Asia-Focused Hedge Funds: Analysis of Performance, Performance Persistence and Survival

DISSERTATION
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences
and International Affairs
to obtain the title of
Doctor of Philosophy in Management

submitted by

Mato Njavro

from

Croatia

Approved on the application of

Prof. Dr. Li Choy Chong

and

Prof. Dr. Andreas Grüner

Dissertation no. 4032

Stämpfli Publikationen AG, Bern 2012

The University of St. Gallen, School of Management, Economics, Law, Social Sciences and International Affairs hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St. Gallen, May 11, 2012

The President:

Prof. Dr. Thomas Bieger

To my parents

Acknowledgments

The process of writing this dissertation has been both exciting and fulfilling. It is only just that I use this opportunity to thank the people who supported me during this rewarding, but often exhausting, journey.

Above all, I would like to thank my supervisor, Prof. Dr. Li Choy Chong, for providing me with this amazing opportunity and for supporting my academic development. Furthermore, I would like to express my gratitude to my co-supervisor, Prof. Dr. Andreas Grüner, whose comments and advice greatly improved the quality of this thesis.

Last but not the least, I would like to thank my parents and my brothers for their love and support throughout my life. Their contributions are invaluable.

Rab, August 2012 Mato Njavro

Table of Contents

List of Tables

List of Appendices

List of Figures

Abstract

The Asian hedge fund industry has been one of the fastest-growing sectors in the global hedge fund universe over the last decade, in terms of both assets under management (AUM) and number of funds.

In the context of rapidly increasing inflows in Asia-focused hedge funds, the issue of the sustainability of hedge fund risk-adjusted performance (alpha) has become more relevant. Therefore, the first part of this dissertation deals with analyzing the risk-adjusted performance of Asia-focused hedge funds during the period from January 2000 until December 2010. My results indicate that Asian hedge funds, as a group, produced statistically significant alpha over the full sample period. In order to account for the possibility of structural breaks in my data, I conduct Chow's (1960) breakpoint test which reveals a structural break in February 2007, corresponding to the beginning of global financial crisis. In line with some previous studies, I find that Asia-focused hedge funds did not produce significant alphas on average during the second sub-period which encompasses the global financial crisis of 2007-2010.

The second part of this dissertation deals with the issue of performance persistence in the context of Asia-focused hedge funds. This issue is of practical relevance to hedge fund investors since evidence of persistence in performance would indicate that active selection is likely to increase the expected return. My results indicate that there is only limited evidence of persistence in Asia-focused hedge fund performance over the full sample period. Similarly, I find only weak evidence of persistence in performance during the second sub-period, which encompasses the global financial crisis of 2007-2010.

Finally, the last part of this dissertation investigates the relationship between characteristics and the survival of Asia-focused hedge funds. More specifically, I examine whether Asia-focused hedge fund mortality can be predicted on the basis of certain hedge fund characteristics: age, performance, standard deviation, size, 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. Consistent with previous research, I find that larger, better performing funds with lower redemption frequencies are more likely to survive.

Zusammenfassung

Der asiatische Hedgefonds-Sektor hat sich über das letzte Jahrzehnt hinweg zu einem der schnellst wachsenden Bereiche der globalen Hedgefonds-Industrie entwickelt, sowohl im Hinblick auf die verwalteten Vermögenswerte, als auch die reine Anzahl von Fonds.

Im Zusammenhang mit den stetig wachsenden Geldzuflüssen in Hedgefonds mit Asienfokus ist insbesondere der Aspekt der Nachhaltigkeit ihrer risikoadjustierten Performance (alpha) relevant. Vor diesem Hintergrund beschäftigt sich der erste Teil der Dissertation mit der Analyse der risikoadjustierten Performance asienfokussierter Hedgefonds im Zeitraum Januar 2000 bis Dezember 2010. Meine Resultate deuten darauf hin, dass Hedgefonds mit Asienfokus als Gruppe in der Lage waren, ein statistisch signifikantes alpha über den gesamten Betrachtungszeitraum zu erwirtschaften. Um meinen Datensatz auf eventuelle Strukturbrüche zu testen, wird der Chow-Test (Chow, 1960) durchgeführt. Im Einklang mit vorangegangenen Studien gelang es mir nachzuweisen, dass asienfokussierte Hedgefonds im Durchschnitt nicht in der Lage waren, in der zweiten Subperiode, welche die Jahre der globalen Finanzkrise 2007-2010 umfasst, signifikante alphas zu generieren.

Der zweite Teil dieser Dissertation beleuchtet die Persistenz von asienfokussierter Hedgefonds-Performance. Dieser Aspekt ist von praktischer Relevanz für Hedgefonds-Investoren, da der Nachweis einer Persistenz in der Performance von asienfokussierten Hedgefonds darauf hindeuten würde, dass sich mit einer aktiven Selektion die erwartete Rendite steigern liesse. Meine Resultate zeigen, dass sich lediglich ein begrenzter Nachweis einer solchen Persistenz für den Betrachtungszeitraum erbringen lässt. In ähnlicher Weise verhält es sich mit der Performance-Persistenz für die Krisenjahre 2007-2010, in denen sich nur ein schwacher Nachweis erbringen lässt.

Abschliessend untersucht der letzte Teil der Dissertation den Zusammenhang zwischen Überlebensdauer und bestimmten Charakteristika von Hedgefonds mit Asienfokus. Im Einzelnen wird untersucht, ob sich die Mortalität eines asienfokussierten Hedgefonds durch die folgenden Charakteristika voraussagen lässt: Alter, Performance, Standardabweichung, Grösse, Verschuldungsgrad, Management- und Erfolgshonorare, Provisionen für Netto-Überschussgewinne, Rücknahmefrequenz, Lock-Up-Provisionen, minimale Anleger-Investitionen, und die Frage ob der Hedgefonds an einer Börse notiert ist. In Übereinstimmung mit früheren Studien konnte ich nachweisen, dass grössere Hedgefonds mit besserer Performance und geringerer Rücknahmefrequenz eine höhere Überlebenswahrscheinlichkeit haben.

1. Introduction

Hedge funds that invest in emerging markets have expanded rapidly over the past decade. Notably, the Asian hedge fund industry has been one of the fastest-growing sectors in the global hedge fund universe in terms of both assets under management (AUM) and number of funds. As alternative investment vehicles, hedge funds offer several advantages relative to traditional investment vehicles, such as mutual funds. As hedge fund managers face few constraints in choosing their investment style, they can take both long and short positions and, hence, offer investors potential upside and limited downside. In fact, many hedge funds claim to be market-neutral investment vehicles. Furthermore, they can use leverage and various derivatives to amplify their investment returns. Equipped with this freedom and flexibility in terms of investment style, hedge funds should be well prepared to deal with the characteristics of emerging markets and to provide value through active management (Strömqvist, 2007).

The extraordinary growth of the hedge fund industry in recent years has generated a large body of academic literature. However, most extant academic research analyzes hedge funds that operate in the United States or Europe (e.g., Fung and Hsieh, 1997; Ackermann, McEnally, and Ravenscraft, 1999; Lo, 2001), while hedge funds that invest in Asia or other emerging markets have generally received little attention in the academic literature (Abugri and Dutta, 2009).

The 2007-2010 global financial crisis had a major impact on the hedge fund industry. It affected almost every type of asset in virtually every market, thereby reducing the positive effects of the diversification in the hedge funds' portfolios (see Strömqvist, 2007). Thus, after experiencing extraordinary growth in the first eight years of the twenty-first century, the Asian hedge fund industry went through a period of large-scale redemptions and closures. However, to date, academic studies of Asia-focused hedge funds have relied on time intervals that exclude the financial crisis of 2007-2010. One possible reason for this is a lack of data for that period. The aim of this dissertation, therefore, is to analyze the performance of hedge funds that focus on Asia using a data sample that encompasses the profound financial crisis of 2007-2010.

1.1 Research objective and key questions

The purpose of this dissertation is three-fold. First, I analyze the performance of Asia-focused hedge funds in the context of the 2007-2010 global financial crisis. Building on the academic work of Ackermann, McEnally, and Ravenscraft (1999), Strömqvist (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Abugri and Dutta (2009), Eling and Faust (2010), and Xu (2010), multi-factor models encompassing both linear and non-linear risk factors are used to evaluate the performance of Asia-focused hedge funds. Following the work of Eling and Faust (2010), this dissertation analyzes sub-periods, different market environments, and breaks. As Xu et al. (2010) note, when the impact of the crisis is not properly accounted for, the accuracy of performance evaluations and empirical models that include the crisis period are in doubt.

Secondly, this study focuses on the returns of Asia-focused hedge funds and investigates whether returns exhibit persistence over time. The author measures survivorship bias and accounts for attrition rates during the time period observed. This is an important question from the perspective of hedge fund investors, who constantly face selection problems when trying to choose hedge funds in which to invest.

Thirdly, similar to Gregoriou (2002), Baba and Goko (2006) and Grecu et al. (2007), the author conducts a the survival analysis of Asia-focused hedge funds in an attempt to investigate whether hedge fund mortality can be predicted according to certain hedge fund characteristics.

In light of the above, the following research topics and research questions have been defined:

Research topic 1: The performance of Asia-focused hedge funds

> *Research question 1.1: Have Asia-focused hedge funds produced alpha over the full sample period?*
>
> *Research question 1.1: Do Asia-focused hedge funds produce alpha over the period of global financial crisis?*

Research topic 2: Performance persistence

> *Research question 2.1: Is performance of Asia-focused hedge funds persistent or is it a product of chance?*

Research topic 3: Survival analysis of Asia-focused hedge funds

Research question 3.1: What are the factors influencing the survival of Asia-focused hedge funds?

1.2 Results and contribution to the existing literature

This section presents the main results of this dissertation and its contribution to the existing academic literature. Section 1.2.1 summarizes the results of the first empirical study of this dissertation presented in the Chapter 5 on the ability of Asia-focused hedge funds to produce risk-adjusted performance (alpha) over the period under investigation. Section 1.2.2 presents the major results of the second empirical study on hedge fund performance persistence, studied in Chapter 6. Finally, section 1.2.3 summarizes the results of the Chapter 4 which analyzes the probability of hedge fund survival in relations to its idiosyncratic characteristics.

1.2.1 Do Asia-focused hedge funds produce alpha?

Chapter 5 analyzes the risk-adjusted performance of Asia-focused hedge funds over the period from January 2000 until December 2010 using the Eurekahedge database. In the academic literature on hedge funds, most studies focus on US-centric and Europe-centric hedge funds while very few studies analyze the performance of Asia-focused hedge funds. This paper addresses that gap and analyzes the performance of Asia-focused hedge funds over the time period which includes the financial crisis of 2007-2010 using three multi-factor models encompassing both linear and non-linear risk factors. My results indicate that Asia-focused hedge funds, as a group, produced statistically significant alpha over the full sample period, as estimated by Teo's (2009) adjusted model and the step-wise regression Asia model. I analyze two sub-periods including the period from February 2007 until December 2010 which encompasses the global financial crisis. I find that during the financial crisis, Asia-focused hedge funds did not produce significant alphas on average. My results are in line with Eling and Faust (2010) who examine the performance of emerging markets hedge fund and find significant alphas during the whole sample period from January 1996 until August 2008, but find insignificant hedge fund alphas during the sub-period from January 2007 until August 2008.

1.2.2 Do Asia-focused hedge funds exhibit persistence in their performance?

Chapter 6 investigates the performance persistence of Asia-focused hedge funds over the horizon of 12 months using the Eurekahedge database from January 2000 until December 2010. Unlike Koh et al. (2003) and Sy et al. (2007) who also examine the performance persistence of Asia-focused hedge funds, this dissertation investigates the largest data sample of Asia-focused hedge funds over a period that includes both bullish and bearish market periods using a parametric methodology. I find only limited evidence of persistence in Asia-focused hedge fund performance for the full sample period, and only among medium and poor performers. In the second sub-period, which encompasses the global financial crisis of 2007-2010, I find only limited evidence of persistence in performance among middle performers. My results are similar to those of Capocci et al. (2005), as I also find that most of the persistence in performance is found in the first, bullish sub-period.

1.2.3 What are the factors influencing the survival of Asia-focused hedge funds?

Chapter 7 attempts to examine whether Asia-focused hedge fund mortality can be predicted on the basis of certain hedge fund characteristics: age, performance, standard deviation, size, 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 issue of hedge fund survival and its relationship to fund characteristics is of significant practical relevance to the growing number of institutional investors who allocate part of their portfolio to hedge funds. To the best of my knowledge, no previous study deals with the issue of hedge fund survival in the context of Asia-focused hedge funds. In order to analyze how hedge fund characteristics influence hedge fund survival, I apply both the parametric probit regression and the semi-parametric Cox proportional hazards analysis. In line with the previous research, I find that larger, better performing funds with lower redemption frequencies are more likely to survive. Somewhat surprisingly, I also find that a higher standard deviation increases the chances of hedge fund survival. One potential explanation of this phenomenon could lie in the nature of the Eurekahedge database, which was used for this study. Most of the hedge funds in the database's 'defunct' group died before the global financial crisis began in 2007. Therefore, the group of surviving funds – funds that were exposed to the market turmoil during the 2007-2010 crisis - has a higher standard deviation than the group of defunct funds. I also show that incentive structure does not appear to influence Asian-focused hedge funds and that the evidence on the effect of leverage on fund survival varies, depending on the statistical model applied.

1.3 Structure of the Dissertation

Chapter 2 presents the hedge fund industry in general. It provides detailed insight into the industry and outlines the categorization of hedge funds. This is followed by a concise account of the historical evolution of hedge funds. Overviews of the global hedge fund industry and the Asian hedge fund industry, as well as current market conditions, are also provided in the first part of this chapter. Chapter 3 presents the theoretical framework upon which the multi-factor performance measurement models are built. Hence, topics such as modern portfolio theory and the capital asset pricing model are discussed in chapter 3. Chapter 4 discusses the research design of this dissertation. Chapter 5 investigates the risk-adjusted performance of Asia-focused hedge funds using three different multi-factor models. Chapter 6 analyzes the performance persistence of Asia-focused hedge funds. Chapter 7 investigates the relationship between hedge fund characteristics and their survival. Chapter 8 concludes this dissertation.

2. The Hedge Fund Universe

2.1 The Evolution of the Hedge Fund Industry

The term “hedge fund” was first coined by journalist Carol Loomis in his article “The Jones Nobody Keeps Up With”, which was published in *Fortune* in April 1966. The article highlighted the outstanding returns of the fund managed by Alfred Winslow Jones, who is widely credited with the creation of the first hedge fund in 1949. The fund was organized as general partnership and, as such, was not subject to regulation under the US Investment Company Act of 1940. To maintain the exemption, the fund had to limit the number of investors to 100 prior to 1996, and thereafter to those investors defined as “qualified investors[1]” (Anderson et al. 2010). In 1952, Jones converted his fund to a limited partnership and added a 20% performance fee to the regular management fee based on the fund’s net assets. Jones was the first fund manager to combine short selling, leverage, and a compensation plan based on investment performance. Furthermore, he acknowledged the necessity of investing his own money in the fund, as he felt it would be inappropriate for him to receive high incentive fees for risking only investors’ money. Jones used two speculative tools – short-selling and leverage – and merged them into a conservative investment system (Coldwell and Kirkpatrick, 1995). In 1984, at the age of 82, Jones revised the fund’s partnership agreement so that it formally became a fund of funds.

After Loomis published his article in 1966, the term “hedge fund” was widely used in the investment community. In a survey for the year ending 1968, the SEC found 215 investment partnerships. 140 of these were classified as hedge funds, the most of which were established that year (Coldwell and Kirkpatrick, 1995).

Over time many hedge fund managers realized that hedging a portfolio using short sales was an expensive, time-consuming activity, especially in a bull market. As a consequence hedge fund managers departed from their original strategies of constructing hedged portfolios using both long and short techniques.

Abandoning the practice of hedging long positions proved to be very costly in the market downturns of 1969-1970 and 1973-1974, when many hedge funds had to be closed due to their leveraged, net-long positions. As a result, after 1974, the hedge fund industry fell out of investment community's favor and remained so until the mid-1980s (Ineichen, 2008).

[1] See The US federal securities laws Rule 501 of Regulation D for exact definition of 'qualified investor'

In 1986, however, the investment community's interest in hedge funds re-emerged when the Institutional Investor magazine published an article about Julian Robertson, Manager of the Tiger Fund. According to the article, Robertson's Tiger Fund had delivered an annual return of 43% during the first six years of its existence. This was considered an impressive achievement, especially when compared with the 18.7% annual return that the S&P 500 delivered during the same period. Another wave of hedge fund formation ensued in the late 1980s, following a period of substantial primary market activity and rapidly rising securities prices (Anderson et al., 2010).

The number of hedge funds is believed to have grown to nearly 1,000 by the early 1990s (Anderson et al., 2010). Hedge funds gained particular notoriety when in 1992, when the Quantum Fund (managed by George Soros) earned USD 1.8 billion by establishing a short position on the British pound and a long position on the Deutschmark. Only a few years later, the dramatic collapse of the Russian ruble in 1998 led to a USD 2 billion loss for the Quantum Fund (Anderson et al., 2010). In addition, the default of the Russian ruble and the market events that ensued led to US $4 billion loss for the Long-Term Capital Management (LTCM) hedge fund and its subsequent collapse in 1998. A widespread market catastrophe was avoided when the Federal Reserve orchestrated the bailout of LTCM. However as Anderson et al. (2010) note, the industry was developing a bad reputation in the general public, a reputation reinforced by the shortage of information available to the public caused by the lack of reporting requirements.

2.2 Hedge Fund Characteristics

Despite the vast interest that hedge funds have attracted from the public, regulators and academics, a commonly accepted definition of "hedge fund" does not exist. According to Lhabitant (2004), hedge funds are unregulated, privately organized, professionally managed pools of capital that are not widely available to the public. Ineichen (2003) defines a hedge fund as: '*an investment program in which the managers or partners seek absolute returns by exploiting investment opportunities while protecting the principal from potential financial loss*.'

These definitions highlight three important aspects of hedge funds. In contrast to mutual funds, which are available to the general public, most hedge funds will accept only individual or institutional investors that meet the requirements of the local regulatory agency (e.g., the SEC in the United States, FSA in the UK). Therefore, participation in hedge funds is restricted to high-net-worth individuals and to institutional investors, such as foundations, life insurance companies, endowments, and investment banks (Gregoriou and Duffy, 2006). Furthermore, the investment philosophy of hedge funds encompasses the aim of producing absolute positive returns by taking risk while simultaneously trying to avoid losses and negative compounding of capital. This investment philosophy differs from that of the traditional money manager, who is focused on performance relative to a market benchmark.

Hedge funds are often perceived as a distinct asset class in the investment community because their performance, correlation, and volatility characteristics differ from those of other asset classes, such as bonds, equities, or commodities. According to Ineichen (2003) one can categorize hedge funds in the following three ways: 1) as a separate asset class; 2) as asset management firm executing alternative investment strategies; and 3) as financial services companies.

Hedge fund managers have the flexibility to engage in both long and short positions, and they are able to borrow and to make widespread use of derivatives in their pursuit of absolute returns. Hedge funds must adhere to certain regulatory requirements in order to avoid the regulations that affect the mutual fund industry under the US Investment Company Act. More specifically, hedge funds must limit the number of investors and they cannot offer their investment services to the general public. From the regulators' perspective, as long as the general public has no access to these private pools of capital, they are not traditional investment vehicles (such as mutual funds). These regulators, therefore, see no need to regulate hedge funds.

Although hedge funds are far from homogeneous, they do share some common characteristics. Unlike mutual funds, which are highly regulated and have a limited array of investment techniques at their disposal, hedge funds are free to pursue any type of investment strategy. More specifically, they can employ leverage, use derivatives or short-selling techniques, and invest in illiquid or unlisted securities. While mutual fund managers pursue returns in excess of certain benchmarks, hedge fund managers aim to pursue absolute returns. They strive to reduce sensitivity to broad market factors relative to traditional investment portfolios. In general, this investment philosophy contributes to the perception of hedge funds as market-neutral investment vehicles that should provide returns irrespective of whether the market rises or falls. This feature makes hedge funds an attractive investment for investors seeking diversification.

Several studies examine hedge funds in relation to other asset classes. Based on data from 1994 through 2004, Garbaravicius and Dierick (2005) report that all correlation coefficients between the CSFB/Tremont Hedge Fund family indices and major stock market indices were below 0.61, and even negative in the case of dedicated short bias and managed futures strategies. However, they also note that in times of stress and financial crises, the return performance correlations can surge if trades are crowded, which was the case in August and September 1998 after the Russian default and the collapse of Long-Term Capital Management. Furthermore, Hasanhodzic and Lo (2007) found that for many hedge fund strategies, more than 70% of total performance mirrors easily tradable market indices.

Stulz (2007) notes that the incentives of hedge fund managers differ significantly from those of mutual fund managers in several ways. First, mutual fund managers' compensation is restricted by regulation, so that incentive compensation must be symmetric; positive performance must have positive effects on compensation, while negative performance must have negative effects. As Elton et al. (2003) note, mutual fund managers generally do not have an incentive compensation clause embedded in their contracts and their compensation primarily depends on the amount of assets under management. In contrast, most hedge fund managers have asymmetric compensation contracts that guarantee them a substantial proportion (usually 20%) of the profits they generate (Ackermann et al., 1999). This characteristic of the compensation contracts of hedge fund managers enables them to earn extremely high levels of compensation if investors experience high returns (Stulz, 2007).

Second, high hedge fund fees can attract managers with poorly established and executed strategies, which can potentially result in large losses for investors (Lhabitat, 2004). Hence, a "high-water mark" is embedded in the compensation contracts of most hedge fund managers. These clauses state that if managers make a loss in one period, they can claim performance fees only after they recover that loss. In theory, in the absence of such a clause, a manager enjoys all of the advantage from successful trades but suffers little from potential losses. Therefore, high-water marks should limit the risk-taking of a hedge fund manager (Stulz, 2007). However, the problem of misaligned interests, where managers enjoy all the upside but suffer little from the downside, is not completely resolved through the introduction of high-water marks. Even with a high-water mark clause in place, the hedge fund manager might choose to close the fund if it incurs a major loss. To demonstrate this point, Stulz (2007) uses the example of the trader who was responsible for most of the US $6 billion loss that brought down the Amaranth fund in September 2006. That trader reportedly earned between US $80 million and US $100 million in 2005. Notably, the trader was not required to return his past compensation to the fund and, after the Amaranth debacle, he was even able to establish his own hedge fund.[2]

For these reasons, most hedge funds request that their managers invest a significant proportion of their personal wealth in the fund alongside other investors (Lhabitat, 2004). Furthermore, many hedge funds invest in invest in illiquid securities, which can include securities that are not actively traded and for which market prices are not always immediately available (see Asness, Krail, and Liew, 2000; Getmansky, Lo, and Makarov, 2004). To provide managers with the flexibility needed to follow through with their investment ideas, hedge funds usually impose certain liquidity constraints, such as lock-up periods, which guarantee long-term capital commitments and minimum notice times for redemptions by investors. The existence of these liquidity constraint provisions allows managers to concentrate fully on investments and performance rather than on liquidity management.

2.3 Hedge Fund Typology

Even though the term "hedge fund" is typically used universally, all hedge funds are not alike. Some even argue that "hedge fund" is merely a term used to describe the entire universe of investment alternatives and that hedge funds simply cannot be defined as a homogeneous asset class (Bookstaber, 2003). To a certain extent, this is true, as a wide array of hedge fund strategies and investment styles exist, each of which have very different approaches and objectives. This, in turn, leads to different returns, volatilities, risk estimations, geographical focal points, and investment strategies. This section, therefore, presents a typology of hedge funds, which aims to reduce complexity by introducing a classification system based on sets of related characteristics.

No universally accepted convention on how to classify various hedge fund strategies exists, as each data provider, investor, or consultant might use a different classification system. Analyzing in details every possible way of categorizing hedge fund strategies is beyond the scope of this study. For detailed hedge fund strategy descriptions see Lhabitant (2006) Furthermore, one needs to be aware that there often exists a degree of overlap between

[2] http://www.bloomberg.com/apps/news?pid=newsarchive&sid=aUlBVaEHAk04&refer=home

certain hedge fund strategies. For the purpose of this dissertation, I use the classification proposed in Teo's (2009) paper where he analyzes the relationship between the risk-adjusted performance of Asia-focused hedge funds and their proximity to investments. Teo (2009) organizes hedge fund strategies into eight major groups: equity long/short, relative value, event driven, macro, directional, fixed income, managed futures (CTA) and others.

Equity long/short funds are by far the largest strategy in my data sample accounting for over 57% of all Asia-focused hedge funds. This strategy involves purchasing equities with superior return characteristics and selling short equities with inferior return characteristics, i.e. those that are expected to decrease in value. Equity long/short strategy covers a wide

Relative value hedge funds (also referred to as arbitrage or market-neutral funds) strive to profit from relative discrepancies in prices between related instruments, such as equities, debt, options, and futures, while trying to avoid exposure to market-wide movements. The most common trading strategy among arbitrage hedge funds is betting that the market prices of two related securities will converge over time. Such strategies usually exploit very small price distortions. Therefore, in order to achieve meaningful profitability of the strategy, managers often employ leverage. This strategy was described by a partner in LTCM as "vacuuming pennies" and others have described it as "picking pennies in front of a steamroller" (see Lowenstein, 2000).

Event-driven strategies concentrate on equity or debt from companies that are in specific stages of their lifecycles, such as mergers and acquisitions, spin-offs, reorganizations, bankruptcies, re-capitalization, or share buybacks. One popular strategy among event-driven funds is merger arbitrage. This strategy typically involves the buying of the shares of a targeted company and the short selling of the shares of the acquiring company.

Macro hedge funds usually rely on a "top-down" global approach whereby they base their investment decisions on fundamental economic, political, and market factors. One common characteristic of these funds is that they establish both long and short positions in an asset class (equities, bonds, currency, or derivatives) with the aim of profiting from movements in the respective markets.

Directional hedge funds generally try to anticipate movements in global equity, bond commodity, and currency markets by placing unhedged bets on the respective assets, often using leverage to amplify their returns. Although directional funds employ an absolute return strategy, they usually take a directional view of the market in which they invest.

Fixed income hedge funds take positions (long, short or both) in various fixed income securities including interest rate swaps, mortgage-back securities, credit default swaps, etc. Furthermore, some fixed income hedge funds invest in distressed debt securities. These debt instruments, often traded at discounts, are issued by companies that are bankrupt or in the process of turnaround. Managed futures or commodity trading advisor (CTA) funds follow a set of systematic strategies to invest in futures, options or foreign exchange contracts. These funds focus predominantly on commodities markets.

