 2010). Since the collapse of the Long Term Capital Management Fund in 1998, for the first time the hedge fund industry suffered net redemptions.

Aragon, Liang and Park (2014) study onshore and offshore US hedge funds. Their findings show that onshore funds invest in more liquid securities and place stronger share restrictions on their investors. This is in response to regulatory restrictions on advertising and the number of investors in onshore funds. This helps to manage funding risk. Offshore funds are larger and the flows they attract are more sensitive to fund performance. According to the authors, these are the consequence of the funds' ability to advertise. Offshore funds also are more likely to suffer decreasing returns to scale.

Cumming and Dai (2009) find that law differences across countries effect hedge fund flows.  Funds located in countries with more distribution channels face more capital inflows and face lower flow performance sensitivity.  Funds located in countries that restrict the location of affiliated service providers receive lower flows.  The authors also find that tax laws influence investors' capital allocation decisions.

Using an event time approach, Aggarwal and Jorion (2010b) investigate both emerging funds and young managers.  This method controls for correlations returns across funds.  They find that the increase in fund age is related to lower performance nonlinearly.  Their argument is that managers outperform because of incentives to build their reputations and increase AUM and ability to trade more.  The authors find evidence of persistence in emerging managers' performance for up to five years after inception.

Jovenvaara and Kosowski (2015) compare Undertakings for Collective Investment in Transferable Securities (UCITS) hedge funds to other hedge funds.  UCITS hedge funds are funds registered in the European Union and face stricter restrictions in their use of leverage and short selling as well as having higher liquidity requirements.  Even though UCITS funds have lower risk-adjusted performance compare to less restricted counterparts, investors still benefit since UCITS funds are less likely to misreport their returns.

## 2.5 Hedge funds domiciled in Asia Pacific

The Asia Pacific hedge fund industry started in the 1980s with a number of fund managers focusing mainly on Japan and almost exclusively with equity long/short strategies. The industry evolved gradually from there with the number of fund managers increasing and trading not only in Japan but throughout Asia Pacific.

Since the 2000, the hedge fund industry in the Asia Pacific has experienced the fastest growth within the global hedge fund industry both in terms of AUM and the number of new funds setup. In terms of AUM, the hedge fund industry grew approximately US $30 billion in 2000 to US $200 billion, excluding Australia and Mainland China, which are estimated to together have a similar AUM as the rest of Asia (Arslanian, 2016). Compared to the global AUM of 14%, the industry achieves a compounded annual growth of roughly 15%. The reported total AUM of the Asia Pacific hedge fund industry varies substantially depending on the sources. Asia Pacific and the rest of the world are becoming more important in the global asset allocation framework even though the US is still preferred location accounting for almost two thirds of AUM in 2007.

Asia Pacific and rest of world investors account for just 12% of all institutional investors active in hedge funds today. Although the proportion is small, some of the world's largest investors are based in these regions. Sovereign wealth funds with massive pools of readily available capital for investments in hedge funds are the most important group of investors. According to the same research, the Government of Singapore Investment Corporation (GIC) invests US$9 billion in hedge funds and nearly US$70 billion in alternative assets as a whole. Many Asia Pacific hedge funds suffered large redemptions during the crisis period of 2007 to 2010, forcing many funds to close or consolidate. There was also a drop in capital flowing to this region. The industry rebounded quickly in the second half of 2009 posting excellent returns and attracted an influx of capital. Asia Pacific, especially China, will take on a more important role in the global hedge fund industry given the rapid economic growth projected for the region.

In the early days, the fund management industry was composed of individuals from overseas. Nowadays many of the new funds are launched by individuals who spent the majority of their careers in Asia giving them experience with the various Asia Pacific markets (Teo, 2009; Sialm, Sun and Zheng 2013). This continuous supply of new talent upholds the attractiveness of the new hedge fund landscape. It was difficult to find the right type of talent from chief operating officers to operations staff as the industry is still young. Investors would apply a discount as they believe that a hedge fund in the Asia Pacific would not be up to par with US. Asia Pacific hedge fund managers incorporated this and often exceeded some of global hedge fund best practices, following the global financial crisis.

Asia Pacific based fund managers are exempt from the SEC under the Foreign Private Advisor Exemption and the Private Fund Advisor Exemption (Arslanian, 2016). The Foreign Private Advisor Exemption applies when the manager has no place of business in US, fewer than 15 US clients and US investors in private funds managed by the non-US advisor, less than $25 million in AUM attributable to such US clients and investors and does not hold itself out generally to the public in the USA as an investment adviser. The

Private Fund Advisor Exemption refers to fund manager advising only private funds such as the master-feeder structure and all the capital is managed from Asia Pacific.

Other advantages of having Asia Pacific hedge funds especially in Hong Kong or Singapore include the rule of law, a deep, well qualified and experienced service provider ecosystem, an active fund management community, lot of government support and an extensive tax treaty network especially in the case of Singapore (Arslanian, 2016). Singapore has tax treaties with many countries, including India and majority of Asia Pacific, making it the perfect jurisdiction to establish the entity. Singapore also follows a territorial tax system where companies are taxed mainly on profits that are accrued in, or derived from, Singapore (17% or 10% in certain cases) and also has no capital gains tax and no withholding on dividends. Likewise, Hong Kong has a very competitive tax agreement with Mainland China that offers beneficial tax rates on capital gains and dividends. Under the territorial-based tax system, any revenues that are derived outside of Hong Kong are exempt from Hong Kong tax (16.5%).

A number of retail initiatives have been launched across Asia Pacific to encourage fund distribution to retail investors and minimise the regulatory hurdles. The Asia region funds passport include Australia, Singapore, South Korea, New Zealand, Philippines, Thailand and Japan and it gives a multilaterally agreed framework to enhance the cross-border marketing of managed funds. The ASEAN framework enables the fund authorised in its home jurisdiction to be offered in other participating jurisdictions under a streamlined authorisation process and involves Singapore, Malaysia and Thailand (ASEAN, 2014). The China-Hong Kong mutual recognition sets the framework for mutual recognition of publicly offered funds between the CSRC and the SFC such that the recognised funds could be available to the general public in both markets (Securities and Futures Commission, 2015).

Teo (2009) finds that after controlling for risk and market location, funds that have an office in the same geographical region to their investment outperform their more distant competitors by 3.72 percent per annum. Also in their sample of Asia focus hedge funds, fund managers who speak the native language enjoy an advantage. More distant funds, however, benefit from the ability to attract more capital and charge higher fees despite their poorer performance.

Sialm. Sun and Zheng (2013) study the hedge fund investments made by FOFs. Their finding is consistent with the home bias phenomenon i.e. FOFs invest more in hedge funds in the same geographic location. Owing to the ability to obtain soft information or making local connections that enable them to access reputable managers, FOFs with stronger home bias experience superior performance. They also find that managers with more personal capital invested and smaller, younger funds are more likely to have higher home bias.

# CHAPTER THREE

# ESSAY ONE

## CAPACITY CONSTRAINTS, FUND FLOWS AND ALPHA

**Abstract**: This paper investigates the alpha generating of the hedge funds domiciled in Asia Pacific based on a recent sample compiled from the Eurekahedge, TASS and Morningstar databases covering both the up and down markets and including the latest financial crisis from January 1994 to June 2012. I find a positive average alpha in the cross-section for the majority of strategies and a positive and significant alpha for roughly half of all funds. Moreover, the alpha of three-quarters of the strategy indices is positive and significant in the time series. A comparison of the stepwise regression factor model and the widely used factor model proposed by Fung and Hsieh (2004a) reveals that the estimated alpha is robust with respect to the choice of the factor model. In contrast to prior research I find little evidence of a decreasing hedge fund alpha over time except for the dedicated short bias strategy. Moreover, I cannot confirm prior evidence pointing to capacity constraints widely documented by the Berk and Green (2004) model.

**Keywords**: Hedge fund performance, capacity constraints, fund flows, financial crises

**JEL classification**: G01; G12; G23

### 3.1 Introduction

This paper investigates hedge fund alpha based on alternative return-based benchmark models. In line with the existing literature, I am able to identify a positive alpha for all strategies in the time series and in the cross-section. However, my analysis challenges the conclusion of some recent research showing a decreasing alpha over time (Fung, Hsieh, Naik, and Ramadorai, 2008; Zhong, 2008) and on capacity constraints in the hedge fund industry (Naik, Ramadorai, and Stromqvist, 2007; Fung et al., 2008).

The amount of capital invested in the hedge fund industry increased significantly during the period 1994 to 2012.[1] An expected consequence of this development is a decrease in hedge fund alpha. As new money flows into the hedge fund industry, managers might be forced not only to invest into the most profitable strategies but to opt for less attractive investments or diversify to other strategies, where their knowledge and experience might be limited. Additionally, there might be a limited dollar amount of alpha in the market, which would then have to be shared among more hedge funds.

The majority of research conducted on hedge fund performance finds that hedge funds on average outperform passive benchmarks (Agarwal and Naik, 2000; Fung and Hsieh, 2004b; Kosowski, Naik, and Teo, 2007; Titman and Tiu, 2008). However, some recent studies suggest that hedge fund alpha has been decreasing over time. Investigating a merged dataset from the three hedge fund databases TASS, HFR and CISDM, Fung et al. (2008) find that alpha generated by an index of funds of hedge funds has significantly declined during the

[1] According to the TASS Asset Flow Report of Q2 2012, it increased in this period from USD 50bn to USD 1,209bn at the end of the fourth quarter, with a peak of 2.1 trillion at the end of Q2 2012.

period April 2000 to December 2004. As they observe increasing capital inflows into the industry over time, they conclude that the declining alpha could be due to decreasing returns to scale caused by capacity constraints. They argue that their results are consistent with Berk and Green's (2004) rational model of active portfolio management, which states that in an economy with competitive provision of capital, and rational investor's differential managerial ability will be reflected in the fees charged and hence risk-adjusted returns in equilibrium will be zero. Fung et al. (2008) show that funds, which are able to deliver alpha, experience far greater capital inflows than their less successful peers and they demonstrate that these capital flows adversely affect the future risk-adjusted performance of funds. Naik et al. (2007) address the same question at the level of hedge fund strategies. Based on self-constructed value-weighted and equally-weighted strategy indices their results suggest that alpha equilibrium will be zero as proposed by Berk and Green (2004).

Zhong (2008) conducts a time series analysis of the distribution of single hedge fund alphas based on the seven-factor model of Fung and Hsieh (2004a) and finds that not only the average alpha has decreased, but also the number of funds generating a positive alpha. The paper also investigates the relationship between fund flows and performance. Zhong (2008) concludes that on a fund level capital flows have a positive (negative) impact on a fund's future performance for smaller (larger) funds. Hence, he confirms the findings of Naik et al. (2007) that fund flows at a strategy level increase the competition within the strategy and exerts pressure on the future performance.

In the existing literature, most hedge funds studies US- and European-centric hedge funds. Research into the rapidly growing group of funds that invest in Asia Pacific is relatively scarce. Based on the data from three hedge fund databases, Eurekahedge, TASS and Morningstar, the number of funds which invest predominately in Asia Pacific have risen dramatically from around 43 in January 1994 to around 3738 in June 2012. This represents a huge increase over the period of around 18.5 years. Furthermore, hedge funds domiciled in Asia Pacific are subjected to less regulation than in the U.S or Europe. They are usually open to retail investors with a dominance of equity based strategies and include emerging markets.

This paper contributes to the existing literature by investigating hedge fund alpha based on a recent (that includes the financial crisis) and comprehensive data set compiled from Eurekahedge, TASS and Morningstar databases while accounting for dynamics and nonlinearities in the factor exposures. I look at hedge funds domiciled in Asia Pacific in particular. Specifically, I establish a factor model, in which I select the risk factors based on a stepwise regression approach. The stepwise regression procedure attempts to determine the statistically optimal combination of risk factors to be included in the factor model (Thompson, 1995). I then compare the results from this stepwise regression approach to those obtained based on the widely used factor model proposed by Fung and Hsieh (2004a). CAPM based alpha systematically mis-measures performance when market has i.i.d. returns since CAPM based beta does not capture skewness and other higher order moments of return distribution. It is common practice for hedge fund managers to trade in options and/or follow dynamic trading strategies that generate non-linear exposures to standard asset classes (Fung and Hsieh, 1997; Fung and Hsieh, 2004a). In the factor model based on the stepwise regression, I account for the possible nonlinearity of hedge fund returns by including option-based return factors and lookback straddles in the set of potential risk factors. By estimating the factor exposures based on rolling-window regressions, I apply these factor models as a dynamic benchmark for the returns of equally-weighted and value-weighted hedge fund strategy indices and single hedge funds.

In line with recent research, I find that hedge fund alpha has been positive most of the time and for the majority of strategies. In general, I find qualitatively similar results based on both alternative factor models throughout the paper. However, for certain hedge fund strategies I find higher r-squares based on the stepwise regression factor model as compared to the Fung and Hsieh (2004a) model. This presumably stems from the fact that the stepwise regression model is less susceptible with respect to omitted variables. The differences in r-squares are particularly large for the strategies convertible arbitrage, emerging markets, and event driven. This can be explained by the addition of a convertible bond factor, an emerging markets equity factor, and the out-of-the money option factors in the factor models based on stepwise regression, respectively. These factors are not included in the original set of Fung and Hsieh (2004a). The effect on alpha resulting from the two alternative models, however, is often very small even when the explanatory power largely differs.

My results challenge some of the findings in earlier research. Most importantly, I cannot confirm a systematic decrease of the alpha over time. The only strategy for which I report a steadily decreasing alpha over time is dedicated short bias, although its alpha has picked up again since 2007.

The paper proceeds as follows. Section 3.2 describes the underlying data set. Section 3.3 describes the methodology applied for the analysis at hand. Section 3.4 summarizes the results of the analysis and Section 3.5 concludes.

**3.2 Data**

I use Eurekahedge, TASS and Morningstar databases covering the period from January 1994 to June 2012. As opposed to mutual funds, hedge funds are not required to publicly disclose their returns. Consequently, the returns from all hedge fund databases contain some biases, such as the selection or backfill bias. For a detailed discussion of these biases, the reader may refer to Fung and Hsieh (2000), Fung and Hsieh (2004a and 2004b), or Titman and Tiu (2008).

In my dataset, the survivorship bias is minimized by including live and dead funds in the sample and restricting the sample period to the post-1993 period, when databases started to keep all hedge funds which stopped reporting in their graveyard database. I control for the backfilling bias (or instant history bias) by deleting all backfilled entries which were added to the database before a fund started reporting to the database. This date is known for roughly 95% of all funds in my sample. For the remaining 5% I follow common practice and delete the first 12 return observations (Fung and Hsieh, 2000; Edwards and Caglayan, 2001).

As I estimate alpha based on rolling 24-month window regression, I require at least 24 non-backfilled return observations for a fund to be included in my analysis (Ackermann, et al, 1999; Edwards and Caglayan, 2001; Bali et al. 2011). This requirement may introduce a sampling bias. However, Fung and Hsieh (2000) investigate this bias, which they call multi-period sampling bias, by comparing the average returns of all funds in the sample to the average returns of the funds with at least a 24 months history of returns, and find it to be very small. Furthermore, I only include hedge funds reporting in USD and funds reporting their AUM. For funds to be included in the equally-weighted strategy index, I additionally require their AUM to exceed USD 5 million at least once during their non-backfilled observations. After all these adjustments, I am left with a sample of 3,491 hedge funds for all analyses conducted on the equally weighted index and 3,738 funds for all analyses conducted on the value-weighted index, where the 5 million AUM requirement is not imposed. The sample used for the analysis at hand includes roughly half of the funds that reported to Eurekahedge, TASS and Morningstar databases and amounts to AUM of USD 530 billion at the end of June 2012.[2]

The illiquidity of some of the markets in which the hedge funds are invested might have an influence on the reported returns, driven by the fact that hedge funds avail the possibility to invest in highly illiquid assets without daily market prices and by the fact that the reported returns are only audited on an annual basis, Agarwal and Naik (2000) point out that some intra-year persistence may be caused by stale prices. In order to adjust for the bias of these stale valuations, the return series of my sample are desmoothed as suggested by

[2] Due to multiple share classes and onshore and offshore funds, my sample might contain some duplicated funds. This might affect my results on hedge fund alpha as better funds are more likely to have multiple entry points in my sample. However, different series of one particular hedge fund are often denominated in different currencies and as I only consider funds reporting in USD many of those duplicated funds are dropped from my sample. In addition, such a double counting of funds only affects the equally-weighted index as the value-weighted index weights each single share class of a hedge fund based on its particular assets under management. As the results from the equally- and value-weighted analyses are qualitatively identical, I believe that a potential bias arising from double counting to be small.

Getmansky, Lo, and Makarov (2004).[3] As well as, although most hedge fund managers are good or honourable people, they have strong incentive to show returns that are consistent and uncorrelated with traditional markets by engaging in unsavoury practice of intentional return smoothing.

Getmansky, Lo, and Makarov (2004) demonstrate that instead of the (serially uncorrelated) true returns of a fund ($R_t$), I only observe reported returns of the funds ($R_t^0$), which feature the following relationship with actual returns:

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \cdots. + \theta_k R_{t-k} \qquad (1.1)$$

$$\text{With } \theta_j \in [0,1], \qquad j = 0, \dots, k \quad (1.2)$$

$$\text{And } 1 = \theta_0 + \theta_1 + \cdots + \theta_k \qquad (1.3)$$

I set $k$ equal to two and estimate $\theta_0$, $\theta_1$, and $\theta_2$ for each hedge fund strategy by estimating this MA(2) model with maximum likelihood.[4] I use these thetas to obtain desmoothed returns which are then included as dependent variables in my multi-factor models. The estimated values for $\theta_0$, $\theta_1$, and $\theta_2$ in Table 3.1 show that as expected hedge fund styles investing in illiquid assets display higher autocorrelations in their returns (e.g., convertible arbitrage, event driven, and funds of funds) than strategies investing in more liquid assets (e.g. managed futures, equity market neutral, global macro).

[3] Jagannathan et al. (2010) find that this procedure of desmoothing the returns leads to a reduction of hedge fund alpha.

[4] As Getmansky, Lo and Makarov (2004), I use a standard MA(k) estimation package (Stata) and transform the resulting estimates by dividing each theta by $1 + \theta_1 + \theta_2$ to satisfy Equation (1.3). In contrast, and also consistent with Getmansky, Lo and Makarov (2004), I do not impose Equation (1.2) when estimating the thetas and use this restriction as a specification test.

**Table 3.1: Theta estimates for all strategies**

This table shows the results from the estimation of $\theta_0$, $\theta_1$, and $\theta_2$ based on the methodology of Getmansky, Lo and Makarov (2004) applied to my sample of single hedge funds for each strategy. The last two columns report the number of funds in my sample for each strategy including (N) and excluding ($N_{(AuMadj)}$)

| | $\theta_0$ | $\theta_1$ | $\theta_2$ | N | $N_{(AuMadj)}$ |
|---|---|---|---|---|---|
| Convertible Arbitrage | 0.7191 | 0.2128 | 0.0680 | 138 | 135 |
| Dedicated Short Bias | 1.0382 | 0.0371 | -0.0753 | 21 | 20 |
| Emerging Markets | 0.8651 | 0.1343 | 0.0007 | 237 | 230 |
| Equity Market Neutral | 1.0195 | -0.0208 | 0.0013 | 216 | 200 |
| Event Driven | 0.7832 | 0.1504 | 0.0664 | 355 | 347 |
| Fixed Income Arbitrage | 0.8639 | 0.1051 | 0.0310 | 173 | 169 |
| Funds of Funds | 0.7649 | 0.1882 | 0.0469 | 716 | 661 |
| Global Macro | 1.0686 | -0.0012 | -0.0674 | 180 | 167 |
| Long/Short Equity | 0.9512 | 0.0611 | -0.0123 | 1,209 | 1,140 |
| Managed Futures | 1.0244 | -0.0127 | -0.0117 | 301 | 244 |
| Multi Strategy | 0.8461 | 0.0821 | 0.0718 | 192 | 178 |

### 3.3 Methodology

While there is an extensive literature on hedge fund performance measurement, there is no consensus so far on which factors to include in a multi-factor model. In an attempt to capture the different investment styles and to minimize the risk of omitted risk factors, I use a systematic procedure to select relevant factors among those frequently used in prior literature. Due to limits of degrees of freedom in estimating the model, I try to keep the amount of factors included in the factor model as low as possible, while still being able to describe the investment opportunities available to hedge funds as appropriately as possible. I follow Agarwal and Naik (2004a) and Titman and Tiu (2008) and use stepwise regressions for the selection of the risk factors to be included in my factor models. The reference point here is Koh, Koh and Teo (2003). They argue that the Fung and Hsieh (2004a) model explains about 64% of the variation in returns. For the selection procedure I start with 23 risk factors (see Table 3.1a). I then regress the returns of an equally-weighted index of all funds within a strategy in my sample on the returns of these factors. The stepwise regression approach is based on the t-values of the slope coefficients over the entire sample period with constant coefficients.

**Table 3.1a: Stepwise regression risk factors**

| **Equity Long/Short** | **Relative Value** |
|---|---|
| MSCEI Asia ex Japan | MSCEI Asia ex Japan |
| Nikkei 225 | MSCEI World ex US |
| Momentum | PTFSIF |
| Silver | HML |
| | JPM Japan Govt. Bond |
| | Oil |
| **Macro** | **Fixed Income** |
| MSCEI Asia ex Japan | MSCEI Asia ex Japan |
| S & P REIT | JPM US Govt. Bond |
| YEN/USD | Credit |
| PTFSSTK | Market |
| Momemtum | PTFSIR |
| SMB | YEN/USD |
| ML High Yield Index | |
| **Even Driven** | **Directional** |
| PTFSIR | MSCEI Asia ex Japan |
| Nikkei 225 | Nikkei 225 |
| Market | Gold |
| **CTA** | **Others** |
| Oil | MSCEI Asia ex Japan |
| Citigroup Bond Index | Nikkei 225 |
| | Silver |
| | Momentum |
| | S & R REIT |
| | MSCEI World ex US |

A factor is added to the model when its marginal significance exceeds the 95% level. I drop any previously chosen factor which is not simultaneously significant with all other factors at least on a 90% confidence level. This iterative procedure is continued until a maximum of seven factors for each hedge fund strategy is obtained or no more significant factors can be identified. I employ the identical risk factors for all funds within a strategy and keep them for the entire sample period. These risk factors are applied to estimate the following linear multi-factor model to explain the return ($R$) for each fund $i$ at time $t$:

$$R_{i,t} - r_{f,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \epsilon_{i,t} \quad t = t_0, \ldots, T \quad i = 1, \ldots, N \quad (1.4)$$

where $r_{f,t}$ is the risk free rate at time $t$, $\alpha_i$ is the intercept of the regression, $\beta_{i,k}$ reflects the exposures of fund $i$ to the $K$ risk factors $F_t$ at time $t$ and $\epsilon_{i,t}$ is the zero-mean normally distributed tracking error of fund $i$ at time $t$ to the benchmark.

To estimate hedge fund alpha based on a factor model, most papers use either zero investment factors or excess returns of buy and hold factors above the risk free rate.[5] The factors I consider include fungible factors of the following asset classes: equities, bonds and credit, interest rates, currencies, options, volatility, dynamic trading strategies, commodities, real estate, and convertible bonds. Most of these factors are excess returns above the risk free rate (i.e., the one-month T-bill); some are zero-investment portfolios. I account for the possibility of non-linear factor exposures of hedge funds by including option-based factors in my factor models. These include the returns of the dynamic trading strategies (based on lookback option straddles) proposed by Fung and Hsieh (2001) and the return of European at-the-money (ATM) call and put options on the S&P 500 index suggested by Agarwal and Naik (2004). Unlike Agarwal and Naik (2004), who use ATM options and 1% out-of-the money (OTM) options, I include ATM options and 7.5% OTM options. I use options that are further out-of-the money in an attempt to capture the possibility of hedge funds sell tail risk and not to include too highly correlated risk factors in my model.

[5] Such papers include Fama and French (1993), Carhart (1997), Edwards and Caglayan (2001), Agarwal and Naik (2004), Capocci and Huebner (2004), Titman and Tiu (2008).

I compare the results of these factor models obtained by stepwise regressions with those from the widely used seven-factor model of Fung and Hsieh (2004a). Titman and Tiu (2008), for example, show the alpha from their stepwise approach to be lower than that resulting from the seven-factor model and the r-squares to be significantly higher. The seven factors proposed by Fung and Hsieh (2004a) include three trend-following risk factors on bonds, currencies and commodities, two equity-oriented risk factors (the S & P 500 monthly total return and a size spread factor – either the Wilshire Small Cap 1750 minus Wilshire Large Cap 750 monthly return or Russel 2000 TR minus S & P 500 TR), and two bond-oriented risk factors (the monthly change in the 10-year treasury constant maturity yield and the monthly change in spread between the Moody's Baa yield less the 10-year treasury constant maturity yield). The changes in spreads are both first differences of the levels.

I apply two different approaches to estimate the factor loadings and alphas. First, I run standard ordinary least squares (OLS) regressions with constant factor loadings over the full sample period as well as for several sub periods. Second, to account for the non-discrete dynamics in the exposures to the different risk factors, I estimate the factor loadings with rolling OLS regressions over 24 months. The statistical significance of the factor loadings and the alpha is estimated based on heteroscedasticity and autocorrelation (HAC)-adjusted standard errors.[6]

[6] Although it is often used in the literature, I cannot think of an economic justification for the choice of a 24-month window for the estimation of the rolling regression. Therefore, I have also tested other lengths for the estimation window (e.g., 12, 36, and 48 months), which does not alter the conclusion with respect to the alpha. If I reduce (increase) the length of the window I report a slightly lower (higher) average alpha.

## 3.4 Results

### 3.4.1 Investigating the alpha

For the assessment of the risk-adjusted performance I focus on the alpha from the factor models based on the stepwise regression approach as well as on the Fung and Hsieh (2004a) seven-factor model. I estimate the alpha on the level of single hedge funds as well as hedge fund strategy indices.

Table 3.2 reports the alphas of the equally-weighted strategy indices based on desmoothed return series. Based on both factor models I find a positive alpha for almost all strategy indices irrespective of the estimation methodology (i.e., constant factor loading OLS and the average alpha of rolling-window OLS), with one exception: the emerging market index exhibits a negative alpha of -8bps per month based on the Fung and Hsieh (2004a) seven-factor model, when estimated with constant factor OLS. Particularly high alphas are observed for the strategies dedicated short bias, managed futures, and multi-strategy. Although being positive for all estimation procedures, the alpha of funds of funds is among the two lowest in each estimation. The alpha based on the rolling-window estimation is in general higher than the alpha based on constant factor loadings. The last row of Table 3.2 shows that the average alpha overall strategy indices is positive for both factors models and estimation methodologies but significant only when estimated with rolling-window OLS.

**Table 3.2: Alpha of equally-weighted hedge fund strategy indices**

The table reports alphas estimated with two alternative factor models and two different estimation methodologies for eleven different hedge fund strategies. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004a) seven-factor model (FH). The factor models are estimated based on a constant-loading OLS approach and OLS estimation over rolling 24-months windows. The table is based on equally-weighted indices of all USD denominated funds with at least 24 non-backfilled observations for each strategy. The returns are desmoothed based on the procedure proposed by Getmansky, Lo and Makarov (2004). All alphas are expressed in monthly percentage returns. N indicates the number of funds in each strategy. The asterisks *, **, and *** indicate statistical significance on the 90%, 95% and 99% confidence level (two-sided) based on HAC-adjusted error terms.

| | Factor Model based on stepwise regression | | | Fung and Hsieh (2004) 7-factor model | | | |
|---|---|---|---|---|---|---|---|
| Strategy | $\alpha_{OLS}$ | $R^2$(adj) | $\alpha_{OLS24mroll}$ | $\alpha_{OLS,FH}$ | $FH\ R^2$(adj) | $\alpha_{OLS24mroll},FH$ | # Funds (N) |
| Convertible Arbitrage | 0.28** | 0.66 | 0.38*** | 0.17 | 0.33 | 0.39*** | 135 |
| Dedicated Short Bias | 0.45** | 0.61 | 0.52*** | 0.48** | 0.60 | 0.36*** | 20 |
| Emerging Markets | 0.16 | 0.81 | 0.33*** | -0.08 | 0.44 | 0.04 | 245 |
| Equity Market Neutral | 0.30*** | 0.30 | 0.29*** | 0.33*** | 0.06 | 0.29*** | 200 |
| Event Driven | 0.15* | 0.69 | 0.20*** | 0.18* | 0.51 | 0.30*** | 372 |
| Fixed Income Arbitrage | 0.10 | 0.30 | 0.16*** | 0.10 | 0.10 | 0.19*** | 169 |
| Funds of Funds | 0.03 | 0.75 | 0.08*** | 0.00 | 0.46 | 0.04 | 661 |
| Global Macro | 0.15 | 0.37 | 0.16*** | 0.14 | 0.24 | 0.07* | 167 |
| Long/Short Equity Hedge | 0.22** | 0.88 | 0.23*** | 0.30** | 0.76 | 0.42*** | 1347 |
| Managed Futures | 0.50** | 0.34 | 0.26*** | 0.69*** | 0.29 | 0.44*** | 244 |
| Multi-Strategy | 0.34*** | 0.48 | 0.38*** | 0.28** | 0.29 | 0.39*** | 178 |
| Average | 0.24 | 0.56 | 0.28*** | 0.23 | 0.37 | 0.27*** | 3738 |

Columns '$R^2(adj)$' and '$FH\ R^2(adj)$' in Table 3.2 confirm that, consistent with Titman and Tiu (2008), I find higher r-squares based on the stepwise regression factor model as compared to the Fung and Hsieh (2004a) model. This presumably stems from the fact that the stepwise regression model is less susceptible with respect to omitted variables. For example, the adjusted r-square of the emerging markets index is substantially higher for the stepwise regression model (0.81) as compared to the Fung and Hsieh (2004a) model (0.44). The main driver is the inclusion of the MSCI emerging markets factor in the former model. The coefficient estimate of this factor is 0.76 indicating a strong long exposure and is highly significant with a t-value of 14.4 for the constant–loading OLS approach. The coefficient values and t-values are similar for the rolling-window approach (0.67 and 13.6) when averaged over time.

As a consequence, the alpha based on the two alternative models differs as well and is higher for the stepwise regression model irrespective of whether estimated in a constant-loading or rolling-window regression. In contrast, for the managed futures strategy, the alphas and r-squares resulting from the two alternative models are qualitatively similar. This is not surprising as the factors chosen by the stepwise regression approach are largely overlapping with those from the Fung and Hsieh (2004a) model and include all three trend following risk factors which show up highly significant in all regressions. Furthermore, the stepwise regression model often chooses less than seven factors and thereby conserves degrees of freedom as compared to the Fung and Hsieh (2004a) model. This helps to increase the adjusted r-squares of the factor model. Overall, for certain hedge fund strategies, the larger set of risk factors to choose from in a stepwise regression model approach seems to substantially increase explanatory power (e.g., emerging markets, convertible arbitrage), while for others the explanatory power of the two models is virtually identical (e.g., dedicated short bias, long/short equity hedge). The effect on alpha resulting from the two alternative models, however, is often very small even when the explanatory power largely differs (e.g., convertible arbitrage, equity market neutral). In general, I find qualitatively similar results based on both factor models throughout the paper.

Unlike Table 3.2, where the alphas are estimated based on the indices for each strategy, Table 3.3 reports the average alpha of all single funds within a strategy. As I have a highly unbalanced panel, the results in Table 3.3 are biased to a more recent time period, when the number of funds in my sample is much larger. In addition to the statistics reported in Table 3.2, Table 3.3 reports the percentage of funds generating a positive and on the 95% confidence level statistically significant alpha. For the model with constant factor loadings the statistical significance is directly measured by the t-statistic of the alpha. For the rolling-window regressions, alpha is considered significant when its t-value over time exceeds the critical value on the 95% confidence level in a one-sided test. The results in Table 3.3 show that the average fund again exhibits a positive alpha (with the exception of the average fund of fund when benchmarked against the stepwise factor model).

As in Table 3.2, the results in Table 3.3 show that the stepwise regression model exhibits substantially higher r-squares for certain strategies as compared to the Fung and Hsieh (2004a) model. For example, the average r-square for the convertible arbitrage funds more than doubles from 0.14 to 0.37. An investigation of the factor loadings of the constant-loading OLS estimation reveals that on average, the funds exhibit a positive and significant exposure to the ML convertible bond factor of 0.67 with a t-value of 2.23 as well as a negative exposure of -0.29 to the Russel 3000 (t-value of -2.35). Furthermore, on average, the

**Table 3.3: Average alphas of single funds within each strategy**

The table reports alphas estimated with two alternative factor models and two different estimation methodologies for eleven different hedge fund strategies. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004a) seven-factor model (FH). The factor models are estimated based on a constant-loading OLS approach and an OLS estimation over rolling 24-months windows. The table is based on all USD denominated funds with at least 24 non-backfilled observations. N indicates the number of funds in each sample and Nt the number of fund-month observations underlying the alpha estimate. For rolling OLS the first 23 observations of each fund are lost for estimating the first alpha. The column 'sign. $\alpha$' reports the proportion of funds in the respective strategies that exhibit an alpha that is greater than zero on a confidence level of 95% (based on HAC-adjusted standard errors) based on the constant factor loading OLS regression and the column 'sign. $\alpha_{roll}$' reports the proportion of funds that have a significantly positive average alpha over time when estimating the alpha over 24 months with rolling regression. The returns are desmoothed based on the procedure proposed by Getmansky, Lo and Makarov (2004). The asterisks *, **, and *** indicate statistical significance on the 90%, 95% and 99% confidence level (one-sided) based on HAC-adjusted error terms.

| | Factor Model based on stepwise regression | | | | | Fung and Hsieh (2004) seven-factor model | | | | | N | Nt | Nt(roll) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Strategy | $\alpha_{OLS}$ | $R^2$(adj) | $\alpha_{roll}$ | sign. $\alpha$ | sign. $\alpha_{roll}$ | $\alpha_{OLS}$ | $R^2$(adj) | $\alpha_{roll}$ | sign. $\alpha$ | sign. $\alpha_{roll}$ | | | |
| Convertible Arbitrage | 0.14** | 0.37 | 0.13 | 27% | 49% | 0.06 | 0.14 | 0.21*** | 16% | 60% | 138 | 8666 | 5492 |
| Dedicated Short Bias | 0.21 | 0.62 | 0.23 | 14% | 38% | 0.16 | 0.62 | 0.13 | 24% | 33% | 21 | 1289 | 806 |
| Emerging Markets | 0.22*** | 0.42 | 0.34*** | 15% | 49% | 0.18** | 0.24 | 0.38*** | 16% | 59% | 237 | 15089 | 9638 |
| Equity Market Neutral | 0.10*** | 0.15 | 0.10** | 25% | 54% | 0.12*** | 0.11 | 0.12*** | 25% | 55% | 216 | 11875 | 6907 |
| Event Driven | 0.20*** | 0.35 | 0.39*** | 25% | 52% | 0.19*** | 0.25 | 0.35*** | 33% | 67% | 355 | 21763 | 13598 |
| Fixed Income Arbitrage | 0.06 | 0.15 | 0.13*** | 31% | 60% | 0.06 | 0.11 | 0.16*** | 32% | 59% | 173 | 9939 | 5960 |
| Funds of Funds | -0.05** | 0.52 | -0.02 | 16% | 43% | -0.09*** | 0.32 | 0.08*** | 10% | 57% | 716 | 41772 | 25304 |
| Global Macro | 0.05 | 0.17 | 0.03 | 23% | 54% | 0.02 | 0.15 | 0.02 | 21% | 47% | 180 | 9678 | 5538 |
| Long/Short Equity Hedge | 0.00 | 0.42 | 0.02 | 17% | 43% | 0.15*** | 0.31 | 0.27*** | 18% | 57% | 1209 | 69092 | 41285 |
| Managed Futures | 0.18 | 0.21 | 0.12 | 13% | 34% | 0.38** | 0.16 | 0.38* | 16% | 49% | 301 | 15527 | 8604 |
| Multi-Strategy | 0.13** | 0.31 | 0.08 | 27% | 45% | 0.19*** | 0.19 | 0.30*** | 32% | 64% | 192 | 12073 | 7657 |
| Average (cross section) | 0.06*** | 0.37 | 0.09*** | 19% | 46% | 0.12 | 0.25 | 0.23 | 20% | 57% | 3738 | 216763 | 130789 |

Convertible arbitrage funds have a positive and significant exposure of 0.44 to the CS high yield index II (t-value of 2.28). All the results are qualitatively identical for the rolling-window approach when averaged over time. The only risk factor the two factor models have in common is the long exposure to credit risk (the change in Baa spread) with t-value of -1.63 and -1.51 for the Fung and Hsieh (2004a) model and the stepwise regression approach, respectively.

Another example of a strategy with remarkably different results emerging from the two alternative factor models is long/short equity hedge. Based on the stepwise regression model I report average alphas of zero and two basis points for the constant-loading and the rolling-window approach, respectively. In contrast, the alphas from the Fung and Hsieh (2004a) model amount to 15 and 27 basis points per month. I first check whether these differences are due to outliers in the cross-sectional alpha distribution resulting from the two alternative factor models. However, while I find a slightly more negatively skewed and leptokurtic alpha distribution for the stepwise regression approach as compared to the Fung and Hsieh (2004a) model, there are no obvious outliers resulting from one or the other approach which may be responsible for the qualitative difference in alphas. The higher explanatory power and lower alpha resulting from the stepwise regression approach seems to be mainly due to the inclusion of the momentum and MSCI emerging markets factors, in which both exhibit positive exposures. Hence, the factors chosen in the stepwise regression model seem to better reflect the investment universe available to long/short equity hedge managers and therefore provide a benchmark which is more difficult to beat. As Table 3.2, however, I find for the majority of hedge fund strategies qualitatively similar results based on both factor models.

When comparing the results in Tables 3.2 and 3.3, I observe that the cross-sectional alpha over all funds is lower than the average alpha overall strategy indices in the time series. Consistently, the alpha in the cross-section is lower for most strategies as compared to the alpha based on the corresponding equally-weighted index. In addition, Table 3.3 shows that roughly 20% of the funds are able to deliver a significant alpha when benchmarked against the constant loading factor models and 50% when benchmarked against the rolling-window OLS models. Hence, more managers are able to outperform the benchmark when benchmarked against a rolling-window factor model, as compared to a constant loading factor model. Finally, on average, the seven-factor model is outperformed by more funds than the factor model in which the factors are selected based on stepwise regression.

To account for the systematic risk, I additionally investigate the appraisal ratio, which is defined as the alpha divided by the residual standard deviation from the alpha-regression of the respective fund. Table 3.4 reports the appraisal ratio for the equally-weighted strategy indices. Similar to the estimation of the alpha based on the equally-weighted indices in Table 3.2, I observe high appraisal ratios for the multi strategy index while funds of funds again rank amongst the least favourable strategies in all estimations. Furthermore, a high appraisal ratio is observed for the equity market neutral strategy index. Obviously the adjustment of the alpha for the unsystematic risk does not alter my main results.

So far I have conducted all analyses based on the desmoothed single fund return data or based on equally-weighted strategy indices of desmoothed returns. The desmoothing of the reported returns as suggested by Getmansky, Lo and Makarov (2004) leads to a reduction in the average alpha overall strategy indices of four basis points on average. This reduction in alpha tends to be higher for strategies investing in in less liquid assets (e.g., funds of funds and convertible arbitrage) as compared to strategies investing in highly liquid assets (e.g., managed futures). In fact, when replicating Table 3.4 based on reported returns, I find the effect of desmoothing to be more pronounced, particularly for strategies that invest in illiquid assets (Agarwal, Daniel and Naik, 2011). This makes intuitively sense, as the standard error of the residuals of the regression in the denominator of the appraisal ratio is strongly affected by the smoothing of the returns (Getmansky, Lo and Makarov, 2004). The desmoothing even alters the ranking of the strategies as measured by the appraisal ratio. Strategies that invest in less liquid assets turn out to be relatively less attractive than those predominately investing in highly liquid assets.

**Table 3.4: Appraisal ratios based on indices of equally-weighted returns**

The table reports appraisal ratios estimated with two alternative factor models and two different estimation methodologies. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004a) seven-factor model (FH). The factor models are estimated based on a constant-loading OLS approach (OLS) and OLS estimation over rolling 24-month windows. The table is based on an equally-weighted index for each strategy. The returns are desmoothed based on the procedure proposed by Getmansky, Lo and Makarov (2004).

| | Stepwise regression | | FH 2004 7-factor | |
|---|---|---|---|---|
| Strategy | Appraisal OLS | Appraisal Roll | Appraisal OLS | Appraisal Roll |
| Convertible Arbitrage | 0.24 | 0.44 | 0.10 | 0.40 |
| Dedicated Short Bias | 0.14 | 0.19 | 0.15 | 0.05 |
| Emerging Markets | 0.07 | 0.24 | -0.02 | 0.16 |
| Equity Market – Neutral | 0.48 | 0.52 | 0.46 | 0.50 |
| Event Driven | 0.14 | 0.41 | 0.14 | 0.47 |
| Fixed Income Arbitrage | 0.09 | 0.38 | 0.09 | 0.51 |
| Funds of Funds | 0.03 | 0.12 | 0.00 | 0.04 |
| Global Macro | 0.11 | 0.16 | 0.09 | 0.05 |
| Long/Short Equity Hedge | 0.23 | 0.28 | 0.22 | 0.44 |
| Managed Futures | 0.18 | 0.10 | 0.24 | 0.22 |
| Multi-Strategy | 0.24 | 0.55 | 0.17 | 0.51 |
| Average (time weighted) | | 0.31 | | 0.31 |

For the majority of analyses in the paper, I use equally-weighted strategy indices and not value-weighted indices. An advantage of value-weighted indices is that they rather reflect the hedge fund universe and consequently are more likely to reflect an investable strategy. However, they are more sensitive with respect to the quality of the AUM data. The main caveat of an equally–weighted index is that it implicitly assumes a monthly rebalancing of the portfolio (due to fund flows, however, this also applies to value-weighted indices). Furthermore, an equally-weighted index is less sensitive with respect to certain incidents affecting large funds such as the fall of LTCM or the wrong figures reported by Fairfield Greenwich (a large feeder fund of Bernhard L. Madoff Securities). However, I find that the choice of the index only has a small impact on my results. Overall, the average monthly alpha based on the value-weighted indices for each strategy increases by five to 12 basis points as compared to the equally weighted indices. This suggests that either some large funds perform very well or some small funds perform relatively poorly.

### 3.4.2 Is alpha disappearing?

Fung et al. (2008) argue that the hedge fund industry has experienced several structural breaks. They find the break points to coincide with extreme market events which might have affected managers's risk taking behaviour. Based on an index of funds of funds, they identify these break points to be the collapse of LTCM in September 1998 and the peak of the technology bubble in March 2000. Meligkotsidou and Vrontos (2008) investigate structural breaks on the level of hedge fund strategies as well as on overall hedge fund indices over the period January 1994 to November 2005. For the majority of single strategy indices they find the same two break points.

I follow Fung et al. (2008) and apply the factor model of Fung and Hsieh (2004a) to the returns of an equally-weighted index of funds of funds and also conduct multiple Chow (1960) tests for the above-mentioned and other possible structural breaks. In doing so, I can confirm structural breaks in September 1998 and March 2000, both on a 99% confidence level. Furthermore, I identify another structural break at the beginning of a long period of low volatilities in equity markets in early 2004.[7] Finally, I find a fourth break in August 2007 after the liquidity shock in the financial industry.[8] Khandani and Lo (2010) argue that the sharp decrease of the S & P index on August 9, 2007 forced many hedge fund managers to de-leverage their portfolio leading to large losses for highly leveraged hedge funds. However, the null hypothesis of identical coefficients can only be rejected on a confidence level of 95%. Nevertheless, based on the knowledge of the importance of the events in summer 2007 for the hedge fund industry, I decide to run a separate OLS estimation for the time period from August 2007 to June 2012.

Fung et al. (2008) find that the average fund of fund has only delivered positive alpha during the short period from October 1998 to March 2000. I reassess this finding based on a more recent sample of single hedge funds and funds of funds. Table 3.5 reports the results from a constant factor loading alpha estimation based on equally-weighted desmoothed strategy indices for the five sub-periods determined by the four structural breaks. When investigating specific sub-periods, alpha varies greatly between the strategies as well as for specific strategies in different sub-periods. Consistent with Fung et al. (2008), I find that until 2004 funds of funds only generate a statistically significant positive alpha during the

[7] In February 2004 the Volatility Index of the CBOT (VIX) dropped below 15% and remained in the range of 10-15% until June 2007.

[8] August 2007 can be considered as the start of the recent liquidity crisis of 2008. During August 2007 the spread between the 3-month USD Libor and the 3-month overnight index swap (OIS) rate increased from 12 to 74 basis points.

short period from October 1998 to March 2000 based on the Fung and Hsieh (2004a) seven-factor model.