Finally, the last hedge fund group, named 'others', contains multi-strategy Asia-focused hedge funds. These funds diversify their asset allocation by investing in more than one of the strategies described here.

There is also another hedge fund strategy, not discussed in this dissertation, known as the funds of hedge funds (FOHF). FOHFs enable investors to access a variety of managers and gain diversification through a single investment vehicle. As all of the strategies described above have different risk-return parameters, some investors might find it attractive to combine several individual hedge funds in a portfolio. This is exactly what FOHFs offer.

2.4 The Global Hedge Fund Industry Today

Since 2000, hundreds of millions of dollars have been channeled into hedge funds, as a growing number of investors around the world have pursued higher returns through alternative asset classes. This, in turn, led to tremendous growth in the hedge fund industry with many new funds appearing to satisfy the growing demand. A large part of that growth was driven by institutional investors and high-net-worth individuals, who allocated money into hedge funds in the hope of obtaining high returns as well as portfolio diversification benefits (see Fung, Hsieh, Naik, and Ramadorai, 2008). In an environment where interest rates were kept at historical lows and capital was abundant, hedge funds were able to lever themselves up to unprecedented levels and, as such, exert enormous power in the global financial markets.

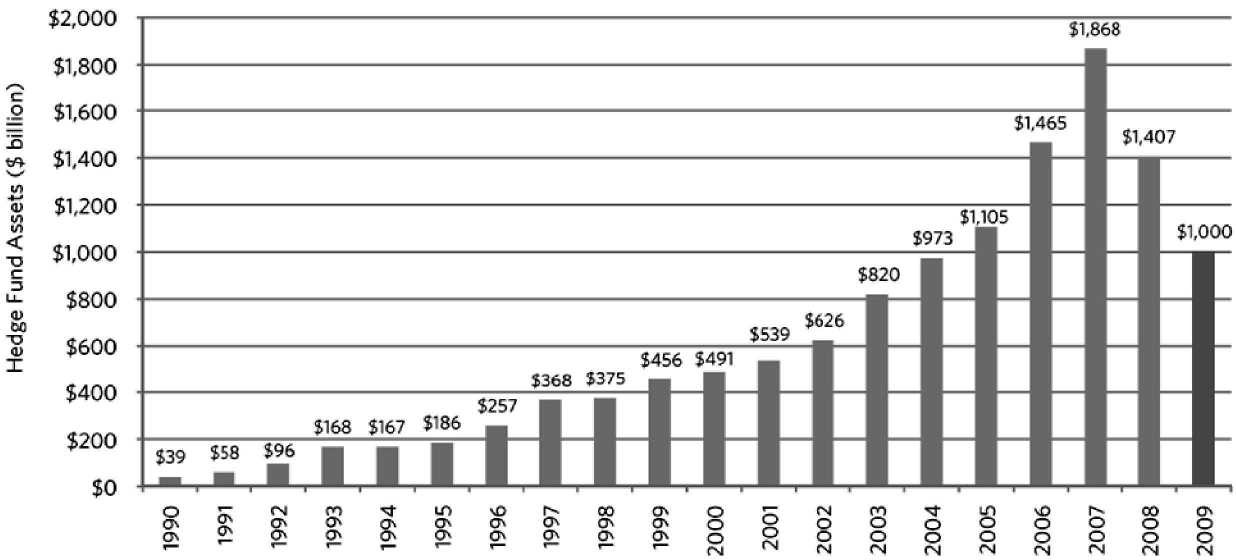
Agarwal and Naik (2005) analyzed the academic research on hedge funds and documented the change in the structure of hedge fund industry. While the macro strategy dominated the industry in 1990, the equity hedge strategy had the largest share of the market in 2004. Furthermore, according to Agarwal and Naik (2005), the typical investor in a hedge fund in

1990 was a high-net-worth individual, while today the typical investor is an institutional investor.

Hedge funds are not subject to the requirements imposed on traditional money managers (such as mutual funds) and as such they are only obliged to report to their investors. The private nature of hedge funds makes it difficult to estimate the true size of the industry. However, in recent years, an increasing number of hedge funds have reported their results to one of the specialized hedge fund databases, such as Hedge Fund Research, TASS, or Eurekahedge. As hedge funds are not allowed to advertise to the general public, the reporting of their results to one of the specialized databases is very important in terms of visibility.

Various databases provide different estimates on the size of the hedge fund industry in terms of assets under management. Until the middle of 2008, the global hedge fund industry experienced continuous expansion in terms of assets under management (AUM) and the number of funds. According to estimates from Hedge Fund Research (HFR), global assets under management grew from US $491 billion in 2000 to a peak of US $1.9 trillion in December 2010, implying a compounded annual growth of 14%. Furthermore, Heidrick and Struggles (2010) estimate that the global hedge fund population grew from about 2,200 funds in 2000 to a peak of more than 12,000 in 2007. Figure 2.1 shows total hedge fund assets, according to research conducted by HFR, The Bank of New York Mellon, and consultant Casey Quirk.

Figure 2.1: Total hedge fund assets – December 1990 through Q2 2009



Source: Hedge Fund Research, the Bank of New York Mellon and Casey Quirk Analysis 2009

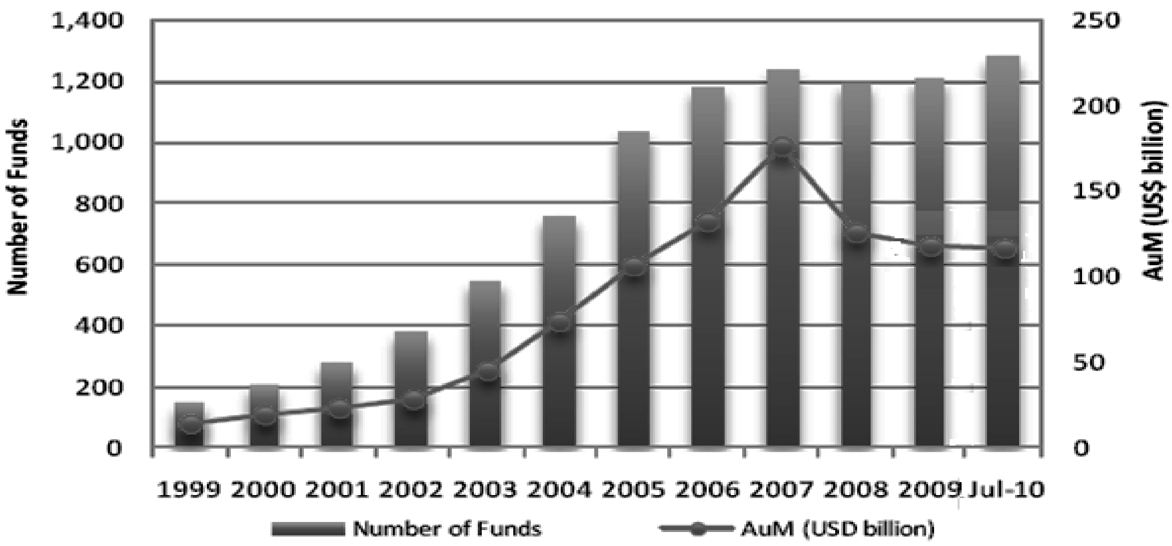
When compared to other asset classes, the hedge fund industry is still relatively small. Furthermore, the global financial crisis of 2007-2010 had a major impact on the hedge fund industry. As the liquidity dried up in the markets, investors fled to cash and other safe assets, and hundreds of hedge funds were closed. According to HFR, global assets under management fell sharply from the peak in June 2008 to US $1.3 trillion in June 2009, implying a 31% decrease in value over one year. Moreover, the number of hedge funds decreased to approximately 8,400 by the middle of 2010. In addition, as Strömqvist (2009) documented, the financial crisis of 2007-2010 has affected almost every type of asset in virtually every market in the world, thereby reducing the positive effects of the diversification of hedge fund portfolios. For the hedge fund industry, one effect of the global financial crisis of 2007-2010 was that the industry experienced net redemptions for the first time since the collapse of the Long-Term Capital Management Fund in 1998. According to the HFR, The Bank of New York Mellon, and Casey Quirk analyses, net asset outflows totaled US $183 billion in the second half of 2008 and an additional US $103 billion was withdrawn by investors in the first quarter of 2009. Had some hedge fund managers not acted to temporarily stop or limit investors' withdrawals, asset outflows would have been even greater.

2.5 The Asian Hedge Fund Industry

Eurekahedge estimates that since 2000, the Asia-Pacific hedge fund industry has experienced the fastest growth within global hedge fund industry in terms of both assets under management (AUM) and the number of new funds established.[3] Eurekahedge estimates that the Asian hedge fund industry grew from approximately US $30 billion in 2000 to US $125 billion as of December 2010 in terms of assets under management. This implies a compounded annual growth of roughly 15% compared to the 14% compounded growth in global hedge fund assets under management during the same period. Moreover, the number of Asia-focused hedge funds grew from 200 in 2000 to 1,278 in 2010. Although the US is still the leading location for hedge funds, accounting for approximately two-thirds of global assets managed in 2007, Asia and the rest of the world are becoming more important in the global asset allocation framework.

[3] The Eurekahedge report, September 2010

Figure 2.2: Growth of the Asian hedge fund industry



Source: Eurekahedge (2010)

According to Preqin Research (2009), Asia and Rest-of-World investors account for just over 12% of all institutional investors active in hedge funds today, compared to approximately 5% in 2002. Although this is a relatively small proportion of the total, some of the world's largest investors in hedge funds are based in these regions. Possibly the most important group of investors based in this region are sovereign wealth funds, which have massive pools of readily available capital for investments in hedge funds. For instance, according to Preqin Research (2009), 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. Nevertheless, the Asian hedge fund industry was not immune to the global financial crisis of 2007-2010, as many Asia-focused hedge funds experienced large redemptions in the midst of the crisis. Subsequently, many funds were forced to close or consolidate. At the same time, there was a sharp reduction in capital flowing into the region. However, Eurekahedge reported that the industry rebounded in second half of 2009, posting excellent returns and attracting more capital. With rapid economic growth projected for the region over the next several years, compared to estimates of roughly 2% growth for developed world (see IMF World Economic Outlook, 2011), Asia – especially China – is taking on a more important role in the global hedge fund industry.

3. Theoretical framework

3.1 An Introduction to Portfolio Theory

The main aim of this chapter is to provide the relevant theoretical framework upon which the multi-factor performance measurement models for analyzing Asia-focused hedge funds are constructed. Topics such as modern portfolio theory and the capital asset pricing model need to be understood before we can shift our focus to hedge fund performance measurement models.

Finance as a decision science originated in the early 1950s when Markowitz developed the basic elements of what is now known as modern portfolio theory (MPT). Modern portfolio theory examines decisions involving outcomes under uncertainty. The theory is concerned with private investors as economic agents acting under uncertainty that are embedded in the financial markets. However, the notion that diversification decreases investment risk existed long before Markowitz formally developed modern portfolio theory (e.g., Williams, 1938; Leavens, 1945).

Prior to Markowitz, investors focused on assessing the risks and returns generated by individual securities without regard to their effects on portfolios as a whole. At the time, no measure of risk was available. Therefore, investors were generally advised to select securities that offered the highest return potential with the lowest possible amount of risk, and then to construct a portfolio on this basis.

Markowitz (1952, 1959) was the first to use mathematical formulations to formally describe the notion of diversification in investing. He proposed the expected (mean) return, E, and the variance of return, V, of the portfolio as a whole as criteria for portfolio selection. He demonstrated that as investors add assets to a given portfolio, the risk of that portfolio as quantified by the variance of total return, V, decreases continuously. He also showed that the expected (mean) portfolio return, E, is the weighted average of the expected returns of the constituent asset's returns.

At the core of Markowitz's modern portfolio theory is the portfolio selection problem described as follows. Markowitz's theory assumes that every investor has an initial sum of money available for investment over a specific period of time, also known as the holding period. An investor considering investing in securities faces the problem of choosing from a large number of securities. Hence, prior to buying securities an investor has to decide which securities he/she wants to buy and hold until the end of a holding period. Considering that portfolio is a combination of more securities, the decision faced by investor is equivalent to choosing optimal portfolio from a set of possible portfolios. Hence, this situation is often referred to as the portfolio selection problem, expressed by Markowitz as an optimization problem. In order to solve the portfolio selection problem, investor first has to identify the risk-return combination available from the set of securities under consideration. Markowitz notes that every risky asset is characterized by an estimated return and the uncertainty of this estimation. In the framework of the modern portfolio theory, the rate of return of any security under consideration is assumed to be random or stochastic variable, characterized by its statistical moments: its mean (expected value) r_i and the standard deviation, σ_i. If investor knew with certainty the future returns of particular securities, then he/she would invest in the security offering the highest return over the holding period. However, this is not the case in reality and the best investors can do is estimate the expected returns (mean returns) of various securities under consideration. Selecting a security only on the basis of its expected return is misguided according to Markowitz as the investor is not only interested in the expected return of a security but also in the likelihood of those returns actually occurring, a fact which is reflected in the standard deviation variable.

Consistent with the framework of modern portfolio theory is the fact that a typical investor, in his will to maximize the expected returns and minimize the risk, faces two conflicting objectives which need to be taken into account when deciding which security to purchase. The investor should estimate the expected returns and standard deviation of each portfolio and then choose the best one on the grounds of the relative magnitudes of these two parameters. Consequently, Markowitz proposes that a typical investor should diversify his/her investments by purchasing several securities rather than just one.

To summarize, Markowitz concludes that investors should base their portfolio decisions only on expected returns (the measure of potential rewards in any portfolio), and standard deviation (the measure of risk). He shows that the standard deviation of the rate of return is a meaningful proxy of portfolio risk under a certain set of assumptions, which include the assumption that projections about securities follow the same probability rules as random variables.

Markowitz's mean-variance analysis is based on several assumptions with respect to the behavior of both the investors and the financial markets:

- Investors have an accurate conception of possible returns, i.e., they can estimate a probability distribution of possible returns over a given holding period,
- In the context of diminishing marginal utility of wealth, all investors aim to maximize their economic utility,
- There are no transaction costs and no taxes,
- All investors are perfectly rational and risk averse,
- All investors are price takers, i.e., their actions do not influence prices,
- Investors care only about the first two moments of a return distribution: expected return (mean) and variance (risk); the third and fourth moments (skewness and kurtosis) are of no interest to investors, and
- Correlations between assets are fixed and constant over time.

3.1.1 Measurement of Return

According to modern portfolio theory, a portfolio's expected rate of return is the weighted average of the expected returns on the component securities in the given portfolio, with portfolio proportions as weights. This can be expressed mathematically as:

$$E\left(R_{port}\right)=\sum_{i=n}^{n}\left\{W_iE\left(R_i\right)\right\}. \tag{1}$$

where $E\left(R_{port}\right)$ is expected return for the portfolio, W_i is the proportion of the funds invested in security *i*, and $E\left(R_i\right)$ is the expected rate of return for security *i*.

3.1.2 Measurement of Risk

The term "risk" usually gives rise to negative associations, as it is linked with the probability of sustaining a loss. In financial theory, however, it is difficult to define risk, as its definition depends on the nature of the investor and the investor's own degree of risk aversion. In the context of modern portfolio theory, the risk of an investment is associated with the likelihood of deviations from the expected return - the greater the deviations, the greater the potential risk. As the expected return is not observable in practice, an estimate of the expected return (arithmetic mean return) is observed instead. Markowitz (1952) demonstrated that the standard deviation of the rate of return is a meaningful measure of portfolio risk. Standard deviation can also be defined as the square root of variance. The standard deviation of any asset's returns, σ_i, is a measure of risk and can be expressed as:

$$\sigma_{\mathrm{i}} = \sqrt{\sum_{i=1}^{n} \left\{ \left[R_i - E(R_i) \right] P_i \right\}}, \qquad (2)$$

where P_i stands for the probability that the expected rate of return, $E(R_i)$, will occur.

The standard deviation of returns does not distinguish between positive and negative deviations from the mean. Hence, it is only an adequate measure of risk when the probability distribution is approximately symmetric around the mean (Bodie, Kane, and Marcus, 2005).

The risk of a portfolio, as measured by standard deviation, is a function of the standard deviations of the individual securities in that portfolio and the covariance between the rates of return for all of the pairs of securities in the portfolio. Covariance is a measure of the degree to which the returns on two risky assets vary together. The covariance between two risky assets can be computed as:

$$\mathrm{Cov}_{\mathrm{i,j}} = \frac{1}{n} \left\{ \sum_{t=1}^{n} \left[(R_{it} - E(R_i)) \left(R_{jt} - E\left(R_j\right) \right) \right] \right\}. \qquad (3)$$

The magnitude of the covariance depends on the magnitude of individual assets' standard deviations and the relationship between their co-movements. The unit of measurement of the covariance is the return units squared. An alternative statistic for interpreting the covariance is the correlation coefficient. It scales the covariance to a value between -1 (perfect negative correlation) and +1 (perfect positive correlation). Essentially, the correlation coefficient measures how closely two random variables move together. Unlike the covariance coefficient, the correlation coefficient does not depend on the unit of measurement. The correlation coefficient can be expressed as:

$$\rho_{i,j} = \frac{Cov_{i,j}}{\sigma_i \sigma_j}. \tag{4}$$

3.1.3 The Investor's Utility Function and Risk Preference

One important factor that needs to be taken into account when selecting the optimal portfolio is the investor's degree of risk aversion. Risk-averse investors attribute less value to the expected returns of risky investments to account for the risk involved. The notion of risk-aversion can be formalized by defining an investor's utility function, which consists of the risk/return pairs that define the trade-off between the expected return and the risk. For a portfolio with an expected return, $E(r_i)$, and a standard deviation, σ_i, Bodie, Kane, and Marcus (2005) propose the following utility function:

$$U = E(r) - 0.005\lambda\sigma^2, \tag{5}$$

where U is the utility value and λ is an index of the investor's risk aversion. The factor 0.005 is a scaling convention that allows for the expression of the expected return and the standard deviation as percentages rather than as decimals. From the aforementioned equation, it is evident that the utility of the portfolio increases with high expected returns and diminishes with high levels of risk. The magnitude of these changes depends on λ – the investor's coefficient of risk aversion.

The utility preference depends on the investor's own investment objectives (which range from capital preservation to long-term wealth generation) and, as such, varies widely from one investor to another. Markowitz classifies investors into the three categories. Risk-averse investors only consider risk-free or speculative prospects with positive risk premia. Risk-neutral investors estimate risky prospects exclusively in terms of their expected rates of return. Finally, risk-lovers are investors willing to engage in fair games and gambles. These investors adjust their expected returns upward to reflect the satisfaction of confronting the prospect's risk.

3.1.4 Efficient Portfolios of Two Risky Assets

Markowitz's most important contribution is the notion that one cannot select assets for a portfolio only on the basis of characteristics that are unique to the security. Hence, the biggest challenge when attempting to construct efficient portfolios from two securities is to comprehend the interrelationship between the two securities and whether the assets' returns move in the same or opposite directions. The variance for a two-asset portfolio consisting of equity (E) and debt (D) can be expressed as:

$$\sigma^2{}_{\text{2asset\_portfolio}} := W_D{}^2\sigma_{\text{D}}{}^2 + W_E{}^2\sigma_{\text{E}}{}^2 + 2W_D W_E Cov(r_{E,}\, r_D), \qquad (6)$$

while the standard deviation can be represented by:

$$\sigma_{\text{2asset\_portfolio}} := \sqrt{W_D{}^2\sigma_{\text{D}}{}^2 + W_E{}^2\sigma_{\text{E}}{}^2 + 2W_D W_E Cov(r_{E,}\, r_D)}. \qquad (7)$$

Given that covariance can be computed from correlation coefficients, we can rewrite the formula for variance and covariance in the following manner:

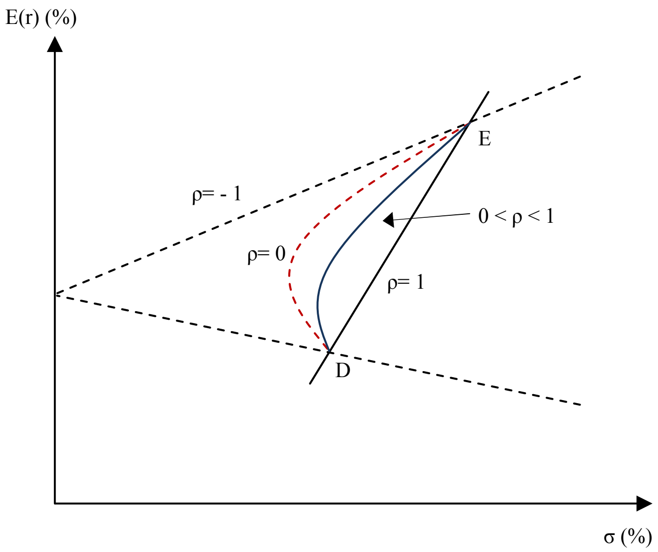
$$\sigma^2{}_{\text{2asset\_portfolio}} := W_D{}^2\sigma_{\text{D}}{}^2 + W_E{}^2\sigma_{\text{E}}{}^2 + 2W_D W_E \rho_{DE}\sigma_D\sigma_{E,} \qquad (8)$$

and

$$\sigma_{\text{p}} := \sqrt{W_D{}^2\sigma_{\text{D}}{}^2 + W_E{}^2\sigma_{\text{E}}{}^2 + 2W_D W_E \rho_{DE}\sigma_D\sigma_E}, \qquad (9)$$

where ρ_{DE} is the correlation between the returns on debt and equity. Figure 3.1 shows the relationship between the standard deviation and the expected return of the portfolio.

Figure 3.1: Portfolio expected return as a function of the standard deviation



Source: Author's own depiction, based on Bodie, Kane, and Marcus (2005)

Figure 3.1 shows that a perfectly positive correlation between two assets (ρ=1) offers no diversification benefits for the portfolio, while the portfolio risk given a negative correlation (ρ= -1), as measured by variance, is equal to zero. Therefore, diversification benefits arise whenever the correlation of two assets in a portfolio is less than 1. The solid curve in Figure 3.1 represents the portfolio opportunity set for 0<ρ<1. It is called the portfolio opportunity set because it shows all combinations of portfolio expected returns and standard deviation that can be constructed from the two available assets. The other lines represent the portfolio opportunity sets for other values of the correlation coefficient.

A similar calculation of portfolio risk methodology applies to the multi-asset portfolio. For a multi-asset portfolio, the standard deviation can be expressed as:

$$\sigma_{\text{multi\_asset}} = \sqrt{\sum_{i=1}^{n}\left(W_i^2 \sigma_i^2\right) + \sum_{i=1}^{n}\left[\sum_{j=1}^{n}\left(W_i W_j Cov_{i,j}\right)\right]}. \; i \neq j \qquad (10)$$

Equation (10) can be rewritten by using Equation (4) as:

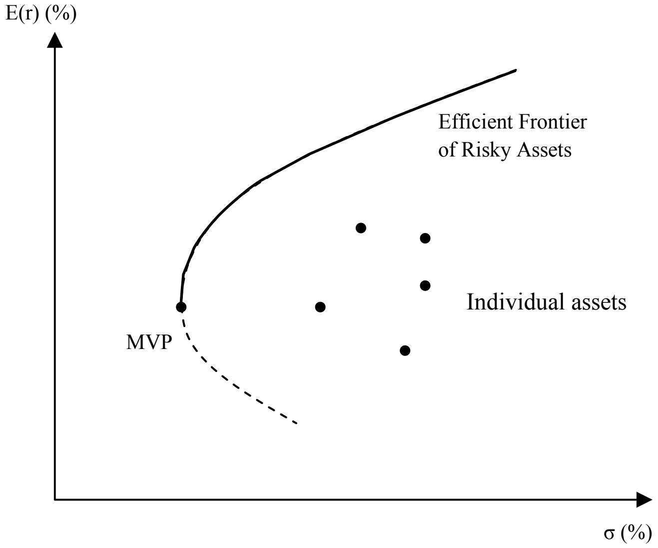
$$\sigma_{\text{multi\_asset}} = \sqrt{\sum_{i=1}^{n}\left(W_{\text{i}}^{2}\sigma_{\text{i}}^{2}\right)+\sum_{i=1}^{n}\left[\sum_{j=1}^{n}\left(W_{\text{i}}W_{\text{j}}\sigma_{\text{i}}\sigma_{\text{j}}\rho_{\text{i,j}}\right)\right]}.\ i \neq j \tag{11}$$

The above equations for the standard deviation of a portfolio show two important things. First, they highlight the importance of diversification and its effects in terms of reducing the total risk of a portfolio. Second, they offer guidance on how to diversify in an effective manner, as they emphasize the correlations among assets as the critical factor that should be considered when constructing portfolios. A combination of assets or portfolios with low correlation coefficients enables an investor to maintain a rate of return while reducing the overall risk of the portfolio. The lower the correlation between the assets, the greater the potential benefit of diversifying the portfolio.

3.1.5 Markowitz's Efficient Frontier

The two-asset portfolio construction problem can be generalized to include many risky securities. Markowitz concluded that no assets are perfectly positively or perfectly negatively correlated. Consequently, the risk in a portfolio composed of various risky assets will be lower than the risk inherent in holding any of the assets individually. Markowitz proposed the concept of the "efficient frontier", which depicts a graphical representation of the risk/return trade-off. The main idea behind the efficient frontier concept is that it displays efficient portfolios, i.e. those portfolios that, for any risk level, achieve the best possible expected level of returns. Alternatively, one can think of the efficient frontier as the set of portfolios that minimize the variance for any targeted expected return. Mathematically, the efficient frontier is the intersection of portfolios with highest maximum returns and the set of minimum variance portfolios. Figure 3.2 presents a graphical representation of the efficient frontier. It depicts the entire investment opportunity set, which can be thought of as the set of all obtainable combinations of risk and return provided by portfolios constructed from two assets in differing proportions.

Figure 3.2: The efficient frontier of risky assets



Source: Author’s own depiction, in reference to Bodie, Kane, and Marcus (2005)

Any portfolio that is positioned beneath the minimum variance portfolio (MVP) point of the curve should be dismissed by investors as being inefficient because for any portfolio on the lower part of the frontier, there is a portfolio with the same risk and higher expected return above it. Furthermore, individual assets lie to the right (inside the frontier), making the portfolios constructed from individual assets inefficient. Therefore, investors will prefer portfolios offering more return and less risk at a given risk level, and they will choose any portfolio that is situated above the minimum variance portfolio (MVP) point on the upward-sloping part of the frontier curve. The solid curve above the MVP point is called the efficient frontier. All of the portfolios that are positioned on the efficient frontier are considered optimal portfolios, as they offer the best risk/return combinations. The decision about exactly which point above the MVP point the investor should choose depends on the investor’s risk preference and utility function.