**Table 3.5: Alphas of equally-weighted indices in different subperiods**

The table reports the alphas of the equally-weighted strategy indices estimated with two alternative factor models. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004a) seven-factor model (FH). The factor models are estimated with constant-loading OLS. The identification of subperiods is based on structural breaks which are obtained from multiple Chow (1960) tests. The returns are desmoothed based on the procedure proposed by Getmansky, Lo and Makarov (2004). All alphas are expressed in monthly percentage returns. The asterisks *, **, and *** indicate a statistical significance on the 90%, 95% and 99% confidence level (two-sided) based on HAC-adjusted error terms

| Strategy | $\alpha_{OLS}$ | $adj\ R^2$ | $\alpha_{OLS,FH}$ | $adj\ R^2\ FH$ |
|---|---|---|---|---|
| Panel A – Subperiod January 1994 to September 1998 | | | | |
| Convertible Arbitrage | 0.30** | 0.68 | 0.38** | 0.55 |
| Dedicated Short Bias | 1.07 | 0.57 | 1.24** | 0.52 |
| Emerging Markets | 0.26 | 0.80 | -1.92*** | 0.52 |
| Equity Market Neutral | 0.56*** | 0.08 | 0.63*** | 0.08 |
| Event Driven | 0.19 | 0.65 | -0.07 | 0.45 |
| Fixed Income Arbitrage | 0.08 | 0.28 | 0.19 | 0.21 |
| Funds of Funds | 0.04 | 0.66 | -0.31** | 0.62 |
| Global Macro | 0.38 | 0.40 | 0.45* | 0.52 |
| Long/Short Equity Hedge | 0.48** | 0.87 | 0.46t*** | 0.80 |
| Managed Futures | 0.46 | 0.55 | 0.65 | 0.50 |
| Multi-Strategy | 0.61** | 0.38 | 0.16 | 0.14 |
| Panel B – Subperiod October 1998 to March 2000 | | | | |
| Convertible Arbitrage | 1.70*** | 0.63 | 1.82*** | 0.22 |
| Dedicated Short Bias | 0.49 | 0.45 | -0.90 | 0.40 |
| Emerging Markets | -0.32 | 0.83 | 0.88 | 0.24 |
| Equity Market Neutral | 0.32* | 0.029 | 0.52** | -0.01 |
| Event Driven | 0.88** | 0.74 | 1.23*** | 0.54 |
| Fixed Income Arbitrage | 0.16 | 0.16 | 0.92*** | 0.52 |
| Funds of Funds | 0.03 | 0.76 | 1.17*** | 0.65 |
| Global Macro | -0.61** | 0.40 | -0.47*** | 0.72 |
| Long/Short Equity Hedge | 0.72*** | 0.97 | 2.18*** | 0.88 |
| Managed Futures | -1.19*** | 0.60 | -1.23*** | -0.01 |
| Multi-Strategy | 0.86*** | 0.47 | 1.24*** | 0.82 |
| Panel C – Subperiod April 2000 to March 2004 | | | | |
| Convertible Arbitrage | 0.41 | 0.58 | 0.11 | 0.18 |
| Dedicated Short Bias | -0.18 | 0.83 | -0.3 | 0.82 |
| Emerging Markets | 0.29 | 0.85 | 0.27 | 0.72 |
| Equity Market Neutral | -0.05 | 0.14 | -0.13 | -0.23 |
| Event Driven | 0.09 | 0.77 | 0.13 | 0.62 |
| Fixed Income Arbitrage | 0.17* | 0.10 | 0.16* | 0.15 |
| Funds of Funds | -0.11 | 0.69 | -0.24*** | 0.67 |
| Global Macro | 0.07 | 0.49 | -0.07 | 0.55 |
| Long/Short Equity Hedge | -0.14 | 0.94 | -0.19* | 0.89 |
| Managed Futures | 0.55 | 0.39 | 0.92** | 0.32 |
| Multi-Strategy | 0.23 | 0.65 | 0.23** | 0.69 |
| Panel D – Subperiod April 2004 to July 2007 | | | | |
| Convertible Arbitrage | 0.32** | 0.61 | 0.00 | 0.29 |
| Dedicated Short Bias | -0.15 | 0.93 | -0.27 | 0.91 |
| Emerging Markets | 0.11 | 0.90 | 1.37*** | 0.35 |
| Equity Market Neutral | 0.07 | 0.53 | 0.13 | 0.27 |
| Event Driven | 0.60** | 0.74 | 0.44*** | 0.72 |
| Fixed Income Arbitrage | 0.10 | 0.47 | 0.14* | 0.30 |
| Funds of Funds | -0.16 | 0.84 | 0.31* | 0.62 |
| Global Macro | 0.10 | 0.65 | 0.25 | 0.44 |
| Long/Short Equity Hedge | -0.03 | 0.91 | 0.39** | 0.73 |
| Managed Futures | 0.22 | 0.37 | 0.49* | 0.53 |
| Multi-Strategy | -0.13* | 0.88 | 0.41** | 0.56 |
| Panel E – Subperiod August 2007 to June 2012 | | | | |
| Convertible Arbitrage | -1.80 | 0.94 | -0.50 | 0.29 |
| Dedicated Short Bias | 0.36 | 0.92 | 0.46*** | 0.96 |
| Emerging Markets | -0.88** | 0.89 | -0.34 | 0.43 |
| Equity Market Neutral | -0.45*** | 0.73 | 0.07 | -0.19 |
| Event Driven | -1.88*** | 0.94 | -0.66* | 0.45 |
| Fixed Income Arbitrage | -0.42 | 0.79 | -0.20 | 0.33 |
| Funds of Funds | -0.25 | 0.90 | -0.49 | 0.27 |
| Global Macro | -0.07 | 0.92 | 0.04 | 0.11 |
| Long/Short Equity Hedge | -0.46*** | 0.95 | -0.36 | 0.60 |
| Managed Futures | 0.38 | 0.83 | 0.95* | -0.14 |
| Multi-Strategy | 0.01 | 0.73 | -0.32 | 0.06 |

(Panel B in Table 3.5). Based on the stepwise model, funds of funds fail to exhibit a statistically significant positive alpha in any of the subperiods. Their estimated alpha is even negative for most sub-periods. Furthermore, an investigation of the reported adjusted r-squares suggests that the stepwise regression model is often capable to explain more of the systematic risk exposure than the seven-factor model of Fung and Hsieh (2004a). Looking beyond the end of the Fung et. al. (2008) sample in December 2004 (Panels D and E), I find a statistically significant positive alpha for funds of funds in the period April 2004 to July 2007 based on the Fung and Hsieh (2004a) factor model.[9] Therefore, beyond the end of the sample of Fung et al. (2008), I do not observe a reduction of hedge fund alpha over time.

## 3.5 Conclusion

This paper investigates the development of hedge fund alpha over the time period from 1994 to 2012 based on the Eurekahedge, TASS and Morningstar databases. I estimate alpha by benchmarking hedge fund returns against two alternative return-based factor models. Specifically, I establish a factor model in which I select the risk factors based on a stepwise regression approach and compare the results to the widely used factor model proposed by Fung and Hsieh (2004a). I account for the dynamics in the factor exposures by using a rolling-window regression approach.

Unlike previous research, I find no systematically decreasing alpha in the hedge fund industry over time. In addition, I find no evidence pointing to capacity constraints (negative

[9] The HAC-adjusted t-value of the alpha for funds od funds increases from 1.8 to 2.2, if only the period subsequent to their sample, i.e., January 2005 to July 2007, is considered.

relationship between fund flows and alpha) in the hedge funds domiciled in Asia Pacific over the full time period from 1994 to 2012.

# CHAPTER FOUR

# ESSAY TWO

## PERSISTENCE OF HEDGE FUND PERFORMANCE

**Abstract:** This paper empirically examines the performance persistence of hedge funds domiciled in the Asia Pacific from the period January 2000 to December 2010 that includes the global financial crisis of 2007. It documents that there is limited evidence of persistence of hedge fund performance for the full sample period except for medium and poor performers. When Teo's (2009) model is used for the full sample period, there are positive, highly significant alphas among the middle and bottom deciles. Most of the performance persistence is found in the first sub period, while results varied for the second sub period dependent on the models used. There is only weak evidence of performance persistence during the second sub period even though the adjusted Teo's (2009) model is better as shown by the higher adjusted $R^2$ for explaining hedge funds domiciled in the Asia Pacific. This paper finds inconclusive evidence of performance persistence for the best and worst performing funds. One of the reasons is many hedge fund managers may apply less risky strategies and thus outperform the market for longer period of time despite taking considerable amount of risk which lead to experiencing significantly superior or inferior returns for a short period of time.

**Keywords**: Persistence, hedge funds, financial crises, institutional investors

**JEL classification**: G01, G12, G23

## 4.1 Introduction

The persistence of hedge fund performance has been a subject of much debate in the academic literature. The literature on fund performance persistence dates back to the emergence of the mutual fund industry. Capon et al. (1996) analyse the selection criteria of 3,386 mutual fund investors and find that previous performance is the most important selection criteria. Sirri and Tufano (1998) study the flow of funds into and out of equity mutual funds. They find that managers invest disproportionally more in funds that performed very well in the prior period and search cost or media attention is an important determinant of fund flows. Funds that have higher fees or higher marketing effort have higher performance.

Research on performance persistence in essence focus on one question: “Do some hedge fund managers achieve consistently higher returns than their counterparts?” From the perspective of hedge fund investors, this is an important question as they constantly face selection problems when trying to choose which hedge funds to invest in. Capocci et al. (2005) observe that active selection is likely to enhance the expected return if performance in hedge fund returns persists. This is because one superior average return period is likely to be followed by another superior average return period.

Hedge funds have many characteristics that make them ideal for studies of performance persistence in the fund management industry. While mutual fund managers are limited in the availability of investment strategies, hedge fund managers have more flexibility and freedom to invest, hence displaying their skills.

This paper looks at the period 2000 to 2010 and examines whether hedge fund domiciled in Asia Pacific generate consistently higher returns than their counterparts. I investigate whether returns of hedge funds persist annually. I first investigate the performance persistence over the full sample period and then break the sample into two sub-periods: January 2000 to January 2007 and February 2007 to December 2010 (Eling, 2009) and investigate performance persistence in different market environments: bullish market and bearish market.

Koh et al. (2003) examine the performance persistence of Asia-focused hedge funds from 1999 to 2003 by combining Eurekahedge and AsiaHedge databases. They find that Asia-focused hedge funds display persistence in performance at monthly and quarterly horizons but not at the annual horizon. The authors use nonparametric statistical methods including a contingency table based test for single period persistence and a Kolmogorov-Smirnov statistic for a multi-period persistence test. This paper extends Koh et al.'s (2003) study on hedge fund performance persistence by examining hedge funds domiciled in Asia Pacific over a longer period that covers both market upswings and market declines. Unlike Koh et al. (2003), who use non-parametric methods to analyse hedge fund performance, this paper use a parametric, regression-based framework.

The rest of this paper is structured as follows. I begin by reviewing the academic literature on performance persistence in Section 4.2. The data set and the methodology are then discussed in Section 4.3 and 4.4 followed by the presentation and discussion of results in Section 4.5.

## 4.2 Literature review

While the issue of performance persistence has been widely studied in the mutual funds industry, research into the persistence of hedge fund performance is a relatively recent phenomenon, with the first articles published near the end of 1990s.

Henricks et al. (1993) show that mutual fund performance exhibits persistence over a short-term horizon of one to three years. They attribute this finding to "hot hands" or common investment strategies. The study use quarterly return data from a sample of open-ended mutual funds covering the period 1974 to 1988. Grinblatt and Titman (1992) study mutual fund data over the 1975 to 1984 period and discover evidence of performance persistence over a longer horizon (five years). The authors contribute this finding to managerial skill. Using a data sample from 1977 until 1989 to examine mutual fund performance persistence, Brown and Goetzmann (1995) find the relative risk-adjusted performance of mutual funds persists and such persistence is mainly due to funds that lag the S & P 500 index. Carhart (1997) investigates mutual fund performance persistence using a sample that covers the period 1962 until 1993. His findings show the strongest unexplained persistence among worst mutual fund performers. To sum, studies on performance persistence among mutual funds generally find mutual funds have inferior performance to passive investment strategies and limited evidence of performance persistence.

Some authors acknowledge it may be different in hedge funds. Brown et al. (1999) is one of the first studies on hedge fund performance and persistence. Using the US Offshore Funds Directory from 1989 to 1995, they find no performance persistence on annual basis.

Agarwal and Naik (2000) discover that mutual fund managers who successfully outperform are more likely to enter to the hedge fund industry. As such, the hedge fund space may be more suitable for testing performance persistence. The authors use both the traditional two-period framework and multi-period framework (a Kolmogorov-Smirnov test) to examine hedge fund performance persistence and find persistence to be strongest at the quarterly horizons. Edwards and Caglayan (2001) find performance persistence at yearly and bi-yearly horizons using alphas from six-factor model and then apply both parametric and non-parametric statistical tests. The authors use the MAR database and over the period 1990 to 1998. Baquero et al. (2005) study hedge fund performance persistence in raw returns and find at the four best deciles, there is evidence of positive performance persistence at quarterly horizons. Kosowski et al. (2007) use the databases of TASS, HFR, CISDM and MSCI datasets and bootstrap and Bayesian methods to examine the persistence of hedge fund performance. They find hedge fund performance persists annually and the best hedge fund performance cannot be explained by luck.

Boyson (2008) investigate the persistence of hedge fund performance using the TASS data set from 1994 to 2004. Her findings show a portfolio of young, small, good past performers outperforms a portfolio of old, large, poor past performers by 9.6 percentage points annually. Koh et al (2003) observe persistence at the monthly and quarterly horizons only by using cross-product ratio, chi square and Kolmogorov-Smirnov tests.

Jagannathan et al. (2010) find strong support of performance persistence among top hedge funds and little support for persistence among bottom funds. They do this by comparing the alphas over the 3 year horizons and using both the weighted least squares approach and a generalized method of moment's estimation model to overcome the measurement errors in alphas.

Lastly, Eling (2009) undertakes a comprehensive literature review on the persistence of hedge fund performance and finds that significance of persistence falls with the length of time horizon and that almost all papers find short–term persistence (up to six months). His study show conflicting conclusions regarding longer horizons. While ten studies find no persistence at the annual horizon, eight studies conclude performance persistence at the annual horizon. Getmansky, Lo and Makarov (2004) relate the short-term hedge fund persistence to the illiquidity induced by the type of assets that hedge funds invest in.

### 4.3 Data

This paper uses the Eurekahedge, TASS and Morningstar databases covering the period January 2000 to December 2010. This period is of significance as it includes the financial crisis of 2007. The three databases cover over 20000 global hedge funds. Nevertheless, the dataset remain is 2739 hedge funds domiciled in the Asia Pacific after accounting for survivorship, instant history and selection bias. This represents the largest sample of hedge funds domiciled in the Asia Pacific used for an academic study.

Several important factors must be accounted for when choosing the period to study. Firstly, due to survivorship bias or limitations in hedge fund data prior to that year (Liang, 2000), examination of hedge fund returns before 1994 may be not worthwhile. Secondly, in academic literature, instead of measuring the performance or performance persistence of fund manager, fund is measured. Realistically, it is the performance of the fund manager that interests academics as performance persistence is linked to the particular set of skills possessed by the fund manager. Academics often use data on fund performance as it is difficult to control for changes in fund managers. Eling (2009) recommends researchers to use time periods not greater than 10 years. Hence, the period of study seems appropriate.

There is no universal method for classifying different hedge funds' investment styles and strategies. This paper follows Teo (2009) in grouping hedge fund strategies into eight primary investment strategies (equity long/short, relative value, even driven, macro, directional, fixed income, managed futures (CTA) and others) even though the databases sorts the hedge funds into different investment strategies.

Hedge fund databases are known to suffer from various biases. One of these biases is known as the survivorship bias or the difference in performance between the portfolio of live funds and the portfolio of dead funds or the portfolio of all funds in the database (Ackermann et al., 1999, Liang 2000). I calculate the survivorship bias for the whole sample period of 0.54% per month using the first definition and 0.16% per month for the second definition. These values are consistent with extant literature (see Liang, 2000; Eling and Faust, 2010; Xu et al., 2010). The results should be less impacted by survivorship bias as the database covers the recent time period of 2000 to 2010. Some authors exclude hedge fund data prior to 1994 as usually hedge fund databases did not include dead funds (see Capocci and Huebner, 2004; Liang and Park, 2007). Survivorship bias should not significantly influence the results as the study period is from 2000 and the databases include both surviving and dissolved funds.

Other relevant biases to affect hedge fund databases include: selection bias, instant history bias, illiquidity bias and multi-period sampling bias. Selection bias occurs when poor performing funds have less incentive to report to database providers then well performing funds. This is a negligible effect as best performing funds are closed to new money and hence do not report to database vendors (Fung and Hsieh, 2000a). Backfill bias arises when database vendors' backfill the historical returns of newly added funds, leading to upward bias in performance measurement results. To overcome this bias, I delete the first 12 months of returns for each hedge fund like Fung and Hsieh (2000a) and Capocci and Huebner (2004). Hedge funds often invest in illiquid or difficult to price securities such as derivatives, small cap stocks and emerging market bonds. Because of the illiquidity nature, these securities do not have daily prices and are not marked to market regularly. Hedge fund managers may be tempted to smooth their returns and systematically understate the volatility of their portfolios, also known as the illiquidity bias. Agarwal and Naik (2000) find that intra-year persistence can be caused by stale valuations since hedge funds only disclose audited returns annually. To control for this bias, I follow Getmansky, Lo and Makarov (2004) desmoothing procedure. Lastly, I follow Fung and Hsieh (2000a) and include only funds with a minimum of 36 months of returns to control for multi-period sampling bias.

### 4.4 Methodology

There are two ways of examining performance persistence. The first method is to examine performance persistence of a fund by measuring it directly without comparing it the median. The second method examines performance persistence by measuring the relative returns of that fund. Hence hedge fund returns are arranged in groups relative to the median return in a given period.

### 4.4.1 Persistence of relative returns

The persistence of relative returns can be analysed using two approaches: two period and multi period statistical approaches (Agarwal and Naik, 2000). While in the multi period approach, a series of consecutive time units is considered, in the two period statistical approaches, two consecutive times units are compared. The two period approach can be further divided into non-parametric and parametric methods.

#### 4.4.1.1 Two period approach – Non-parametric approach

According to this approach, funds that outperform the median return of all funds following the same strategy over the given time period are labelled as winners, while funds that underperform the median returns of all funds following same strategy are labelled as losers. Persistence refers to those funds that are labelled as winners over two consecutive periods (WW) or losers over two consecutive periods (LL). Funds that are winners in the first period and losers in the second (WL) or losers in the first period and winners in the second (LW) do not exhibit persistence. The non-parametric approach focuses on the formation of two-way winners and losers contingency tables. Agarwal and Naik (2000) use the cross product ratio (CPR) to examine persistence in hedge fund returns. CPR is defined as the ratio of the funds that exhibit performance persistence to those that do not:

$$CPR = \frac{(WW.LL)}{(WL.LW)}$$

The null hypothesis is CPR is equal to 1 to show no persistence in performance. In other words, each of the four previously mentioned classifications (WW, LL, WL, LW) represent 25% of all the funds. By calculating the Z statistic, which is the ratio of the natural logarithm to CPR to the standard error of the natural logarithm of the CPR, I can test the statistical significance of the CPR.

$$Z = \frac{\ln(CPR)}{\alpha_{\ln(CPR)}}$$

The standard error of the natural logarithm of the CPR can be calculated as:

$$x = \sqrt{\frac{1}{WW} + \frac{1}{WL}} + \frac{1}{LW} + \frac{1}{LL}$$

A Z statistic greater than 1.96 (2.58) implies significant persistence at the 5% (1%) (see Agarwal and Naik, 2000; Edwards and Caglayan, 2001, Koh et al; 2003)

Alternatively, the chi-square method can be used to test for persistence in returns. The chi square test compares the distribution of the observed frequencies of the four categories (WW, LL, WL, and LW) with the expected frequencies of the distribution. It can be written as:

$$x^2 = \frac{(WW - D1)^2}{D1} + \frac{(WL - D2)^2}{D2} + \frac{(LW - D3)^2}{D3} + \frac{(LL - D4)^2}{D4}$$

Where $D1 = \frac{(WW+WL)*(WW+LW)}{N}$; $D2 = \frac{(WW+WL)*(WL+LL)}{N}$; $D3 = \frac{(LW+WL)*(WW+LW)}{N}$;

$D4 = \frac{(LW+LL)*(WL+LL)}{N}$ and where N represents the number of all funds.

The chi square distribution with one degree of freedom with an $x^2$ value larger than 3.84 (6.64) means the statistically significant persistence of returns at the 5% (1%) confidence level.

Carpenter and Lynch (1999) find that in the presence of survivorship bias in the hedge fund data, the chi square method is more robust. This method is used by Agarwal and Naik (2000), Koh et al. (2003), Malkiel and Saha (2005), and Agarwal, Daniel and Naik (2009). One weakness of the CPR and chi-square methods is incorporating substantial differences in fund evaluation such that the worst funds of the upper decile are comparing to the best funds of the lower decile.

Another non-parametric test is the Spearman's rank correlation test (Park and Staum, 1998). As it measures the strength of association between two variables, it can be used to test performance persistence. Performance rankings are compared for different time intervals. The value is always between 1 and -1. 1 means perfect positive correlation and perfect positive persistence and vice versa. A value of zero means no persistence in returns over two periods.

#### 4.4.1.2 Two period approach – Parametric approach – Cross sectional regression

One can regress the current period's measurement value (raw returns, alpha or another measure) onto the previous periods' measurement value to measure performance persistence. A positive and statistically slope coefficient implies that a hedge fund performed well during the previous period will perform well in the current period. If the t value is greater than 1.96 (2.58) that means persistence in performance and significant at the 5% (1%) confidence level. Mathematically, it can be expressed as:

$$R_{it} - R_{ft} = \alpha_i + \beta * R_{t-1}$$

This cross sectional regression has been used by Brown et al. (1999), Brown and Goetzmann (2003), Agarwal and Naik (2000), Edwards and Caglayan (2001) and Boyson and Cooper (2004).

Although the cross sectional regression can output evidence of performance persistence, it does not mean the availability of economically worthwhile investment strategies (Hendricks et al. 1993). The authors suggest ranking portfolios of mutual funds based on last year's performance results into decile portfolios. For the purpose of this paper, I adopt this approach to examine performance persistence.

#### 4.4.1.3 Multi period approach – Kolmogorov-Smirnov goodness of fit test

The Kolmogorov-Smirnov test gives more robust results in contrast to two period tests. It attempts to measure whether two data sets differ significantly. A series of wins and losses for each fund and accordingly labels as either a winner or a loser will be recorded. In short, the Kolmogorov-Smirnov method is used to investigate whether the distribution of winner or loser funds is statistically different from the theoretical frequency distribution of two or more consecutive wins or losses (Agarwal and Naik, 2000; Koh et al. 2003; Eling, 2009). The theoretical probability of three consecutive winning periods (WWW) or losing periods (LLL) is one eighth while that of WWWW and LLLL is one sixteenth if there is no persistence in returns. There are two advantages of the Kolmogorov-Smirnov method: data requirements are low and the distribution of the test statistic itself does not depend on the underlying cumulative distribution (Gehin, 2004). Bollen and Pool (2012) set up a set of flags based on suspicious patterns in hedge fund returns for example higher than normal instances of repeated returns, too many zero returns relative to a theoretical distribution, and the presence of a kink in the distribution of funds' returns. The frequent trigger to these flags is funds charged with misappropriation, overvaluation, and misrepresentation. In Bollen and Pool (2009), they also find significant discontinuity in hedge fund returns at zero. This finding is attributed in part to managers overstating their returns.