3.1.6 Capital Allocation Line (CAL)

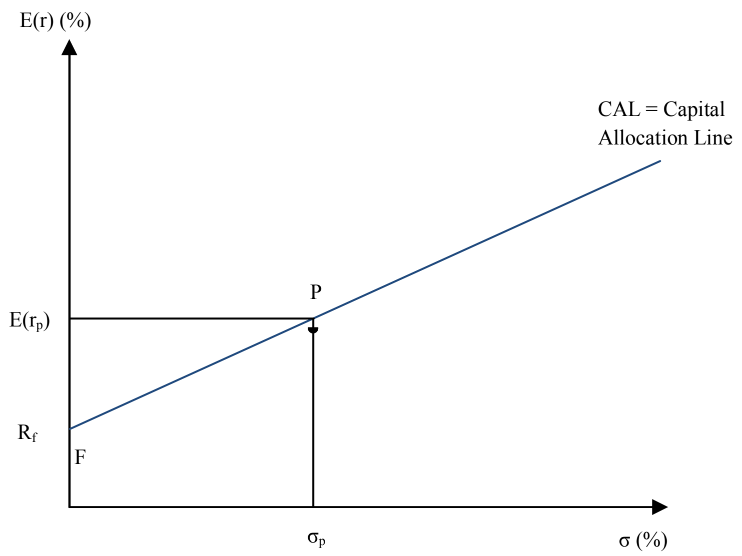
As previously described, the efficient frontier does not account for the existence of a risk-free asset, this sub-section deals with the risk/return combinations available to the investors when a risky asset is combined with a risk-free asset. A risk-free asset has, by definition, zero variance in returns and is uncorrelated with other assets. The expected return of the portfolio, C, constructed from risky asset, r_p, and risk-free asset, r_f, can be expressed as:

$$E(R_C) = r_f + y\left[E(r_p) - r_f\right]. \tag{12}$$

where y represents the proportion of the investment budget allocated to a risky asset. Figure 3.3 plots the portfolio characteristics in the expected return-standard deviation plane. The straight line is called the capital allocation line (CAL) and it shows all of the risk/return combinations available to investors (Bodie, Kane, and Marcus 2005). The formula for the slope of the CAL is:

$$CAL_S = \frac{E(r_p) - r_f}{\sigma_p} \tag{13}$$

Figure 3.3: Capital allocation line (CAL)



Source: Author's own depiction, in reference to Bodie, Kane, and Marcus (2005)

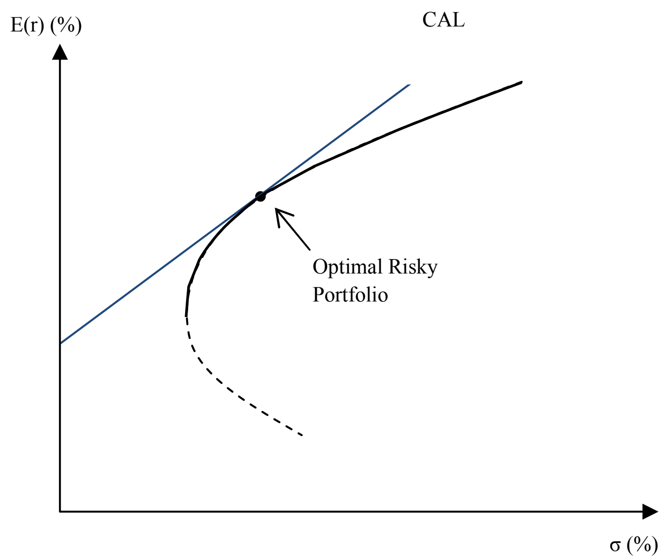
Tobin (1958) shows that Markowitz's framework implies that the investment choice process can be divided into two phases:

1) The selection of an optimal mix of risky assets (same for all investors, as it is independent of individual investors' risk tolerance), and

2) The allocation of capital between the optimal risky portfolio and a single risk-free asset (different for every investor, as it depends on individual risk aversion).

Tobin's separation theorem essentially demonstrates that by combining a risk-free asset with a portfolio located on the efficient frontier, one can obtain a portfolio with risk-return characteristics that are superior to those of portfolios on the efficient frontier. According to Tobin (1958), investors should hold only two portfolios: an efficient risky portfolio and a riskless asset. The crucial point here is that the optimal portfolio or risky set of assets, P, is the same for all clients. The construction of the risky portfolio, P, is independent of investors' differing degrees of risk aversion and preferences, and depends only on the expected returns and covariances of returns among risky assets. Hence, all investors should be satisfied with a universe of only two portfolios: a risk-free portfolio and an optimal risky portfolio, P, located on the tangency point of the CAL and the efficient frontier, as shown in Figure 3.4.

Figure 3.4: Determination of the optimal portfolio



Source: Author's own depiction, in reference to Bodie, Kane, and Marcus (2005)

3.2 Capital Asset Pricing Model (CAPM)

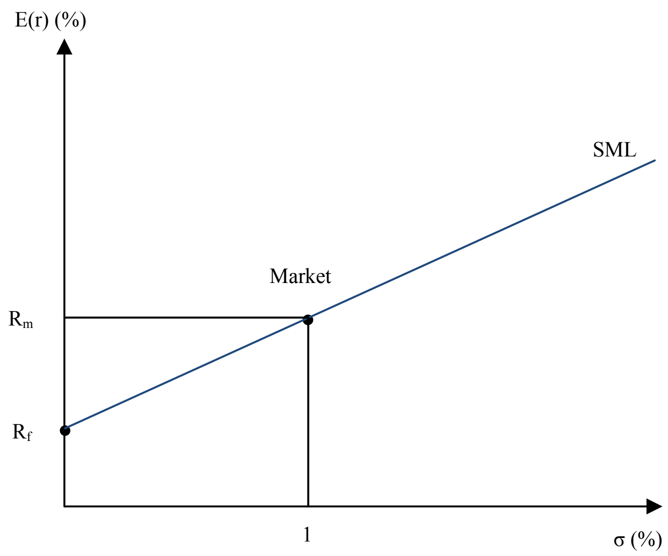
After Markowitz laid the foundations for portfolio theory in the early 1950s, several other authors built on his work and improved it further. Tobin (1958) was the first to use the theory for a positive capital markets model. However, the implementation of Markowitz's and Tobin's portfolio selection models required the inversion of the covariance matrix of returns among all pairs of available securities. At the time, when computer power was limited, doing so was considered an almost impossible task. In 1964, Sharpe introduced a capital asset pricing model (CAPM) that materially simplified the computational procedure needed to undertake a portfolio analysis. As most modern performance evaluation models are rooted in CAPM, it is important to comprehend the intuition behind the model as well as its main assumptions, conclusions, and implications with regard to performance measurement models.

As the centerpiece of modern financial economics, CAPM is a set of predictions concerning the relationship between risk and expected returns on risky assets. One of the cornerstones of CAPM is the proposition that the volatility of an asset can be split into two parts: systematic risk and idiosyncratic risk. While systematic risk is part of the general market risk and cannot be eliminated through diversification, idiosyncratic risk is specific to each asset or security, and can be eliminated through diversification. Furthermore, CAPM assumes that risk-averse investors do not want to expose themselves to a risk that can be eliminated through diversification. Sharpe demonstrated that if all investors follow Markowitz's mean-variance method, the expected return on a given risky asset will be equal to the risk-free interest rate and a risk premium, which in turn depends linearly on the market risk exposure (i.e., the beta of the security) and the market risk premium (i.e., the return above the risk-free rate). Hence, the expected return on a risky asset is given by:

$$E(R_P) = R_f + \beta_P\left[E(R_M) - R_f\right], \tag{14}$$

where $E(R_P)$ is the expected rate of return on portfolio P, R_f is the return on the risk-free asset, $E(R_M)$ is the expected rate of return on the market portfolio, M, and β_P is the systematic risk of the portfolio. The CAPM is a single-risk-factor model used for determining theoretically appropriate asset returns. The term $\left[E(R_M) - R_f\right]$ is called the market risk premium. All else equal, high-beta assets should produce higher expected returns relative to the market, while low-beta assets should produce lower expected returns relative to the market. Sharpe (1964) made a simplifying assumption that the return on a risky asset could be regarded as being linearly related to certain index, hence removing the need to observe any direct relationships between risky assets. Graphically, CAPM implies that all fairly priced securities and portfolios should lie along the security market line (SML). The intercept of the SML is the risk-free rate, while the slope is determined by the market risk premium.

Figure 3.5: The security market line (SML)



Source: Author's own depiction, in reference to Bodie, Kane, and Marcus (2005)

3.3 The Market Model

CAPM is a theoretical, economic equilibrium model that provides a framework for predictions about the expected relationship between risk and return. In theory, it should only be used as an ex ante predictive model. However, when measuring the performance of a certain investment vehicle, one needs to assess the historical data. Hence, in the context of performance analysis, an ex ante model must be transformed into an ex post testable model (Lhabitant, 2004). The ex post model usually takes the form of a times-series regression of excess returns of individual assets on the excess returns of some market index. The model is called the market model and can be written as:

$$R_{\mathrm{i}} = \alpha_{\mathrm{i}} + R_{\mathrm{f}} + \beta_i (R_{\mathrm{m}} - R_{\mathrm{f}}) + \varepsilon_i, \tag{15}$$

where R_{i} and R_{f} are the realized returns on portfolio *i* and the market index, respectively; α_{i}, is the firm-specific return; and ε_i is the unexplained firm-specific return. Assuming that CAPM holds and that the markets are efficient, α_{i} should not be statistically different from zero and ε_i should have a mean of zero. The coefficients α_{i} and β_i are the intercept and the slope of the regression line, respectively.

4. Research Design

4.1 Introduction

According to (Kerlinger and Lee, 1964), a research design is:

… the plan and structure of investigation so conceived as to obtain answers to research questions. The plan is overall scheme or program of the research. It includes an outline of what the investigator will do from writing hypotheses and their operational implications to the final analysis of data. A structure is the framework, organization, or configuration of… the relations among variables of a study. A research design expresses both the structure of the research problem and the plan of investigation used to obtain empirical evidence on relations of the problem.

Black (1999) describes research design as an integrative collection of the following elements: statement of the research questions, determination of hypothesizes (derived from prior observations and existing theories), definition and operationalization of manifest and latent variables, selection of statistical techniques to test hypothesizes, identification of population and sample, data collection, data analysis and interpretation of the results and finally, the overall evaluation of the process.

This chapter presents the outline of the research plan, starting with an overview of the different types of studies and research methods. The three statistical techniques (multivariate linear regression, probit regression model and semi-parametrical Cox proportional hazards model) as well as the data used in this dissertation are described in more details in the following chapters (five, six and seven respectively). Finally, in the last section of this chapter, the author describes the logic behind the research process applied in this dissertation.

4.2 Types of Studies

In this dissertation, the author aims to use scientific research methodologies to achieve the main objectives of the research. According to Black (1999), the term “scientific” refers to a systematic, empirically based, and replicable approach that contributes to the process of theory development. However, as McGrath, (1982) points out, it is impossible to undertake a flawless study, as all research methods are inherently flawed. Researchers must therefore adopt the least-flawed, most appropriate option. Cooper and Schindler (2002) classify the different types of studies in the following way:

- A *reporting study* is conducted when the main goal of the research is to provide a fundamental understanding of the problem by providing a summation of data or by generating statistics.
- A *descriptive study* is used when the researcher attempts to describe or define a subject. Descriptive studies try to answer questions such as “Who?”, “What?”, “Where?”, or “How many?”.
- An *explanatory study* is used when a deeper understanding of a subject is required. These studies go beyond description and attempt to explain the reasons for a phenomenon that a descriptive study would only observe. Explanatory studies try to describe causal relations between different concepts and answer the questions “Why?” and “How?”
- A *normative study* is used when a researcher wishes to find means of improving the object of study and to suggest improvements.

Academic research on hedge funds and their performance in the context of the 2007-2010 financial crisis is scarce. Moreover, considering the growth and importance of Asia in the global financial markets, there are disproportionally few academic studies on Asia-focused hedge funds. As a body of knowledge on hedge funds and, to a certain extent, on Asia-focused hedge funds already exists, this study uses a combination of explanatory and normative studies.

4.3 Qualitative vs. Quantitative Methods

Research methodologies can be either qualitative or quantitative. These two types of research methods are genuinely different and are not limited by the nature of the data.

Qualitative empirical research methods have a long tradition dating back to Aristotelian epistemology (Lhabitant, 2004). They are subjective in nature and are used when the intent of the study is to gain a deeper knowledge of a specific domain, usually without any claim to universality. Strauss and Corbin (1990) define qualitative research methods as: “… any kind of research that produce findings not arrived at by means of statistical procedures or other means of quantification.” Qualitative empirical methods often use non-structured, unsystematic observations, such as in-depth interviews, focus groups, and participant observation. The strength of qualitative research lies in its ability to provide complex textual descriptions of the problem under consideration. In the context of hedge fund research, qualitative analysis is interested in topics such as: “Who are hedge fund managers?”, “What is their background, experience, and level of education?”, “Do they use leverage?”, What strategies does a hedge fund follow?”, “Has the fund radically changed exposure recently?”, and “Does the fund use options to hedge?”.

Quantitative research, on the other hand, is centered on deductive reasoning and used when researchers want to look for law-like relationships among certain phenomena of interest by means of quantification and accurate measurement. Quantitative methods, such as statistical analyses of experimental, survey, or archival data, intend to reveal common patterns that either characterize a population or a sample thereof on a large-scale basis (Bentz and Shapiro, 1998).

Quantitative research is based on the collection of a considerable amount of data from representative samples for a few variables, while qualitative research tends to pursue fewer subjects but investigates them in greater depth (Black, 1999). Quantitative methods are well suited to identifying overall patterns, testing theories, and developing predictions. In the context of hedge funds, quantitative research methods might focus on hedge fund performance analysis, investment style analysis, hedge fund portfolio optimization, or extreme risk analysis.

The types of analyses performed in this dissertation – a multi-factor performance analysis, a probit regression analysis that examines the factors that might contribute to hedge fund demise and portfolio optimization with Asia-focused hedge funds – all rely on the numerical evaluation of hedge fund returns. Therefore, this dissertation uses quantitative research methodologies.

4.4 Validity and reliability

4.4.1 Validity

A rigorous research methodology requires that the approach to research questions be reliable and valid. In this context, “validity” refers to the logic of the inferences drawn from a study. According to Cook and Campbell (1976), validity is the extent to which the results of the study can be attributed to the predictor variables rather than to systematic or non-random errors. Validity is a multifaceted concept that consists of three features: internal validity, external validity, and construct validity. Internal validity concerns causality and, as Sackett and Larsson (1990) note, a cause-and-effect relationship can only be asserted if there is true covariation between the variables under investigation, if the cause can be shown to precede the effect, and if alternative explanations can be discarded. External validity refers to generalizing across times, settings, and individuals (Cook and Campbell, 1976; Sackett and Larsson, 1990), and is similar to the common idea of generalizability.

Finally, construct validity concerns how well the measures employed fit the theories for which a test is designed (Scandura and Williams, 2000). Although numerous models for the measurement of hedge fund performance are proposed in the literature, this dissertation adopts Fung and Hsieh's (2004), Teo's (2009) adjusted, and a model that selects the relevant risk factors for each strategy based on the stepwise regression approach. Fung and Hsieh's (2004) and adjusted Teo's (2009) multi-factor models are well accepted in the hedge fund literature. Furthermore, the probit regression model and the semi-parametric Cox proportional hazards model have previously been used in the context of hedge fund survival analysis. Hence, the issue of validity should be minimal in this context. As Neuman (2000) writes, accurate validity is more important in an academic study than reliability; a study that is reliable but does not measure what it is meant to measure is inherently flawed.

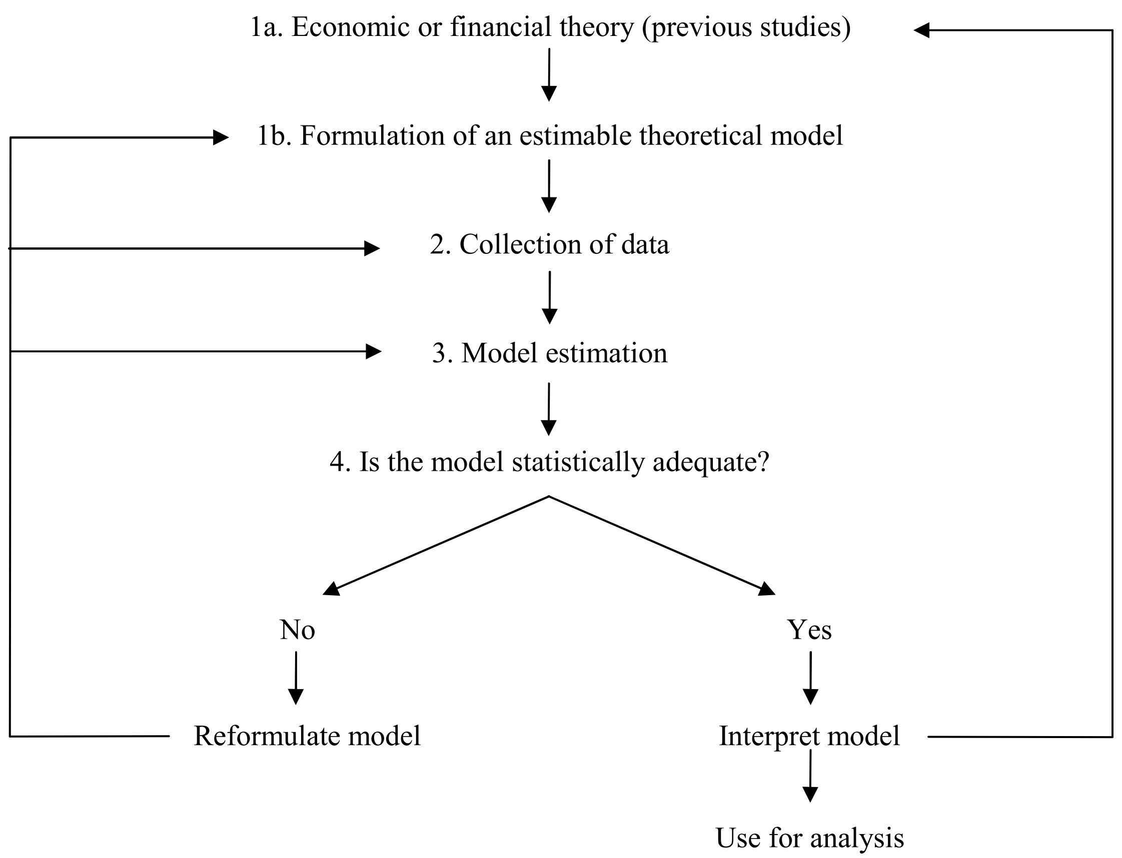
4.4.2 Reliability

Reliability refers to the accuracy and precision of the measurements in question, and it is an indication of the consistency of a study. In other words, it is concerned with estimates of the degree to which a measurement is free of random or unsystematic error. High reliability implies that another study performed under identical or similar conditions to the first would give the same results (Neuman, 2000). In order for a study to be reliable, it is necessary to choose accurate research objectives when measuring. In this dissertation, the author uses the performance data of hedge funds provided by the hedge fund database vendor Eurekahedge. The fact that a single database provider is used might affect the reliability of this study. Ideally, the author would have access to several database providers which cover most of the Asia-pacific hedge fund universe.

4.5 Research Process

The research process applied in this thesis is described in Figure 4.1. The author begins by formulating the research gap and the subsequent research questions. However, this is only possible after a thorough literature review has been completed. The next step in the research process is to collect the data relevant to the study. Data can be primary (such as survey or interview data collected by the researcher) or secondary (data collected by someone other than the researcher). In the third step, the author specifies the estimation method that is relevant to the research question raised in the first step. The fourth step involves the statistical evaluation of the model. When deciding on the adequacy of particular statistical method for the purpose of my research, I consult previous academic studies on similar topics. If the researcher is satisfied with the statistical adequacy of the model, it can then be used to test the theory proposed in step 1.

Figure 4.1: Research process



Source: Author’s own depiction, based on Brooks (2008)

5. Investigating the Risk-adjusted Performance of Asia-focused Hedge Funds

5.1 Introduction

The objective of this chapter is to assess the performance of Asia-focused hedge funds by investigating hedge fund alphas using three different multi-factor models. The results are in line with findings presented in extant research, as I am able to identify positive and significant alphas for Asian hedge funds over the full sample period under investigation. However, during the financial crisis of 2007-2010, Asia-focused hedge funds did not produce significant alphas on average. Previous research on the performance of hedge funds has shown that, on average, hedge funds outperform passive benchmark indices (e.g., Fung and Hsieh, 2004; Hasanhodzic and Lo, 2007; Kosowski et al., 2007; Titman and Tiu, 2008).

Over the past two decades, the amount of money invested in hedge funds has increased substantially.[4] As a result, hedge fund alphas have decreased (Fung et al. 2008; Zhong 2008). With new money being allocated to the ever increasing number of hedge funds, some fear that opportunities to earn risk-adjusted returns in the market are vanishing. This, in turn, might force hedge fund managers to diversify away from their core strategies into strategies where their skills and experience might not be applicable. Several recent academic studies corroborate this conclusion. Using a merged dataset from the TASS, HFR, and CISDM hedge fund databases, Fung et al. (2008) found that the average fund of hedge funds delivered alpha only between October 1998 and March 2000, and that the alpha declined significantly from April 2000 to December 2004. The authors conclude that their results were consistent with the assumptions of the Berk and Green's (2004) rational model of active portfolio management, which states that significant differences exist in the ability of mutual funds to generate alpha, that these funds face diminishing returns to scale in deploying their funds, and that investors are rational, i.e., they direct capital towards funds that generate alpha. Provided that these assumptions are satisfied, equilibrium in the Berk and Green (2004) model implies that the alpha available to investors is zero. Furthermore, Fung et al. (2008) showed that funds that deliver alpha receive greater inflows than funds that do not. Naik et al. (2007) found that hedge funds produced alpha only during the bull market period between October 1998 and March 2000, while the alpha decreased

[4] According to the *TASS Asset Flow Report*, hedge fund assets increased from approximately USD 50bn in 1994 to USD 1,430bn at the end of September 2010.

significantly from April 2000 to December 2004. Furthermore, they find that for four out of their eight hedge fund strategies, capital inflows preceded negative movements in alpha. Similarly, Zhong (2008) studied the distribution of individual hedge fund alphas and found a decrease in average hedge fund alpha, which he attributed to the capacity constraint hypothesis. The author also found that the number of funds generating positive alpha had fallen from January 1994 to December 2005.

In the existing hedge fund literature, most studies focus on funds operating in the developed financial markets of the US or Europe. Little research centers on hedge funds operating in Asia or, more generally, in emerging markets. This is mainly due to a lack of data. To the best of the author's knowledge, only three studies have examined hedge funds investing in Asia and none of these focuses specifically on alpha creation among Asia-focused hedge funds. Koh, Koh, and Teo (2003) use a high-resolution hedge fund dataset covering the period from 1999 to 2003 to analyze the return persistence properties, styles, and fund characteristics of Asian hedge funds. They extract seven common risk factors in Asian hedge funds using principal component analysis and find that these seven components explain around 64% of the variation in returns. They also find that Asian funds largely co-move with a common Asian equity markets component. Hakamada, Takahashi, and Yamamoto (2007) study portfolio optimization and undertake a factor analysis of Asia-Pacific hedge funds. They find that the returns of hedge funds investing in "Asia excluding Japan" can be explained by linear factor models without any non-linear factors. Finally, Teo (2009) examines the relationship between the risk-adjusted performance of Asia-focused hedge funds and their proximity to investments. The author uses an augmented version of Fung and Hsieh's (2004b) multi-factor model to obtain an indication of risk-adjusted performance. This study concludes that, in the context of the augmented Fung and Hsieh (2004b) multi-factor model, the hedge funds with a physical presence in their investment region outperform other hedge funds by 3.72% per year. Furthermore, authors find that Asia-focused hedge funds created positive alpha from January 2000 to December 2006.

If we move outside the domain of Asia-focused hedge funds into the wider sphere of emerging market hedge funds, the academic literature remains scarce. Fung and Hsieh (1997) and Capocci and Huebner (2004) examine the performance of hedge funds focusing on emerging markets as one of the many possible hedge fund strategies. However, few studies concentrate specifically on emerging market hedge funds. Sancetta and Satchell (2005) examine a sample of 15 emerging market hedge funds over a period of 60 months.

The authors apply a nonparametric statistical technique to the study of the market timing component in performance measurement using a sample of emerging market hedge funds. Strömqvist (2007) analyzes the risk-adjusted performance and capital flows of emerging market hedge funds from the investors' point of view using a data sample covering the period from 1994 until 2004. She finds that emerging market hedge funds generate alpha only in the last sub-period under investigation (2000 to 2004). In another study, Abugri and Dutta (2009) investigate whether emerging market hedge funds follow a pattern similar to that reported for advanced-market hedge funds after 2006. The authors use a modified version of Sharpe's (1992) style regression to obtain risk-adjusted returns. They find that, on a risk-adjusted basis, emerging market hedge funds do not consistently outperform the benchmarks. Finally, Eling and Faust (2010) investigate the value added of emerging market hedge funds. Using a multi-factor model developed specifically for emerging market hedge funds, the authors measure fund performance between January 1995 and August 2008. They find that emerging market hedge funds delivered positive alpha from 2000 to 2008.

This chapter analyzes the performance and alpha creation of Asia-focused hedge funds from January 2000 to December 2010. This is a particularly interesting time span, as it encompasses two periods with significantly different market environments. The first part of the data sample covers the bullish period from 2000 until the first half of 2007, whereas the second part encompasses the global financial crisis from the second half of 2007 to 2010. Hedge funds are viewed as absolute return investment vehicles, implying that they should produce risk-adjusted returns (alphas) regardless of whether the markets rise or decline. Hence, the relevance of this study is increased by the fact that the data set encompasses both bullish and bearish market environments.

The remainder of the chapter is structured as follows. The author begins by describing the theoretical framework of this thesis. Topics like modern portfolio theory and the capital asset pricing model are discussed. The second part of this chapter examines extant academic literature on performance measurement models, firstly in the context of stock markets and secondly in the context of hedge funds. The author then describes the methodology and data set, and then presents the results. This chapter concludes with a discussion of the results.

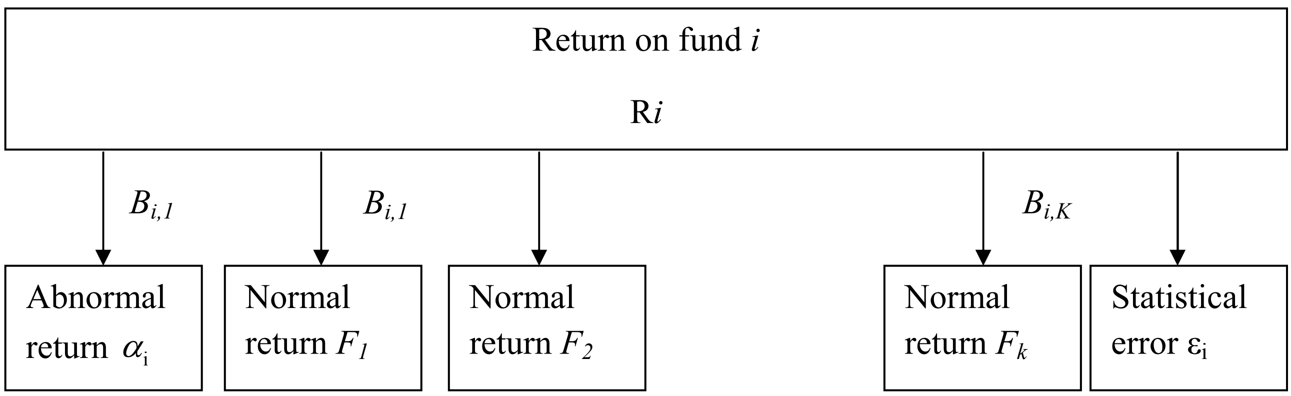
5.2 Literature Review

5.2.1 Hedge Fund Performance Measurement Models

Hedge funds managers make alpha and beta bets in order to generate returns. Beta can be interpreted as the exposure of the fund to various market-based factors, while alpha is usually interpreted as the proportion of the return that is not explained by market-based factors. In the academic literature, the latter is typically viewed as a reflection of a manager's skill. As hedge funds as a group are perceived and marketed as absolute-return investment vehicles, i.e., alpha generators, and as they charge substantially higher fees than traditional fund managers, it is of the utmost importance to determine whether they really deliver alpha or whether their returns can be explained by factor loadings on beta.

Research conducted on the sources of hedge fund returns can be broadly divided into two categories. The first category investigates the impact of microeconomic factors (firm-specific characteristics, such as fund age, size, fees, and lock-up periods) on the performance of hedge funds. The second category focuses on the impact of macroeconomic factors (exposure to various asset classes) on fund performance. In this context, one can think of hedge fund returns as a function of carefully selected macroeconomic and microeconomic factors (Lhabitant, 2004).

Figure 5.1: The sources of return on a risky asset in a multi-factor model



Source: Author's own depiction, based on Lhabitant (2004)

A linear multi-factor model allows one to abstract from the influence of the market factors on hedge fund returns and focus specifically on the risk-adjusted performance of hedge funds, i.e., the alpha. Unlike mutual funds, which apply a single strategy (long only) to a limited number of assets (equities or bonds), hedge funds are exposed to a variety of asset classes and employ dynamic strategies that often include the use of short sales, leverage, and derivatives. More specifically, hedge fund returns can be described in terms of three key determinants: the returns from assets in the managers' portfolio (location component), the trading strategies (strategy component), and the use of leverage (quantity component). Therefore, multi-factor models must be extended to accommodate the specific characteristics of alternative investments.

Fung and Hsieh (1997) extend Sharpe's (1992) model for analyzing mutual funds' investment management styles (relative-return target) to incorporate hedge fund managers with absolute return targets. Sharpe's (1992) original model focused mostly on the key determinant of mutual fund returns – location. Fung and Hsieh (1997) extend Sharpe's model by incorporating the other two key determinants of fund returns – the strategy component and the quantity component. To do so, they use principal component analysis to determine the dominant styles in hedge funds. The idea behind factor analysis is the following: if two managers use similar location choices and trading strategies, their returns should be correlated. PCA analysis can extract the dominant common styles, regardless of whether they are correlated with the asset classes. Fung and Hsieh (1997) apply a Sharpe's style asset class model to analyze 409 hedge funds as a single group. They find five dominant investment styles in hedge funds: System/Opportunistic, Global/Macro, Value, System/Trend Following, and Distressed. They also find that hedge funds generate returns that have a low correlation to the returns of standard asset classes, unlike mutual funds. These five components explain approximately 43% of the cross-sectional return variance. Fung and Hsieh (1997) also perform multi-factor regression of hedge fund returns on the eight standard asset classes: three equity classes (MSCI US equities (MSCIUS), MSCI Non-US equities (MSCIexUS), IFC Emerging Markets equities (IFCEM), two fixed income indices (JP Morgan US Government Bonds (JPMUSB); JP Morgan Non-US Government Bonds (JPMNONUS)), gold (GLD; London morning fixing), the one-month Eurodollar Deposit Return of the previous month (EURUSD) and currencies (Federal Reserve Trade-Weighted Index of the US Dollar (USD)):

$$\begin{aligned} R_{\mathrm{it}} - R_{\mathrm{ft}} = \alpha_{\mathrm{i}} &+ \beta_{iMSCIUS} MSCIUS_t + \beta_{iMSCIexUS} MSCIexUS_t + \beta_{iIFCEM} IFCEM_t \\ &+ \beta_{iJPMUSB} JPMUSB_t + \beta_{iJPMNONUS} JPMNONUS_t + \beta_{iUSD} USD_t \\ &+ \beta_{iEURUSD} EURUSD_{t-1} + \beta_{iGLD} GLD_t + \varepsilon_{it}. \end{aligned} \tag{16}$$

Schneeweis and Spurgin (1998) use the LaPorte database covering the period from 1990 until 1995 to examine the performance of commodity trading advisors (CTAs), hedge funds and mutual funds. In order to better capture the return characteristics of hedge funds, the authors propose a common set of factors that account for the possibilities of trending prices, short sales, and volatility. They apply a multi-factor model whereby they use CTA, hedge fund and mutual fund returns as the explanatory variables, and the nominal values, absolute values, and intermonth standard deviations of various indices as independent variables. According to the authors, that these common factors might explain the differences in returns as well as some differences within each investment type.

Agarwal and Naik (2000b) use the HFR database to analyze the style of various hedge fund strategies. They relax the constraints of the conventional style analysis – namely, that the style weights have to add up to one hundred percent - and conduct a generalized style analysis. Agarwal and Naik (2000b) emphasize that the problem with conventional style analysis is that it does not distinguish significant style weights from insignificant style weights. Therefore, the authors estimate a stepwise regression in which they drop indexes with insignificant style weights. They then reiterate the procedure until they are left only with indices with significant style weights. They conclude that the generalized style analysis procedure is more robust for estimating the risk exposure of the hedge funds that take short positions in various asset classes and occasionally hold a considerable portion of their portfolio in cash. Furthermore, the authors show that hedge fund strategies claiming to be non-directional are not truly market neutral, although these hedge funds gain less when the market improves and they lose less when the market falls. At the same time, Agarwal and Naik (2000b) find that directional strategies perform significantly better than non-directional strategies during market upturns and significantly worse during market downturns, with the exception of the short strategy, which moves in a direction opposite to that of the market.

Brown and Goetzmann (2003) adopt a systematic quantitative approach that utilizes both the return history and the self-reported style information to analyze and categorize the major hedge fund styles. The authors study monthly returns of hedge funds over the period 1989-

1999 using the TASS database. They utilize Sharpe's style regression to break observed returns down into those attributable to style and those attributable to skill. The authors then implement the generalized least square technique to classify funds into style categories. Brown and Goetzmann (2003) find at least eight distinct hedge fund styles. According to the authors, hedge fund risk exposure depends, to a large extent, on the style category. Furthermore, they find that about 20% of the cross-sectional variability in hedge fund returns can be explained by differences in investment styles.

5.2.2 Non-Linear Characteristics of Hedge Fund Risk and Return

Several recent studies have found that the relationship between hedge fund returns and market returns is nonlinear. Therefore, the standard linear multi-factor performance measurement model is often unable to account for the dynamic trading strategies that many hedge fund managers execute in the various markets and asset classes (see Fung and Hsieh, 2001; Mitchell and Pulvino, 2001; Capocci and Huebner, 2004; Agarwal and Naik, 2004). Fung and Hsieh (2001) acknowledge that linear-factor models using benchmark asset indices have difficulty explaining hedge fund returns. They focus on a popular strategy commonly referred to as "trend following." In their earlier work (1997), Fung and Hsieh found that the trend-following strategy exhibited option-like features – the returns associated with these strategies tended to be large and positive during the best and worst performing months on the world equity markets. Therefore, Fung and Hsieh use look-back straddles[5] to model trend-following strategies. The authors find that look-back strategies are able to explain the returns of trend-following funds better than standard asset indices. On the basis of nearly four more years of data, Fung and Hsieh (2002) provide an out-of-sample validation of their 2001 model. The authors document that their model correctly predicts the return behavior of trend-following hedge fund strategies during out-of-sample periods, especially during stressful market conditions, such as those seen in September 2001.

In a similar way, Fung and Hsieh (2002b) study the risk in fixed-income hedge fund styles. They apply a principal component analysis to groups of fixed-income hedge funds in order to extract common sources of risk and return. They then relate these common sources of risk to market risk factors, such as changes in interest rate spreads and options on interest rate

[5] The owner of a look-back call option has the right to buy the underlying asset at the lowest price over the life of the option. Similarly, a look-back put option allows the owner to sell the asset at the highest price. The combination of the two options is a look-back straddle.

spreads. The innovation in this article is authors' attempt to model convergence trading using options. A typical convergence trading strategy is to bet that the price difference between two assets with similar, but not identical, characteristics will converge over time. The strategy usually involves buying the cheaper asset and selling the more expensive asset. The opposite of the convergence trading strategy is the trend-following strategy, which attempts to take advantage of large price movements (up or down). As Fung and Hsieh (2002b) note, assuming that the identical sets of key prices are used, the trend-following trader and the convergence trader will make similar entry and exit decisions but in exact opposite directions. In their earlier work, Fung and Hsieh (2001) model trend-following strategies as a long position in a look-back straddle. Considering that convergence trading is the opposite of a trend-following strategy, Fung and Hsieh (2002b) model convergence trading as a short position in a look-back straddle.

Mitchell and Pulvino (2001) use a sample of almost 5,000 transactions announced from 1963 until 1998 to model the returns of merger arbitrage funds. Their results demonstrate that risk arbitrage returns have large positive correlations in falling equity market conditions but zero correlation in appreciating equity market conditions. The authors conclude that risk arbitrage is comparable to writing uncovered put options. They rely on a contingent claims analysis that incorporates the non-linearity in returns, as such an analysis provides a more accurate description of the risk/return relationship for risk arbitrage hedge funds. After controlling for both the non-linear return profile and transaction costs, the authors find that risk arbitrage generated excess returns of 4% per year.

Agarwal, Fung, Loon, and Naik (2005) use data on Japanese and US convertible bonds and underlying stocks to analyze the risk-return characteristics of convertible arbitrage hedge funds. In theory, convertible arbitrage is a market-neutral strategy that involves the simultaneous purchase of convertible securities and the hedging of equity risk by selling the underlying stock short. The authors hypothesize that there are three primitive trading strategies which explain convertible arbitrage hedge funds' returns: positive carry, volatility arbitrage, and credit arbitrage. Their results show that these factors can explain significant portions of the return variation in four popular convertible arbitrage indices.

Agarwal and Naik (2004) characterize the systematic risk exposure of equity-oriented hedge fund strategies by using buy-and-hold and option-based strategies. They find that the non-linear, option-like payoffs are not restricted to trend followers and risk arbitrageurs. They are also an integral part of wider equity-oriented hedge fund strategies. Their results show that the payoffs on a large number of equity-oriented hedge fund strategies resemble those of writing a put option on an equity index. The authors propose a two-step approach to characterizing hedge fund risks. In the first step, they suggest estimating the risk exposure of hedge funds using a multi-factor model composed of excess returns on standard asset classes and options written on those assets as risk factors. In the second step, they suggest investigating the ability of these risk factors to replicate the out-of-sample performance of hedge funds. This analysis substantiates the conclusion that the risk factors chosen in the first step represent the underlying economic risk exposures of hedge funds.

Fung and Hsieh (2004b) investigate the risk and return characteristics of equity long/short hedge funds. They find that the equity long/short hedge funds are exposed to the stock market and to the spread between returns on large-capitalization equities and small-capitalization equities.

In their seminal paper, Fung and Hsieh (2004a) build on previous work on the asset-based style (ABS) to propose a multi-factor model for measuring hedge fund returns. Their model is similar to models based on arbitrage pricing theory and it encompasses dynamic risk-factor coefficients. They find seven ABS factors that explain up to 80% of monthly return variations in global hedge fund portfolio returns (as proxied by indices of hedge funds and funds of hedge funds). To develop ABS factors, the authors use principal component analysis to extract common sources of risk from subgroups of hedge funds classified by database vendors as having similar styles. They subsequently link these common sources of risk to observable market prices. The authors conclude that because the ABS factors are directly observable from market prices, this model provides a standardized framework for analyzing hedge fund performance.

The authors use two equity-focused risk factors – an equity market factor (the S&P 500 index excess returns (SNPMRF)) and a factor that proxies for 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). However, as the Wilshire indices stopped reporting in December 2006, as a size proxy I use the Russell 2000 index minus the S&P 500 index (SCMLC) as a size proxy, as suggested by David Hsieh[6]. Moreover, the authors use two fixed income ABS factors and three trend following factors. The two fixed income factors are the monthly change in the 10-year Treasury constant

[6] The original seven-factor model presented in Fung and Hsieh (2001, 2004) contains Wilshire indices, which ceased publication in December 2006. On his webpage, David Hsieh recommends using the Russell 2000 index instead

maturity yields (BD10RET)7 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. Fung and Hsieh (2004b) claim that credit spread is significant, as hedge funds often finance their operations through lending, typically in the form of 10-year treasuries. Furthermore, Fung and Hsieh (2004b) argue that hedge funds often invest in corporate bonds and that any change in credit risk premiums (BAA yield) affects hedge funds. The three so-called "primitive trend-following factors" (PTFS) are based on the previously mentioned Fung and Hsieh (2001) paper and are the following: the Bond Trend-Following Factor (PTFSBD), the Currency Trend-Following Factor (PTFSFX), and the Commodity Trend-Following Factor (PTFSCOM):[8]

$$\begin{aligned} R_{\mathrm{it}} - R_{\mathrm{ft}} = \alpha_{\mathrm{i}} &+ \beta_{iSNPMRF} SNPMRF_t + \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t \\ &+ \beta_{iBAAMTSY} BAAMTSY_t + \beta_{iPTFSBD} PTFSBD_t + \beta_{iPTFSFX} PTFSFX_t \\ &+ \beta_{iPTFSCOM} PTFSCOM_t + \varepsilon_{it}. \end{aligned} \tag{17}$$

The Fung and Hsieh (2004a) seven-factor model for hedge fund performance is the most widely used model of this type in the academic literature. Some examples of recent studies using this model include Kosowski et al. (2007), Naik et al. (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Titman and Tiu (2008), Sun, Wang, and Zheng (2009), Ammann, Huber, and Schmid (2009, 2010a, 2010b), and Eling and Faust (2010).

5.2.3 Multi-factor Performance Model for Asia-Focused Hedge Funds and Emerging Market Hedge Funds

Teo (2009) augments Fung and Hsieh's seven-factor model (2004a) with additional factors: the excess returns on the MSCI All Countries Asia excluding Japan equity market index and the excess return on the Nikkei 225 Japan equity market index. Furthermore, he adds two option-based factors to account for the fact that the payoffs of many hedge funds resemble those from writing naked out-of-the-money put options. For the purpose of this analysis, I

[7] Data on the Treasury yields and BAA corporate bond yields were obtained from the Federal Reserve website at http://www.federalreserve.gov/.

[8] Monthly return data on the PTFS factors can be obtained from the website of David Hsieh: http://faculty.fuqua.duke.edu/~dah7/HFData.htm

adjust Teo’s (2009) model by removing the two option-based equity factors, which, according to Teo's (2009) analysis, do not explain much of the variation in Asia-focused hedge funds’ returns. Teo (2009) states that this could be due to the underdeveloped nature of investment markets in Asia. His adjusted model is given by:

$$\begin{aligned} R_{\mathrm{it}} - R_{\mathrm{ft}} = \alpha_{\mathrm{i}} &+ \beta_{iSNPMRF} SNPMRF_t + \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t \\ &+ \beta_{iBAAMTSY} BAAMTSY_t + \beta_{iPTFSBD} PTFSBD_t + \beta_{iPTFSFX} PTFSFX_t \\ &+ \beta_{iPTFSCOM} PTFSCOM_t + \beta_{ASIAMRF} ASIAMRF_t + \beta_{JAPMRF} JAPMRF + \varepsilon_{it}. \end{aligned} \tag{18}$$

Abugri and Dutta (2009) examine the performance of hedge funds focusing on emerging markets in order to investigate whether these hedge funds follow a pattern similar to those found for advanced market hedge funds. In the scope of their analysis, they also analyze the performance of Asia-focused hedge funds using the following multi-factor model:

$$\begin{aligned} R_{\mathrm{it}} - R_{\mathrm{ft}} = \alpha_{\mathrm{i}} &+ \beta_{iMSCIAsia} MSCIAsia_t + \beta_{iMSCIEM} MSCIEM_t \\ &+ \beta_{iMSCINonUS} MSCINonUS + \beta_{iBCLMNEmBnd} BCLMNEmBnd_t \\ &+ \beta_{iEuURUSDindx} EURUSDindx_t + \beta_{iGold} Gold_t + \beta_{iJPMTrWindx} JPMTrWindx_t, \end{aligned} \tag{19}$$

where MSCI Asia is the return on the MSCI Asia Equities Index, MSCIEM is the return on the MSCI Emerging Market Equities Index, MSCINonUSE is the return on the MSCI Non-US Equities Index, BCLMNmBnd is the return on the Barclays-Lehman Emerging Market Composite Bond Index, EURUSDindx is the 1-month Eurodollar Deposit, Gold is the spot price for gold and JPMTrWindx is the JP Morgan Trade Weighted Dollar Index.

In order to analyze the performance of Asia-focused hedge funds and to extract alpha, this dissertation utilizes three different models. Two of these models are widely used in the literature: the Fung and Hsieh (2004a) seven-factor model for hedge fund performance and Teo’s (2009) model, which is basically an extension of Fung and Hsieh (2004a) seven-factor model to account for specific characteristics of Asian hedge funds. In addition to these two models, the author constructs a stepwise model for every Asia-focused strategy. As we will see in the next subsection, the stepwise model reduces the risk of omitted risk factors by using a systematic technique that selects relevant risk factors from those that were often used in previous research.

5.3 Data

5.3.1 Data Selection

This section describes the data used in this dissertation as well as the biases that are well documented in the hedge fund literature. The three databases commonly used in hedge fund research are HFR, TASS, and CISDM (formerly MARHedge). However, as Koh et al. (2003) note, these databases cover mostly US-centric hedge funds. Therefore, in order to study Asia-focused hedge funds, this dissertation relies on data provided by Singapore-based data vendor Eurekahedge. The Eurekahedge database has previously been used in studies by Koh et al. (2003), Henn and Meier (2004), Hakamada et al. (2007) and Teo (2009). The Eurekahedge Asia Pacific database covers 2,242 hedge funds (as of May 2011). The sample examined in this study covers the period from January 2000 to December 2010.

Two important factors were considered before selecting the investigation period. First, as Liang (2000) demonstrates, the examination of hedge fund returns before 1994 may not be worthwhile due to survivorship bias, which is an essential characteristic of hedge fund data prior to that year. Second, hedge fund managers generally do not work for more than a period of ten years in a single fund, so using a period that is too long might be meaningless. Therefore, the period from January 2000 to December 2010 seemed appropriate for this study.

The adjustment of the initial sample for various biases, which are often found in hedge fund databases, removed approximately half of these funds. Therefore, the final sample consists of 1,169 hedge funds. The final dataset includes information on such hedge fund characteristics as: investment strategy, management fee, performance fee, redemption frequency, notification period, lock-up period, fund location, fund size, inception date, and minimum investment. These fund idiosyncrasies are noted in the year 2010 and are assumed to be constant over the sample period.

There is no universal method for classifying different hedge funds' investment styles and strategies. Eurekahedge sorts Asia-Pacific hedge funds into fourteen different investment strategies (arbitrage, bottom-up, CTA, distressed debt, diversified debt, dual approach, event-driven, fixed income, long-short equity, macro, multi-strategy, relative value, Value and others). The author follows Teo (2009) in condensing this variety of hedge fund strategies into eight primary investment strategies (long-short equity, relative value, event-driven, macro, directional, fixed income, CTA, and others). From a geographical perspective, the database covers funds that invest in at least one of the following nine geographic regions: Asia excluding Japan, Asia including Japan, Japan only, Australia/New Zealand, greater China, Taiwan, Korea, India and emerging markets,.

Table 5.1 provides an overview of the Eurekahedge database and some basic statistics, such as the total number of funds, the total number of dead funds, and the number of observations (return months). As is evident in Table 5.1, equity long/short funds constitute more than 50% of all Asia-focused hedge funds, with the second most-common strategy being directional funds. In terms of geographical dispersion, Japan constitutes the largest market for hedge funds (344 funds), while the second-largest group of funds is Asia excluding Japan.

In this dissertation, when I analyze the performance of Asia-focused hedge funds, I construct equally-weighted indices for various hedge fund strategies and use them as dependent variables. In addition, I repeat the analysis using individual hedge fund returns as dependent variables. This allows for an in-depth analysis of the characteristics and distributions of hedge fund alphas, coefficients, *t*-statistics, and adjusted R^2.

Table 5.1 Summary statistics

Investment style	Total funds	Dead funds	Observations
Panel A: By investment style			
Equity long/short	669	271	41,169
Relative value	50	19	3,568
Event-driven	41	18	2,258
Macro	24	8	1,363
Directional	204	39	15,672
Fixed income	45	9	3,045
CTA	11	4	623
Others	125	43	7,897
Total	1169	411	75,595
Panel B: By investment geography			
Asia excluding Japan	256	70	16,970
Asia including Japan	215	74	13,460
Australia/New Zealand	70	26	4,936
Emerging markets	70	23	5,261
Greater China	132	27	7,615
India	60	14	3,279
Japan	344	172	22,489
Korea	15	3	1,204
Taiwan	7	2	411
Total	1169	411	75,595

The excess returns of the passive benchmark indices (returns in excess of the risk-free rate) are used as the dependent variables. Data on these passive benchmark indices were obtained from Bloomberg, Thomson Financial Datastream, the US Federal Reserve website, and the websites of David A. Hsieh and Kenneth R. French. Equity market returns are proxied by returns on the S&P 500, the Nikkei225, MSCI EM, MSCI Asia ex-Jap, MSCI Asia Pacific, Russel 3000, and MSCI World indices.

As discussed in second chapter of this dissertation, hedge funds are not required to reveal their returns or asset information to anyone other than their current investors. Hedge funds that choose to submit data to hedge fund data vendors do voluntarily. Therefore, the existing hedge fund databases do not represent the entire universe of hedge funds. It is important to be aware of the biases arising from this fact when investigating the performance of hedge funds, as they can have a considerable effect on return measurements. The most frequent biases in this regard are selection bias, instant history bias, survivorship bias, illiquidity bias, and multi-period sampling bias. In the following sub-section, I elaborate upon the biases in the hedge fund literature and describe the actions taken to alleviate these biases.

5.3.2 Data Biases

5.3.2.1 Survivorship Bia

Survivorship bias is one of the most widely studied biases in the literature on performance analysis. This bias occurs when only the performance statistics for those funds that are alive at the end of the sample period are included in the database, while those funds that have died or stopped reporting for some reason are excluded from the database. This, in effect, leaves the database with information on only the surviving funds. Fung and Hsieh (2000a) note that this could occur because the subscribers to hedge fund databases are only interested in funds that accept new capital.

The Eurekahedge database distinguishes between “live” and “dead” funds. “Live” funds are those still operating and reporting to Eurekahedge at the end of the data sampling period. Funds that close due to bankruptcy or liquidation and stop reporting to the database are classified as “dead” funds. Well-performing funds that shut down create a downward bias, whereas poorly performing funds that shut down create an upward bias.

Survivorship bias is especially severe for the period prior to 1994, as most of the database providers started tracking dead funds only after 1994. For example, the TASS database includes historical data of defunct funds starting in 1994 and the same is true for the MAR database as of 1995. The Eurekahedge database tracks hedge fund performance starting in 2000, but it contains information on fund returns since inception.

Two definitions of survivorship bias are common in mutual fund and hedge fund literature. The first definition, used by Ackermann et al. (1999), defines survivorship bias as the difference in performance between the portfolio of live funds and the portfolio of dead funds. The second definition, which is used by Liang (2000), defines survivorship bias as the difference in performance between the portfolio of live funds and the portfolio of all funds in the database. The literature on hedge funds provides several estimates of survivorship bias. Liang (2000) estimated the bias at 0.6% per year using the HFR database and at 2.24% per year using the TASS database, which can be compared to the 0.16% bias per year that Ackermann et al. (1999) obtained using the combined HFR/MAR database. Fung and Hsieh (2000a), and Brown et al. (1999) estimated the survivorship bias for hedge funds at around 3% per year, while Amin and Kat (2003) documented it at around 2%.