### 4.4.2 Persistence of relative returns

#### 4.2.2.1 The Hurst exponent

The Hurst exponent is defined as a measure of trend: negative or positive will persist or mean revert to the historical average. Rather than measuring hedge performance persistence relative to some other return, it attempts to do so directly (De Souza and Gokcan, 2004). There are no assumptions about the frequency distribution of the underlying data. It can be written as such:

$$RS_t \cong (ct)^H \; or \ln RS_t = \ln(c) + Hln(t)$$

where $RS_t$ is the range of cumulative deviation from the mean divided by the standard deviation and H represents the Hurst exponent, varying from zero to one. Reversed persistence is when the value of the Hurst exponent is between 0 and 0.5 (Qian and Rasheed, 2004). A positive persistence in performance is when the value of the Hurst exponent lies between 0.5 and 1. Random performance is when the value of the Hurst exponent is equal to 0.5. The disadvantage of this method is that it involves more data points.

### 4.4.3 Performance measurement

This section describes briefly the two multi factor performance measurement models used to investigate performance persistence of hedge funds domiciled in the Asia Pacific: the Fung and Hsieh (2004a) seven factor model and an adjusted Teo's (2009) model. In the hedge fund literature, the Fung and Hsieh (2004a) model is one of the most widely used multi factor models. The model uses two equity focused risk factors – and equity market factor (the S & P 500 index excess returns (SNPMRF)) and a factor which proxies the exposure of hedge funds to the spread between returns on large-cap equities and returns on small-cap equities (the Wilshire Small Cap 1750 Index minus the Wilshire Large Cap 750 Index). As the Wilshire indices stopped reporting in December 2006, the Russell 2000 index minus the S & P 500 index (SCMLC) as suggested by David Hsieh on his website as a size proxy. In addition, the authors use two fixed income factors and three trend following factors. The two fixed income factors are the change in the 10 year Treasury yields (BD10RET) as a fixed income factor and the spread of the change in the Moody's Baa yield over the change of the 10 year Treasury yield (BAAMTSY) as a credit spread factor. The three primitive trend following strategies (PTFS) are based on the previously mentioned Fung and Hsieh (2001) paper. They are the bond trend following factor (PTFSBD), the currency trend following factor (PTFSFX) and the commodity trend following factor ($PTFSCOM$)[13]:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iSNPMRF} SNPMRF_t + \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t + \beta_{iBAAMTSY} BAAMTSY_t + \beta_{iPTFSBD} PTFSBD_t + \beta_{iPTFSFX} PTFSFX_t + \beta_{iPTFSCOM} PTFSCOM_t + \varepsilon_{it}$$

Teo (2009) augments Fung and Hsieh's seven factor model (2004a) with additional factors: the excess return on the MSCI All Countries Asia ex Japan equity market index and the excess return on the Nikkei 225 Japan equity market index. Additionally, he adds two option based factors to account for the fact that the payoffs of numerous hedge funds resemble those from writing naked out of the money put options. In this paper, I adjust Teo's (2009) model by removing the two option based equity factors since they do not explain much of the variation of Asia Pacific hedge funds returns in the analysis. The model is stated as:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iSNPMRF} SNPMRF_t + \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t + \beta_{iBAAMTSY} BAAMTSY_t + \beta_{iPTFSBD} PTFSBD_t + \beta_{iPTFSFX} PTFSFX_t + \beta_{iPTFSCOM} PTFSCOM_t + \beta_{ASIAMRF} ASIAMRF_t + \beta_{JAPMRF} JAPMRF + \varepsilon_{it}$$

Teo (2009) extends the Fung and Hsieh (2004a) seven factor model to control for specific characteristics associated with Asia-focused funds by including two Asia equity based factors and two option based factors. To identify the additional asset based styles, the principal component analysis is used. He finds the model to explain the performance of Asia focused hedge funds better and the adjusted $R^2$ is 29% greater than the Fung and Hsieh (2004a) model.

## 4.5 Results

### 4.5.1 Persistence in one year sorted returns over the full period

In this section, the persistence of the hedge fund performance is analysed. Firstly, all hedge funds domiciled in the Asia Pacific is ranked based on their total returns for the previous year. Next, portfolio performance is estimated using the Fung and Hsieh (2004a) and adjusted Teo's (2009) models. Carhart (1997) and Hendricks et al, (1993) also used this method to evaluate mutual funds.

10 equally weighted portfolios of hedge funds are formed on the basis of the previous year's reported returns, ranking from highest to lowest on January 1st every year. The best (portfolio 1) and the worst (portfolios 10) portfolios are further subdivided into thirds using the same criteria. This procedure is repeated again on the following January 1. Hedge funds that dissolve during the year are included in the equally weighted average, after which the portfolio weights are readjusted accordingly.

A time series of monthly returns on each decile portfolio from January 2001 till December 2010 is formed when this procedure is applied to the entire period. The portfolios ranked by this method indicate strong variability in monthly mean returns, as shown in Tables 4.1 and 4.2. While portfolio D10 yielded a mean monthly return of 0.98%, portfolio D1 yielded a monthly average return of 0.78%. There is a monotonically decrease in the monthly excess returns between portfolio D1 and D3 but increase from portfolio D3 to D10. Portfolio D1 is similar to portfolio D8 in terms of monthly return (0.78% versus 0.77%). Importantly, the portfolio comprised of previous year's biggest losers outperformed the portfolio comprised of previous year's top performers by 21 basis points. The spread between portfolios D1 and D10 is -0.21%. A spread of 0.02% per month is observed when comparing the extreme sub-divided portfolios D1a and D10c.

Variation in the monthly performance is larger among the portfolios of previous year's top performing funds than among the portfolios of previous year's poor performers in the cross section. The monthly spread between portfolios D1a and D1c is 0.35% while the monthly spread between portfolios D10a and D10c is 0.16%.

**Table 4.1 Portfolios of hedge funds formed on lagged one year returns, estimated using Fung and Hsieh (2004a) model and from January 2001 to December 2010.**

On January 1 each year hedge funds are ranked according to their performance in the previous calendar year. The portfolios are equally weighted monthly such that when a fund disappears the weights are readjusted. Funds with the highest past annual performance comprise of decile 1 and funds with the lowest comprise of decile 10. The factors are: S&P 500 return minus the risk free rate (SNPMRF); Russell 2000 minus the S&P (SMCL); bond factor (BD10RET); credit spread factor (BAAMTSY); bond PTFS (PTFSBD); currency (PTFSFX) and commodities (PTFSCOM).

| Portfolio | Excess return | St. dev. | α | SNPMRF | SCMLC | BD10RET | BAAMTSY | PTFSBD | PTFSCOM | PTFSFX | Adj. $R$^2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| D1a | 1.05 | 6.25 | 0.92 | 0.43 | 0.11 | -2.57 | -4.38 | 0.01 | 0.05 | -0.02 | 0.13 |
| | | | 1.94 | 2.73 | 0.58 | -1.12 | -1.9 | 0.17 | 1.21 | -0.76 | |
| D1b | 0.55 | 4.67 | 0.42 | 0.46 | 0.02 | -1.57 | -3.58 | -0.01 | 0.01 | -0.02 | 0.31 |
| | | | 1.19 | 4.87 | 0.15 | -1.02 | -2.35 | -0.45 | 0.7 | -0.83 | |
| D1c | 0.6 | 3.87 | 0.66 | 0.42 | -0.02 | -1.21 | -2.09 | 0 | 0.05 | -0.04 | 0.39 |
| | | | 2.28 | 5.69 | -0.18 | -0.97 | -2.05 | 0.21 | 1.85 | -2.18 | |
| D1 | 0.78 | 4.49 | 0.67 | 0.44 | 0.04 | -1.79 | -3.35 | 0 | 0.04 | -0.02 | 0.34 |
| | | | 2.01 | 4.53 | 0.31 | -1.17 | -2.22 | -0.03 | 1.37 | -1.26 | |
| D2 | 0.66 | 3.69 | 0.61 | 0.44 | 0.02 | -1.41 | -3.17 | 0.01 | 0.03 | -0.02 | 0.44 |
| | | | 2.36 | 6.8 | -0.03 | -1.18 | -2.58 | 0.59 | 1.23 | -1.12 | |
| D3 | 0.51 | 3.12 | 0.4 | 0.33 | 0.05 | -1.62 | -4.08 | 0 | 0.02 | -0.01 | 0.46 |
| | | | 1.89 | 6.27 | 0.74 | -1.57 | -3.67 | -0.33 | 1.15 | -0.54 | |
| D4 | 0.52 | 2.61 | 0.41 | 0.31 | 0.09 | -0.78 | -2.88 | 0 | 0.01 | 0 | 0.52 |
| | | | 2.42 | 7.72 | 1.51 | -1.21 | -4.61 | 0.13 | 0.36 | 0.41 | |
| D5 | 0.53 | 2.74 | 0.38 | 0.34 | 0.09 | -1.2 | -2.85 | -0.01 | 0.01 | 0.01 | 0.55 |
| | | | 2.06 | 9.03 | 1.37 | -1.34 | -3.65 | -0.55 | 0.72 | 0.66 | |
| D6 | 0.59 | 2.33 | 0.51 | 0.3 | 0.05 | 0.41 | -2.22 | 0 | 0.01 | 0.02 | 0.57 |
| | | | 3.36 | 10.43 | 0.76 | 0.76 | -2.74 | 0.26 | 0.51 | 1.53 | |
| D7 | 0.73 | 2.88 | 0.67 | 0.36 | 0.05 | 0.22 | -2.29 | 0.02 | -0.02 | 0.02 | 0.51 |
| | | | 3.43 | 8.83 | 0.68 | 0.23 | -1.68 | 1.24 | -1.3 | 1.33 | |
| D8 | 0.77 | 3.1 | 0.7 | 0.38 | 0.12 | 1.13 | -1.62 | 0.02 | -0.02 | 0.02 | 0.49 |
| | | | 3.17 | 7.7 | 1.35 | 1 | -0.9 | 1.39 | -0.94 | -0.98 | |
| D9 | 0.8 | 3.65 | 0.7 | 0.44 | 0.09 | 0.12 | -3.15 | 0.01 | 0 | 0.01 | 0.48 |
| | | | 2.49 | 6.33 | 0.79 | 0.11 | -1.64 | 0.49 | -0.05 | 0.72 | |
| D10 | 0.98 | 4.78 | 0.91 | 0.51 | 0.1 | 1.15 | -4.61 | 0.03 | -0.02 | 0.03 | 0.43 |
| | | | 2.39 | 5.48 | 0.65 | 0.86 | -1.66 | 0.98 | -0.79 | 1.08 | |
| D10a | 0.87 | 4.18 | 0.81 | 0.48 | 0.03 | 0.6 | -4.07 | 0.02 | -0.02 | 0.02 | 0.46 |
| | | | 2.51 | 6.63 | 0.25 | 0.43 | -1.73 | 0.95 | -0.79 | 0.99 | |
| D10b | 1.06 | 4.88 | 0.99 | 0.52 | 0.09 | 2.6 | -2.09 | 0.02 | 0 | 0.03 | 0.33 |
| | | | 2.42 | 5.14 | 0.57 | 1.7 | -0.69 | 0.69 | -0.02 | 1.13 | |
| D10c | 1.03 | 6.28 | 0.94 | 0.56 | 0.17 | 0.17 | -8.01 | 0.05 | -0.04 | 0.04 | 0.39 |
| | | | 1.84 | 4.31 | 0.79 | 0.11 | -2.39 | 1.11 | -1.22 | 0.98 | |
| 1-10 spread | -0.21 | 5.14 | -0.41 | -0.07 | -0.07 | -2.96 | 1.18 | -0.03 | 0.06 | -0.06 | 0.02 |
| | | | -0.85 | -0.53 | -0.33 | -1.53 | 0.34 | -0.79 | 1.68 | -1.67 | |
| 1a-10c spread | 0.02 | 7.5 | -0.19 | -0.13 | -0.07 | -2.75 | 3.54 | -0.04 | 0.09 | -0.06 | 0.02 |
| | | | -0.29 | -0.63 | -0.23 | -1.09 | 0.82 | -0.75 | 2.03 | -1.35 | |
| 1-2 spread | 0.11 | 1.89 | -0.11 | 0 | 0.04 | -0.39 | -0.27 | -0.01 | 0.01 | -0.01 | -0.04 |
| | | | -0.7 | -0.09 | 0.6 | -0.57 | -0.5 | -0.75 | 0.93 | -0.79 | |
| 9-10 spread | -0.18 | 1.93 | -0.39 | -0.07 | -0.01 | -1.04 | 1.37 | -0.02 | 0.02 | -0.02 | 0.09 |
| | | | -2.19 | -1.75 | -0.14 | -1.68 | 1.24 | -1.27 | 1.38 | -1.34 | |

**Table 4.2 Portfolios of hedge funds formed on lagged one year returns, estimated using adjusted Teo's (2009) model and from January 2001 to December 2010.**

On January 1 each year hedge funds are ranked according to their performance in the previous calendar year. The portfolios are equally weighted monthly such that when a fund disappears the weights are readjusted. Funds with the highest past annual performance comprise of decile 1 and funds with the lowest comprise of decile 10. The factors are: S&P 500 return minus the risk free rate (SNPMRF); Russell 2000 minus the S&P (SMCL); bond factor (BD10RET); credit spread factor (BAAMTSY); bond PTFS (PTFSBD); currency (PTFSFX) and commodities (PTFSCOM); MSCI Asia ex Japan index return minus the risk free rate (ASIA); and Nikkei 225 index return minus the risk free rate (JAP).

| Portfolio | Excess return | St. dev. | α | SNPMRF | SCMLC | BD10RET | BAAMTSY | PTFSBD | PTFSCOM | PTFSFX | ASIA | JAP | Adj. $R$^2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| D1a | 1.05 | 6.25 | 1 | -0.12 | -0.1 | -2.39 | -2.63 | -0.01 | 0.04 | 0 | 0.23 | 0.47 | 0.27 |
| | | | 1.85 | -0.68 | -0.67 | -1.12 | -1.27 | -0.23 | 1.21 | 0.02 | 1.28 | 2.52 | |
| D1b | 0.55 | 4.68 | 0.3 | -0.12 | -0.11 | -0.86 | -1.94 | -0.02 | 0.01 | -0.01 | 0.38 | 0.26 | 0.51 |
| | | | 0.94 | -1.08 | -0.88 | -0.73 | -1.22 | -0.92 | 0.62 | -0.34 | 4.38 | 3.26 | |
| D1c | 0.7 | 3.87 | 0.54 | -0.03 | -0.12 | -0.55 | -0.76 | 0 | 0.04 | -0.03 | 0.33 | 0.18 | 0.55 |
| | | | 2.33 | -0.58 | -1.21 | -0.58 | -0.73 | -0.2 | 2.12 | -2.08 | 4.79 | 3.16 | |
| D1 | 0.78 | 4.49 | 0.62 | -0.09 | -0.11 | -1.29 | -1.78 | -0.01 | 0.03 | -0.01 | 0.31 | 0.3 | 0.49 |
| | | | 2 | -0.91 | -1.03 | -1.11 | -1.24 | -0.52 | 1.42 | -0.68 | 3.21 | 3.47 | |
| D2 | 0.66 | 3.69 | 0.52 | -0.04 | -0.12 | -0.85 | -1.8 | 0 | 0.02 | -0.01 | 0.31 | 0.22 | 0.66 |
| | | | 2.55 | -0.51 | -1.39 | -1.18 | -1.48 | 0.14 | 1.46 | -0.61 | 5.23 | 4.94 | |
| D3 | 0.51 | 3.12 | 0.29 | -0.13 | -0.05 | -1.02 | -2.79 | -0.01 | 0.02 | 0 | 0.31 | 0.18 | 0.74 |
| | | | 1.95 | -2.57 | -0.76 | -1.65 | -3 | -1.19 | 1.63 | 0.02 | 8.01 | 5.04 | |
| D4 | 0.52 | 2.61 | 0.35 | -0.05 | 0 | -0.4 | -1.85 | 0 | 0 | 0.01 | 0.22 | 0.18 | 0.78 |
| | | | 2.92 | -1.06 | 0.1 | -0.89 | -3.59 | -0.45 | 0.17 | 1.83 | 6.71 | 5.23 | |
| D5 | 0.53 | 2.74 | 0.33 | 0 | 0 | -0.82 | -1.84 | -0.01 | 0.01 | 0.01 | 0.22 | 0.18 | 0.77 |
| | | | 2.43 | -0.07 | -0.08 | -1.28 | -3.6 | -1.07 | 0.77 | 1.89 | 5.28 | 5.06 | |
| D6 | 0.59 | 2.33 | 0.44 | -0.03 | -0.03 | 0.84 | -1.29 | 0 | 0 | 0.02 | 0.22 | 0.14 | 0.84 |
| | | | 4.82 | -0.83 | -0.73 | 1.9 | -2.75 | -0.34 | 0.43 | 3.69 | 8.87 | 5.74 | |
| D7 | 0.73 | 2.88 | 0.51 | -0.03 | -0.01 | 0.51 | -1.25 | 0.01 | -0.02 | 0.02 | 0.31 | 0.08 | 0.75 |
| | | | 3.73 | -0.68 | -0.14 | 0.97 | -1.06 | 1.09 | -1.95 | 2.11 | 9.33 | 2.38 | |
| D8 | 9.77 | 3.1 | 0.59 | 0.08 | 0.05 | 1.7 | -0.59 | 0.02 | -0.02 | 0.02 | 0.28 | 0.12 | 0.68 |
| | | | 3.51 | 0.02 | 0.71 | 1.5 | -0.36 | 1.47 | -1.41 | 1.59 | 6.31 | 2.58 | |
| D9 | 0.8 | 3.65 | 0.53 | -0.04 | 0.01 | 0.89 | -1.86 | 0 | 0 | 0.02 | 0.36 | 0.13 | 0.7 |
| | | | 2.69 | -0.67 | 0.13 | 0.83 | -1.19 | 0.3 | -0.24 | 1.25 | 6.51 | 2.47 | |
| D10 | 0.98 | 4.78 | 0.74 | -0.08 | -0.01 | 2.01 | -2.99 | 0.02 | -0.02 | 0.04 | 0.43 | 0.2 | 0.62 |
| | | | 2.64 | -0.89 | -0.06 | 1.49 | -1.31 | 0.91 | -1.15 | 1.73 | 5.13 | 2.81 | |
| D10a | 0.87 | 4.18 | 0.64 | 0.01 | -0.04 | 1.39 | -2.81 | 0.02 | -0.02 | 0.03 | 0.37 | 0.12 | 0.62 |
| | | | 2.62 | 0.13 | -0.37 | 1.12 | -1.45 | 0.86 | -1.07 | 1.45 | 5.54 | 1.87 | |
| D10b | 1.06 | 4.88 | 0.83 | -0.04 | -0.01 | 3.42 | -0.57 | 0.01 | 0 | 0.04 | 0.4 | 0.18 | 0.49 |
| | | | 2.44 | -0.39 | -0.08 | 2.03 | -0.22 | 0.56 | -0.17 | 1.65 | 3.82 | 1.89 | |
| D10c | 1.05 | 6.28 | 0.76 | -0.21 | 0.01 | 1.19 | -5.83 | 0.03 | -0.04 | 0.05 | 0.53 | 0.32 | 0.59 |
| | | | 1.97 | -1.62 | 0.04 | 0.71 | -2.71 | 1.03 | -1.67 | 1.68 | 4.96 | 3.52 | |
| 1-10 spd | -0.21 | 5.14 | -0.29 | -0.01 | -0.1 | -3.32 | 1.11 | -0.03 | 0.05 | -0.05 | -0.12 | 0.1 | 0.01 |
| | | | -0.59 | -0.06 | -0.46 | -1.61 | 0.33 | -0.82 | 1.57 | -1.47 | -0.74 | 0.77 | |
| 1a-10c spd | 0.02 | 7.5 | 0.07 | 0.1 | 0.11 | 3.59 | 3.1 | 0.01 | 0.08 | 0.05 | 0.3 | 0.15 | 0.02 |
| | | | 0.09 | 0.44 | -0.36 | -1.22 | 0.76 | -0.74 | 1.92 | -1.14 | -1.27 | 0.66 | |
| 1-2 spd | 0.11 | 1.89 | -0.08 | -0.06 | 0.01 | -0.45 | -0.08 | -0.01 | 0.01 | 0 | 0 | 0.08 | -0.03 |
| | | | -0.4 | -0.56 | 0.13 | -0.6 | -0.15 | -0.81 | 0.84 | -0.36 | 0.02 | 1.25 | |
| 9-10 spd | -0.18 | 1.93 | -0.38 | 0.04 | 0.02 | -1.14 | 1.03 | -0.01 | 0.02 | -0.02 | -0.07 | -0.07 | 0.13 |
| | | | -2.29 | 0.69 | 0.29 | -1.82 | 1 | -1.11 | 1.54 | -1.62 | -1.41 | -1.52 | |

Compared to the middle decile portfolios, the standard deviation of average monthly return is considerably higher for the previous year's best and worst performing funds. D1a and D10c show standard deviations of 6.25% and 6.28% respectively while portfolios D4, D5, and D6 have standard deviations of 2.61%, 2.74% and 2.33% respectively.

To explain the relative returns on these portfolios and analyse the performance persistence of these portfolio returns, I then use the Fung and Hsieh (2004a) and adjusted Teo's (2009) models to control for the risk factors. Table 4.1 shows the portfolios' performance as estimated using the Fung and Hsieh (2004a) model. After controlling for risk factors, the spread between D1a and D10c falls from 0.02% to -0.19%, although the latter is insignificant. On the other hand, the spread between D9 and D10 moves from -0.18% to -0.39%, which is significant at the 5% level. Column 5 of Table 4.1 indicates that all portfolios have significant exposure to the US equity factor. Column 7 shows that low decile funds have positive exposure to the bond factor while the inverse is true for the top decile hedge funds. These exposures to the bond factor statistically insignificant though. The exposure of all hedge fund portfolios to primitive trend-following strategies is negligible and statistically insignificant. One of the reason for not able to explain the hedge fund performance is that Fung and Hsieh (2004a) built these primitive trend following strategies from US hedge funds. The credit spread factor is negative and significant for portfolios D1 through D6 and for the sub portfolios D1b and D1c.

The most important information for persistence analysis is in Column 4 of Table 4.1. A statistically significant alpha will give evidence of persistence in performance among portfolios ranked based on their previous year's performance. While sub-portfolios D1a and D10c have the highest alpha values of 0.92% and 0.94%, none of these alphas is statistically significant, signalling no persistence among the extreme best and extreme worst performing hedge funds. While portfolio D3 has an insignificant alpha, portfolios D1 and D2 display a positive alpha that is significant at the 5% level. Portfolios D6, D7, and D8 are the only portfolios with positive alphas significant at the 1% level, implying persistence in performance among the middle lower decile funds.