In order to examine survivorship bias in the Eurekahedge sample, I use both Ackermann et al.'s (1999) and Liang's (2000) formulae. Table 5.2 reports the average performance, standard deviations, and number of observations (number of monthly reruns) of active and inactive hedge funds from January 2000 to December 2010. The table shows that the cross-sectional means of the monthly hedge fund returns vary from -2.48% in 2008 (29.76% annually) to 2.33% in 2009 (27.96% annually). The survivorship bias is reported for the entire period under observation and for each of the two sub-periods: 2000-2007 and 2007-2010. Panel A of Table 5.2 presents the figures for survivorship bias calculated using Ackermann et al.'s (1999) formula and shows a monthly survivorship bias of 0.54% (6.53% per year) for the entire period. Panel B reports the figures for survivorship bias calculated using Liang's (2000) formula, which shows a monthly survivorship bias of 0.16% (1.92% per year). The latter value is relatively close to that obtained by Eling and Faust (2010), who use the same formula and the Center for International Securities and Derivatives Markets (CISDM) database to calculate the monthly survivorship bias for emerging market hedge funds (0.21%; 2.6% per year). The second sub-period, which ranges from February 2007 to December 2010, represents the time of global financial crisis. The monthly survivorship bias during this period is relatively high at 0.83% (9.96% per year) when calculated using the first formula, but much lower at 0.14% (1.68% per year) when calculated using the second formula. The monthly survivorship bias for the first sub-period (January 2000 until February 2007) amounts to 0.38% (4.56% per year) when the first formula is used or 0.17 (1.98% per year) when the second formula is used. However, as both active and dissolved funds are included in the hedge fund database used in this study, survivorship bias should not be a problem.

Table 5.2 Survivorship bias in Asia-focused hedge funds

Year	All funds			Surviving funds			Dissolved funds		
	Return	St. Dev.	Obs.	Return	St. Dev.	Obs.	Return	St. Dev.	Obs.
2000	-0.38	2.85	1719	-0.48	2.98	1198	-0.16	2.73	562
2001	0.76	2.48	2289	0.84	2.80	1535	0.60	2.00	847
2002	0.29	1.96	2999	0.32	2.28	1965	0.23	1.45	1201
2003	2.28	2.08	4155	2.74	2.37	2467	1.68	1.78	1867
2004	0.87	1.45	5473	1.03	1.71	3343	0.66	1.22	2576
2005	1.38	1.85	7118	1.50	2.13	4486	1.22	1.50	3360
2006	1.10	1.99	2006	1.51	2.26	5798	0.54	1.65	4031
2007	1.36	2.20	10056	1.62	2.35	7213	0.91	1.93	4034
2008	-2.48	4.10	10310	-2.47	4.27	8391	-2.52	3.65	3464
2009	2.33	3.15	9066	2.57	3.42	9156	1.13	2.03	1819
2010	0.84	2.50	7922	0.89	2.55	10138	-0.22	1.74	647
Mean (2 sub-periods)									
2000/01-2007/01	0.90			1.06			0.68		
2007/02-2010/12	0.49			0.63			-0.20		
Mean (entire period)									
2000/01-2010/12	0.76			0.91			0.37		

Panel A: Living funds – Dissolved funds			Panel B: Living funds – All funds		
Bias 2000/01-2007/01	0.38	per month	Bias 2000/01-2007/01	0.17	per month
	4.56	per year		1.98	per year
Bias 2007/02-2010/12	0.83	per month	Bias 2007/02-2010/12	0.14	per month
	9.96	per year		1.68	per year
Bias 2000/01-2010/12	0.54	per month	Bias 2000/01-2010/12	0.16	per month
	6.48	per year		1.92	per year

5.3.2.2 Selection Bias

The fact that hedge funds are not required to share their information with third parties creates a possibility of selection bias. In all likelihood, hedge funds with good performance have more incentive to report to the database vendors than funds with poor performance. However, an offsetting factor is also at play. Some managers with superior performance may refrain from reporting to data vendors because they are not interested in attracting more capital. Fung and Hsieh (2000a) use the example of George Soros's Quantum Fund, which was closed to new investments in 1992 even though its performance was stellar. As a result of this offsetting factor, Fung and Hsieh, (2000a) believe that this bias is negligible.

5.3.2.3 Instant History Bias

Instant history bias (also called backfill bias) is another important source of bias. It is present whenever a database vendor backfills data on earlier good returns for funds entering the database but leaves out data on poorer returns. It is in a hedge fund's interest to display the best performance possible and, hence, most managers will to go through an incubation period during which they do not report any returns. If the fund performs better during the incubation period than the average fund in the database, the hedge fund manager will opt to include all of the fund’s performance figures in the database. This will most likely positively bias the performance of the funds included in the database. This bias can be calculated as the difference between the performance of an adjusted observable portfolio (in which the returns for incubation periods are omitted) and the performance of a non-adjusted portfolio.

Using the TASS database, Fung and Hsieh, (2000a) calculated an instant history bias of 1.4% for the period 1994 until 1998. Edwards and Caglayan (2001) apply the same approach using the MAR database and calculate the instant history bias at 1.2%. Barry (2002) analyze the TASS database and observe that around 80% of all hedge funds backfill at least six months of data, around 65% of all hedge funds backfill at least 12 months, and 50% backfill more than two years. In order to account for the possibility of this bias, I delete the first 12 months of returns for every hedge fund.

5.3.2.4 Illiquidity Bias

Hedge funds often invest in illiquid, such as over-the-counter securities, distressed assets, small cap stocks, and emerging market bonds. These illiquid securities typically do not trade at the end of every month and are thus not marked to market. Marking these securities to market is often difficult due to the unavailability of publicly available traded prices. Therefore, hedge fund managers might be tempted to smooth their returns and systematically understate the volatility of their portfolios.

Asness, Krail, and Liew (2001b) investigate this possibility using the CSB/Tremont database for the period 1994-2000. The authors observe that non-synchronous pricing problems, regardless of whether they are caused by stale or managed prices, are a significant issue in monthly hedge fund data and can result in considerably understated approximations of hedge fund risk. After accounting for this effect, Asness et al. find that the market exposure of the corresponding hedge funds rises significantly. Similarly, Getmansky et al. (2004) explore the sources of serial correlation in hedge fund returns.

They find that the most likely explanation for this phenomenon is illiquidity exposure and smoothed returns. The authors argue that the reported hedge fund returns do not reflect the true economic returns of a fund (R_t). Instead, hedge funds report returns R_t^o, which reflect the weighted average of the true returns, R_t, over the recent k+1 periods, including the current period. They define the relationship between the true economic returns and reported returns as the following:

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \ldots + \theta_k R_{t-k} \tag{20}$$

with two conditions:

$$\theta_j \in [0,1], \quad j = 0, \ldots, k \tag{21}$$

and

$$1 = \theta_0 + \theta_1 + \ldots + \theta_k \tag{22}$$

After some intermediate developments of equation 20, θ can be estimated using the maximum likelihood technique. After the θ_i are estimated, the true return is obtained by plugging θ_i into the inverted version of the equation 20:

$$R_c^t = \frac{R_0^t - \theta_1 R_{c-1}^t - \ldots - \theta_k R_{c-1}^t}{\hat{\theta}_0} \tag{23}$$

An iterative application of the equation 23 on the reported hedge fund returns produces a series of de-smoothed returns, free of serial correlation. In order to account for the possibility of serial correlation in my Asian hedge fund dataset, and to avoid relying on returns that might understate the volatility and overstate the statistical significance of risk adjusted measures such as alpha (Getmansky et al., 2004), I follow the work of Teo (2009) and calculate the de-smoothed returns using the Getmansky et al. (2004) correction procedure.

I begin by mapping the fund categories found in Table 8 of Getmansky et al. (2004) to the fund categories used in this study. Then, in a fashion similar to Teo (2009), I take the smoothing parameter (θ_0, θ_1, and θ_2) estimates for each hedge fund strategy from Getmansky et al.’s Table 8 and use the formula in equation x to apply them to my dataset of Asian hedge fund returns to obtain the de-smoothed returns. All of the analyses in this study are conducted using the de-smoothed returns obtained in this manner.

5.3.2.5 Multi-Period Sampling Bias

Multi-period sampling bias might occur if the historical period being analyzed is too short. Ackermann et al. (1999) propose an estimation period encompassing at least 24 monthly observations. Fung and Hsieh (2000a) require at least 36 months to include a fund in their analysis. In the analyses presented in this dissertation, I follow Fung and Hsieh's (2000a) proposal and include only funds with a minimum of 36 months of returns (including the 12 months deleted to account for the instant history bias).

5.4 Methodology

The aim of this chapter is to provide insight into types of analyses conducted in this chapter. Therefore, the multifactor models, Chow test, and stepwise regression techniques are discussed.

5.4.1 Multivariate Models

Brooks (2008) defines multivariate models as structural models, which attempt to explain changes in a variable by associating them to the movements in the current or past values of other (explanatory) variables. In the context of hedge funds, multivariate models explain the movements of hedge fund returns by referencing them to movements in other passive indices or strategies. In contrast, Brooks (2008) describes univariate models as those which attempt to model financial variables using only the information contained in their own past values.

For the purposes of this dissertation, the author uses multivariate models as these models are commonly used in the literature to measure the performance of hedge funds.

The multi-factor model is a form of multiple linear regression. A regression is a set of statistical procedures used for examining and modeling the functional dependence of one metrically scaled dependent variable, Y, on one or more metrically scaled independent variables, which are usually denoted X_1, X_2, … X_k. One can think of regression as an extension of the correlation, covariance, and scatter plot concepts. Essentially, a regression fits a curve through available data on a scatter plot and describes the relationship through a mathematical equation of the following kind:

$$Y_i = \alpha_0 + \beta_1 x_{1i} + ... + \beta_n x_{ni} + \varepsilon_i, \qquad (24)$$

where Y is the dependent or explained variable, X_1, X_2, and X_n are independent or explanatory variables, and ε is an error term. When analyzing hedge performance, the dependent variable is either the monthly returns on an equally weighted index of hedge funds or the monthly returns of individual hedge funds. The independent variables are the monthly returns on various passive risk factors (equities, bonds, options, etc.).

5.4.2 Issues with model specifications

In this sub-section, the main issues that can arise if one applies a multi-factor regression model without properly accounting for and understanding the underlying basic assumptions of regression are discussed. In this discussion, I follow the classification presented by Lhabitant (2004). Furthermore, researchers need to be aware that all models are misspecified and are simplifications of reality to a certain extent.

5.4.2.1 Omitted Variable Bias

The validity of the multi-factor regression model can be affected by omitted variable bias in two ways. First, if an omitted variable is not correlated with other independent variables in the model, its impact is captured by the intercept and the error term. This can have two consequences. On the one hand, the intercept could be biased upwards or downwards. In the context of hedge funds, this means that the intercept, or the alpha, which is interpreted as risk-adjusted return or managerial skill, could be biased and thus an unreliable measure of hedge fund performance. On the other hand, as the error term contains a part of the omitted variable, the assumption of normality of the error term could be violated.

Second, if the omitted variable is correlated with some of the independent variables in the model, then the coefficients of these independent variables will be biased upwards or downwards. This happens because the coefficients of the independent variables will reflect not only an estimate of the impact of the variable with which they are associated but also, to some extent, the effect of the omitted variable. One possible symptom of an omitted variable is a low R^2, which indicates that the model does not describe the relationships between the variables well. The author believes that the problem of omitted variables is minimized in this dissertation, as the R^2 values that are obtained are relatively high and the models adopted here have been used extensively in the existing literature.

5.4.2.2 Unnecessary Variable Bias

The problem of unnecessary variables can be viewed as the direct opposite of the omitted variable problem. It manifests when an explanatory variable that has no impact on the dependent variable is included in the regression model. In this regard, one needs to differentiate between two cases depending on whether the unnecessary variable is correlated or uncorrelated with other independent variables. In the former case – when the unnecessary variable is not correlated with other independent variables – the impact of other variables on the dependent variable will not be affected. The unnecessary variable can be easily identified by the presence of a low t-statistic and then removed from the model altogether. If the unnecessary variable is correlated with some of the independent variables, the effect is a reduction in the precision of the estimates. Overall, the problem of unnecessary variables is not as serious as the problem of omitted variables, as the ordinary least squares (OLS) estimation yields unbiased coefficient estimates even when unnecessary variables are included in the model. However, the standard errors are larger and thus the precision of the estimates will be reduced. In order to avoid the problem of unnecessary variables in the multi-factor model, the author uses a stepwise regression procedure to arrive at the model best suited for every Asian hedge fund strategy.

5.4.2.3 Multicollinearity

Multicollinearity is a statistical phenomenon that occurs when independent variables in a multi-factor regression model exhibit a strong correlation. Two independent variables that are highly correlated basically transmit the same information and neither of the variables contribute substantially to the model when the other is also included. Multicollinearity does not influence the reliability of the model per se. However, it does influence the estimates of individual factor coefficients. Hence, if the researcher aims to predict the dependent variable from the set of independent variables, multicollinearity does not pose a significant problem. This is because multicollinearity will not affect the accuracy of the predictions and the adjusted R^2 will specify how well the model predicts the dependent variables. If, on the other hand, the researcher wishes to understand the impact of the independent variable on the dependent variables, multicollinearity becomes a serious issue, as it increases the standard errors of the estimates. This, in turn, decreases the t-statistics and reduces the confidence that can be placed in the estimates.

In order to reduce the danger of multicollinearity in the models used here, two multi-factor regression models that are used extensively in the previous academic studies are utilized. In addition, I conduct a comprehensive correlation analysis when deciding which factors to include in the stepwise regression model. Following the suggestion of Eling and Faust (2010), I calculate the correlation coefficients for each pair of independent variables and ensure that the pairs with significantly high correlation are removed from the model. The correlation between passive investment strategies are presented in the table in the appendix to this dissertation.

5.4.2.4 Heteroscedasticity

One of the basic assumptions underlying classical regression analysis is that the variance of the disturbance term (ε) should be constant for all values of the independent variables. This property is called homoscedasticity. If this assumption is violated, the disturbance term is considered heteroscedastic. This means that the parameter estimates are still consistent but no longer efficient and, hence, any inferences based on standard errors might be misleading. For the purpose of this dissertation, all results are determined using a heteroscedasticity consistent covariance matrix (White, 1980).

5.4.2.5 Serial Correlation

The concept of serial correlation was discussed in the context of data biases that characterize the hedge fund databases. One of the assumptions of the OLS regression is that the disturbance term of two different independent variables are uncorrelated. In other words, the disturbance terms of the OLS estimates must be distributed independently of each other. We have accounted for the problem of serial correlation using Getmansky et al.'s (2004) adjustment, as shown in the data subsection of this chapter.

5.4.3 Stability of Parameters - Chow test

When statistical models are applied for analyzing financial time-series data, a basic assumption is that the parameters of the model are stable over time. Fung et al. (2008) documented that a static analysis of hedge fund returns is not appropriate if the funds change their strategies during the period under investigation. Following Fung et al. (2008), Naik et al. (2007), Eling and Faust (2010), and Xu et al. (2010), an analysis is conducted in this dissertation not only for the whole sample period (January 2000 to December 2010) but also for two sub-periods (January 2000 to February 2007 and February 2007 to December 2010). This allows for an examination of the alpha creation ability of Asia-focused hedge funds in different market environments.

The implicit assumption that the parameters are stable over time can be tested using the Chow (1960) test.

The main concept behind Chow’s breakpoint (1960) test is to separate the full data sample into two sub-samples and subsequently to estimate the model separately for each of the two sub-samples and the full sample. The aim is then to compare the residual sum of squares (RSS) of each of the three models.

Formally this can be expressed as a hypothesis-testing problem whereby the linear model of a sort $Y = \beta x + \varepsilon$ is considered. Assuming that the full sample is divided into two sub-periods (1) and (2), with potentially different coefficients, one can express the model as follows:

$$Y = \begin{Bmatrix} \beta_1 x_i + \varepsilon_i \\ \beta_2 x_i + \varepsilon_i \end{Bmatrix} . \begin{matrix} i \in (1) \\ i \in (2) \end{matrix} \tag{25}$$

where $\hat{\beta}_1$ and $\hat{\beta}_2$ are the coefficient estimates from the sub-period regressions, and $\hat{\varepsilon}_1$ and $\hat{\varepsilon}_2$ are the residuals and RSS1 and RSS2 are the sum of squares. The hypothesis to be tested is H0: β1 = β2, which essentially states that the coefficients are equal across the sub-samples. The regression estimated over the whole sample period is defined as the restricted regression while the regressions estimated over each of the two sub-samples are defined as the unrestricted regressions (Brooks 2008). Hence, in order to find out whether the parameters are stable over time and whether there is breakpoint in data, one needs to calculate how much the residual sum of squares for the whole sample period (RSS) differs from the sum of the residual sum of squares for the two sub-periods (RSS1 + RSS2). If the nul hypothesis from above holds, there should be no significant difference between the restricted residual sum of squares (RSS) and the unrestricted residual sum of squares (RSS1 + RSS2). A formal test is conducted by computing the F-statistics as follows:

$$F = \frac{RSS - (RSS_1 + RSS_2)}{RSS_1 + RSS_2} \times \frac{T - 2k}{k}, \tag{26}$$

where RSS denotes the residual sum of squares for the whole sample, RSS1 is the residual sum of squares for the sub-sample 1, RSS2 is the residual sum of squares for the sub-sample 2, T denotes the number of observations, 2k is the number of explanatory variables in the unrestricted equation and k is the number of explanatory variables in each unrestricted regression.

5.4.4 Stepwise Regression

One important shortcoming of hedge fund multi-factor models is the lack of guidance as to which factors and should be included in the model. The answer to this question depends on the methodology used to construct the factor model. There are two main techniques to determine factors: principal component analysis (PCA) and common factor analysis. Principal component analysis is a statistical procedure used for finding patterns in a multi-dimensional data set. The goal of PCA is to transform a number of possibly correlated variables into a set of uncorrelated variables called factors. It is beyond the scope of this thesis to examine the characteristics of this technique in detail.

In common factor analysis, the selected factors are observable and explicitly stated through specific analyses (Lhabitant 2004). One such analysis is to screen many potential factors through stepwise regression procedure (Agarwal and Naik 2004; Titman and Tiu, 2008; Zhong, 2008; Ammann, Huber, and Schmid, 2009, 2010a, 2010b; Eling and Faust, 2010). This method commonly causes somewhat higher in-sample R^2 but a lower out-of-sample R^2. Alternatively, one can specify a certain number of variables that are considered to be of economic relevance. This procedure leads to lower in-sample R^2 but higher out-of-sample R^2. Hence, choosing the right method requires consideration of the tradeoff between robustness (lower with stepwise regression, higher with economic rationale) and goodness of fit (higher with stepwise regression, lower with economic rationale).

5.5 Empirical Analysis

This chapter focuses on the alpha creation and return decomposition of Asia-focused hedge funds. In order to measure hedge fund performance, and isolate alpha as an indicator of managerial skill and hedge fund value creation, I use three different multi-factor models: the Fung and Hsieh model (2004), the adjusted Teo model (2009), and the model obtained by applying the stepwise regression procedure. In order to estimate alpha, I use the returns of equally weighted hedge fund strategy indices as well as the individual hedge fund returns as the dependent variables. In other words, I estimate alpha for every hedge fund in the database using the previously mentioned three models, and calculate the average of these alphas.

5.5.1 Summary Statistics

Tables 5.2 and 5.3 present the descriptive statistics for the monthly returns of passive benchmark indices and Asia-focused hedge funds, respectively, from January 2000 until December 2010. Both tables show the first four statistical moments: mean, standard deviation, skewness, and kurtosis.

I follow Capocci and Huebner (2004) in the use of equally weighted portfolio excess return for each hedge fund strategy. Unlike most equity indices, all Asian hedge fund strategies provide positive average monthly returns over the sample period, with a considerably lower standard deviation than the passive benchmark indices. While S&P 500 and the market proxy[9] delivered monthly returns of -0.39% and -0.12% with standard deviations of 4.68% and 4.94%, respectively, the Asian equity long/short hedge fund strategy delivered an average monthly return of 0.54% with a standard deviation of 2.50%. The fixed income and relative value strategies were the best-performing Asian hedge fund strategies – both delivered monthly returns of 0.7%. However, the relative value strategy achieved that return with a standard deviation of 3.22%, while the fixed income strategy delivered same monthly returns with standard deviation of only 1.95%. The most volatile of the Asian hedge fund strategies was the CTA strategy, which delivered a monthly return of 0.33% with a standard deviation of 4.79%. In terms of the performance of the Asian equity long/short hedge fund strategy relative to the performance of Asian equity indices, the Asian hedge funds following the equity long/short strategy provided larger returns (0.54%) than most Asian equity indices (-0.23% for MSCI Asia, -0.59% for Nikkei225, and 0.29% for MSCI Asia ex Japan) with a considerably lower standard deviation (2.5% versus 5.42%, 5.96%, and 6.92%, respectively). Overall, my results are in line with suggestions found in existing literature that hedge funds deliver positive returns with lower volatility than conventional investment vehicles or passive benchmark indices (e.g., Fung and Hsieh, 2004; Hasanhodzic and Lo, 2007; Kosowski et al., 2007; Titman and Tiu, 2008). While the first two moments of return distribution (mean and standard deviation) are certainly important, some investors might care more about the third and fourth moments (skewness and kurtosis), which provide more information about the shape of the distribution of the returns and extreme values. Previous research has shown that return-maximizing investors prefer high values of skewness and low kurtosis (Kraus and Litzenberger, 1976). Table 5.3 shows that hedge funds, on average, display negative skewness and positive kurtosis, which might make hedge funds unattractive for some investors.

[9] Value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks used in Fama and French (1993) and Carhart (1997)

Table 5.2 Descriptive statistics for passive benchmark indices[10]

Index	Mean	St.dev	Skew.	Kurt.	Min. (%)	25% (%)	Median (%)	75% (%)	Max. (%)
Market proxy	-0.12	4.94	-0.63	3.69	-18.54	-2.67	0.82	3.27	11.04
S&P 500	-0.39	4.68	-0.52	3.62	-17.02	-2.66	0.38	2.16	9.38
MSCI North Am.	-0.36	4.77	-0.54	3.80	-18.15	-2.52	0.30	2.59	9.75
Russell 2000	0.13	6.24	-0.37	3.38	-20.98	-3.88	0.89	4.39	15.99
MSCI EM Total	0.54	7.12	-0.62	4.12	-27.58	-3.29	0.76	5.47	16.66
MSCI EM Asia	0.40	7.46	-0.27	3.27	-24.23	-4.75	0.52	5.90	18.94
MSCI Asia ex Japan	0.29	6.92	-0.41	3.65	-24.25	-4.10	0.42	5.06	16.49
MSCI Pacific	-0.31	5.14	-0.37	3.31	-18.00	-4.03	-0.16	3.46	11.03
MSCI Asia Pacific	-0.16	5.42	-0.47	3.57	-19.79	-3.78	0.62	3.65	12.39
MSCI Asia	-0.23	5.42	-0.34	3.33	-18.81	-3.88	-0.05	3.62	12.62
Nikkei 225	-0.59	5.96	-0.52	3.79	-23.91	-4.50	-0.22	3.83	12.85
Size	0.52	3.68	0.17	9.22	-16.36	-1.37	0.47	2.54	18.43
SMB*	0.50	3.98	0.93	11.75	-16.67	-1.53	0.14	2.62	22.19
HML*	0.69	3.81	-0.04	5.53	-12.78	-1.04	0.47	2.65	13.84
Momentum*	0.10	6.72	-1.40	9.31	-34.75	-2.13	0.41	3.24	18.39
Bond *	-0.02	0.24	-0.28	5.71	-1.11	-0.16	-0.04	0.11	0.65
Credit*	0.01	0.25	1.06	13.40	-0.99	-0.09	-0.01	0.11	1.45
PTFSBD*	-3.16	13.43	1.10	4.17	-25.36	-12.16	-6.26	2.03	43.65
PTFSFX*	0.66	18.91	1.30	4.84	-30.00	-11.59	-4.00	8.40	69.22
PTFSCOM*	-1.08	13.81	1.11	4.18	-23.04	-9.97	-3.66	5.03	40.59
PTFSIR*	4.00	33.27	3.89	21.39	-30.60	-12.74	-4.57	8.67	221.92
PTFSSTK*	-5.16	12.51	0.91	4.62	-26.60	-14.57	-6.94	2.58	41.67
Gold	1.05	4.75	-0.19	3.85	-17.06	-2.23	1.17	4.26	12.59
Crude Oil	1.33	11.60	-0.24	3.79	-35.63	-6.36	2.29	8.09	36.09

Table 5.3 Descriptive statistics for Asia-focused hedge fund indices

Strategy	Mean	St.dev.	Skew	Kurt	Min	25% (%)	Median	75% (%)	Max
Equity long/short	0.54	2.50	-0.46	3.95	-7.12	-0.91	0.77	2.18	8.85
Relative value	0.70	3.22	-0.15	8.33	-13.74	-0.84	0.81	2.37	15.45
Event driven	0.55	2.27	-0.83	4.72	-6.95	-0.47	0.90	1.85	7.16
Macro	0.69	5.12	0.15	6.29	-20.38	-1.24	0.48	2.07	17.26
Directional	0.60	5.31	-0.83	4.67	-21.57	-2.13	1.30	4.10	14.40
Fixed income	0.70	1.95	-1.41	10.32	-10.28	-0.08	0.76	1.66	6.12
CTA	0.33	4.79	1.08	8.88	-12.88	-1.07	0.20	1.67	24.70
Others	0.54	2.52	-0.62	4.42	-9.20	-0.79	0.66	2.15	7.19

[10] All indices are analyzed on the basis of excess returns, unless indicated with an asterix (*).

5.5.2 Performance Measurement Results for the Full Period

Tables 5.3 reports the alphas, t-statistics and adjusted R-squareds of equally weighted strategy indices, which are calculated using the three performance measurement models for the eight Asia-focused hedge fund strategies for the full sample period. The last row of the table represents the average figures across all eight Asia-focused hedge fund strategies. Columns 1 to 3 report the alphas, t-statistics, and adjusted R-squareds from the Fung and Hsieh (2004) (henceforth FH) model. Columns 4 to 6 report the alphas, t-statistics, and adjusted R-squareds from the adjusted Teo (2009) model (henceforth Teo). Lastly, columns 7 to 9 report the alphas, t-statistics, and adjusted R-squareds from the model obtained using the stepwise regression approach (henceforth SW Asia).

All three performance measurement models find a positive and, in most cases, significant alpha over the full sample period. However, while the t-statistics remain relatively unchanged for all three models, the results for the alphas and adjusted R-squareds are slightly different for each model. In five of the eight cases, the FH model finds a positive alpha that is statistically significant at 1%. In two cases (macro and directional strategy), alpha is positive and significant at 5%, while it is positive and insignificant for the CTA strategy. In the case of the CTA strategy, all of the three models estimate a positive and insignificant alpha and a negligible adjusted R^2. The FH model arrives at an average adjusted R^2 across all strategies of 0.40, which is in line with the 0.46 obtained by Teo (2009) using the same model for the sample of Asian hedge funds from January 2000 to December 2006.

Teo's model adds two additional Asian equity factors to the FH model, namely the MSCEI Asia excluding Japan index and the Nikkei 225 index. The addition of these two factors increases the average adjusted R^2 across strategies from 0.40 in the FH model to 0.59 in Teo's model. However, this relatively small increase in average adjusted R^2 across strategies masks some large changes at the level of the individual strategies. The highest percentage increase of the adjusted R^2 resulting from the addition of the two Asian equity factors in Teo's model[11] is observed for the equity long/short strategy, where the adjusted R^2 rises from 0.50 to 0.82. In this case, alpha decreases from 0.57 to 0.48 and remains significant at the 1%.

[11] The coefficients on the MSCI Asia ex Japan and Nikkei 225 are positive and highly significant with *t*-values of 8.56 and 6.07

Table 5.4

Panel A

Alphas of equally weighted hedge fund strategy indices (January 2000 to December 2010)

	FH			Teo			SW Asia		
	α	t	Adj. R^2	A	t	Adj. R^2	α	t	Adj. R^2
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equity long/short	0.57	3.35	0.50	0.48	4.46	0.82	0,46	4,83	0,82
Relative value	0.73	3.06	0.49	0.54	3.15	0.72	0,52	3,87	0,75
Event driven	0.62	3.46	0.29	0.52	3.74	0.56	0,51	3,68	0,59
Macro	0.92	2.02	0.25	0.76	1.70	0.31	0,45	1,18	0,51
Directional	0.76	2.30	0.61	0.58	3.36	0.90	0,49	3,30	0,90
Fixed income	0.67	4.52	0.50	0.65	4.21	0.55	0,69	5,66	0,58
CTA	0.40	0.88	0.01	0.28	0.59	0.01	-0,05	-0,11	0,07
Others	0.56	3.33	0.57	0.46	4.20	0.83	0,54	5,58	0,85
Average	0.66	2.86	0.40	0.53	3.18	0.59	0,45	3,50	0,63

Panel B

Alphas of equally weighted hedge fund strategy indices (January 2000 to December 2010)

	FH			Teo			SW Asia		
	α	t	Adj. R^2	α	t	Adj. R^2	α	t	Adj. R^2
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equity long/short	0.63	1.49	0.21	0.36	1.16	0.37	0.24	1.20	0.35
Relative value	0.75	2.46	0.27	0.56	2.19	0.33	0.34	1.90	0.33
Event driven	0.65	2.17	0.25	0.42	1.90	0.35	0.43	2.10	0.35
Macro	0.38	1.48	0.23	0.31	1.37	0.36	0.26	1.52	0.32
Directional	0.83	1.44	0.41	0.54	1.21	0.59	0.18	1.00	0.56
Fixed income	0.63	2.78	0.32	0.52	2.65	0.35	0.49	2.84	0.37
CTA	0.58	1.62	0.11	0.50	1.48	0.15	0.47	1.66	0.06
Others	0.70	2.09	0.21	0.48	1.76	0.30	0.39	1.82	0.31
Average	0.64	1.94	0.25	0.46	1.71	0.35	0.35	1.76	0.33

Panel C

Alphas of equally weighted hedge fund strategy indices (February 2007 to December 2010)

	FH			Teo			SW Asia		
	α	t	Adj. R^2	α	t	Adj. R^2	α	t	Adj. R^2
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equity long/short	0.69	2.00	0.62	0.31	1.65	0.91	0,21	1,27	0,88
Relative value	1.25	2.35	0.66	0.81	2.21	0.83	0,71	2,50	0,83
Event driven	0.58	1.82	0.54	0.34	1.69	0.86	0,71	2,50	0,83
Macro	0.60	2.57	0.29	0.39	2.67	0.69	0,31	1,90	0,67
Directional	0.93	1.35	0.70	0.38	1.23	0.95	0,14	0,53	0,94
Fixed income	0.51	1.88	0.60	0.43	1.46	0.66	0,44	1,87	0,72
CTA	0.59	3.29	0.27	0.55	2.99	0.24	0,48	2,32	0,10
Others	0.68	2.12	0.67	0.32	2.00	0.93	0,23	2,34	0,95
Average	0.73	2.17	0.55	0.44	1.99	0.76	0,40	1,90	0,74

As expected, the two additional equity factors do not explain as much of the hedge fund returns for the fixed income, macro, and CTA strategies. However, they do significantly improve the explanatory power of the following strategies: relative value, event driven, directional, and others. Overall, alphas decrease in Teo's model but remain significant at levels similar to those in the FH model.

Consistent with the findings of Titman and Tiu (2008) and Ammann et al. (2009), I find that the stepwise regression model produces the highest adjusted R^2 figures of all of the models. However, the average adjusted R^2 across all strategies increases by only 0.04 from that of Teo's model. The highest percentage increase of the adjusted R^2 in the stepwise Asia model occurs for the macro strategy, where it increases by 0.20.

While panel A of Table 5.4 presents the results based on the returns for equally weighted hedge fund strategy indices, panel B of Table 5.4 presents the results obtained when the individual hedge fund returns are used as the dependent variables. Most of the funds in my sample came into existence towards the middle or end of the sample period. Therefore, the results in panel B are biased towards the most recent period when the number of hedge funds in the sample is the largest. I find qualitatively similar results for hedge fund alpha but significantly lower t-statistics and adjusted R-squareds for all hedge fund strategies. This is in line with Eling and Faust (2010), who also use equally weighted indices and individual hedge fund returns to examine emerging market hedge fund performance. They find that the adjusted R^2 decreases significantly when the average of individual hedge fund returns is used as the dependent variable. In this case, when I use individual hedge fund returns as the dependent variable, the adjusted R^2 decreases from 0.40, 0.59, and 0.63 to 0.25, 0.35, and 0.33 for the FH, Teo, and SW Asia models, respectively. The FH model finds a positive alpha that is statistically significant at 5% for the relative value and fixed income strategies, while the alpha of the largest group among Asia focused hedge funds – equity long/short – is positive but insignificant for all three models. Event-driven and others strategies exhibit alphas significant at 1% for all three models. When I use individual hedge fund returns as the dependent variable, Teo's adjusted model produces a higher adjusted R^2 (0.35) than the stepwise Asia model (0.33).

Tables 5.5, 5.6, and 5.10 present the results derived by estimating the FH seven-factor model, Teo's nine-factor model, and the stepwise-Asia model across all hedge fund strategies for the full sample period. The FH model in the table 5.5 shows that seven of the eight Asian hedge fund strategies have positive and statistically significant factor loadings at

1% to the US equity market factor (S&P 500). The only strategy with insignificant exposure to the US equity factor is the CTA strategy. Credit spread is significant and negative for six of the eight strategies, while bond factor is significant and negative for two of the Asian strategies. One can interpret the negative sign of credit spread in the following way. Hedge funds often buy low-quality, higher-yielding corporate bonds, the acquisition of which is financed by lending 10-year US treasuries. The yield of low-quality bonds increases faster than the yield of 10-year US treasuries, leading to a decrease in value of the low-quality bonds, which subsequently decreases the returns of hedge funds. According to the FH model, primitive trend-following strategies do not explain much of the Asia-focused hedge fund returns.

Table 5.6 shows the results of Teo's adjusted model. As expected, both Asian equity risk factors are positive and significant at 1% for most of the strategies (equity long/short, relative value, event driven macro, directional, and others). The US equity market factor (S&P 500), which was positive and significant in the FH model for seven of the eight strategies, becomes insignificant in the adjusted Teo model for all strategies except event driven and equity long/short, where it is negative and significant at 1% and 5%, respectively. As expected, the two additional equity factors do not explain as much of the hedge fund returns for the fixed income, macro, and CTA strategies.

Table 5.11 shows the results of the SW Asia estimation model. The MSCI Asia ex Japan index is included in every Asian hedge fund strategy, while the Nikkei 225 and the momentum factor are present in four of the eight strategies. The largest increase in adjusted R^2 occurs for the macro strategy, where adjusted R^2 moves from 0.31 in Teo's model to 0.51 in the SW Asia model. Macro strategy has a negative, significant at 1%, factor loading to momentum and primitive trend-following strategy on the stock index look-back straddle (PTFSSTK) and S&P REIT risk factors. Momentum and PTFSSTK were constructed to mimic the trend-following characteristic of hedge funds, while the S&P REIT proxies exposure to the real-estate sector. The fact that the Asian macro strategy has negative factor loadings to these three factors suggests that this strategy is "contrarian". These hedge funds focus on securities with similar fundamental values – when their prices diverge, they tend to buy undervalued securities (losers) and sell overvalued securities (winners). This is exactly the opposite of the trend-followers' tendency to buy winners and sell losers.

Table 5.5

Hedge fund portfolio performance is estimated relative to Fung and Hsieh's (2004) model for Asia-focused hedge fund strategies. The factors are: S&P 500 return minus the risk-free rate (*SNPMRF*), Russell 2000 minus the S&P 500 return (*SCMLC*), the change in the constant maturity yield of the US ten-year Treasury bond adjusted for the duration of the ten-year bond (*BD10RET*), the change in the spread of Moody's BAA bond over the ten-year Treasury bond (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), and commodities PTFS (*PTFSCOM*). The sample period is from January 2000 to December 2010.

Strategy	α	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSCOM	PTFSFX
Equity long/short	0.57	0.32	0.04	-0.06	-2.11	0.01	0.02	0.00
	(3.35)	(8.64)	(1.11)	(-0.09)	(-2.27)	(0.90)	(1.28)	(0.05)
Relative value	0.73	0.38	-0.07	-2.50	-5.27	0.01	-0.01	0.02
	(3.06)	(6.84)	(-1.09)	(-2.45)	(-3.06)	(0.54)	(-0.56)	(1.05)
Event driven	0.62	0.19	-0.01	-0.22	-2.41	0.03	-0.00	-0.01
	(3.46)	(4.03)	(-0.16)	(-0.29)	(-2.99)	(1.91)	(-0.21)	(-1.11)
Macro	0.92	0.50	0.18	4.15	2.41	0.06	-0.03	-0.02
	(2.02)	(5.04)	(1.43)	(1.60)	(1.18)	(1.24)	(-0.69)	(-1.08)
Directional	0.76	0.77	0.04	-1.75	-4.39	0.04	0.01	-0.01
	(2.30)	(10.69)	(0.59)	(-1.30)	(-2.68)	(1.65)	(0.60)	(-0.75)
Fixed income	0.67	0.19	0.02	-2.86	-3.43	0.02	-0.01	-0.00
	(4.52)	(5.03)	(0.29)	(-3.63)	(-4.50)	(1.77)	(-1.15)	(-0.18)
CTA	0.40	0.11	0.18	1.89	0.07	0.03	0.03	0.03
	(0.88)	(0.87)	(1.19)	(1.02)	(0.05)	(0.61)	(1.03)	(1.15)
Others	0.56	0.32	0.08	-0.07	-2.63	0.00	0.02	-0.00
	(3.33)	(9.21)	(1.92)	(-0.12)	(-3.21)	(0.04)	(1.50)	(-0.41)

Table 5.6

Hedge fund portfolio performance is estimated relative to adjusted Teo's (2009) adjusted model for Asia-focused hedge fund strategies. The factors are: S&P 500 return minus the risk-free rate (*SNPMRF*), Russell 2000 minus the S&P 500 return (*SCMLC*), the change in the constant maturity yield of the US ten-year Treasury bond adjusted for the duration of the ten-year bond (*BD10RET*), the change in the spread of Moody's BAA bond over ten-year Treasury bond (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), commodities PTFS (*PTFSCOM*), MSCI Asia ex Japan index return minus the risk-free rate (*ASIAMRF*), and Nikkei 225 index return minus the risk-free rate (*JAPMRF*). The sample period is from January 2000 to December 2010

Strategy	α	*SNPMRF*	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSBD	PTFSCOM	ASIAMRF	JAPMRF
Equity long/short	0.48	-0.08	0.01	0.49	-0.35	-0.00	0.01	0.01	0.29	0.16
	(4.46)	(-2.17)	(0.16)	(1.01)	(-0.59)	(-0.67)	(1.32)	(1.51)	(9.18)	(6.28)
Relative value	0.54	-0.08	-0.08	-1.63	-3.39	-0.01	-0.01	0.02	0.40	0.06
	(3.15)	(-1.50)	(-1.69)	(-2.33)	(-2.45)	(-0.36)	(-1.41)	(1.74)	(8.83)	(1.74)
Event driven	0.52	-0.16	-0.03	0.32	-0.94	0.01	-0.01	-0.00	0.27	0.10
	(3.74)	(-3.32)	(-0.57)	(0.51)	(-1.69)	(1.53)	(-0.85)	(-0.59)	(7.15)	(3.09)
Macro	0.76	0.09	0.16	4.92	4.14	0.04	-0.03	-0.02	0.36	0.07
	(1.70)	(0.52)	(1.47)	(1.83)	(1.88)	(0.96)	(-0.87)	(-0.75)	(2.80)	(0.52)
Directional	0.58	-0.05	-0.04	-0.66	-0.79	0.01	-0.00	0.01	0.57	0.35
	(3.36)	(-0.94)	(-0.69)	(-0.88)	(-0.99)	(0.73)	(-0.07)	(0.87)	(13.19)	(7.79)
Fixed income	0.65	0.06	0.01	-2.70	-2.89	0.02	-0.01	0.00	0.09	0.05
	(4.21)	(1.08)	(0.09)	(-3.34)	(-3.97)	(1.47)	(-1.58)	(0.33)	(2.43)	(1.64)
CTA	0.28	-0.01	0.20	2.32	0.50	0.03	0.03	0.02	0.17	-0.08
	(0.59)	(-0.05)	(1.31)	(1.14)	(0.38)	(0.56)	(1.10)	(0.97)	(0.97)	(-0.61)
Others	0.46	-0.06	0.05	0.49	-1.02	-0.01	0.01	0.00	0.28	0.13
	(4.20)	(-1.63)	(0.91)	(1.19)	(-1.74)	(-1.91)	(1.68)	(0.72)	(9.11)	(5.45)

Table 5.7

Hedge fund portfolio performance is estimated relative to Fung and Hsieh's (2004) model for Asia-focused hedge fund strategies. The factors are: S&P 500 return minus the risk-free rate (*SNPMRF*), Russell 2000 minus the S&P 500 return (*SCMLC*), the change in the constant maturity yield of the US ten-year Treasury bond adjusted for the duration of the ten-year bond (*BD10RET*), the change in the spread of Moody's BAA bond over the ten-year Treasury bond (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), and commodities PTFS (*PTFSCOM*). The sample period is from February 2007 to December 2010.

Strategy	α	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSCOM	PTFSFX
Equity long/short	0.69	0.49	-0.25	2.10	-0.84	0.04	-0.00	-0.01
	(2.00)	(8.21)	(-1.78)	(0.93)	(-0.68)	(1.47)	(-0.02)	(-0.23)
Relative value	1.25	0.66	-0.40	-0.79	-3.57	0.06	-0.04	0.02
	(2.35)	(6.76)	(-2.09)	(-0.33)	(-1.90)	(1.60)	(-0.76)	(0.48)
Event driven	0.58	0.37	-0.20	1.64	-1.44	0.06	-0.02	-0.00
	(1.82)	(5.75)	(-1.38)	(0.88)	(-1.41)	(2.60)	(-0.64)	(-0.13)
Macro	0.60	0.19	-0.12	0.65	-0.22	0.02	-0.01	0.01
	(2.57)	(4.85)	(-1.41)	(0.66)	(-0.31)	(1.02)	(-0.24)	(0.60)
Directional	0.93	1.03	-0.48	0.73	-1.61	0.09	-0.02	-0.04
	(1.35)	(9.11)	(-1.78)	(0.20)	(-0.83)	(1.59)	(-0.30)	(-0.84)
Fixed income	0.51	0.21	-0.11	-1.84	-2.38	0.02	-0.03	-0.02
	(1.88)	(3.89)	(-1.16)	(-1.79)	(-2.61)	(0.81)	(-1.10)	(-0.86)
CTA	0.59	0.08	-0.09	1.36	0.57	-0.02	0.03	0.01
	(3.29)	(2.50)	(-1.46)	(2.00)	(1.09)	(-1.16)	(1.74)	(0.56)
Others	0.68	0.43	-0.26	1.22	-1.66	0.03	0.00	-0.02
	(2.12)	(7.06)	(-1.97)	(0.73)	(-1.61)	(1.27)	(0.02)	(-0.88)

Table 5.8

Hedge fund portfolio performance is estimated relative to adjusted Teo's (2009) adjusted model for Asia-focused hedge fund strategies. The factors are: S&P 500 return minus the risk-free rate (*SNPMRF*), Russell 2000 minus the S&P 500 return (*SCMLC*), the change in the constant maturity yield of the US ten-year Treasury bond adjusted for the duration of the ten-year bond (*BD10RET*), the change in the spread of Moody's BAA bond over the ten-year Treasury bond (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), and commodities PTFS (*PTFSCOM*). The sample period is from February 2007 to December 2010.

Strategy	α	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	ASIAMRF	JAPMRF
Equity long/short	0.31	-0.11	-0.07	1.88	-0.42	0.02	-0.01	0.02	0.40	0.09
	(1.65)	(-1.62)	(-1.06)	(1.80)	(-0.58)	(1.16)	(-0.82)	(1.51)	(10.07)	(1.90)
Relative value	0.81	0.01	-0.18	-0.95	-3.14	0.03	-0.06	0.05	0.44	0.08
	(2.21)	(0.06)	(-1.41)	(-0.77)	(-1.96)	(1.24)	(-1.70)	(1.92)	(5.23)	(1.12)
Event driven	0.34	-0.17	-0.08	1.00	-0.94	0.03	-0.03	0.02	0.30	0.17
	(1.69)	(-3.31)	(-1.02)	(1.09)	(-1.34)	(1.98)	(-1.94)	(2.13)	(7.41)	(3.05)
Macro	0.39	-0.12	-0.01	0.58	-0.01	0.01	-0.01	0.03	0.21	0.04
	(2.67)	(-2.58)	(-0.27)	(0.99)	(-0.02)	(0.44)	(-0.92)	(2.40)	(6.01)	(1.03)
Directional	0.38	-0.09	-0.21	-0.43	-0.61	0.03	-0.04	0.01	0.65	0.32
	(1.23)	(-0.92)	(-1.92)	(-0.39)	(-0.66)	(1.18)	(-1.40)	(0.50)	(10.87)	(4.33)
Fixed income	0.43	0.00	-0.08	-2.16	-2.16	0.01	-0.03	-0.01	0.11	0.08
	(1.46)	(0.04)	(-0.68)	(-1.69)	(-2.27)	(0.34)	(-1.31)	(-0.36)	(1.67)	(0.78)
CTA	0.55	0.04	-0.07	1.43	0.57	-0.02	0.03	0.01	0.04	-0.01
	(2.99)	(0.66)	(-1.24)	(1.90)	(1.11)	(-1.03)	(1.55)	(0.63)	(0.71)	(-0.29)
Others	0.32	-0.10	-0.08	1.13	-1.32	0.01	-0.01	0.00	0.36	0.06
	(2.00)	(-2.24)	(-1.40)	(2.01)	(-1.96)	(1.11)	(-0.84)	(0.30)	(10.53)	(2.01)

5.5.3 Performance Measurement Results for the Sub-periods

Admati and Ross (1985) note that a static analysis of hedge fund returns is inappropriate if funds change strategies and exposures over time. Using the monthly data on funds of funds, Fung et al. (2008) test for the presence of structural breaks in hedge fund data. They find two structural breaks: one in September 1998, which is associated with the Long Term Capital Management (LTCM) crisis, and one in March 2000, which is associated with the NASDAQ crash.

Following Fung et al. (2008), I apply the three factor models to the returns of equally weighted indices of hedge funds and I test for the presence of structural breaks in Asian hedge fund data by conducting multiple Chow (1960) tests. The results of the Chow (1960) tests for all hedge fund strategies are presented in table 5.9. I find a structural break for most of the Asia-focused hedge fund strategies in February 2007, which corresponds to the start of the global financial crisis. Although Khandani and Lo (2008) propose the August of 2007 as the beginning of financial crisis, I follow Xu et al. (2010) in adopting February 2007 as the start of the financial crisis. The presence of this structural break motivates my investigation of two different sub-periods: January 2000 to January 2007 (sub-period 1) and February 2007 to December 2010 (sub-period 2). The results of the first sub-period from January 2000 to January 2007 are reported in the appendix. For the first sub-period, the alphas, adjusted R-squareds, t-statistics, and other coefficient estimates are qualitatively similar to the results obtained for the full sample.

Table 5.9 Chow's Breakpoint test: February 2007

		FH			**Adj. Teo**			**SW Asia**	
	F stat	*Log like.*	Prob.	F stat	*Log like.*	Prob.	F stat	*Log like.*	Prob.
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equity long/short	2.75	22.97	**0.008**	2.84	29.87	**0.004**	3.44	13.91	**0.011**
Relative value	3.66	29.76	**0.001**	2.45	26.15	**0.012**	2.98	18.35	**0.010**
Event driven	2.13	18.17	**0.039**	1.75	19.27	0.079	1.76	9.23	**0.126**
Macro	3.57	29.05	**0.001**	5.54	53.01	**0.000**	5.15	40.10	**0.000**
Directional	2.16	18.38	**0.036**	1.24	14.02	0.270	1.03	4.32	0.395
Fixed income	2.20	18.67	**0.033**	1.58	17.52	0.122	0.52	4.00	0.821
CTA	0.29	2.65	0.967	0.23	2.75	0.992	0.97	1.99	0.381
Others	2.49	20.93	**0.016**	2.33	25.08	**0.016**	3.09	18.96	**0.008**

I am particularly interested in the analysis of Asian hedge fund performance during the time of the global financial crisis of 2007-2010. Table 5.4, panel C presents the alphas, t-statistics, and adjusted R-squared estimated using the three performance measurement models for the second sub-period. Somewhat surprisingly, all three performance measurement models find positive alphas during the sample period encompassing the global financial crisis. However, alphas are not statistically significant to the extent they were in the full period under investigation. Furthermore, the explanatory power of the three models increases slightly in this sub-period, as proven by the marginal increases in the average adjusted R^2 across strategies.

The FH model finds positive and significant (at 5%) alphas for seven of the eight hedge fund strategies. In the full sample, the FH model produces an irrelevant adjusted R^2 of 0.01 for the CTA strategy, while the same model produces a meaningful adjusted R^2 of 0.27 in sub-period 1.

The Teo's adjusted model finds positive and significant alphas for four hedge fund strategies. Alpha is significant at 1% only for the macro and CTA strategies, while the largest adjusted R^2 is obtained for directional strategy (0.95). This shows that Teo's model explains almost all variation for that particular strategy. Teo's adjusted model produces an average adjusted R^2 across strategies of 0.76, which represents a meaningful 0.17 p.p. increase over the adjusted R^2 for the full period. As expected, the SW Asia model shows the lowest alpha values. The alphas are still positive but they are significant at 1% for only the CTA strategy, which in turn has a low adjusted R^2 of only 0.13. The SW Asia model estimates positive but insignificant alphas for the equity long/short, event driven, and directional strategies. All of these strategies are heavily dependent on the equity markets, which performed poorly during the course of global financial crisis. Overall, the average adjusted R^2 across strategies increases by 0.11 in the SW Asia model when compared to the full sample period.

Table 5.10

Decomposing Asia-focused hedge fund returns: stepwise Asia model (January 2000 to December 2010)

Equity long/short			**Relative value**		
Adj. R^2	0,82		Adj. R^2	0,75	
α	0,46	(4,83)	α	0,52	(3,87)
MSCEI Asia ex. Japan	0,25	(10,65)	MSCEI Asia ex. Japan	0,37	(11,89)
Nikkei 225	0,15	(6,26)	MSCEI World ex. US	0,08	(2,66)
Momentum	0,05	(2,65)	PTFSIR	-0,01	(-3,14)
Silver	0,03	(1,77)	HML	0,12	(4,00)
			JPM Japan govt. bond	0,15	(3,20)
			Oil	(0,03)	(1,61)
Event Driven			**Macro**		
Adj. R^2	0,59		Adj. R^2	0,51	
α	0,51	(3,68)	α	0,45	(1,18)
PTFSIR	0,25	(6,21)	MSCEI Asia ex. Japan	0,51	(6,56)
Nikkei 225	-0,01	(-3,84)	S&P REIT	-0,37	(-5,59)
Market	0,10	(3,18)	YEN/USD	0,30	(2,41)
			PTFSSTK	-0,08	(-3,02)
			Momentum	-0,18	(-3,19)
			SMB	0,26	(2,98)
			ML High Yield Index	-0,22	(-2,09)
Directional			**Fixed income**		
Adj. R^2	0,90		Adj. R^2	0,58	
α	0,49	(3,30)	α	0,69	(5,66)
MSCEI Asia ex. Japan	0,54	(14,54)	MSCEI Asia ex. Japan	0,08	(2,42)
Nikkei 225	0,34	(9,35)	JPM US govt. bond	0,44	(5,33)
Gold	0,07	(2,34)	Credit	-1,98	(-2,80)
			Market	0,13	(2,62)
			PTFSIR	-0,01	(-3,32)
			YEN/USD	-0,10	(-2,43)
CTA			**Others**		
Adj. R^2	0,07		Adj. R^2	0,85	
α	-0,05	(-0,11)	α	0,54	(5,58)
Oil	0,11	(2,34)	MSCEI Asia ex. Japan	0,29	(12,30)
Citigroup Bond Index	0,79	(1,49)	Nikkei 225	0,12	(6,07)
			Silver	0,03	(2,34)
			Momentum	0,05	(2,33)
			S&P REIT	-0,06	(-3,62)
			MSCEI World ex. US	0,10	(4,74)

Table 5.11

Decomposing Asia-focused hedge fund returns: stepwise Asia model
(January 2007 to December 2010)

Equity long/short			**Relative value**		
Adj. R^2	0,88		Adj. R^2	0,83	
α	0,21	(1,27)	α	0,71	(2,50)
MSCEI Asia ex. Japan	0,32	(8,78)	MSCEI Asia ex. Japan	0,44	(9,96)
Nikkei 225	0,09	(1,73)	MSCEI World ex. US	0,11	(2,46)
Momentum	0,03	(1,07)	PTFSIR	-0,01	(-1,72)
Silver	0,03	(0,76)	HML	0,14	(1,60)
			JPM Japan gov. bond	0,28	(2,87)
			Oil	(0,02)	(0,39)
Event Driven			**Macro**		
Adj. R^2	0,83		Adj. R^2	0,67	
α	0,71	(2,50)	α	0,31	(1,90)
PTFSIR	0,44	(9,96)	MSCEI Asia ex. Japan	0,19	(6,37)
Nikkei 225	0,11	(2,46)	S&P REIT	-0,08	(-2,33)
Market	-0,01	(-1,72)	YEN/USD	0,03	(0,50)
			PTFSSTK	0,00	(0,11)
			Momentum	-0,06	(-2,28)
			SMB	-0,04	(-0,51)
			ML High Yield Index	0,00	(0,02)
Directional			**Fixed income**		
Adj. R^2	0,94		Adj. R^2	0,72	
α	0,14	(0,53)	α	0,44	(1,87)
MSCEI Asia ex. Japan	0,57	(8,80)	MSCEI Asia ex. Japan	0,08	(1,53)
Nikkei 225	0,32	(4,42)	JPM US gov. bond	0,46	(3,00)
Gold	0,10	(1,68)	Credit	-2,33	(-2,99)
			Market	0,13	(1,53)
			PTFSIR	-0,01	(-2,66)
			YEN/USD	-0,13	(-2,14)
CTA			**Others**		
Adj. R^2	0,10		Adj. R^2	0,95	
α	0,48	(2,32)	α	0,23	(2,34)
Oil	0,04	(1,55)	MSCEI Asia ex. Japan	0,35	(14,97)
Citigroup Bond Index	0,06	(0,48)	Nikkei 225	0,11	(5,23)
			Silver	0,03	(2,94)
			Momentum	-0,01	(-0,56)
			S&P REIT	-0,13	(-6,55)
			MSCEI World ex. US	0,12	(3,78)

Table 5.7 presents the more detailed results obtained from estimating the FH model across all hedge fund strategies for the second sub-period that includes financial crisis. The FH model shows results similar to those derived for the full sample – seven of the eight Asian hedge fund strategies have positive and statistically significant factor loadings at 1% to the US equity market factor (S&P 500). However, contrary to the results for the full sample period, all eight strategies show positive and significant exposure to the size factor (*SCMLC*), measured as Russell 2000 returns minus S&P 500 returns. Normally, the fact that hedge funds have exposure to the size factor has an intuitive explanation: the universe of small stocks is less researched and, hence, has a greater amount of undervalued stocks. However, it is difficult to argue that Asian hedge funds decided to invest heavily in smaller stocks in the midst of financial crisis. Rather, I believe that the FH model lacks the power to capture the full extent of the variability of Asia-focused hedge funds.