Using the same ten portfolios, Table 4.2 estimates the performance relative to the adjusted Teo's (2009) model. This model includes two equity factors to explain the hedge funds domiciled in the Asia Pacific – the MSCI Asia ex Japan index and the Nikkei index. No doubt the adjusted Teo's (2009) model is more suited to explain the performance since the values of adjusted $R^2$ are significantly higher. The middle decile portfolios: D3 to D7 produce the highest adjusted $R^2$. The exposure of portfolios to the US equity factor drops to a very low, likewise the statistical significance (t statistics) of the exposure. The two Asian equity factors explain most of the spread and pattern in these portfolios, which have significant exposure to both of these factors. All other portfolios display positive and statistically significant exposure at 1% to the MSCI Asia ex Japan index except portfolio D1a. D1 to D6 or the upper decile portfolios have positive and statistically significant exposure to the Nikkei 225 index even at the 1% level while D7 to D10 is only significant at the 5% level. Similarly, the sensitivities to primitive trend following strategies remain small. The middle decile portfolios: D 3 to D6 show strong negative exposure to the credit spread factor, which is significant at the 1% level.

Column 4 is the key in this analysis as it contain information about the alpha and its significance. The middle and bottom decile performers tend to exhibit strongest evidence of performance persistence. Significant alpha values are found in almost all portfolios except

D1b, with the most significant values (at the 1% level) evident in portfolios D6 to D10. In these lower decile portfolios, the hedge funds are characterized by strong, positive exposure to Asian equity factors. This strong equity exposure might be the source of their sustained performance.

### 4.5.2 Persistence in one year sorted returns in sub period 1

Using the multiple Chow (1960) tests, I identify the presence of two structural breaks in the hedge fund data. There is a structural break in February 2007 or the start of financial crisis (Khandani and Lo, 2008). Tables 4.3 and 4.4 present the results of the persistence analyses for the period January 2001 to January 2007 estimated using both the Fung and Hsieh (2004a) and the adjusted Teo's (2009) models. Tables 4.3 displays the results estimated using the Fung and Hsieh (2004a) model. Despite some differences, the results are similar to those gathered from the full period. Although the monthly excess returns decrease monotonically between portfolio D1 and D6 over the first sub period, it increases again from portfolio D7 to D10. Portfolio 1 provided a monthly average return of 1.32% while portfolio 10 provided 1.27% over the first sub period. The spread between portfolios D1 and D10 and D1a and D10c are modest in the range of 0.05% to 0.06% range per month. The standard deviation of average monthly returns is considerably higher for the top and bottom decile portfolios than for middle decile portfolios, with D6 only showing standard deviation of 1.99% and D1a and D10c showing standard deviations of 5.74% and 4.77%. Similarly, cross sectional variation in monthly performance is greater among the portfolios of previous year's top performing funds than among previous year's poor performers. During the first sub period when portfolio performance is estimated using the Fung and Hsieh (2004a) model, most of the portfolios display a positive, significant exposure to the US equity factor. Portfolios D3, D4, D5, and D8 show positive significant exposure to the size factor at the 1%

level. The credit spread factor is mostly negative and is significant only for portfolio 9 at the 1% level. There is no evidence of any significant exposure to the bond factor in this sub period and much the same for the primitive trend following strategies. I find the highest alpha values among the top decile funds after controlling for the risk factors using the Fung and Hsieh (2004a) model.

**Table 4.3 Portfolios of hedge funds formed on lagged one year returns, estimated using Fung and Hsieh (2004a) model and from January 2001 to January 2007.**

On January 1 each year hedge funds are ranked according to their performance in the previous calendar year. The portfolios are equally weighted monthly such that when a fund disappears the weights are readjusted. Funds with the highest past annual performance comprise of decile 1 and funs with the lowest comprise of decile 10. The factors are: S&500 return minus the risk free rate (SNPMRF); Russell 2000 minus the S&P (SMCL); bond factor (BD10RET); credit spread factor (BAAMTSY); bond PTFS (PTFSBD); currency (PTFSFX) and commodities (PTFSCOM).

| Portfolio | Excess return | St. dev. | α | SNPMRF | SCMLC | BD10RET | BAAMTSY | PTFSBD | PTFSCOM | PTFSFX | Adj. $R$^2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| D1a | 1.8 | 5.74 | 1.62 | 0.16 | 0.37 | 0.76 | 1.42 | 0.01 | 0.07 | 0.02 | 0 |
| | | | 2.38 | 0.73 | 1.41 | 0.27 | 0.19 | 0.39 | 1.55 | 0.81 | |
| D1b | 1.15 | 3.21 | 0.93 | 0.32 | 0.27 | -0.05 | 1.26 | 0 | 0.02 | 0 | 0.17 |
| | | | 2.68 | 3.42 | 2.07 | -0.03 | 0.38 | 0.05 | 0.79 | -0.01 | |
| D1c | 0.96 | 3.08 | 0.81 | 0.35 | 0.14 | -0.36 | -0.84 | 0 | 0.04 | -0.03 | 0.25 |
| | | | 2.51 | 3.4 | 1.15 | -0.25 | -0.23 | -0.04 | 1.87 | -1.69 | |
| D1 | 1.32 | 3.22 | 1.13 | 0.27 | 0.26 | 0.13 | 0.65 | 0 | 0.04 | 0 | 0.14 |
| | | | 3.13 | 2.42 | 1.9 | 0.08 | 0.18 | 0.2 | 1.77 | -0.2 | |
| D2 | 1.07 | 2.48 | 0.92 | 0.36 | 0.15 | -1.27 | -1.42 | 0.01 | 0.03 | 0 | 0.39 |
| | | | 3.94 | 5.74 | 1.72 | -1.02 | -0.57 | 0.95 | 1.94 | -0.2 | |
| D3 | 0.93 | 2.05 | 0.69 | 0.23 | 0.2 | -1.01 | -2.04 | -0.01 | 0.03 | 0.01 | 0.36 |
| | | | 3.68 | 4.95 | 3.21 | -1.01 | -1.07 | -0.59 | 2.03 | 0.67 | |
| D4 | 0.86 | 2.03 | 0.6 | 0.24 | 0.23 | -1.34 | -2.76 | 0 | 0.01 | 0.01 | 0.44 |
| | | | 2.93 | 5.62 | 3.73 | -1.4 | -1.23 | -0.06 | 0.63 | 0.63 | |
| D5 | 0.81 | 2.34 | 0.51 | 0.34 | 0.21 | -1.51 | -1.26 | -0.01 | 0.02 | 0.01 | 0.46 |
| | | | 2.3 | 6.15 | 2.74 | -1.13 | -0.59 | -0.79 | 1.24 | 1.18 | |
| D6 | 0.68 | 1.99 | 0.5 | 0.29 | 0.14 | 0.06 | -0.46 | 0 | 0.02 | 0.01 | 0.42 |
| | | | 2.64 | 6.06 | 2.34 | 0.05 | -0.21 | -0.07 | 1.33 | 1.49 | |
| D7 | 0.74 | 2.58 | 0.54 | 0.38 | 0.12 | -1.96 | -3.99 | 0.02 | 0 | 0.02 | 0.47 |
| | | | 2.44 | 6.82 | 1.78 | -1.32 | -1.63 | 1.7 | -0.3 | 1.28 | |
| D8 | 0.81 | 2.82 | 0.57 | 0.39 | 0.2 | -0.89 | -4.2 | 0.02 | -0.01 | 0 | 0.49 |
| | | | 2.23 | 7.17 | 2.8 | -0.56 | -1.54 | 1.43 | -0.39 | 0.03 | |
| D9 | 0.93 | 3.18 | 0.59 | 0.39 | 0.17 | -2.2 | -7.92 | 0 | 0.02 | 0 | 0.43 |
| | | | 1.9 | 4.64 | 1.46 | -1.48 | -2.59 | 0.04 | 1.25 | 0.19 | |
| D10 | 1.27 | 3.97 | 0.88 | 0.41 | 0.17 | -0.93 | -9.87 | 0 | 0.02 | 0.02 | 0.36 |
| | | | 2.34 | 3.92 | 1.66 | -0.5 | -2.05 | 0.05 | 0.84 | 0.93 | |
| D10a | 0.96 | 3.54 | 0.66 | 0.39 | 0.08 | -0.85 | -9.15 | 0.01 | 0 | 0.01 | 0.37 |
| | | | 1.84 | 4.59 | 0.86 | -0.42 | -1.96 | 0.41 | 0.13 | 0.81 | |
| D10b | 1.13 | 4.63 | 0.78 | 0.45 | 0.11 | -1.31 | -10.81 | 0 | 0.04 | 0.01 | 0.26 |
| | | | 1.61 | 3.38 | 0.82 | -0.64 | -1.93 | 0.15 | 1.38 | 0.38 | |
| D10c | 1.74 | 4.77 | 1.22 | 0.41 | 0.32 | -0.65 | -9.72 | -0.01 | 0.02 | 0.03 | 0.29 |
| | | | 2.64 | 3.06 | 2.05 | -0.27 | -1.79 | -0.26 | 0.65 | 1.14 | |
| 1-10 spd | 0.05 | 4.09 | 0.03 | -0.14 | 0.08 | 0.97 | 10.23 | 0 | 0.02 | -0.02 | 0.04 |
| | | | 0.07 | -0.89 | 0.48 | 0.54 | 1.87 | 0.12 | 0.86 | -0.92 | |
| 1a-10c spd | 0.06 | 7.06 | 0.18 | -0.24 | 0.04 | 1.32 | 10.84 | 0.02 | 0.05 | -0.01 | -0.02 |
| | | | 0.22 | -0.85 | 0.14 | 0.52 | 1.15 | 0.44 | 1.19 | -0.19 | |
| 1-2 spd | 0.25 | 2.04 | 0 | -0.09 | 0.11 | 1.3 | 1.78 | -0.01 | 0.02 | 0 | -0.03 |
| | | | 0 | -1.11 | 1.06 | 1.26 | 0.69 | -0.55 | 0.99 | -0.08 | |
| 9-10 spd | -0.34 | 1.82 | -0.51 | -0.02 | -0.01 | -1.37 | 1.66 | 0 | 0 | -0.01 | -0.02 |
| | | | -2.25 | -0.28 | -0.14 | -1.36 | 0.58 | 0.05 | 0.08 | -1.07 | |

**Table 4.4 Portfolios of hedge funds formed on lagged one year returns, estimated using adjusted Teo's (2009) model and from January 2001 to January 2001 to January 2007.**

On January each year hedge funds are ranked according to their performance in the previous calendar year. The portfolios are equally weighted monthly such that when a fund disappears the weights are readjusted. Funds with the highest past annual performance comprise of decile 1 and funds with the lowest comprise of decile 10. The factors are: S&P 500 minus the risk free rate (SNPMRF); Russell 2000 minus the S&P (SMCL); bond factor (BD10RET); credit spread factor (BAAMTSY); bond PTFS (PTFSBD), currency (PTFSFX) and commodities (PTFSCOM); MSCI Asia ex Japan index return minus the risk free rate (ASIA); and Nikkei 225 index return minus the risk free rate (JAP).

| Portfolio | Excess ret | St. dev. | α | SNPMRF | SCMLC | BD10RET | BAAMTSY | PTFSBD | PTFSCOM | PTFSFX | ASIA | JAP | Adj. $R$^2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| D1a | 1.8 | 5.47 | 1.74 | 0.04 | 0.2 | 0 | -2.1 | 0.01 | 0.04 | 0.04 | -0.21 | 0.51 | 0.1 |
| | | | 2.37 | 0.16 | 0.79 | 0 | -0.33 | 0.29 | 1.13 | 1.5 | -0.71 | 2.65 | |
| D1b | 1.15 | 3.21 | 0.88 | -0.01 | 0.1 | 0.27 | 0.54 | 0 | 0 | 0.01 | 0.15 | 0.28 | 0.33 |
| | | | 2.65 | -0.07 | 0.82 | 0.17 | 0.13 | -0.18 | 0.08 | 0.3 | 1.75 | 2.97 | |
| D1c | 0.96 | 3.08 | 0.73 | 0.05 | 0.01 | 0.06 | -1.02 | 0 | 0.03 | -0.03 | 0.18 | 0.2 | 0.37 |
| | | | 2.55 | 0.36 | 0.04 | 0.05 | -0.36 | -0.21 | 1.37 | -1.69 | 2.07 | 2.92 | |
| D1 | 1.32 | 3.22 | 1.13 | 0.03 | 0.1 | 0.1 | -0.87 | 0 | 0.02 | 0.01 | 0.04 | 0.33 | 0.31 |
| | | | 3.27 | 0.21 | 0.8 | 0.07 | -0.26 | 0.01 | 1.27 | 0.33 | 0.3 | 3.84 | |
| D2 | 1.07 | 2.48 | 0.87 | 0.09 | 0.01 | -1 | -1.99 | 0.01 | 0.01 | 0 | 0.13 | 0.23 | 0.59 |
| | | | 4.67 | 1.1 | 0.1 | -1.11 | -0.99 | 0.75 | 1.25 | 0.2 | 2.33 | 5.18 | |
| D3 | 0.93 | 2.05 | 0.61 | -0.08 | 0.06 | -0.51 | -1.99 | -0.01 | 0.02 | 0.01 | 0.21 | 0.18 | 0.66 |
| | | | 4.29 | -1.41 | 1.36 | -0.75 | -1.11 | -1.06 | 2.05 | 1.11 | 4.79 | 4.6 | |
| D4 | 0.86 | 2.03 | 0.53 | -0.03 | 0.1 | -0.99 | -3.03 | 0 | 0 | 0.01 | 0.15 | 0.19 | 0.69 |
| | | | 3.48 | -0.46 | 2.43 | -1.36 | -1.58 | -0.38 | -0.2 | 1.57 | 3.19 | 5.05 | |
| D5 | 0.81 | 2.34 | 0.46 | 0.09 | 0.08 | -1.2 | -1.58 | -0.02 | 0.01 | 0.02 | 0.14 | 0.19 | 0.63 |
| | | | 2.51 | 1.08 | 1.31 | -1.21 | -0.88 | -1.01 | 0.66 | 1.83 | 2.12 | 4.13 | |
| D6 | 0.68 | 1.99 | 0.4 | -0.04 | 0.01 | 0.63 | -0.26 | 0 | 0 | 0.02 | 0.23 | 0.17 | 0.76 |
| | | | 3.38 | -0.83 | 0.12 | 0.97 | -0.21 | -0.51 | 0.94 | 2.69 | 4.98 | 5.3 | |
| D7 | 0.74 | 2.58 | 0.39 | -0.02 | -0.02 | -1.08 | -3.05 | 0.02 | -0.01 | 0.02 | 0.34 | 0.12 | 0.75 |
| | | | 2.41 | -0.34 | -0.44 | -1.02 | -1.89 | 1.42 | -0.97 | 1.52 | 7.44 | 3.09 | |
| D8 | 0.81 | 2.82 | 0.43 | -0.05 | 0.03 | -0.07 | -3.68 | 0.01 | -0.02 | 0 | 0.32 | 0.19 | 0.77 |
| | | | 2.6 | -0.98 | 0.51 | -0.07 | -2.64 | 1.77 | -1.51 | 0.26 | 6.58 | 3.75 | |
| D9 | 0.93 | 3.18 | 0.41 | -0.12 | -0.03 | -1.13 | -6.95 | -0.01 | 0.01 | 0 | 0.41 | 0.18 | 0.73 |
| | | | 1.86 | -1.97 | -0.34 | -1.29 | -3.08 | -0.37 | 0.83 | 0.29 | 6.66 | 3.17 | |
| D10 | 1.27 | 3.97 | 0.66 | -0.23 | -0.07 | 0.37 | -8.76 | -0.01 | 0.01 | 0.02 | 0.5 | 0.23 | 0.66 |
| | | | 2.5 | -2.59 | -0.71 | 0.29 | -2.68 | -0.37 | 0.5 | 1.42 | 5.5 | 3.12 | |
| D10a | 0.96 | 3.54 | 0.49 | -0.1 | -0.1 | 0.2 | -8.13 | 0 | -0.01 | 0.01 | 0.4 | 0.16 | 0.59 |
| | | | 1.8 | -1.14 | -0.96 | 0.14 | -2.2 | 0.14 | -0.36 | 1.09 | 5.76 | 2.17 | |
| D10b | 1.13 | 4.63 | 0.53 | -0.28 | -0.17 | 0.19 | -9.46 | 0 | 0.03 | 0.01 | 0.58 | 0.25 | 0.54 |
| | | | 1.46 | -2.52 | -1.33 | 0.11 | -2.44 | -0.21 | 1.33 | 0.55 | 4.15 | 2.33 | |
| D10c | 1.74 | 4.77 | 0.98 | -0.32 | 0.04 | 0.78 | -8.64 | -0.02 | 0 | 0.03 | 0.56 | 0.29 | 0.55 |
| | | | 2.45 | -2.06 | 0.25 | 0.37 | -2.2 | -0.58 | 0.09 | 1.43 | 4.43 | 3.18 | |
| 1-10 spd | 0.05 | 4.09 | 0.25 | 0.26 | 0.17 | -0.37 | 7.59 | 0.01 | 0.02 | -0.01 | -0.47 | 0.1 | 0.18 |
| | | | 0.53 | 1.62 | 0.97 | -0.21 | 1.61 | 0.25 | 0.72 | -0.51 | -2.6 | 0.81 | |
| 1a-10c spd | 0.06 | 7.06 | 0.54 | 0.36 | 0.16 | -0.88 | 6.23 | 0.03 | 0.04 | 0.01 | -0.77 | 0.23 | 0.1 |
| | | | 0.59 | 1.23 | 0.5 | -0.3 | 0.82 | 0.55 | 0.97 | 0.39 | -2.12 | 0.96 | |
| 1-2 spd | 0.25 | 2.04 | 0.05 | -0.06 | 0.09 | 1 | 0.82 | -0.01 | 0.01 | 0 | -0.1 | 0.1 | -0.1 |
| | | | 0.17 | -0.72 | 0.82 | 0.92 | 0.34 | -0.53 | 0.66 | 0.31 | -0.99 | 1.43 | |
| 9-10 spd | -0.34 | 1.82 | -0.47 | 0.11 | 0.04 | -1.61 | 1.5 | 0 | 0 | -0.01 | -0.09 | -0.05 | 0 |
| | | | -2.11 | 1.1 | 0.49 | -1.61 | 0.6 | 0.14 | 0.32 | -1.07 | -1.34 | -0.84 | |

The results show that there is performance persistence among most of the hedge funds domiciled in Asia Pacific during the first, bullish sub period. For instance, portfolios D1b, D1, D2, D3, D4 and D6 have positive significant alphas at the 1% level. As well as, the portfolio of previous year's worst performing funds (D10c) shows a very high, significant alpha at the 1% level of 1.22%.

By applying the adjusted Teo's (2009) model that is more suitable for explaining the performance of hedge funds domiciled in Asia Pacific, I estimate the performance of these portfolios. Again referring to the Table 4.4, this result is clearly obvious by the significantly higher adjusted $R^2$ values. Most portfolios show positive, significant exposure to the two Asian equity factors as anticipated. No portfolio displays significant loadings to the size factor except portfolio D4 where there is small positive exposure. Lower decile funds have negative, significant exposure to the credit factor while their exposure to the bond factor is low and insignificant. Fund exposures to primitive trend following strategies are negligible and mainly insignificant. Column 4 indicates that most portfolios display persistence in performance. While other portfolios have positive, significant alphas at the 5% level, portfolios D1, D2, D3, D4, D6 and D8 have positive significant alphas at the 1% level. D10a and D10b are the only portfolios with positive but statistically insignificant alphas.

### 4.5.3 Persistence in one year sorted returns in sub period 2

Tables 4.5 and 4.6 show the findings of the performance persistence analysis for hedge funds domiciled in the Asia Pacific during the sub period that encompasses the global financial crisis. Table 4.5 displays the performance results computed using the Fung and Hsieh (2004a) model and Table 4.6 shows the results using the Teo's (2009) model.

The second sub period displays some interesting finding when I study the figures for monthly excess return. Interestingly, the monthly excess return of portfolio D1 is equal to that of D10c, meaning the previous year's best performing funds is the same as the previous year's worst performing funds in terms of monthly excess returns. In comparing the cross sectional variation in returns to the middle decile funds, the top and bottom decile funds show a larger variation and a similar pattern to sub period 1.