Table 5.8 shows the results obtained using the Teo model for the second sub-period. The table demonstrates that both the US equity factor and the size factor lose the significance they had in the FH model. In fact, the US equity factor shows negative factor loadings and is significant for three strategies. As in the full sample, Teo's model shows that the MSCI Asia ex Japan factor is positive and significant at 1% for six of the eight strategies. The second Asian equity factor (Nikkei 225) is significant for four of the eight strategies. Finally, the SW Asia strategy shows similar coefficient exposures in the sub-period to the exposures obtained for the full sample period. The MSCI Asia ex Japan index is positive and significant at 1% for five strategies, indicating positive exposure to Asian equity markets during the financial crisis. The SW Asia model estimates significant alpha at 1% for the relative value and event-driven strategies, while alpha is significant at 1% for the macro, directional, and CTA strategies. Finally, Table 5.11 presents the results obtained from estimating the stepwise Asia model for the second sub-period. The MSCEI Asia ex. Japan index is positive and significant at 1% for all Asian hedge fund strategies, indicating positive exposure to Asian equities during the period of financial crisis.

5.5.4 Conclusion

In the academic literature on hedge funds, very few studies analyze the performance of hedge funds during the latest financial crisis of 2007-2010. This paper addresses that gap and analyzes the performance of Asia-focused hedge funds over the time period which includes the financial crisis of 2007-2010. This paper investigates the performance of the

Asia-focused hedge funds using the data sample of 1,169 Asian hedge funds covering the period from January 2000 to December 2010. In order to explain hedge fund performance and investigate whether Asian hedge funds produce alpha, I benchmark hedge fund returns against three multi-factor performance models: Fung and Hsieh's (2004) model, Teo's (2009) adjusted model, and a stepwise regression Asia model. Teo's adjusted model and the SW Asia model explain a significant proportion of hedge fund returns, as proven by the high values of adjusted R^2. I find that the FH model is not well suited to explaining Asian hedge fund returns.

Applying the Chow (1960) test I also identify a structural break in the data, which motivates the investigation of two sub-periods. Structural breaks in hedge fund data imply that hedge fund managers changed their risk exposure at a particular point in time. My results indicate that Asian hedge funds, as a group, produced statistically significant alpha over the full sample period, as estimated by Teo's adjusted model and the SW Asia model. However, during the financial crisis, Asia-focused hedge funds did not produce significant alphas on average. These results are in line with Xu et al. (2010), who examine the performance of global hedge funds during the financial crisis and find that hedge funds did not deliver significantly positive risk-adjusted excess returns during that period.

6. Persistence of Asia-focused hedge fund performance

6.1 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. Sirri and Tufano (1998) study the flow of funds into and out of mutual funds. They find that investors base their fund selection procedure on the fund's prior performance – they invest in the previous year's best performers and withdraw money from the previous year's losers. Capon et al. (1996) analyze the selection criteria of 3,386 mutual fund investors and find that previous performance is the most important selection criteria employed.

Research on performance persistence essentially deals with one question: "Do some hedge fund managers achieve consistently higher returns than their competitors?". This is an important question from the perspective of hedge fund investors, who constantly face selection problems when trying to choose hedge funds in which to invest. Capocci et al. (2005) note, that if performance in hedge fund returns persists, active selection is likely to increase the expected return because one superior average return period is likely to be followed by another superior average return period. In other words, one can regard the measure of performance persistence as a quantitative characteristic of the hedge fund manager's selection process.

Certain characteristics of hedge funds make them an ideal subject for studies of performance persistence in the money management sector. Unlike traditional mutual fund managers, who are limited in terms of the investment strategies at their disposal, hedge fund managers have more flexibility and freedom when it comes to investment decisions and thus have a better chance at displaying their skills.

This chapter looks at the period 2000 to 2010 and investigates whether some Asia-focused hedge fund managers deliver consistently higher returns than their competitors. More specifically, I analyze whether the returns of Asia-focused hedge funds persist at a yearly horizon. In addition to investigating performance persistence over the full sample period, I break the sample into two sub-periods and investigate performance persistence in different market environments. These sub-periods are the same as those used in the Chapter 5: January 2000 to January2007 and February 2007 to December 2010. Therefore, this chapter investigates Asia-focused hedge fund performance persistence during a period that encompasses both a bullish market (2000 to 2007) and a bearish market (2007 to 2010).

Koh et al. (2003) merge the Eurekahedge and AsiaHedge databases to study the performance persistence of Asia-focused hedge funds from 1999 through 2003. On the basis of nonparametric statistical methods, including a contingency table based test for single-period persistence and a Kolmogorov-Smirnov statistic for a multi-period persistence test, Koh et al. (2003) examine the period from January 1999 until March 2003 and find that Asia-focused hedge funds exhibit persistence in performance at monthly and quarterly horizons but not at the annual horizon. This chapter expands Koh et al.'s (2003) work on hedge fund performance persistence by analyzing Asia-focused hedge funds over a longer investigation period that encompasses both market upswings and market declines. Furthermore, unlike Koh et al. (2003), who use non-parametric methods to investigate hedge fund performance, this dissertation applies a parametric, regression-based framework to analyze performance persistence. In this regard, this study is similar to Capocci et al. (2005), who use the MAR database to analyze the persistence of hedge fund performance during a period that includes both an improving and a declining market. The authors document that most of the predictability of superior performance is to be found during the bull market period. Furthermore, they find limited evidence of performance persistence among average performers.

The rest of this chapter is structured as follows. I begin by presenting extant academic literature on performance persistence. The data set and the methodology are then described before the results are presented and discussed.

6.2 Literature Review

Academic research into the persistence of hedge fund performance is a relatively recent phenomenon, with the first articles on this topic published near the end of 1990s. However, the issue of performance persistence has been widely researched in the context of mutual funds and the results of the main performance persistence studies of mutual funds are relevant in the current context.

Hendricks et al. (1993) study quarterly return data from a sample of open-ended mutual funds covering the period 1974 to 1988 and demonstrate that mutual fund performance exhibits persistence over a short-term horizon of one to three years. They attribute this persistence to "hot hands" or common investment strategies. Brown and Goetzmann (1995) investigate mutual fund performance persistence using a data sample from 1977 until 1989 and find that the relative risk-adjusted performance of mutual funds persists. However, they also find that such persistence is mostly due to funds that lag the S&P 500 index. Grinblatt and Titman (1992) study mutual fund data over the 1975 to 1984 period and find evidence of performance persistence over a longer horizon (five years). The authors attribute this persistence in returns to managerial skill. Finally, Carhart (1997) investigates mutual fund performance persistence using a sample that covers the period 1962 until 1993. He finds that common factors in stock returns and investment expenses explain persistence in mutual funds' returns. Furthermore, Carhart (1997) finds that the strongest unexplained persistence among the worst mutual fund performers. In summary, most studies on performance persistence among mutual funds confirm that, on average, mutual funds have inferior performance to passive investment strategies and they find only limited evidence of performance persistence.

Some authors acknowledge that the situation might be different in terms of hedge fund performance persistence. Agarwal and Naik (2000) note that mutual fund managers who successfully outperform passive investment strategies tend to switch into the hedge fund industry. Consequently, the hedge fund arena may be better suited for measurements of performance persistence. Brown et al. (1999) conduct one of the first studies on performance persistence in hedge funds, using the US Offshore Funds Directory over the period 1989 through 1995. They find no performance persistence at the yearly horizon. Agarwal and Naik (2000) use both the traditional two-period framework as well as a multi-period framework (a Kolmogorov-Smirnov test) to study hedge fund performance persistence, and they find persistence to be strongest at the quarterly horizons. Brown and Goetzmann (2003) use the TASS database to study persistence of returns for the period 1989 to 1999. They find no persistence at the yearly horizon. Similarly, Capocci et al. (2005) use the MAR database to investigate hedge fund performance at the yearly horizon over the period 1994 to 2002, a period that includes both bullish and bearish market environments. Furthermore, in the second sub-period, which is characterized by a bearish market environment, the authors find only negative persistence among past losers, suggesting that poor performance is a decisive factor in hedge fund attrition.

Edwards and Caglayan (2001) use the MAR database to study hedge fund performance over the period 1990 to 1998. The authors investigate performance persistence at yearly and bi-yearly horizons using alphas obtained from a six-factor model as a measure of performance, and they apply both parametric and non-parametric statistical tests. The authors find evidence of significant persistence among both winners and losers. Baquero et al. (2005) investigate hedge fund performance persistence in raw returns and find evidence of positive performance persistence at quarterly horizons, especially for the four best deciles. They also find evidence of positive persistence at the annual horizon, although it is statistically insignificant. Kosowski et al. (2007) use bootstrap and Bayesian methods to investigate the persistence of hedge fund performance. The authors rely on the union of the TASS, HFR, CISDM, and MSCI datasets, which provides them with the data for 9,338 hedge funds.[12] They find that the best hedge fund performance cannot be explained by luck and that hedge fund performance persists at the annual horizon.

Sy et al. (2007) use the Eurekahedge database to investigate the performance persistence of 206 Asia-focused long/short equity hedge funds over the period January 2004 to June 2006. They perform performance persistence tests on quarterly raw returns, and use both parametric (regression-based) and non-parametric methods (contingency table) methods. Furthermore, they expand the two independent binomials contingency table into a multinomial contingency table. They find that the independent binomials and the regression analyses show significant evidence of persistence in performance over two consecutive periods. They also find that the persistence in the performance of Asia-focused long/short hedge funds decreases in the third and fourth quarters when compared to performance in the first quarter. Hence, they conclude that although investors can make their investment decisions for the second quarter based on the hedge fund's performance in the first quarter, the fund's performance in the first quarter alone will not provide enough information to predict its performance in the third or fourth quarters.

Boyson (2008) uses the TASS data set for the period 1994 to 2004 to investigate the persistence of hedge fund performance. She finds that 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) investigate hedge fund performance persistence using cross-product ratio, chi square and Kolmogorov-Smirnov tests. They find persistence at the monthly and quarterly horizons, but not at the annual horizon.

[12] After various adjustments, the number of hedge funds decreases to 5,544.

Jagannathan et al. (2010) estimate hedge fund performance persistence by comparing the alphas over the 3 year horizons. The authors control for the measurement errors in alphas by applying both weighted least squares approach and a generalized method of moments estimation model. The authors find strong evidence of performance persistence among top hedge funds while they find little evidence of persistence among bottom funds.

Finally, Eling (2009) conducts an extensive literature review on the persistence of hedge fund performance and documents that nearly all studies find short-term (up to six months) persistence and that the significance of persistence decreases with the length of time horizon. Furthermore, he finds that the studies come to conflicting conclusions regarding longer horizons. Eight studies document performance persistence at the annual horizon, while ten studies find no persistence at that horizon. Several authors offer various theories for the occurrence of performance persistence. Getmansky et al. (2004) attribute short-term hedge fund persistence to the illiquidity induced by the type of assets in which hedge funds often invest. For an extensive examination of the literature on the persistence in hedge fund performance, see the updated version of Eling's (2009) literature review in Table 6.1. As this literature review highlights, research on persistence in hedge fund returns has produced conflicting results and there is no consensus on this issue among *academics*.

Table 6.1 Literature review of studies on hedge fund performance persistence

Authors	Database	Nr. Of funds	Investigation period	Time horizon (in months)	Performance measure	Persistence measure	Results
Agarwal, Daniel and Naik (2009)	CISDM, HFR, MSCI, and TASS	7,535	1994–2002	12	Return	Chi-square, regression	Persistence at yearly horizon
Agarwal and Naik (2000)	HFR	746	1982–1998	3,6,12	Alpha, appraisal ratio	Cross-product ratio, chi-square, regression, Kolmogorov-Smirnov	Persistence at quarterly horizon
Agarwal and Naik (2000c)	HFR	167	1995–1998	3	Alpha, appraisal ratio	Cross-product ratio, regression	Persistence at quarterly horizon
Amenc et al., 2003	CSFB/Tremont indices	9	1994–2000	1	Return	Regression	Persistence at monthly horizon
Ammann et al., 2010	TASS and CISDM	4,311	1994–2008	6,12,24,36	Alpha, returns	Regression	Persistence up to 36m horizon
Baquero et al., 2005	TASS	1,797	1994–2000	3,12,24	Return, alpha	Descriptive comparison of rankings	Persistence at quarterly and yearly horizons, but not at two-year horizon
Bares et al., 2003	Financial Risk Management	4,934	1992–2000	1,3,6,12		Descriptive comparison of rankings	Persistence at monthly and quarterly horizons
Boyson and Cooper, 2004	TASS	1,659	1994–2000	3	Alpha	Regression	Persistence at quarterly horizon
Brown and Goetzmann, 2003	TASS	1,295	1992–1998	12	Return	Regression	No persistence at yearly horizon
Brown et al., 1999	US Offshore Funds Directory	399	1989–1995	12	Return, alpha, appraisal ratio	Regression	No persistence at yearly horizon
Capocci et al., 2005	MAR	2,894	1994–2002	12	Alpha	Regression	No persistence at yearly horizon
Capocci and Huebner, 2004	HFR, MAR	2,796	1988–1995	12	Alpha	Regression	No persistence at yearly horizon
Chen and Passow, 2003	TASS, HFR	76	1990–2002	12	Alpha	Regression	No persistence at yearly horizon
De Souza and Gokcan, 2004	HFR	314	1997–2002	24, 36	Return, standard deviation, Sharpe ratio	Cross-product ratio, regression,	No persistence at two- and three-year horizons with returns, but persistence with risk
Edwards and Caglayan, 2001	MAR	1,665	1990–1998	12, 24	Alpha	Cross-product ratio, regression	Persistence at one- and two-year horizons
Eling, 2009	CISDM	4,314	1996–2005	1, 2, 3, 6, 12, 24	Return, Sharpe ratio, alpha, appraisal ratio	Cross-product ratio, chi-square, rank information coefficient, Spearman, regression, Hurst, Kolmogorov/Smirnov	Persistence at monthly, two-monthly, quarterly, and half-yearly horizons
Gregoriou and Rouah, 2001	Zurich/LaPorte	n/a	1988–1999	12	Alpha	Descriptive comparison of rankings	No persistence at yearly horizon
Harri and Brorsen, 2004	LaPorte	1,209	1977–1998	1, 2, 3, . . . to 24	Return, information ratio, Sharpe ratio, alpha	Spearman, regression	Persistence at all horizons
Henn and Meier, 2005	Eurekahedge	1,217	1994–2004	1, 3, 12	Return	Cross-product ratio	Persistence at monthly, quarterly, and yearly horizons
Herzberg and Mozes, 2003	HedgeFund.net, Altvest, Spring, and Mountain Capital	3,300	1995–2001	12	Return, Sharpe ratio, max. draw, standard deviation, correlation	Rank information coefficient	No persistence at yearly horizon with returns, but persistence with risk
Jagannathan et al., 2010	HFR	1,755	1996–2005	36	Alpha	Regression	Evidence of persistence at three-year horizon among top funds
Kat and Menexe, 2003	TASS	324	1994–2001	36	Return, standard deviation, skewness, kurtosis, correlation	Cross-product ratio, regression	No persistence at three-year horizon with returns, but with the higher mo.
Koh et al., 2003	Eurekahedge, AsiaHedge	3,810	1999–2003	1, 2, 3, 6, 9, 12	Return, alpha	Cross-product ratio, chi square, Kolmogorov- Smirnov	Persistence at monthly and quarterly horizons, but not at yearly horizon
Kosowski et al., 2007	TASS, HFR, CISDM, and MSCI	9,338	1990–2002	12	Alpha	Regression, bootstrap approach, Bayesian approach	Persistence at yearly horizon
Kouwenberg, 2003	MAR	2,614	1995–2000	36	Return, alpha, Sharpe ratio	Chi-square	Persistence at three-year horizon
Malkiel and Saha, 2005	TASS	2,065	1996–2003	12	Return	Chi-square	No persistence at yearly horizon
Navone and Belleri, 2007	Global Hedge Source	3,627	1997–2004	3, 6, 12	Return, alpha	Regression	Persistence at quarterly, half-yearly, and yearly horizons
Park and Staum, 1998	TASS	n/a	1986–1997	12	Appraisal ratio	Chi square, Spearman	Persistence at yearly horizon
Sy et al., 2007	Eurekahedge	206	2004–2006	1,3,9,12	Return, alpha, and appraisal ratio	Regression, contingency table approach	Persistence at quarterly, but not at half-yearly or yearly horizons
This study	Eurekahedge	1.169	2000–2010	12	Alpha	Regression	

Source: Author’s own depiction, based on Eling (2009)

6.3 Data

This study uses the Eurekahedge database covering the period January 2000 to December 2010. This period is of specific importance, as it encompasses the financial crisis of 2007 to 2010. The Eurekahedge Asia Pacific database covers 2,242 hedge funds. However, after adjusting for survivorship, instant history, and selection bias, the data set encompasses 1,169 hedge funds. This constitutes the largest sample of Asia-focused hedge funds used in an academic study to date.

When choosing a period of investigation, several important factors must be considered. First, examination of hedge fund returns before 1994 may not be worthwhile due to survivorship bias, which is an essential characteristic of hedge fund data prior to that year (see Liang, 2000). Second, in the academic literature, most studies measure the performance or performance persistence of the fund rather than the fund manager. In reality, however, it is the performance of the fund manager that interests academics, as performance persistence is related to the particular set of skills possessed by the fund manager. Nonetheless, it is hard to control for changes in fund managers. For that reason, academics usually use data on fund performance. As a result, Eling (2009) recommends that researchers use time periods not longer than 10 years. In that light, the decision to study the period January 2000 to December 2010 seems appropriate.

As mentioned in Chapter 2, there is no universal method for classifying different hedge funds' investment styles and strategies. While Eurekahedge sorts Asia-Pacific hedge funds into 14 different investment strategies, this paper follows Teo (2009) in condensing hedge fund strategies into eight primary investment strategies (equity long/short, relative value, event driven, macro, directional, fixed income, managed futures (CTA) and others).

Hedge fund databases are known to suffer from various biases. One such bias – survivorship bias – is defined in the literature as the difference in performance between the portfolio of live funds and the portfolio of dead funds. (Ackermann et al., 1999), or the difference between the difference in performance between the portfolio of live funds and the portfolio of all funds in the database (Liang, 2000). Using the first definition, I calculate a survivorship bias for the whole sample period of 0.54% per month, while the second definition gives a survivorship bias of 0.16 per month. These values are in line with those found in the extant literature (see Liang, 2000; Eling and Faust, 2010; Xu et al., 2010). In addition, as the database used here covers a recent time period (2000 to 2010), the results should be less affected by survivorship bias than hedge fund studies that focus on older time periods. In general, hedge fund databases did not include dead funds before 1994 and, for that reason, some authors exclude hedge fund data prior to 1994 (see, e.g., Capocci and Huebner, 2004; Liang and Park, 2007). Hence, as the data sample covers a period starting in 2000 and as Eurekahedge includes both surviving and dissolved funds, survivorship bias should not significantly affect the results.

Apart from survivorship bias, four other relevant biases are known to affect hedge fund databases: selection bias, instant history bias, illiquidity bias, and multi-period sampling bias. Selection bias occurs when well-performing funds have more incentive to report to database providers than poorly performing funds. However, Fung and Hsieh (2000a) find this bias to be negligible as a result of an offsetting effect, in which the best-performing hedge funds do not report to database vendors because they are closed to new money. Instant history bias arises when database vendors backfill the historical returns of newly added funds, which could subsequently lead to upward bias in performance measurement results. To address this bias, I follow Fung and Hsieh (2000a) and Capocci and Huebner (2004) in that I delete the first 12 months of returns for each hedge fund. Illiquidity bias occurs because hedge funds often invest in illiquid or difficult-to-price securities (such as derivatives, small-cap stocks, and emerging markets bonds). These illiquid securities do not have daily prices and are thus not marked-to-market regularly. In that situation, hedge fund managers may be tempted to smooth their returns and systematically understate the volatility of their portfolios. Agarwal and Naik (2000) document that intra-year persistence can be caused by stale valuations as most hedge funds only disclose audited returns on an annual basis. In order to account for this bias, I follow Getmansky et al.'s (2004) desmoothing procedure. Finally, in order to account for multi-period sampling bias, I follow Fung and Hsieh (2000a), and include only funds with a minimum of 36 months of returns.

6.4 Methodology

Performance persistence can be observed from two different perspectives. The first perspective looks at the performance persistence of a fund by measuring the relative returns of that fund. Hedge fund returns are therefore arranged in groups relative to the median return in a given period or classified into deciles according to the previous sub-period’s returns. The second perspective looks at the performance persistence of a fund by measuring it directly without comparing it to the median.

6.4.1 Persistence of Relative Returns

The persistence of relative returns can be analyzed using two approaches, as shown by Agarwal and Naik (2000), who differentiate between the two-period and multi-period statistical approaches to the measurement of performance persistence. In the two-period statistical approach, two consecutive time units are compared, while in the multi-period approach, a series of consecutive time units is considered. One can further divide statistical techniques that build upon the two-period approach into non-parametric and parametric methods.

6.4.1.1 Two Period Approach – Non-parametric Approach

The non-parametric approach centers on the formation of two-way winners and losers contingency tables. Funds that outperform the median return of all funds following the same strategy over the given time period are categorized as winners, while funds that underperform the median returns of all funds following same strategy are categorized as losers. In this approach, persistence refers to those funds that are categorized 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. Agarwal and Naik (2000) use the cross-product ratio (CPR) examine persistence in hedge fund returns. CPR is defined as the ratio of the funds that exhibit performance persistence to those that do not:

$$CPR = \frac{(WW \cdot LL)}{(WL \cdot LW)}. \tag{25}$$

In the case of the null hypothesis, CPR is equal to 1, which indicates no persistence in performance. This means that each of the four previously mentioned classifications (WW, LL, WL, LW) represent 25% of all the funds. One can test the statistical significance of the CPR by calculating Z statistics, which correspond to the ratio of the natural logarithm of the CPR to the standard error of the natural logarithm of the CPR. This can be written as:

$$Z = \frac{\ln(CPR)}{\alpha_{\ln(CPR)}}, \tag{26}$$

where $\alpha_{\ln(CPR)}$, the standard error of the natural logarithm of the CPR is computed as:

$$x = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}. \qquad (27)$$

For instance, a Z statistic greater than 1.96 (2.58) indicates significant persistence at the 5% (1%). The cross-product test is used by Agarwal and Naik (2000), Edwards and Caglayan (2001), Kat and Menexe (2002), Koh et al. (2003) and De Souza and Gokcan (2004).

Alternatively, the chi-square method can be used to test for persistence in returns. As Géhin (2004) notes, the Chi-square test compares the distribution of the observed frequencies of the four categories (WW, LL, WL, LW) with the expected frequencies of the distribution. The chi-square test can be expressed as:

$$\chi^2 = (WW - D1)^2 / D1 + (WL - D2)^2 / D2 + (LW - D3)^2 / D3 + (LL - D4)^2 / D4, \qquad (28)$$

where $D1 = (WW + WL) \cdot (WW + LW) / N$, $D2 = (WW + WL) \cdot (WL + LL) / N$, $D3 = (LW + WL) \cdot (WW + LW) / N$, and $D4 = (LW + LL) \cdot (WL + Ll) / N$, and where N represents the number of all funds.

In the case of chi-square distribution with one degree of freedom, an χ^2 value greater than 3.84 (6.64) implies the statistically significant persistence of returns at the 5% (1%) confidence level.

Carpenter and Lynch (1999) note that the chi-square test is a more robust method in the presence of survivorship bias inherent to hedge fund data. The chi-square test method has been applied by Park and Staum (1998), Agarwal and Naik (2000), Koh et al. (2003), Malkiel and Saha (2005), and Agarwal Daniel and Naik (2009), among others. One drawback of the CPR and chi-square methods is that these methods categorize funds with similar performance into different tranches, hence incorporating substantial differences in the evaluation of these funds; for instance, they compare the worst funds of the upper decile with the best funds of the lower decile.