**Table 4.5 Portfolios of hedge funds formed on lagged one year returns, estimated using Fung and Hsieh (2004a) model and from February 2007 to December 2010.**

On January 1 each year hedge funds are ranked according to their performance in the previous calendar year. The portfolios are equally weighted monthly such that when a fund disappears the weights are readjusted. Funds with the highest past annual performance comprise of decile 1 and funds with the lowest comprise of decile 10. The factors are: S&P 500 minus the risk free rate (SNPMRF); Russell 2000 minus the S&P (SMCL); bond factor (BD10RET); credit spread factor (BAAMTSY); bond PTFS(PTFSBD); currency (PTFSFX) and commodities (PTFSCOM).

| Portfolio | Excess return | St. dev. | α | SNPMRF | SCMLC | BD10RET | BAAMTSY | PTFSBD | PTFSCOM | PTFSFX | Adj. $R$^2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| D1a | -0.1 | 6.81 | 1.62 | 0.16 | 0.37 | 0.76 | 1.42 | 0.01 | 0.07 | 0.02 | 0 |
| | | | 2.38 | 0.73 | 1.41 | 0.27 | 0.19 | 0.39 | 1.55 | 0.81 | |
| D1b | -0.37 | 6.24 | 0.93 | 0.32 | 0.27 | -0.05 | 1.26 | 0 | 0.02 | 0 | 0.17 |
| | | | 2.68 | 3.42 | 2.07 | -0.03 | 0.38 | 0.05 | 0.79 | -0.01 | |
| D1c | 0.29 | 4.85 | 0.81 | 0.35 | 0.14 | -0.36 | -0.84 | 0 | 0.04 | -0.03 | 0.25 |
| | | | 2.51 | 3.4 | 1.15 | -0.25 | -0.23 | -0.04 | 1.87 | -1.69 | |
| D1 | -0.06 | 5.87 | 1.13 | 0.27 | 0.26 | 0.13 | 0.65 | 0 | 0.04 | 0 | 0.14 |
| | | | 3.13 | 2.42 | 1.9 | 0.08 | 0.18 | 0.2 | 1.77 | -0.2 | |
| D2 | 0.03 | 4.99 | 0.92 | 0.36 | 0.15 | -1.27 | -1.42 | 0.01 | 0.03 | 0 | 0.39 |
| | | | 3.94 | 5.74 | 1.72 | -1.02 | -0.57 | 0.95 | 1.94 | -0.2 | |
| D3 | -0.13 | 4.23 | 0.69 | 0.23 | 0.2 | -1.01 | -2.04 | -0.01 | 0.03 | 0.01 | 0.36 |
| | | | 3.68 | 4.95 | 3.21 | -1.01 | -1.07 | -0.59 | 2.03 | 0.67 | |
| D4 | 0 | 3.26 | 0.6 | 0.24 | 0.23 | -1.34 | -2.76 | 0 | 0.01 | 0.01 | 0.44 |
| | | | 2.93 | 5.62 | 3.73 | -1.4 | -1.23 | -0.06 | 0.63 | 0.63 | |
| D5 | 0.11 | 3.23 | 0.51 | 0.34 | 0.21 | -1.51 | -1.26 | -0.01 | 0.02 | 0.01 | 0.46 |
| | | | 2.3 | 6.15 | 2.74 | -1.13 | -0.59 | -0.79 | 1.24 | 1.18 | |
| D6 | 0.45 | 2.78 | 0.5 | 0.29 | 0.14 | 0.06 | -0.46 | 0 | 0.02 | 0.01 | 0.42 |
| | | | 2.64 | 6.06 | 2.34 | 0.05 | -0.21 | -0.07 | 1.33 | 1.49 | |
| D7 | 0.71 | 3.3 | 0.54 | 0.38 | 0.12 | -1.96 | -3.99 | 0.02 | 0 | 0.02 | 0.47 |
| | | | 2.44 | 6.82 | 1.78 | -1.32 | -1.63 | 1.7 | -0.3 | 1.28 | |
| D8 | 0.7 | 3.48 | 0.57 | 0.39 | 0.2 | -0.89 | -4.2 | 0.02 | -0.01 | 0 | 0.49 |
| | | | 2.23 | 7.17 | 2.8 | -0.56 | -1.54 | 1.43 | -0.39 | 0.03 | |
| D9 | 0.61 | 4.28 | 0.59 | 0.39 | 0.17 | -2.2 | -7.92 | 0 | 0.02 | 0 | 0.43 |
| | | | 1.9 | 4.64 | 1.46 | -1.48 | -2.59 | 0.04 | 1.25 | 0.19 | |
| D10 | 0.54 | 5.81 | 0.88 | 0.41 | 0.17 | -0.93 | -9.87 | 0 | 0.02 | 0.02 | 0.36 |
| | | | 2.34 | 3.92 | 1.66 | -0.5 | -2.05 | 0.05 | 0.84 | 0.93 | |
| D10a | 0.73 | 5.02 | 0.66 | 0.39 | 0.08 | -0.85 | -9.15 | 0.01 | 0 | 0.01 | 0.37 |
| | | | 1.84 | 4.59 | 0.86 | -0.42 | -1.96 | 0.41 | 0.13 | 0.81 | |
| D10b | 0.95 | 5.23 | 0.78 | 0.45 | 0.11 | -1.31 | -10.81 | 0 | 0.04 | 0.01 | 0.26 |
| | | | 1.61 | 3.38 | 0.82 | -0.64 | -1.93 | 0.15 | 1.38 | 0.38 | |
| D10c | -0.06 | 7.99 | 1.22 | 0.41 | 0.32 | -0.65 | -9.72 | -0.01 | 0.02 | 0.03 | 0.29 |
| | | | 2.64 | 3.06 | 2.05 | -0.27 | -1.79 | -0.26 | 0.65 | 1.14 | |
| 1-10 spd | -0.61 | 6.46 | 0.03 | -0.14 | 0.08 | 0.97 | 10.23 | 0 | 0.02 | -0.02 | 0.04 |
| | | | 0.07 | -0.89 | 0.48 | 0.54 | 1.87 | 0.12 | 0.86 | -0.92 | |
| 1a-10c spd | -0.04 | 8.16 | 0.18 | -0.24 | 0.04 | 1.32 | 10.84 | 0.02 | 0.05 | -0.01 | -0.02 |
| | | | 0.22 | -0.85 | 0.14 | 0.52 | 1.15 | 0.44 | 1.19 | -0.19 | |
| 1-2 spd | -0.09 | 1.57 | 0 | -0.09 | 0.11 | 1.3 | 1.78 | -0.01 | 0.02 | 0 | -0.03 |
| | | | 0 | -1.11 | 1.06 | 1.26 | 0.69 | -0.55 | 0.99 | -0.08 | |
| 9-10 spd | 0.06 | 2.07 | -0.51 | -0.02 | -0.01 | -1.37 | 1.66 | 0 | 0 | -0.01 | -0.02 |
| | | | -2.25 | -0.28 | -0.14 | -1.36 | 0.58 | 0.05 | 0.08 | -1.07 | |

**Table 4.6 Portfolios of hedge funds formed on lagged one year returns, estimated using adjusted Teo's (2009) model and from February 2007 to December 2010.**

On January 1 each year hedge funds are ranked according to their performance in the previous calendar year. The portfolios are equally weighted monthly such that when a fund disappears the weights are readjusted. Funds with the highest past annual performance comprise of decile 1 and funds with the lowest comprise of decile 10. The factors are: S&P 500 return minus the risk free rate (SNPMRF); Russell 2000 minus the S&P (SMCL); bond factor (BD10RET); credit spread factor (BAAMTSY); bond PTFS (PTFSBD); currency (PTFSFX) and commodities (PTFSCOM); MSCI Asia ex Japan index return minus the risk free rate (ASIA); and Nikkei 225 index return minus the risk free rate (JAP).

| Portfolio | Excess ret | St. dev. | α | SNPMRF | SCMLC | BD10RET | BAAMTSY | PTFSBD | PTFSCOM | PTFSFX | ASIA | JAP | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| D1a | -0.1 | 6.81 | -0.11 | -0.07 | -0.5 | -2.85 | -0.32 | -0.02 | 0.07 | -0.09 | 0.51 | 0.26 | 0.64 |
| | | | -0.19 | -0.34 | -1.76 | -1.18 | -0.16 | -0.32 | 1.29 | -1.8 | 3.53 | 1.67 | |
| D1b | -0.37 | 6.24 | -0.55 | -0.09 | -0.37 | -0.82 | -1.04 | -0.04 | 0.05 | -0.05 | 0.53 | 0.14 | 0.61 |
| | | | -0.99 | -0.51 | -1.37 | -0.37 | -0.5 | -0.81 | 0.95 | -1 | 3.61 | 1.14 | |
| D1c | 0.29 | 4.85 | 0.2 | -0.12 | -0.24 | -1.13 | -0.63 | -0.01 | 0.06 | -0.04 | 0.44 | 0.16 | 0.66 |
| | | | 0.5 | -0.92 | -1.21 | -0.73 | -0.42 | -0.18 | 1.36 | -1.16 | 4.31 | 1.47 | |
| D1 | -0.06 | 5.87 | -0.15 | -0.09 | -0.37 | -1.6 | -0.65 | -0.02 | 0.06 | -0.06 | 0.49 | 0.19 | 0.66 |
| | | | -0.31 | -0.59 | -1.51 | -0.84 | -0.36 | -0.48 | 1.27 | -1.4 | 3.99 | 1.51 | |
| D2 | 0.03 | 4.99 | 0.01 | -0.08 | -0.26 | -0.44 | -0.79 | -0.01 | 0.05 | -0.04 | 0.43 | 0.18 | 0.72 |
| | | | 0.03 | -0.71 | -1.42 | -0.29 | -0.48 | -0.16 | 1.41 | -1.23 | 4.47 | 1.92 | |
| D3 | -0.13 | 4.23 | -0.14 | -0.08 | -0.21 | -0.72 | -2.02 | 0 | 0.03 | -0.03 | 0.37 | 0.14 | 0.81 |
| | | | -0.55 | -1.04 | -1.54 | -0.66 | -1.85 | -0.08 | 1.1 | -1.19 | 5.71 | 1.98 | |
| D4 | 0 | 3.26 | 0.08 | 0.02 | -0.19 | 0.23 | -1.28 | 0 | 0.01 | 0 | 0.24 | 0.15 | 0.86 |
| | | | 0.46 | 0.32 | -2.13 | 0.3 | -1.96 | 0.2 | 0.56 | -0.08 | 6.52 | 2.54 | |
| D5 | 0.11 | 3.23 | 0.13 | -0.03 | -0.13 | -0.36 | -1.65 | 0 | 0.01 | 0 | 0.26 | 0.14 | 0.91 |
| | | | 0.84 | -0.65 | -1.75 | -0.51 | -2.96 | -0.24 | 0.65 | 0 | 7.85 | 3.45 | |
| D6 | 0.45 | 2.78 | 0.45 | 0.04 | -0.05 | 1.76 | -1.71 | 0.01 | -0.02 | 0.03 | 0.24 | 0.05 | 0.93 |
| | | | 3.72 | 1.02 | -1.14 | 3.45 | -4.09 | 1.37 | -2.34 | 3.44 | 10.49 | 1.51 | |
| D7 | 0.71 | 3.3 | 0.61 | 0.01 | -0.02 | 2.38 | -1.2 | 0.01 | -0.04 | 0.03 | 0.31 | 0.01 | 0.76 |
| | | | 2.58 | 0.11 | -0.14 | 1.97 | -1.1 | 0.54 | -2.21 | 1.59 | 5.15 | 0.16 | |
| D8 | 0.7 | 3.48 | 0.65 | 0.05 | 0.05 | 2.65 | -1.19 | 0.02 | -0.05 | 0.06 | 0.26 | 0.04 | 0.63 |
| | | | 2.06 | 0.55 | 0.32 | 1.82 | -0.76 | 0.73 | -1.8 | 1.79 | 3.17 | 0.51 | |
| D9 | 0.61 | 4.28 | 0.58 | 0.06 | -0.03 | 2.16 | -1.85 | 0.04 | -0.06 | 0.05 | 0.33 | 0.06 | 0.68 |
| | | | 1.66 | 0.61 | -0.14 | 1.34 | -1.12 | 1 | -1.69 | 1.33 | 3.45 | 0.65 | |
| D10 | 0.54 | 5.81 | 0.68 | 0.08 | 0 | 3.64 | -3.26 | 0.09 | -0.13 | 0.09 | 0.39 | 0.09 | 0.63 |
| | | | 1.26 | 0.5 | -0.01 | 1.53 | -1.24 | 1.77 | -2.28 | 1.46 | 2.7 | 0.69 | |
| D10a | 0.73 | 5.02 | 0.73 | 0.11 | -0.03 | 2.04 | -2.86 | 0.05 | -0.08 | 0.06 | 0.35 | 0.05 | 0.63 |
| | | | 1.58 | 0.78 | -0.16 | 1.04 | -1.29 | 1.08 | -1.46 | 1.1 | 2.79 | 0.47 | |
| D10b | 0.95 | 5.23 | 1.02 | 0.19 | 0.04 | 5.39 | -0.87 | 0.06 | -0.12 | 0.12 | 0.29 | 0.06 | 0.55 |
| | | | 1.83 | 1.17 | 0.15 | 2.27 | -0.32 | 1.22 | -2.08 | 1.74 | 2.04 | 0.54 | |
| D10c | -0.06 | 7.99 | 0.32 | -0.03 | -0.04 | 3.57 | -6.34 | 0.18 | -0.19 | 0.11 | 0.55 | 0.16 | 0.64 |
| | | | 0.45 | -0.12 | -0.09 | 1.1 | -1.91 | 2.6 | -2.85 | 1.44 | 2.81 | 0.86 | |
| 1-10 spd | -0.61 | 6.46 | -0.95 | -0.17 | -0.36 | -5.21 | 2.53 | -0.11 | 0.18 | -0.15 | 0.1 | 0.1 | 0.01 |
| | | | -1.03 | -0.6 | -0.73 | -1.37 | 0.62 | -1.32 | 2.08 | -1.51 | 0.38 | 0.43 | |
| 1a-10c spd | -0.04 | 8.16 | -0.55 | -0.04 | -0.46 | -6.4 | 5.94 | -0.19 | 0.26 | -0.19 | -0.04 | 0.09 | 0.07 |
| | | | -0.49 | -0.1 | -0.7 | -1.27 | 1.25 | -1.84 | 2.61 | -1.74 | -0.14 | 0.31 | |
| 1-2 spd | -0.09 | 1.57 | -0.28 | -0.01 | -0.1 | -1.14 | 0.06 | -0.01 | 0.01 | -0.01 | 0.07 | 0.01 | 0.01 |
| | | | -1.22 | -0.14 | -1.1 | -1.42 | 0.1 | -0.75 | 0.26 | -0.83 | 1.24 | 0.17 | |
| 9-10 spd | 0.06 | 2.07 | -0.22 | -0.02 | -0.02 | -1.46 | 1.33 | -0.06 | 0.07 | -0.04 | -0.07 | -0.03 | 0.29 |
| | | | -0.76 | -0.2 | -0.14 | -1.46 | 1.13 | -2.41 | 2.48 | -1.51 | -0.92 | -0.44 | |

The largest monthly excess returns were produced by the ‘extreme loser’ portfolios D10a and D10b, with monthly excess returns of 0.73% and 0.95% respectively. The previous year’s best performing funds, grouped in portfolios D1a and D1b produced monthly excess returns of -0.1% and -0.37%. Portfolios in the middle decile showed strong positive monthly excess returns with a significant lower standard deviation than the top and bottom decile portfolios. In general, the portfolios do not display any exposure to the bond and primitive trend following factors while portfolios D3, D4, D5 and D8 show positive and significant exposure to the size factor at the 1% level. Portfolios D9, D10, D10a display negative, significant exposure to the credit factor. Alphas calculated using the Fung and Hsieh (2004a) model are significantly positive for most of the portfolios and equally for the portfolio sensitivities to the equity factor. Positive and significant alphas can be found in portfolios D1b, D2, D3, D4, D6 and D10c at the 1% level. While the rest of the portfolios show positive and significant alphas at the 5% level, portfolios D9, D10a and D10b show positive and insignificant alphas.

While Table 4.5 displays strong evidence of persistence in performance, when using the adjusted Teo’s (2009) model to estimate performance persistence, the situation is slightly different. Only portfolios D6, D7, D8 have positive statistically significant alphas according to the Table 4.6. The evidence of performance persistence is weak in the middle decile portfolio. Portfolios D6 and D8 which had positive significant alphas in the first sub period managed to uphold the performance persistence during the financial crisis. This means that the superior performance is predictable regardless of the market environment. Portfolio D6 is the only portfolio to show a positive and significant alpha at the 1% level, also displays positive and significant exposure to the bond factor at the 1% level, and negative, high and significant exposure to the credit factor at the 1%. In addition, portfolio D6 shows small but significant, negative exposure to the primitive trend following strategy on commodities and a small positive but highly significant exposure to primitive trend following strategy on foreign exchange. Lastly, portfolio D6 with a high adjusted $R^2$ of 93% illustrates the ability of the adjusted Teo's (2009) model to nearly fully explain the portfolio's return. It has positive significant exposure to the MSCI Asia ex Japan index at the 1% level and insignificant exposure to the Nikkei 225 index. Even though portfolios D1a, D1b, D1 and D3 have negative alphas, they are insignificant; therefore, I find no evidence of persistence in negative performance.

### 4.6 Conclusion

Although the issue of persistence in hedge fund performance has been discussed widely in the academic literature, there is widely differing and, at most times, conflicting results. As performance frequently act as the basis for hedge fund investment decisions, this issue is particularly relevant from the point of hedge fund investor. In addition, hedge funds domiciled in the Asia Pacific have grown rapidly over the last ten years both in terms of the amount of AUM and in terms of the number of funds.

Therefore, the main aim of this paper is to shed some light on this issue by examining a relatively large set of databases of hedge funds domiciled in the Asia Pacific from the period January 2000 till December 2010, a period that includes the global financial crisis of 2007. I divide the sample into two sub periods by following Capocci et al. (2005) to investigate persistence in hedge fund performance in two uniquely market environments. The contribution of this paper is it studies the largest data sample of hedge funds domiciled in the Asia Pacific over a time period that includes both the bullish and bearish market periods using a parametric methodology. The advantage of potential persistence in performance is that investors can replicate the strategy and invest in those hedge funds that show potential persistence in performance.

Previous research has shown that various bias such as survivorship, backfilling and illiquidity induced return smoothing can impact on the measure of performance persistence and overstate persistence. Whether in actual fact, the persistent result is due to managerial skill or the biases. To control for this threat, I account for the likelihood of both the survivorship and backfilling bias. Since the databases include both surviving and dissolved funds and the data sample covers the period from 2000 onwards, survivorship bias should not impact the results significantly. I delete the first 12 months of returns for the individual hedge fund to control for backfilling bias. I follow Getmansky, Lo and Makarov (2004) desmoothing procedure also used in first paper to control for illiquidity induced return smoothing.

I find only limited evidence of persistence in hedge fund performance for the full sample period. Superior performance is more predictable among medium and poor performers in the analysis of the full sample period. I find positive and highly significant alphas among the middle and bottom deciles for the full sample period when I use both Teo's (2009) and Fung and Hsieh (2004a) model. These results are similar to Capocci et al. (2005), as I also find most of the persistence in performance in the first bullish sub period. In first sub period, both performance measurement models show most of the portfolios with positive performance persistence. In the second sub period, the results differ depending on the performance model used. I find most of the portfolios display positive, statistically significant persistence in performance. The results changes significantly when I use Teo's (2009) model to explain performance. Only three middle decile portfolios show significant persistence in performance.  There is only weak evidence of performance persistence during the second sub period even though the adjusted Teo's (2009) model is better for explaining hedge funds persistence with its considerably higher adjusted $R^2$ statistics.

In addition, I cannot conclude evidence of performance in persistence in performance for the best and worst performing funds.  The explanation may be that some hedge fund managers take on a considerable amount of risk which subsequently leads them to experience significantly superior or inferior returns for a short period of time. Many hedge fund managers apply less risky strategies and are therefore able to outperform the market for a longer period of time.

# CHAPTER FIVE

# ESSAY THREE

## HEDGE FUND FACTORS AND SURVIVAL ANALYSIS

**Abstract:** This paper investigates the issue of hedge fund attrition in the context of hedge funds domiciled in the Asia Pacific from January 1994 to June 2012. Using the parametric probit regression model and the less restrictive semi parametric Cox proportional hazard model, larger, better performing funds with lower redemption frequency have a higher likelihood of survival. Higher standard deviation is positively related to the survival of hedge funds domiciled in the Asia Pacific. This is because most of the defunct funds died before the global financial crisis began in 2007 and the remaining surviving funds have a higher standard deviation. Management fees, incentive fees and lock up provisions as part of the hedge fund incentive structure do not seem to impact on fund attrition. Lastly, the probit model shows that higher leverage is beneficial for fund survival.

**Keywords**: Survival, hedge funds, fund characteristics

**JEL classification**: G23, G01

## 5.1 Introduction

Using the Eurekahedge, TASS and Morningstar databases, I analyse the survival of hedge funds domiciled in the Asia Pacific. The survival analysis is used to examine whether the hedge fund mortality can be predicted from certain hedge fund characteristics. The aim is to see whether the fund characteristics such as age, performance, standard deviation, size, leverage, lock up period and management fee impact on the survival time of individual hedge funds. I use a parametric probit regression method to examine the hedge fund survival status on several explanatory variables. To study the factors that influence the survival and mortality patterns of hedge funds, I use the less restrictive, semi parametric Cox proportional hazard model.

Institutional investors, such as endowments, foundations, and pension funds make up a larger portion of the hedge fund universe as time goes by. These investors have a preference for investing on a long-term basis due to the illiquidity nature of hedge funds. Since investors are constantly faced with selection problems when trying to choose and invest in hedge funds, the issue of hedge fund survival and mortality patterns is relevant. If the probability of hedge fund death can be predicted based on some explanatory variables, then the selection of hedge funds based on these variables should increase future portfolio performance. Investor concerns regarding illiquidity, when investing in hedge funds such as redemption and lock-up provisions, will be reduced when hedge fund with a higher chance of longevity is selected. Survival analysis allow for the identification of hedge funds with a higher probability of survival and a good long term outlook, hence reducing liquidation risk and the associated loss of capital.

As discussed, the research into the sources of hedge fund returns can be classified into macroeconomic and microeconomic factors. The macroeconomic factors are exposure to various asset classes on the performance of hedge funds. The microeconomic factors are firm specific characteristics like fund age, size, fees and lock up periods on the performance. So far I concentrate on the impact of macroeconomic factors and hedge fund performance. This paper I look at firm specific characteristics on the survival probability of hedge funds.

The reminder of this paper is structured as follows: Section 5.2 reviews the literature on the relationship between hedge fund performance and certain fund characteristics. Section 5.3 discusses the data and sections 5.4 the methodology used in this paper. Section 5.5 reports and discusses the results while Section 5.6 concludes.

### 5.2 Literature review

#### 5.2.1 Fund size

There are lot of academic studies that investigate the relationship between hedge fund performance and hedge fund characteristics as fund size, age, management fees, and incentive fees and lock up periods. While the relationships between hedge fund size and its potential impact on fund performance is the most studied in the hedge fund studies, the conclusions and the impact of hedge fund size on performance are conflicting.

The link between the fund size and performance is important from the point view of the hedge fund manager as decision is made regarding the optimal size of the fund. From the investors' view point, the size of the hedge fund is one of the important characteristic to analyse before investing. Smaller funds face higher expenses and suffer diseconomies of scale. Some papers find that hedge funds beyond certain size will become inefficient to manage. When they execute trades, the ability of such funds to move the market arises and problems may occur in liquidating if the market is tough. The argument is smaller funds are more agile and more liquid and consequently perform better.

Using the TASS database from January 1994 to April 2005, Ammann and Moerth (2005) examine the impact of hedge fund size on fund performance. The impact of fund size relative to hedge fund returns, standard deviations, Sharpe ratios, and alphas derived from multi factor models is analysed. The authors find fund size is negatively related to returns when using the cross sectional regression. At the low end of the size spectrum or the very small funds, there is underperformance on average which the authors attribute to the higher total expenses ratios. Amenc et al. (2003) study various performance measurement models like standard CAPM, CAPM adjusted for stale prices, an implicit factor model derived from the principal component analysis to investigate the hedge fund characteristics on fund performance. The authors discover that the average alpha for large hedge funds is greater than the average alpha for small funds. These results are statistically significant, meaning that large hedge funds outperform small funds on average.

Boyson (2003a) examines how hedge fund managers' career concerns impact their decisions using various theories of reputation. The paper studies the link between fund size and performance after observing that a manager's compensation is connected to both fund performance and size. She finds a positive relationship between fund size and fund survival and fund size and performance.

Using the TASS database from January 1994 until December 2002, Getmansky (2005) examines the relationship between industry and fund specific factors and the probability of hedge fund survival and performance. She discovers that hedge funds have hedge funds have an optimal size and exceeding that size has negative impacts on performance, in other words a positive, concave relationship between past fund asset size and current fund performance. For different hedge fund categories, the performance size relationship takes on different functional forms. Relatively more illiquid hedge fund strategies such as convertible arbitrage or emerging markets (when compared to liquid hedge fund strategies as equity long/short or dedicated short bias) are subject to limited opportunities and more likely to show a concave relationship between performance and fund size. The optimal size for these funds can be determined.

Edwards and Caglayan (2001) use the MAR database to examine the relationship between individual funds' excess returns and various fund characteristics from January 1990 to August 1998. Like Fama and French (1992 and 1990), excess returns are estimated using the multi factor model. The paper finds hedge fund performance rises at a declining rate as fund size increases.

Koh et al. (2003) examine the relationship between hedge fund size and performance in the Asian context. The authors regress monthly fund returns on stock characteristics in both the univariate and multivariate settings in the cross sectional Fama and MacBeth (1973) framework. Their findings show weak statistically insignificant relationship between fund size and fund returns. Malkiel and Saha (2005) use probit regression analysis to investigate the factors that cause the probability of a fund's demise. Their result shows a negative, highly significant coefficient for hedge fund size, smaller funds have a lower probability of dissolution than larger hedge funds.

### 5.2.2 Fund age

Assuming investors will not continue to retain and pay investment managers who underperform other managers and funds, according to Edwards and Caglayan (2001), the age or longevity of a hedge fund can illustrate the fund manager's skill.

Amenc et al. (2003) find the average alpha for newer funds is greater than the average alpha for older funds when different performance measurement models are used. Age is the length of time in operation prior to the beginning of their study. Most significant results are derived from the CAPM and explicit factor models while other varies. Using the cross sectional Fama and MacBeth (1973) framework, Koh et al. (2003) document no relationship between hedge fund age and performance. Edward and Caglayan (2001) on the hand find positive, statistically significant relationship for hedge fund strategies as global macro funds, global funds, and market neutral funds. Getmansky (2005) reveals that an increase in the hedge fund age is negatively related to fund flows. Brown et al. (2001) discover older hedge funds have a higher likelihood of survival. They use probit analysis to study hedge fund characteristics as absolute and relative performance, excess volatility, fund age and relate to fund termination. Using the same methodology, Liang (2000) finds younger funds have poor performance and smaller size funds have a higher chance of dissolution.

### 5.2.3 Performance fees

Edwards and Caglayan (2001) find that hedge fund performance is positively related to the performance fee charged. The authors argue that some of the positive excess returns generated by hedge funds can be explained by the fund managers' skill. This result challenges the mutual fund literature such as (Carhart, 1997b) that finds the negative relationship between high fees and fund performance. Amenc et al. (2003) also study the impact of incentive fees to fund performance. The funds are divided into two groups: one where the incentive fees are 20% or more and the other where the incentive fees are less than 20%. Various methodologies are used to study the relationship between incentive fees and fund performance. The findings show the average alpha for the second group is lower than the first group. Koh et al. (2003) find that hedge funds with lower performance fees show higher post fee return than funds with higher performance fees.

### 5.2.4 Other factors

Using a sample of 982 hedge funds in the TASS database, Boyson (2003) investigates the impact of manager's tenure on fund performance from the period January 1994 to December 2000. The underlying hypothesis is career concerns increase over time and as their career progresses, manager become more risk averse. Risk taking behaviour as measured in terms of manager tenure differs systematically among managers with different levels of experience. The results show that as managers' age, their risk taking behaviour increases. Compare to less experienced managers, they increase their volatility and herd less. More experienced managers tend to tolerate more risk resulting in higher returns for their funds. These results are consistent with theoretical evidence on agency costs and career concerns of hedge fund managers and also in line with the mutual fund industry.

Koh et al. (2003) investigate how the hedge funds' characteristics like redemption periods, size of holding companies and size of minimum investment affect fund performance. In relation to performance, they find a statistically significant relationship to redemption period and holding company size. No significant relationship between fund performance and size of minimum investment is found. Schneeweis et al. (2002) find higher performance is associated with longer lock up periods for hedge funds adopting similar strategies than funds with shorter lock up periods. Redemption periods play a key role on fund performance.

### 5.2.5 Hedge fund survival and hedge fund characteristics

Various academic studies have linked the relationship between hedge fund characteristics to probability of hedge fund demise. Liang (2000) analyses the reasons for hedge fund resolutions using the TASS database and the probit regression. The probability of hedge fund demise is studied in relation to various hedge fund characteristics as average monthly returns, assets under management, managers' personal investments, incentive fees, management fees, fund age, and leverage ratios. The funds with smaller asset under management and younger funds with poor performance are more likely to dissolve. With the exception of management fees, the authors find statistically significant probability to fund characteristics. Brown et al. (2001) do a similar study with same database from the period 1994 to 1998. Industry benchmarks and poor hedge fund performance compare to the high water mark threshold increases the probability of fund dissolution. Hedge funds are more likely to shut down if the underperform the industry average. The authors reveal that risk and fund age have significant effects on hedge fund dissolution whereby relatively riskier and younger hedge funds are associated with higher probability of dissolution.

Malkiel and Saha (2005) also study the relationship between fund characteristics and the probability of fund demise through using the probit analysis and the TASS dataset. The hedge fund characteristics are slightly different namely: past performance, risk, past performance relative to the industry and fund size. In determining the probability of a fund's demise, the previous fund performance and risk are most important. Malkiel and Saha (2005) document that larger funds have a higher probability of dissolution which contradicts the finding of Liang (2000). Consistent with the previous literature, risker funds have a lower probability of survival.

Baquero et al. (2005) use the longitudinal probit method to study the liquidation process of hedge funds. Historical performance is an important factor to explain fund liquidation empirically while funds with high returns are much less likely to liquidate. They also find smaller funds are more likely to liquidate than larger funds and that fund age, investment style and magnitude of incentive fees are also related to hedge fund survival. Xu et al. (2010) use a probit analysis to the CISDM database to capture how hedge fund characteristics impact fund attrition. The period of study includes the financial crisis of 2007 to 2009. Older funds with better pre crisis performance and frequent audited funds have a higher probability of surviving the financial crisis and leveraged funds were more likely to close down. The fund characteristics tested include size, age, performance, risk, leverage and the regularity of an audit.

Brown et al. (2001) were the first to use the Cox model to study hedge fund mortality. They find younger hedge funds with low past returns are more likely to fail consistent with the probit model. As well as, a strong relation between volatility and fund failure is documented. This has implications for managers of hedge fund managers whose returns fall below the high water mark, as their incentives to increase volatility to improve future returns will be mitigated by the increased risk of fund failure arising from higher volatility.

Gregoriou (2002) applies survival analysis to the Zurich Capital Markets database from 1990 to 2001 to see if the explanatory variables explain the hedge fund failure. Various survival methods including the product limit estimate, the life table method, the accelerated failure time model and the semi parametric Cox (1972) proportional hazards model are used. While larger, low leveraged, better performing funds have a higher probability of survival, funds with a higher minimum investment requirement tend to die quicker.

Baba and Goko (2006) also use the survival analysis to study the individual hedge funds in the TASS database. Similarly various methodologies such as the non-parametric survival analysis, the Cox (1972) proportional hazards model with shared frailty and a logit analysis. They find large funds with higher returns, recent fund flows, lower volatilities, and higher skewness of returns and assets under management have a lower probability of failure. Funds with longer redemption notice period and a lower redemption frequency have a higher probability of survival. The authors did not find significant relationship between leverage and chance of fund survival.

Liang and Park (2010) compare the effectiveness of various downside risk measures to predict hedge fund failure. The result is funds with high historical performance and high water mark provisions are less likely to fail.

### 5.3 Data

I use the same databases: Eurekahedge, TASS and Morningstar like in previous two papers to investigate the relationship between the characteristics of hedge funds domiciled in the Asia Pacific and hedge fund survival. Following Xu et al. (2010) who argue that a set of 24 monthly returns guarantees adequate monthly observations for the estimation of performance and risk in the pre crises period, I select only those hedge funds that have complete monthly data.

The final dataset contains 3491 hedge funds domiciled in the Asia Pacific and includes information on such fund characteristics as fund size, inception date, fund location, management fee, performance fee, investment strategy, redemption frequency, notification period, lock up period, minimum investment and use of leverage. I record management fee, performance fee, lock up period, minimum investment and use of leverage as of January 2007 and assumed to be constant over the sample period. This assumption is unreasonable for the fund size characteristic as hedge fund size varies over time. Instead, I use the mean asset value of the fund in the pre-crisis period as a proxy for fund size.

In the hedge fund literature, the issue of survivorship bias is well documented. This bias is most visible in hedge funds returns prior to 1994. I gather both live and dissolved funds to reduce this bias. Reported returns can be affected as hedge funds operate in illiquid markets. To overcome this illiquidity bias, I use the desmoothed returns obtained from the Getmansky, Lo and Makarov (2004) procedure.

Since detailed information on defunct hedge funds is hard to retrieve, defining hedge fund dissolution is not that simple. The difference between failed and liquidated hedge funds is not clear in earlier studies. Fund liquidation does not necessarily imply fund failure as successful funds can be liquidated by hedge fund managers for a few reasons. Getmansky, Lo, and Mei (2004) differentiate the various reasons for fund exclusion from the database of live funds by using the status codes provided in the TASS database. Other than fund liquidation, fund exclusion can include: stop reporting, unable to contact, closed to new investments, merged into another fund, and dormant fund.

Three possible reasons for why successful hedge funds might liquidate without being considered as failures according to Liang and Park (2009). Firstly, hedge funds that successfully liquidate in anticipation of market crash should be treated as liquidated rather than failed funds. Secondly, after launching new funds, hedge fund managers could liquidate successful start-up funds. This is because the terms of the new funds can be defined in a more beneficial way by adding lock up periods or extending redemption frequency. Thirdly, some liquidated hedge funds should not be regarded as failed ad they have not failed terms of downside risk management.

## 5.4 Methodology

This section outlines the methods used to test the relationship between the probability of hedge fund mortality and fund characteristics. Given the widespread use of the probit model in the academic literature of hedge funds, I continue to use it and to check the robustness of my findings, I include the Cox semi parametric hazard rate regression.

### 5.4.1 Probit analysis

In the context of hedge fund mortality, a probit model can be used to explain how various fund characteristics or independent variables impact the dependent variable $y_i$. This $y_i$ is binary in nature. It is constructed as dichotomous measure where the occurrence of the dissolution of the hedge fund during the crisis is coded 1, and the absence of the dissolution event is coded 0.

The easiest method of handling with dichotomous dependent variables is the linear probability model which is based on the assumption that the probability of an event occurring, $P_i$ is linearly associated with a set of independent variables $x_{2i}, x_{3i}, \ldots . x_{4i.}$ The linear probability model is equivalent to the quantitative outcome dependent variables explained using linear regression analysis. The fitting of a binary dependent ($y_i$) to a set of explanatory variables using the linear regression framework is inappropriate as it will generate fitted values not restricted to lying between 0 and 1, required for the dependent variable. Using a function to overcome this limitation, a probit model transforms the regression model in a way that fitted values are bounded within the (0,1) interval. Under the assumption that the probability of $y_i$ being equal to 1, the probit model is:

$$P(y_i = 1 \vdots x_i, \beta) = \emptyset(x_i' \beta)$$

The probability of $y_i$ being equal to 0 is:

$$P(y_i = 0 \vdots x_i, \beta) = 1 - \emptyset(x_i' \beta)$$

where $\emptyset(.)$ denotes the cumulative distribution function of the standard normal distribution. The probit analysis enables one to examine the probability of hedge fund demise as a function of some explanatory variables, $x_i' = (x_{1,i,\ldots\ldots,}x_{n,I})$. The probit model can then be rewritten as:

$$E(y_i : x_i, \beta) = \emptyset = \emptyset(x_i'\beta)$$

The probit model can also be written in the form of the regression:

$$y_i = \emptyset(x_i'\beta) + \varepsilon_i$$

where $\varepsilon_i$ or the residual indicates the deviation of the $y_i$ or the dichotomous variable from its conditional mean, $x_i'$ are the variables that explain the probability of hedge fund death and $\beta$ are the parameters to be estimated.

The methods to estimate the parameters involve nonlinear approaches such as maximum likelihood estimations procedures. Specifically, given the assumption of random exogenous sampling, the parameters of the probit model are estimated by maximizing the log likelihood function with respect to $\beta$:

$$\hat{\beta}=\sum_{i=1}^{N}(y_i \, ln\emptyset(x_i'\beta) + (1 - y_i)\ln(1 - \emptyset(x_i'\beta)))$$

The first order conditions for the likelihood equation, obtained by maximizing the log likelihood equation with respect of $\beta$ are nonlinear. Hence, the parameter estimates are obtained by iterative solution. For statistical inference purposes, the asymptotic covariance matrix can then be estimated by using the inverse of the Hessian evaluated at the maximum likelihood estimates (Greene and Zhang, 2003).

There are several methods to test the goodness of fit of the probit model like in the linear regression framework. Even though the goodness of fit such as RSS or $R^2$ are easily calculable in linear regression framework, there is no meaning in the nonlinear probit model. Various other measures need to be computed to check the goodness of fit of the probit model. One of the measures is the percentage of $y_i$ values correctly predicted by the model. According to Brooks (2008), this is the 100x number of observations correctly predicted divided by the total number of observations.

$$Percent\ correct\ prediction = 100/N \sum_{i=1}^{N} y_i I(\widehat{P}_i) + (1 - y_i)(1 - I_i(\widehat{P}_i))$$

where $I(yi)$=1 if $\widehat{y}_i > \bar{y}$ and 0 otherwise. The higher the number, the better the fit of the model. Or, one can the pseudo $R^2$, a measure similar to $R^2$. This is defined as:

$$Pseudo - R^2 = 1 - \frac{LLF}{LLF_0}$$

where LLF is the maximized value of the log likelihood function for the probit model and $LLF_0$ is the value of the log likelihood function for a restricted model in which all of the slope parameters are set to zero. Its value is always between 0 and 1. The pseudo $R^2$ is not good for comparing models with different sets of data even though it can compare difference specifications.

### 5.4.2. Cox semi parametric hazard rate regression approach

The Cox model is a regression based model to investigate the relationship between the multiple explanatory variables and the survival times in survival studies. The aim is to model time to event data whereby event is considered death and is operationalized through dichotomous variable. These analyses are longitudinal in nature and they enable for the effect of censoring and the dependency of survival times on explanatory variables. Essentially, survival analysis enables one to examine the probability of a hedge fund failure given some explanatory variables. Survival analysis estimate how is the duration of life time hedge funds domiciled in the Asia Pacific influenced by explanatory variables as funds' past monthly returns, volatility, age, size, management fees, use of leverage and lock up periods.

Traditional statistical models such as multiple linear regressions are not suitable as due to censoring and non-normality which are both characteristic of survival data. A standard normal distribution is symmetrical by nature as it includes both positive and negative values. Survival data (duration), only assumes positive values and thus violates the normality assumption. Timmermann et al. (1999) suggest the probit analysis is too restrictive. They encourage the use of the Cox hazard rate regression approach. The Cox method does not require the exact nature of the survival function. The problems with Cox are the restrictive assumption of proportional hazards for explanatory variable effects and the loss of the baseline hazard function.

Multiple regression methods do not account for censoring. The databases include censored funds because it includes both dead and live funds. Censored observations occur when the dependent variable exemplifies the time to the terminal event and the duration of the study is limited. Thus, the event of interest is very rarely observed in all subjects. If the period of observation expires or the subject is removed from the study prior to the event of interest occurs, it is known as right censoring. Censoring arises in the context of survival analysis of hedge funds. Some hedge funds die during the observed period which is immediately registered in the database together with the time of death, thus making the lifetimes of these hedge funds fully transparent. Funds that are still alive and operating at the end of the observation period are censored as the exact time of their death is unknown. Not including these censored funds in the analysis will generate a downward bias of the sample's survival time as the lifetimes of censored funds also provide important relevant information relating the overall hedge fund survival.

I define hedge fund's survival time or duration as a random variable denoted by T whereby T>0 from Gregoriou (2002). The entry date by hedge fund to the database is denoted as zero. Lastly, the survival function, denoted as S(t) shows the probability that the hedge fund will survive longer than time t:

$$S(t) = P(T > t)$$

Another important feature of the survival model is the hazard rate, represented as

$$\gamma_t = \lim_{\Delta t \to 0} \frac{P\{t \le T < t + \Delta t \colon T \ge t)}{\Delta t} = \frac{f(t)}{S(t)}$$

The hazard function is a derivative of the survival function. They converted to each other hence. In short, the survival study is to estimate hazard function $\gamma_i(t)$ using the semi-parametric Cox regression approach. Cox's method is similar to the multiple regression approach except the dependent variable is the hazard function:

$$\gamma(t) = \gamma_0(t)\exp(age\beta_1 + perf\beta_2 + stdev\beta_3 + size\beta_4 + lev\beta_5 + mnfee\beta_6 + perffee\beta_7 + hwm\beta_8 + redfreq\beta_9 + lockup\beta_{10} + mininv\beta_{11} + listed\beta_{12})$$

where the quantity $\gamma_0(t)$ is the baseline hazard function and is equal to the probability of fund dissolution when all the covariates are zero. The value of the hazard function corresponds to the product of the baseline hazard and a covariate effect. The baseline hazard function is similar to the intercept in the ordinary multiple regression. The covariate effect is the same for all time points while the baseline hazard is dependent upon time. The ratio of their covariate effects is the ratio of the hazards of any two cases at any point in time. $\beta_1$ to $\beta_7$ show the proportional change that can be expected in the hazard relative to changes in the explanatory variables. The assumption for the Cox model to work is the constant relationship between the dependent variable and the explanatory variables.

The main aim of the Cox model is not to retrieve actual estimates of survival times. Instead, it is carried out to determine the relative influence of explanatory variables on survival. Hazard ratios help in the assessment. If it is greater than one, it means a decrease in survival. To test the strength of the relationship between the explanatory variable and the dependent variable, the magnitude, significance and direction of each beta are used.

### 5.4.3 Explanatory variables

The main aim of this paper is to investigate empirically the extent that certain hedge fund characteristics explain the survival of hedge funds. The explanatory variables used in this analysis are described and likewise the motivation for inclusion.

Previous academic literature when studying the attrition of hedge funds include the following characteristics as performance, risk, fund size, age, leverage, fees, high water marks, lock up provisions, minimum investment size and listing on an exchange. The decision to include performance and risk as independent variables of hedge fund survival is simple. According to Liang (2000), Brown et al. (2001) and Malkiel and Saha (2005), funds with lower risk and better performance are less likely to close down. While the risk is measured by the standard deviation of returns over the sample period, the performance of the hedge fund is estimated by average monthly returns during the period. In the academic literature, the influence of fund size on attrition of hedge fund is ambiguous. Since bigger hedge funds have a larger and more stable asset base, size can be beneficial for fund survival. Malkiel and Saha (2005) use AUM recorded in December 2005 to represent size and held this fixed over the period study. In contrast, they find smaller, nimbler hedge funds are more likely to survive.

In the studies of fund survival, leverage is another important hedge fund characteristic often discussed. Hedge funds that use leverage will be at a higher risk of liquidation that those funds that do not. The extensive use of leverage by hedge funds is widely perceived as volatile (Baba and Goko, 2006). The databases contain a binary variable of yes or no for leverage. Similarly, I treat leverage as a fixed binary variable with 0 meaning no use of leverage and 1 meaning the use of leverage. Survival analysis can also be linked to the age of hedge fund.

I use the independent variables as management fee, performance fee and high water mark to examine the effect of the incentive structure on the attrition probability of hedge funds. Performance fee is an idiosyncratic feature of the hedge fund industry while management fee is paid to all fund managers. As a result of the convexity in compensation it creates for fund managers, participants believe that high performance is associated with more risk (Panageas and Westerfield, 2009). In short, high performance fees increase the risk associated with hedge funds and hence increase the probability of liquidation.

Another feature to protect the investor is the high water mark. It laids out the potential payout of the performance fee when the share price is greater than its previous highest value. The manager is required to bring the value back above the previous level before he or she can receive the performance fees when the investment drops in value. The relationship between the liquidation probability of hedge funds and high water mark provisions is not clear. While high water mark provisions can provide fund managers an incentive to manage funds more prudently, they can increase the risk taking behaviour of managers, leading to an increased probability of liquidation. Panageas and Westerfield (2009) find that the managers' risk taking behaviour depends on the time horizon they have. If the time horizon is finite, their model predicts more risk taking behaviour.

I also link the impact of lock up period and redemption frequency with hedge fund survival. Investors are concerned as the presence of lock up period and a lower redemption frequency illustrate a lower liquidity for investment. In relating the impact of lock up periods and redemption frequencies to the survival of hedge funds, there are two opposing hypotheses. The first hypothesis argues that hedge funds with lock up provisions and longer redemption frequencies have more control over unforeseen outflows that could have destabilizing effect on fund survival. On the other hand, the second hypothesis state that lock up provisions and long redemption periods prevent fund managers from increasing their assets under management. Such liquidity constraints deter investors to invest in them.

The other factor I consider to impact on hedge fund dissolution is the minimum required investment. Hedge funds are more likely to experience larger outflows, therefore destabilizing funds' operations if they have a higher minimum investment. Alternatively, funds are more likely to have smaller outflows and more risk adverse investors if they have smaller minimum investment amounts.

I also examine the survival of hedge funds relative to being listed on an exchange. This status is beneficial for hedge fund managers. There is no risk of fund withdrawal at unfavourable times as the investor capital is tied up. Using the Barclay Hedge database, Gregoriou et al. (2009) discover that compare to the non-listed funds, the listed hedge funds tend to survive on average approximately two years longer. The period used is from 2000 to 2007. Similarly, I expect the dichotomous variable as to whether the fund is listed or not to have a positive effect on the hedge fund survival.

### 5.5 Results

The probit method models the chances of hedge fund dissolution as a function of specified idiosyncratic fund characteristics. The dependent variable is a binary, with the value of 1 if the fund is defunct and 0 if the fund is live. A negative coefficient for an explanatory variable shows that a higher value of that variable decreases the chances of fund dissolution. Using the maximum likelihood method, the coefficients for the probit model are estimated. The probit model is too restrictive in its strong distributional assumptions. Timmermann et al. (1999) prefer the use of Cox semi parametric hazard model. The following sections show the results derived from the probit regression and the Cox semi parametric proportional hazard model.

### 5.5.1. Probit regression analysis

Table 5.1 reports the results obtained through the probit regression analysis. I find older hedge funds domiciled in the Asia Pacific have a higher probability of survival with the coefficient estimate for age negative and statistically significant at 1%. Larger funds with better performance has a higher probability of survival as the coefficients for fund size and mean returns are negative and significant at 1%. Surprisingly, the coefficients for standard deviation and leverage are negative and statistically significant at the 5% level. These mean funds that use leverage and have highly volatile returns are more likely to survive. This is unexpected as many recent hedge fund failures have been associated with excessive use of leverage and volatility in returns. I discuss the effect of leverage and standard deviation in more detail later.

Funds with lower redemption frequency have a higher probability of survival as the coefficient for redemption frequency is positive and significant at the 5%. The listed hedge funds domiciled in the Asia Pacific have a lower probability of survival as the coefficient is positive and significant at the 1%. This finding is in contrast to Gregoriou et al. (2009) where they associate the lower probability of liquidation with listed hedge funds. The independent variables that make up the incentive structure aspect of hedge fund investing such as management fee, performance fee and high water mark are insignificant. Likewise, the lock up and minimum investment variables also gave insignificant coefficient estimates. Table 5.1 reports the parameter $R^2$ from the probit regression of hedge fund failures.

**Table 5.1 Probit analysis**

| Variable | Coefficient | Std. Error | Z statistic | Prob. |
|---|---|---|---|---|
| Intercept | 0.39 | 0.26 | 1.53 | 0.13 |
| Age | -0.01 | 0 | -5.42 | 0 |
| Mean return | -0.39 | 0.06 | -6.43 | 0 |
| Standard deviation | -0.03 | 0.02 | -2.05 | 0.04 |
| AUM | 0 | 0 | -3.95 | 0 |
| Leverage | -0.19 | 0.08 | -2.22 | 0.03 |
| Management fee | -0.15 | 0.1 | -1.5 | 0.13 |
| Performance fee | 0.01 | 0.01 | 1.01 | 0.31 |
| High water mark | 0.11 | 0.16 | 0.72 | 0.47 |
| Redemption frequency | 0 | 0 | 2.74 | 0.01 |
| Lock up | -0.2 | 0.14 | -1.47 | 0.14 |
| Minimum investment | 0 | 0 | -0.25 | 0.81 |
| Listed | 0.35 | 0.09 | 3.84 | 0 |
| Pseudo R^2 | 17 | | | |

### 5.5.2 Cox regression analysis

Table 5.2 displays the results of testing the Cox semi parametric proportional hazard model to the hedge fund domiciled in the Asia Pacific. This model produces similar results to the probit regression model. The negative estimated coefficient for the explained variable in the Cox model or the hazard rate means the variable lowers the hazard rate. The mean returns are statistically significant predictor of the chances of fund failure at the 1% as the mean of fund returns is negative and highly significant. With the standard deviation, the estimated coefficient is consistent with the results from the probit model. It is negative and statistically significant meaning that a higher level of standard deviation leads to a lower chance of fund dissolution. This finding contradicts the pervious literature and reasons will be outline later.

Larger assets under management have a lower probability of failure since the size coefficient is negative and significant at the 1%. Funds with a higher redemption frequency face a higher probability of failure as the coefficient is positive and significant at the 5%. The estimated coefficient for leverage is negative but statistically insignificant. Likewise, the coefficients for management and performance fees, high water mark, lock up, minimum investment and the exchange listed variable are not statistically significant (refer to Table 5.2). Higher redemption frequency cause harm to the survival probability of hedge funds as the coefficient is positive and statistically significant.

In the Cox proportional hazard model, the hazard ratio enables the survival of different levels of explanatory variables to be compared. A hazard ratio higher than 1 implies that the independent variables have a negative effect on survival time or that a higher value of independent variable will lead to a shorter survival time. The opposite is true. A hazard ratio lower than 1 means positive effect on survival time – a higher value of an independent variable implies a longer survival time. While the hazard ratio for redemption frequency is greater than one, the hazard ratios for funds' mean returns, sizes, and standard deviations are all lower than one. The results are consistent with the literature except the hazard ratios for standard deviation which in the literature assumes a value higher than 1, meaning the higher volatility is harmful for fund survival.

**Table 5.2 Cox proportional hazards regression analysis**

| Variables | Estimate of regression coefficient | Standard errors | Wald | Sig. | Hazard ratio |
|---|---|---|---|---|---|
| Mean return | -0.65 | 0.04 | 266.83 | 0 | 0.52 |
| St. dev. Return | -0.14 | 0.02 | 46.68 | 0 | 0.87 |
| AUM | -0.01 | 0 | 59.66 | 0 | 0.99 |
| Leverage | -0.1 | 0.09 | 1.26 | 0.26 | 0.9 |
| Management fee | 0.18 | 0.12 | 2.12 | 0.15 | 1.19 |
| Performance fee | 0.02 | 0.01 | 2.73 | 0.1 | 1.02 |
| High water mark | 0.09 | 0.17 | 0.28 | 0.6 | 1.09 |
| Redemption freq. | 0 | 0 | 4.27 | 0.04 | 1 |
| Lock-up | 0.11 | 0.16 | 0.47 | 0.49 | 1.12 |
| Minimum investment | 0 | 0 | 0.88 | 0.35 | 1 |
| Listed | 0.04 | 0.1 | 0.19 | 0.66 | 1.05 |

### 5.5.3 Discussion

In this chapter, I confirm empirically the results found in most academic studies on hedge funds. The result is expected and intuitive as better performing funds are associated with lower probability of liquidation. The positive effects are not obvious when the likelihood of fund survival is tested on the fund volatility as measured by the standard deviation of returns. The higher volatility is often linked to higher probability of closure by the market participants. In contrary to most of the academic literature, using both the probit and Cox models, I find higher standard deviation enhance chances of fund survival. This may be explained by the nature of the databases. The group of surviving funds compare to the group of defunct funds has a higher standard deviation over the full sample period. This can be problematic as it leads to wrong conclusion that defunct hedge funds are less risky than surviving hedge funds.

I break the full sample period into two parts, with the breakpoint set as the start of the financial crisis in February 2007 to analyse the result further (Xu et al., 2010). I find the pre-crisis average standard deviation is lower than for surviving funds than for dead funds. Upon examining the databases, I noted most the dead funds in the databases do not have returns from 2007 to 2010, a period of highly volatile investment climate. The volatility for dead funds is lower than the surviving funds as most of the dead funds do not have returns during that period. The coefficient for standard deviation loses its statistical significance when the probit model is re run on the pre-crisis period from January 1994 to February 2007.

Funds that use leverage have a higher probability of survival based on the probit model as the coefficient is negatively significant. This is new as one would expect highly leveraged funds to have a higher chance of dissolution. The databases do not show the amount of leverage except whether the fund uses leverage. The leverage variable has no significant effect on liquidation hazard ratios according to the Cox model.

In my sample of hedge funds domiciled in the Asia Pacific, the incentive structure to explain the effect on the mortality rates using both models is zero. The coefficients for management fees, performance fees and high water mark policies are insignificant under the probit and Cox models. The variable to proxy for minimum investments is also insignificant in both models. I find that lower redemption frequency lowers the probability of hedge fund dissolution similar to Baba and Goko (2006). The lower liquidity relative to fund survival hypothesis is supported.

## 5.6 Conclusion

In recent years, institutional investors such as pension funds, governments have come to represent a significant proportion of hedge fund investors. The issue of hedge fund survival is crucial interest for them as it linked to their capital preservation/loss in the long term horizon. For these institutional investors it is important to choose hedge funds that will produce consistent returns.

While the previous chapter examines the issue of how to identify hedge funds that produce persistent returns, this chapter focuses on the likelihood of hedge fund survival and hedge fund selection. The period used is from January 1994 to June 2012. Various academic studies investigate the issue of hedge fund survival, but none examines in the context of hedge funds domiciled in the Asia Pacific.

To find the factors that influence the survival and mortality patterns of these hedge funds, I use both the parametric probit regression model and the less restrictive semi parametric Cox proportional hazard model. Firstly, the two models gave conflicting results on the impact of leverage on hedge fund survival. While the Cox model shows that leverage has no effect on hedge fund survival, the probit model displays that higher leverage is beneficial for fund survival. Secondly, the incentive structure of hedge funds (management fees, incentive fees, and lock up provisions) does not have an effect on fund survival. Thirdly, there is a positive relationship between standard deviation and survival of hedge funds. One of the possible reasons is that the defunct funds died before the global financial crisis began in 2007. Last but not the least, larger, better performing funds with lower redemption frequency is related to higher likelihood of survival in line with extant literature.

# CHAPTER SIX

# CONCLUSION

## 6.1 Summary of findings

In the past twenty years, alternative asset classes and hedge funds particularly have become increasingly popular among investors. Today institutional investors such as endowments, foundations, pension funds compose a larger percentage of the hedge fund universe while the typical investor in the 1990 was a high net worth individual.

Hedge funds domiciled in the Asia Pacific have been a particularly nimble and dynamic sector of the global hedge fund industry. In terms of AUM, these hedge fund increase from approximately US $30 billion in 2000 to US $200 billion, excluding Australia and Mainland China, which are estimated to together have a similar AUM as the rest of Asia (Arslanian, 2016) or an annual compounded growth rate of 15%. Though most of the academic research focuses on US and Europe centric funds, growth rate in these hedge funds has outpaced that of global hedge fund industry. I focus my research on three particular aspects of these hedge funds given its growing importance.

Using the Eurekahedge, TASS and Morningstar databases, I analysed the risk adjusted performance of hedge funds domiciled in the Asia Pacific. Very few studies analyse the performance of hedge funds domiciled in the Asia Pacific in the academic literature (Koh, Koh and Teo, 2003; Teo, 2009) , most studies focus on US-centric and Europe-centric hedge funds (Brown, Yu, Ray and Teo, 2018). Using Fung and Hsieh (2004a) model and the step wise regression model that include both the linear and non-linear risk factors, results show positive average alpha in the cross-section for majority of strategies and a positive and significant alpha for roughly half of funds. A comparison of the stepwise regression factor model and the widely used factor model proposed by Fung and Hsieh (2004a) reveals the estimated alpha is robust to the choice of the factor model. In contrast to prior research I find little evidence of a decreasing alpha over time.

The second aspect relates to an important question from the point of hedge fund investors. They face frequently selection problems when deciding on which hedge funds to invest in. Do the alphas reflect managerial skill or luck when there is significant risk adjusted performance (alpha)? Referring to Capocci et al. (2005), the answer to this question is crucial as active selection is likely to enhance the expected return if performance persists since one superior average return is likely to be followed by another superior average return period. The results are mixed in the academic literature for issue of performance persistence. Adopting the methodology from Hendricks et al. (1993), Carhart (1997), and Capocci et al. (2005), 10 portfolios are constructed at the beginning of every year based on funds' performance in the prior year. This produces a time series of portfolio returns as the procedure is repeated for the whole time period. Effectively, to analyse these hedge fund performance, I divided the sample into two sub periods or two distinctive market environments. Using the two multi factor performance measurement models, I estimate the portfolio returns using the Fung and Hsieh (2004a) model and an adjusted version of Teo's adjusted (2009) model.

Over the full sample period from January 2000 until December 2010, I find only limited evidence of performance persistence. Among medium and poor performers, my analysis of the full sample period shows that superior performance is more predictable. I find positive significant alphas at the 1% for the middle and bottom deciles when using Teo's adjusted (2009) model over the full sample period. Similar to Capocci et al. (2005), I find most of the performance persistence in the first, bullish sub period. In contrast to the second sub period, that includes the global financial crisis of 2007, I find only weak evidence of performance persistence using Teo's adjusted (2009) model. The significant persistence in performance in only located in the middle decile. For the best or worst performing funds, there is inconclusive evidence of performance persistence.

Third, I relate the hedge fund characteristics to the probability of survival. The question of hedge fund survival is of crucial interest if survival is linked to capital preservation/loss among institutional investors and also the fact that institutional investors make up a large proportion of hedge fund investors. No academic study examines the issue of hedge fund survival in the context of hedge funds domiciled in the Asia Pacific. Consequently, I test whether this hedge fund mortality can be predicted on the basis of certain hedge fund characteristics such as age, size, performance, standard deviation, leverage, management and performance fees, high water mark provisions, redemption frequency, lockup provisions, minimum investment requirements and whether the fund is listed on an exchange. The methodology use includes the parametric probit regression and the semi parametric Cox proportional hazards analysis. I find larger, better performing funds with lower redemption frequencies are more likely to survive consistent with the extant literature.

### 6.1.1 Relating Results to Recent Literature

Manager skill is usually measured by the alpha or the portion of a fund's return not attributed to systematic risk exposures. Early literature generally concludes that hedge fund managers create positive, statistically significant risk-adjusted performance. In practice, it is difficult to identify alpha. First, researchers may detect alpha when estimating multifactor models, this result though may be due to luck or model uncertainty. Researchers addressed this concern by using different statistical approaches and studying persistence in hedge fund performance. Second, while hedge funds may generate abnormal performance, the opacity surrounding hedge funds makes it difficult to determine how that superior performance was achieved. Using other data sources such as funds' quarterly equity and option holdings as well as their daily trades, researchers have attempted to identify the sources of managers' skill. Finally, researchers have also tried to separate managerial skill into stock selectivity and timing components.

In the first paper, I find a positive average alpha in the cross-section for the majority of strategies and similarly for half of all funds. Aramov et al. (2011) study whether hedge fund managers are able to generate alpha given some macroeconomic conditions. They find that strategies such as global macro perform better in times of crisis than others such as equity long/short.

They use the Bayesian framework of Avramov and Wermers (2006) to compare groups of hypothetical hedge fund investors with varying beliefs about the predictability of managerial skill. I use the stepwise regression factor model and the widely used factor model proposed by Fung and Hsieh (2004a).

Jovenvaara, Kosowski and Tolonen (2014b) investigate the size performance relation and confirm previous findings that the relation between size and past (future) performance is positive (negative). In the paper, there is support for decreasing returns to scale as well as managers seek to increase fund size since their compensation increases with fund size. This is consistent with the Berk and Green (2004) model. I find little evidence of a decreasing hedge fund alpha over time. This result is consistent with the smart money effect in hedge funds.

Some papers also investigate if a fund's geographical location, relative to the market in which it invests, affect managers' ability to deliver alpha. There are two arguments for this. Firstly, the information asymmetry between competitors in a market should benefit the informed. Secondly, fund managers can exploit the knowledge of the local culture, language and other hard to quantify factors all convey information about companies and securities.

Teo (2009) finds that after controlling for risk and market location, funds that have an office in the same geographical region to their investment outperform their more distant competitors by 3.72 percent per annum. Also in their sample of Asia focus hedge funds from 2000 to 2006, fund managers who speak the native language enjoy an advantage. More distant funds however benefit from the ability to attract more capital and charge higher fees despite their poorer performance. My paper focuses on funds located in the Asia Pacific and other than the Fung and Hsieh (2004a) model, I also use the stepwise regression model. Additionally, Teo (2009) uses the databases of Eurekahedge, Asiahedge and Hedge Fund Research while I obtained my data from Eurekahedge, TASS and Morningstar. The choice of databases can impact the hedge fund performance that researchers find (Jovenvaara, Kosowski and Tolonen, 2014a).

Another way to separate luck and managerial skill is to test whether a manager's abnormal performance is persistent. In the second paper, I do an empirical test of performance persistence. Glode and Green (2011) give a theoretical argument where they assume the ability to hide one's proprietary strategy is the key determinant of persistence and not managerial skill. Managers calculate the benefits of raising capital from new investors against the costs linked with disclosing the trading strategy to potential investors. The two assumptions they make are that anyone can profit from the strategy once they know about it and these strategies face decreasing returns to scale. Consequently, adding new investors increases the number of parties using the strategy and lowers the profitability of the strategy. In their paper, as long as the manager shares information rents with initial investors so they do not share the proprietary strategy with others not linked to the fund, performance persistence will prevail.

Jagnnathan, Malakhov and Novikov (2010) also examine whether hot hands exist among hedge fund managers. They use relative fund performance to predict future relative performance. Using both generalized method of moments (GMM) and weighted least squares (WLS) techniques to reduce measurement error, they model individual fund performance as a function of overall equity market and fund style index performance. Their findings show performance persistence over a 3 year horizon and this persistence is largely driven by persistence in top performers. I find only limited evidence of persistence in hedge fund performance for the full sample period and among medium and poor performers. When I use Teo's (2009) and Fung and Hsieh (2004a) model, I find positive and highly significant alphas among the middle and bottom deciles similar to Capocci et al. (2005). During the sub period analysis, my results show persistence during the bull period and inconclusive evidence during the bear period.

Researchers have also tried to use new data sources to identify managerial skill in hedge funds. Several papers use the 13F data on hedge fund company holdings to examine if funds have stock picking or market timing ability. Cao et al. (2014) use holdings data to examine whether managers following merger arbitrage strategy possess skill. They argue this is a logical way to find skill since there are two easily identifiable benchmarks: the entire sample of mergers and other institutional investors that follow this strategy. Their findings show that this set of managers has skill and this is because of their ability to handle downside risk rather than ability to predict merger outcomes.

Agarwal et al. (2013) use the portion of a hedge fund company's portfolio that is not initially disclosed in a 13F filing to study whether hedge fund managers possess skill. Their results show that managers are likely to request confidential treatment if they have more concentrated portfolios and more unique strategies. These stocks in the concealed holdings have smaller market capitalization and lower analyst coverage. They also outperform for the next twelve months. These findings suggest that hedge fund managers display skill in selecting certain stocks but do not immediately disclose these holdings. Aragon, Hertz, and Shi (2013) also examine hedge funds' confidential holdings and find that funds using confidentiality have better future performance.

The 13F data has several limitations. Firstly, the disclosure is at the fund company level and not at the fund level. Secondly, disclosure occurs only on a quarterly basis. Thirdly, fund companies managing less than $100 million are not required to disclose. Lastly, the disclosure includes only the fund companies' holdings and not their actual trades. Jame (2014) overcomes these limitations partly by using Abel Noser's trade level data to examine whether hedge fund managers exhibit superior performance and how they generate this performance. The performance of managers in the top 10% of the cross sectional return distribution is too large to simply occur by chance and this superior performance persists.

In the third paper, my findings show that larger, better performing funds with lower redemption frequency have a higher likelihood of survival. The methodologies use are the parametric probit regression model and the less restrictive semi parametric Cox proportional hazard model. This paper can also provide explanation for the growth of the hedge fund industry as investors' desire for an asset class that has low correlation to the systematic risk factors among others.

Bollen (2013) uses r-squared to compare the performance of funds. He shows that low r squared funds have a higher probability of failure and face significant downside risk. He argues the difference in performance is likely due to an omitted risk factor.

Siegmann, Stefanova and Zamojski (2013) study the first mover benefits such as entering early in a given asset class or investment focus in the hedge fund industry. There is economically large outperformance of 0.5% greater excess returns per month. First movers can charge higher incentive fees and survive longer (Clifford, Ellis and Gerken, 2014). I find that management fees, incentive fees and lock up provisions as part of the hedge fund incentive structure do not impact on fund attrition.

Recently, literature also examines the active role played by hedge funds in the governance and operational aspects of corporations. Lim (2014) uses financially distressed firms to examine the impact of hedge fund activists. In these firms, hedge funds are involved with higher percentage of restructuring, quicker resolution of distress and reduction in leverage. This better contracting helps to create value.

Aslan and Kumar (2015) visit the potential activism impact on targets' customers, suppliers and rivals. Results show rival firms' suffer decreased cash flows and profits three years after the activist effort commences. Also as targeted firms subsequently remove a greater portion of the surplus, customers and suppliers are adversely affected.

Gantchev, Gredil and Jostikasthira (2015) find that after a competitor is targeted by a hedge fund, firms make governance changes. The findings show the firms increase their leverage, payout policies and improve their operating efficiency. This in turn reduces the probability of being subsequently targeted.

Three key results prevail from these studies. Hedge fund activism corroborates the positive impact on target firms. They can be long term shareholders who are willing to engage in improving the operational performance of target firms. Other than target firms, hedge fund activists impact on non-target firms in terms of governance and profitability.

There are natural biases in all hedge fund databases since hedge fund managers are not required to report their performance. As well researchers can create certain biases, in the choice of their empirical setup,. The challenges are to interpret these empirical findings and to measure the risk-adjusted performance since the indices funds are formed using funds from these databases.

## 6.2 Contribution to academic research

This thesis contributes to the academic literature on hedge funds in several ways. Firstly, it analyses the risk adjusted performance of a large sample of hedge funds domiciled in the Asia Pacific over a 16 year period that includes the global financial crisis of 2007 by way of two multi factor performance measurement models. Previous studies on the performance of hedge funds covered shorter time periods and excluded periods in which global markets declined. The inclusion of the global financial crisis of 2007, the large sample, and the relatively long period add to the robustness of my results. Secondly, I expand the work of Koh et al. (2003), who used non-parametric methods to analyse the performance persistence of hedge funds in Asia. I use a parametric methodology similar to Capocci et al. (2005) to investigate the largest data sample of hedge funds domiciled in the Asia Pacific and over a period that include both bullish and bearish market periods. Finally, this thesis adds to the understanding of the relationship between these hedge funds characteristics and the probability of hedge fund survival to the academic literature.

### 6.3 Limitations and areas for future research

There are three limitations to this thesis that is data availability, the assumptions made and the inherent constraints in the applied methodologies. I use the regression based, parametric, multi factor models to examine hedge fund performance in the first part of this thesis. Hedge fund performance measures do not always follow parametric normal distributions argued by some authors (Fung and Hsieh, 2001; Mitchell and Pulvino, 2011; Agarwal and Naik, 2004). Future research could then apply methodologies like bootstrap and Bayesian methodologies used by Kosowoski et al. (2007) that do not require hedge fund performance to be normally distributed. The conclusions are made based on the validity of the data reported by hedge funds to the database providers (Jovenvaara, Kosowski and Tolonen, 2014a; Patton, Ramadorai and Streatfield, 2013; Liang and Qiu, 2015; Aragon and Nanda, 2017; Jorion and Schwarz, 2014). Every investor has to be apprehensive about the possibility of incorrect information in historical data as a result of the largely unregulated nature of the industry. More research can be done on how to protect against such risk. The evidence of decreasing returns to scale is more robust to evidence of smart money effect in hedge funds which is consistent with the Berk and Green (2004) model (Chakravarty and Sovan Deb, 2013; Fung et al. 2014). There is scope for future research on the relation of fund flows and both past and future performance as the assets of the hedge fund industry are becoming increasingly concentrated in relatively fewer fund firms.

Future research could test long term performance persistence over time horizons of 12 to 36 months considering the redemption periods. This thesis examines performance persistence of hedge funds domiciled in the Asia Pacific over the 12 month time horizons. This thesis focuses on conventional hedge funds and the financial crises. Future research could study flows, persistence, and performance sensitivity of socially responsible hedge funds during exogenous events such as environmental disaster and corporate accounting scandals (Bialkowski and Starks, 2016).

All hedge funds exits are treated as a single group rather than try to differentiate among various types of exits due to data availability. The group of failed hedge funds does not mean funds that were liquidated given the voluntary nature of inclusion in the databases. Some funds may have existed the database because they were closed to new investments. Compare to liquidated funds, these funds have better returns. Databases do not provide distinct reasons why hedge funds enter the graveyard group or differentiate among the various exit types. The strength of the relationships between covariates and the probability of fund survival might be biased as in this dissertation as all exits are treated as liquidations. Following Rouah (2005) and Liang and Park (2009), one can collect data on the reasons for exits and re running the analysis, allowing for multiple exit types for improvement.

The semi-parametric Cox proportional hazards model used assume covariates are not time dependent. While some authors such as Rouah (2005) propose the use of Cox model to control for time dependent covariates, Gregoriou (2002) and Gregoriou et al., (2009) used a similar model to semi-parametric. The applicability of this approach could be investigated in future research.

Future research could examine the qualitative aspect of hedge fund domiciled in Asia Pacific regions to further understand the investment strategies employed, the portfolio structure, hedge fund managers and managers' attitude towards risk. This thesis primarily used the quantitative approach to examine the performance and survival of hedge funds domiciled in the Asia Pacific.

Finally, there is scope for future studies to focus on the optimal contracting in the industry. These may consider the managers' direct and indirect incentives and restrictions that investors face for withdrawals to maximize fund performance. This is because I assume managers' compensation contracts are set at inception and will not change and other studies have found managers take actions to enhance fund size at the expense of fund performance (Yin, 2013).

# CHAPTER SEVEN

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