The Spearman's rank correlation test (see Park and Staum, 1998) is another non-parametric test. It measures the strength of association between two variables and can thus be used to measure persistence in performance. In a Spearman's rank correlation test, performance rankings are compared for different time intervals. The result of this test is always between 1 (indicating perfect positive correlation and hence perfect positive persistence) and -1 (indicating perfect negative correlation and hence perfect negative persistence). A value of the Spearman's rank correlation test around zero implies no persistence in returns over two periods.

6.4.1.2 Two period approach – parametric approach – cross-sectional regression

One can measure the persistence in fund performance by regressing the current period's measurement value (raw returns, alpha, or another measure) onto the previous periods' measurement value. A positive and statistically significant slope coefficient constitutes evidence of persistence in performance, as it shows that a hedge fund that performed well during the previous period will perform well in the current period. One can test the statistical significance of the parameter using t-statistics, where a t value greater than 1.96 (2.58) indicates persistence in performance, significant at the 5% (1%) confidence level. This act of regressing returns onto lagged returns can be expressed as the following equation:

$$R_{\mathrm{it}} - R_{\mathrm{ft}} = \alpha_{\mathrm{i}} + \beta \cdot r_{t-1}. \qquad (29)$$

Several authors have used cross-sectional regression including Brown et al. (1999), Brown and Goetzmann (2003), Agarwal and Naik (2000), Edwards and Caglayan (2001), and Boyson and Cooper (2004).

However, as Hendricks et al. (1993) note, the evidence of persistence in performance that is obtained by applying a cross-sectional regression does not necessary imply that economically worthwhile investment strategies are available. Therefore, Hendricks et al. (1993) suggest ranking the portfolios of mutual funds into decile portfolios based on their performance results for the last year. This approach to measuring performance persistence differs from traditional cross-sectional regression insofar as it enables investors to take advantage of potential persistence in performance by replicating this strategy and investing in hedge funds that exhibit potential persistence in performance. For the purpose of this dissertation, I use this particular approach to examine the performance persistence of Asia-focused hedge funds.

6.4.1.3 Multi-period approach – Kolmogorov-Smirnov goodness-of-fit test

The Kolmogorov-Smirnov test attempts to ascertain whether two data sets differ significantly. In contrast to two-period tests, this multi-period approach delivers more robust results. The researcher records a series of wins and losses for each fund, and accordingly labels the fund as either a winner or a loser. Eling (2009) notes that in the context of hedge fund performance persistence, the Kolmogorov-Smirnov method is employed to investigate whether the distribution of funds labeled as winners or losers is statistically different from the theoretical frequency distribution of two or more consecutive wins or losses. For instance, assuming that there is no persistence in returns, 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. One advantage of the Kolmogorov-Smirnov method, according to Géhin (2004), is that the distribution of the test statistic itself does not depend on the underlying cumulative distribution function that is being tested. Another attractive feature is that its data requirements are low. On the other hand, one important limitation is that the test can only be applied to a continuous distribution. Agarwal and Naik (2000), Koh et al. (2003), and Eling (2009) are among the authors who used the Kolmogorov-Smirnov test in their analyses.

6.4.2 Persistence of Relative Returns

6.4.2.1 The Hurst Exponent

De Souza and Gokcan (2004) introduced the Hurst exponent as an attempt to measure hedge fund performance persistence directly rather than in relation to some other return. The authors define the Hurst exponent as a measure of whether a trend, be it negative or positive, will persist or mean-revert to some historical average. Unlike most other statistical tests for persistence, the Hurst exponent makes no assumptions about the frequency distribution of the underlying data. It can be defined as follows:

$RS_t \cong (ct)^H$ or $\ln RS_t = \ln(c) + H\ln(t)$, where RS_t is the range of cumulative deviation from the mean divided by the standard deviation and H represents the Hurst exponent, which varies between zero and one. If the value of the Hurst exponent lies between 0 and 0, then that implies reversed persistence. If on the other hand, the value of the Hurst exponent lies between 0.5 and 1, that implies positive persistence in performance. Finally, an exponent of 0.5 indicates random performance. The drawback of the Hurst exponent methodology is that it requires more data points than previously mentioned methods. More details on the Hurst exponent can be found in Couillard (2005).

6.4.3 Performance Measurement

This section briefly describes the two multi-factor performance measurement models used in this paper to examine the performance persistence of Asia-focused hedge funds: the Fung and Hsieh (2004a) seven-factor model and an adjusted Teo's (2009) model of hedge fund performance. The Fung and Hsieh (2004a) model is one of the most widely used multi-factor models in hedge fund literature. The authors use two equity-focused risk factors – an 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 mentioned in Chapter 5, since the Wilshire indices stopped reporting in December 2006, as a size proxy I use instead the Russell 2000 index minus the S&P 500 index (SCMLC) as suggested by David Hsieh on his website. Moreover, 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 so-called "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]:

[13] Monthly return data on the PTFS factors can be obtained from the website of David Hsieh: http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

$$\begin{aligned}R_{\mathrm{it}} - R_{\mathrm{ft}} &= \alpha_{\mathrm{i}} + \beta_{iSNPMRF} SNPMRF_t + \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t \\ &+ \beta_{iBAAMTSY} BAAMTSY_t + \beta_{iPTFSBD} PTFSBD_t + \beta_{iPTFSFX} PTFSFX_t \\ &+ \beta_{iPTFSCOM} PTFSCOM_t + \varepsilon_{it}.\end{aligned} \tag{17}$$

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. Furthermore, 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. However, in this dissertation I adjust Teo's (2009) model by removing the two option-based equity factors which according to Teo's (2009) analysis do not explain much of the variation of Asia-focused hedge funds returns. His adjusted model is given by:

$$\begin{aligned}R_{\mathrm{it}} - R_{\mathrm{ft}} &= \alpha_{\mathrm{i}} + \beta_{iSNPMRF} SNPMRF_t + \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t \\ &+ \beta_{iBAAMTSY} BAAMTSY_t + \beta_{iPTFSBD} PTFSBD_t + \beta_{iPTFSFX} PTFSFX_t \\ &+ \beta_{iPTFSCOM} PTFSCOM_t + \beta_{ASIAMRF} ASIAMRF_t + \beta_{JAPMRF} JAPMRF + \varepsilon_{it}.\end{aligned} \tag{18}$$

Teo (2009) uses principal component analysis to identify additional asset-based styles in the Asian hedge fund space. His model extends the Fung and Hsieh (2004a) seven-factor model to account for specific characteristics of Asia-focused hedge funds by adding two Asia equity-based factors and two option-based factors. Teo (2009) documents that his model does a much better job at explaining the performance of Asia-focused hedge funds. The adjusted R^2 for the augmented model is a considerable 29% higher than for the regular Fung and Hsieh (2004a) model.

6.5 Results

6.5.1 Persistence in One-Year Sorted Returns Over the Full Period

In this section, I analyze the persistence of Asia-focused hedge fund performance. In the first step, I rank all Asia-focused hedge funds based on their total returns for the previous year. In the second step, the performance of these portfolios is estimated using Fung and

Hsieh (2004a) and adjusted Teo's (2009) models. This method has been previously used in the context of mutual funds by Hendricks et al. (1993) and Carhart (1997).

On every January 1, 10 equally weighted portfolios of hedge funds are formed on the basis of the previous year's reported returns, ordered from highest to lowest. The best (portfolio 1) and the worst (portfolios 10) portfolios are further subdivided into thirds using the same criteria. The portfolios are then held until following January 1, at which time the procedure is repeated again. Hedge funds that dissolve during the course of the year are incorporated in the equally weighted average until their dissolution, after which the portfolio weights are readjusted accordingly.

The application of this procedure to the entire time period produces a time series of monthly returns on each decile portfolio from January 2001 until December 2010. The portfolios ranked by this methodology show strong variation in monthly mean returns, as shown in Tables 6.2 and 6.3. Portfolio D1 yielded a monthly average return of 0.78%, while portfolio D10 yielded a mean monthly return of 0.98% over the period under investigation. The monthly excess returns decrease monotonically between portfolio D1 and D3 but then increase from portfolio D3 to D10. The monthly return on portfolio D1 (0.78%) is similar to the month return on portfolio D8 (0.77%). Interestingly, the spread between portfolios D1 and D10 is -0.21%, indicating that the portfolio composed of previous year's biggest losers managed to outperform the portfolio composed form previous year's top-performers by 21 basis points. However, when the extreme sub-divided portfolios D1a and D10c are compared, a spread of 0.02% per month is observed.

Cross-sectional variation in monthly performance is substantially larger among the portfolios of previous year's top-performing funds than among the portfolios of previous year's poor performers. The spread between portfolios D1a and D1c is 0.35% per month, while the spread between portfolios D10a and D10c is a modest 0.16% per month.

Table 6.2 Portfolios of hedge funds formed on lagged one-year returns, estimated using Fung and Hsieh (2004) model. January 2001-December 2010

Hedge funds are ranked on January 1 each year according to their performance in the previous calendar year. The portfolios are equally weighted monthly so that the weights are readjusted whenever a fund disappears. Funds with the highest past annual performance comprise decile 1 and funds with the lowest comprise 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	0.14
			(1.94)	(2.73)	(0.58)	(-1.10)	(-1.89)	(0.17)	(1.21)	(-0.76)	
D1b	0.55	4.68	0.42	0.46	0.02	-1.57	-3.58	-0.01	0.02	-0.02	0.31
			(1.19)	(4.87)	(0.15)	(-1.02)	(-2.35)	(-0.45)	(0.70)	(-0.83)	
D1c	0.70	3.87	0.66	0.43	-0.02	-1.21	-2.09	0.00	0.05	-0.04	0.36
			(2.28)	(5.69)	(-0.20)	(-0.95)	(-2.00)	(0.21)	(1.85)	(-2.18)	
D1	0.78	4.49	0.67	0.44	0.04	-1.79	-3.35	-0.00	0.04	-0.02	0.30
			(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	-0.00	-1.41	-3.17	0.01	0.03	-0.02	0.44
			(2.36)	(6.80)	(-0.03)	(-1.27)	(-2.58)	(0.59)	(1.23)	(-1.12)	
D3	0.51	3.12	0.40	0.33	0.05	-1.62	-4.08	-0.00	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	0.00	0.01	0.00	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	-1.20	-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	0.30	0.05	0.41	-2.22	0.00	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)	(-1.30)	(1.33)	
D8	0.77	3.10	0.70	0.38	0.12	1.13	-1.62	0.02	-0.02	0.02	0.49
			(3.17)	(7.70)	(1.35)	(1.00)	(-0.90)	(1.39)	(-0.94)	(0.98)	
D9	0.80	3.65	0.70	0.44	0.09	0.12	-3.15	0.01	-0.00	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	0.10	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	0.60	-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	2.60	-2.09	0.02	-0.00	0.03	0.33
			(2.42)	(5.14)	(0.57)	(1.70)	(-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	7.50	-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	-0.00	0.04	-0.39	-0.27	-0.01	0.01	-0.01	-0.04
			(-0.70)	(-0.09)	(0.60)	(-0.57)	(-0.50)	(-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 6.3 Portfolios of hedge funds formed on lagged one-year returns, estimated using to adjusted Teo's (2009) model. January 2001-December 2010

Hedge funds are ranked on January 1 each year according to their performance in the previous calendar year. The portfolios are equally weighted monthly so that the weights are readjusted whenever a fund disappears. Funds with the highest past annual performance comprise decile 1 and funds with the lowest comprise 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	Exc. return	St.dev.	A	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSCOM	PTFSFX	ASIA	Jap.	Adj. R^2
D1a	1.05	6.25	1.00	-0.12	-0.10	-2.39	-2.63	-0.01	0.04	0.00	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	0.30	-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	0.70	3.87	0.54	-0.05	-0.12	-0.55	-0.76	-0.00	0.04	-0.03	0.33	0.18	0.55
			(2.33)	(-0.58)	(-1.21)	(-0.58)	(-0.73)	(-0.20)	(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	0.30	0.49
			(2.00)	(-0.91)	(-1.03)	(-1.11)	(-1.24)	(-0.52)	(1.49)	(-0.68)	(3.21)	(3.47)	
D2	0.66	3.69	0.52	-0.04	-0.12	-0.85	-1.80	0.00	0.02	-0.01	0.31	0.22	0.66
			(2.55)	(-0.51)	(-1.30)	(-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	0.00	0.31	0.18	0.74
			(1.95)	(-2.57)	(-0.76)	(-1.65)	(-3.00)	(-1.19)	(1.63)	(0.02)	(8.01)	(5.04)	
D4	0.52	2.61	0.35	-0.05	0.00	-0.40	-1.85	-0.00	0.00	0.01	0.22	0.18	0.78
			(2.92)	(-1.06)	(0.10)	(-0.89)	(-3.59)	(-0.45)	(0.17)	(1.83)	(6.71)	(5.23)	
D5	0.53	2.74	0.33	-0.00	-0.00	-0.82	-1.84	-0.01	0.01	0.01	0.22	0.18	0.77
			(2.43)	(-0.07)	(-0.08)	(-1.28)	(-3.60)	(-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	-0.00	0.00	0.02	0.22	0.14	0.84
			(4.82)	(-0.92)	(-0.73)	(1.90)	(-2.75)	(-0.34)	(0.43)	(3.69)	(8.87)	(5.74)	
D7	0.73	2.88	0.51	-0.03	-0.01	0.91	-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	0.77	3.10	0.59	0.00	0.05	1.70	-0.59	0.02	-0.02	0.02	0.28	0.12	0.68
			(3.51)	(0.02)	(0.71)	(1.50)	(-0.36)	(1.47)	(-1.41)	(1.59)	(6.31)	(2.58)	
D9	0.80	3.65	0.53	-0.04	0.01	0.89	-1.86	0.00	-0.00	0.02	0.36	0.13	0.70
			(2.69)	(-0.67)	(0.13)	(0.83)	(-1.19)	(0.30)	(-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	0.20	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	-0.00	0.04	0.40	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	1.03	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)	(-2.17)	(1.03)	(-1.67)	(1.68)	(4.96)	(3.52)	
1-10 spread	-0.21	5.14	-0.29	-0.01	-0.10	-3.32	1.11	-0.03	0.05	-0.05	-0.12	0.10	0.01
			(-0.59)	(-0.06)	(-0.46)	(-1.61)	(0.33)	(-0.82)	(1.57)	(-1.47)	(-0.74)	(0.77)	
1a-10c spread	0.02	7.50	0.07	0.10	-0.11	-3.59	3.10	-0.04	0.08	-0.05	-0.30	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 spread	0.11	1.89	-0.08	-0.06	0.01	-0.45	-0.08	-0.01	0.01	-0.00	0.00	0.08	-0.03
			(-0.40)	(-0.96)	(0.13)	(-0.60)	(-0.15)	(-0.81)	(0.84)	(-0.36)	(0.02)	(1.25)	
9-10 spread	-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)	(1.00)	(-1.11)	(1.54)	(-1.62)	(-1.41)	(-1.52)	

The standard deviation of average monthly return is substantially higher for the previous year's best- and worst-performing funds than for the middle-decile portfolios. 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.

I then use the Fung and Hsieh (2004a) and adjusted Teo's (2009) models to control for the risk factors, explain the relative returns on these portfolios, and analyze whether the returns among these hedge fund portfolios demonstrate persistence. Table 6.2 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. Furthermore, the spread between D9 and D10 moves from -0.18% to -0.39%, which is significant at the 5% level. Column 5 of Table 6.2 suggests that all portfolios have significant exposure to the US equity factor. Column 7 indicates that top-decile hedge funds have negative exposure to the bond factor, while the opposite is true for the lower-decile funds. However, these exposures to the bond factor are statistically insignificant. The exposure of all hedge fund portfolios to primitive trend-following strategies is negligible and statistically insignificant. The inability of primitive trend-following factors to explain Asia-focused hedge fund performance can be explained by the fact that Fung and Hsieh (2004a) constructed these primitive trend-following strategies based on US-centric hedge funds. The credit-spread factor is negative and significant for portfolios D1 through D6, and for the sub-portfolios D1b and D1c.

Column 4 of Table 6.2 contains the most important information for the purpose of persistence analysis. A statistically significant alpha would provide evidence of persistence in performance among portfolios ranked based on their previous year's performance. Sub-portfolios D1a and D10c have the highest alpha values at 0.92% and 0.94%, respectively. However, neither of these alphas is statistically significant, which indicates no persistence among the extreme-best and the extreme-worst-performing hedge funds. Portfolios D1 and D2 exhibit a positive alpha value that is significant at the 5% level, while portfolio D3 has an insignificant alpha. Portfolios D6, D7, and D8 are the only portfolios with positive alphas significant at the 1% level, which indicates persistence in performance among the middle-lower decile funds.

Table 6.3 estimates the performance of the same ten portfolios relative to the adjusted Teo's (2009) model. This model adds two equity factors that are relevant when attempting to explain the Asia-focused hedge funds' performance – the MSCI Asia ex Japan index and the

Nikkei 225 index. The values of adjusted R^2, which are significantly higher than those produced in the previous model, confirm that the adjusted Teo's (2009) model is better able to explain the performance of Asia-focused hedge funds. The adjusted R^2 values are highest for middle-decile portfolios (D3 to D7). As a result of the addition of two Asia-focused equity factors, the exposure of portfolios to the US equity factor decreases to a negligible level, as does the statistical significance (*t* statistics) of that 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. Portfolio D1a is the only portfolio with non-significant exposure to the MSCI Asia ex Japan index, while all other portfolios exhibit positive and statistically significant exposure at 1%. The upper-decile portfolios (D1-D6) have positive exposure to the Nikkei 225 index, which is statistically significant at the 1% level, while portfolios D7 to D10 have positive exposure to the same factor but with significance at only the 5% level. The sensitivities to primitive trend-following strategies remain negligible when using the adjusted Teo's (2009) model. The middle-decile portfolios (D3 to D6) show strong negative exposure to the credit spread factor, which is significant at the 1% level. A further examination of the pattern of loading to risk premia proposes that top-decile portfolios have negative, albeit insignificant, sensitivities to the bond factor, while lower-decile portfolios have positive, insignificant sensitivities to the same factor.

Column 4 is of most interest in this analysis, as it contains information on alpha and its significance. The results show that the strongest evidence of performance persistence is again found among the middle- and bottom-decile performers. 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, where I find evidence of persistence, after accounting for risk in both models, the Asia-focused hedge fund strategies are characterized by strong, positive exposure to Asian equity factors. This strong Asian equity exposure might be the source of their sustained performance.

6.5.2 Persistence in One-Year Sorted Returns in Sub-period 1

I perform the same analyses for the two sub-periods identified by testing for the presence of structural breaks in Asian hedge fund data using multiple Chow (1960) tests. I find a structural break in February 2007, which is used in this paper as the start of financial crisis (Khandani and Lo, 2008, propose August 2007 as the beginning of financial crisis). Tables 6.4 and 6.5 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 6.4 displays the results estimated using the Fung and Hsieh (2004a) model. The results are similar to those obtained for the full period, although there are some important differences. The monthly excess returns over the first sub-period decrease monotonically between portfolio D1 and D6 but then increases again from portfolio D7 to D10. Portfolio 1 yielded a monthly average return of 1.32%, while portfolio 10 yielded 1.27% over the first sub-period. The spread between portfolios D1a and D10c is a modest 0.06% per month, while the spread between portfolios D1 and D10 is 0.05% per month. The standard deviation of average monthly returns is substantially higher for the top- and bottom-decile portfolios than for the middle-decile portfolios, with D1a and D10c showing standard deviations of 5.74% and 4.77%, respectively, and portfolio D6 showing a standard deviation of only 1.99%. Again, 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. Similar to the analysis of the full period, most of the portfolios show a positive, significant exposure to the US equity factor during the first sub-period when portfolio performance is estimated using the Fung and Hsieh (2004a) model. In addition, some portfolios display positive and significant exposure to the size factor. More specifically, portfolios D3, D4, D5, and D8 exhibit positive exposure to the size factor, which is significant at the 1% level. The credit spread factor is mostly negative and is significant only for portfolio 9 at the 1% level. Hedge fund portfolios do not display any significant exposure to the bond factor in this sub-period. As in the full-period analysis, exposure to primitive trend-following strategies is negligible and generally insignificant in this sub-period. After controlling for the risk factors using the Fung and Hsieh (2004a) model, I find the highest alpha values among the top-decile funds.

Table 6.4 Portfolios of hedge funds formed on lagged one-year returns, estimated using Fung and Hsieh (2004) model. January 2001-January 2007

Hedge funds are ranked on January 1 each year according to their performance in the previous calendar year. The portfolios are equally weighted monthly so that the weights are readjusted whenever a fund disappears. Funds with the highest past annual performance comprise decile 1 and funds with the lowest comprise 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	1.80	5.74	1.62	0.16	0.37	0.76	1.42	0.01	0.07	0.02	-0.00
			(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	0.00	0.02	-0.00	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	-0.00	0.04	-0.03	0.25
			(2.51)	(3.40)	(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	0.00	0.04	-0.00	0.14
			(3.13)	(2.42)	(1.90)	(0.08)	(0.18)	(0.20)	(1.77)	(-0.20)	
D2	1.07	2.48	0.92	0.36	0.15	-1.27	-1.42	0.01	0.03	-0.00	0.39
			(3.94)	(5.74)	(1.72)	(-1.02)	(-0.57)	(0.95)	(1.94)	(-0.20)	
D3	0.93	2.05	0.69	0.23	0.20	-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	0.60	0.24	0.23	-1.34	-2.76	-0.00	0.01	0.01	0.44
			(2.93)	(5.62)	(3.73)	(-1.40)	(-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
			(2.30)	(6.15)	(2.74)	(-1.13)	(-0.59)	(-0.79)	(1.24)	(1.18)	
D6	0.68	1.99	0.50	0.29	0.14	0.06	-0.46	-0.00	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	-0.00	0.02	0.47
			(2.44)	(6.82)	(1.78)	(-1.32)	(-1.63)	(1.70)	(-0.30)	(1.28)	
D8	0.81	2.82	0.57	0.39	0.20	-0.89	-4.20	0.02	-0.01	0.00	0.49
			(2.23)	(7.17)	(2.80)	(-0.56)	(-1.54)	(1.43)	(-0.39)	(0.03)	
D9	0.93	3.18	0.59	0.39	0.17	-2.20	-7.92	0.00	0.02	0.00	0.43
			(1.90)	(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	0.00	0.02	0.02	0.36
			(2.34)	(3.92)	(1.66)	(-0.50)	(-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	0.00	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	0.00	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 spread	0.05	4.09	0.03	-0.14	0.08	0.97	10.23	0.00	0.02	-0.02	0.04
			(0.07)	(-0.89)	(0.48)	(0.54)	(1.87)	(0.12)	(0.86)	(-0.92)	
1a-10c spread	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 spread	0.25	2.04	-0.00	-0.09	0.11	1.30	1.78	-0.01	0.02	-0.00	-0.03
			(-0.00)	(-1.11)	(1.06)	(1.26)	(0.69)	(-0.55)	(0.99)	(-0.08)	
9-10 spread	-0.34	1.82	-0.51	-0.02	-0.01	-1.37	1.66	0.00	0.00	-0.01	-0.02
			(-2.25)	(-0.28)	(-0.14)	(-1.36)	(0.58)	(0.05)	(0.08)	(-1.07)	

Table 6.5 Portfolios of hedge funds formed on lagged one-year returns, estimated using adjusted Teo's (2009) model. January 2001-January 2007

Hedge funds are ranked on January 1 each year according to their performance in the previous calendar year. The portfolios are equally weighted monthly so that the weights are readjusted whenever a fund disappears. Funds with the highest past annual performance comprise decile 1 and funds with the lowest comprise 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	Exc. return	St.dev.	α	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSCOM	PTFSFX	ASIA	Jap.	Adj. R^2
D1a	1.80	5.74	1.74	0.04	0.20	0.00	-2.10	0.01	0.04	0.04	-0.20	0.51	0.10
			(2.37)	(0.16)	(0.79)	(0.00)	(-0.33)	(0.29)	(1.13)	(1.50)	(-0.71)	(2.65)	
D1b	1.15	3.21	0.88	-0.01	0.10	0.27	0.54	-0.00	0.00	0.01	0.15	0.28	0.33
			(2.65)	(-0.07)	(0.82)	(0.17)	(0.13)	(-0.18)	(0.08)	(0.30)	(1.75)	(2.97)	
D1c	0.96	3.08	0.73	0.05	0.01	0.06	-1.02	-0.00	0.03	-0.03	0.18	0.20	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	0.10	0.10	-0.87	0.00	0.02	0.01	0.04	0.33	0.31
			(3.27)	(0.21)	(0.80)	(0.07)	(-0.26)	(0.01)	(1.27)	(0.33)	(0.30)	(3.84)	
D2	1.07	2.48	0.87	0.09	0.01	-1.00	-1.99	0.01	0.01	0.00	0.13	0.23	0.59
			(4.67)	(1.10)	(0.10)	(-1.11)	(-0.99)	(0.75)	(1.25)	(0.20)	(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)	(4.60)	
D4	0.86	2.03	0.53	-0.03	0.10	-0.99	-3.03	-0.00	-0.00	0.01	0.15	0.19	0.69
			(3.48)	(-0.46)	(2.43)	(-1.36)	(-1.58)	(-0.38)	(-0.20)	(1.57)	(3.19)	(5.05)	
D5	0.81	2.34	0.46	0.09	0.08	-1.20	-1.58	-0.02	0.01	0.02	0.14	0.19	0.63
			(2.51)	(1.08)	(1.31)	(-1.12)	(-0.88)	(-1.01)	(0.66)	(1.83)	(2.12)	(4.13)	
D6	0.68	1.99	0.40	-0.04	0.01	0.63	-0.26	-0.00	0.01	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)	(5.30)	
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	0.00	0.32	0.19	0.77
			(2.60)	(-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	0.00	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	0.50	0.23	0.66
			(2.50)	(-2.59)	(-0.71)	(0.29)	(-2.68)	(-0.37)	(0.50)	(1.42)	(5.50)	(3.12)	
D10a	0.96	3.54	0.49	-0.10	-0.10	0.20	-8.13	0.00	-0.01	0.01	0.40	0.16	0.59
			(1.80)	(-1.14)	(-0.96)	(0.14)	(-2.20)	(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	-0.00	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	0.00	0.03	0.56	0.29	0.55
			(2.45)	(-2.06)	(0.25)	(0.37)	(-2.20)	(-0.58)	(0.09)	(1.43)	(4.43)	(3.18)	
1-10 spread	0.05	4.09	0.25	0.26	0.17	-0.37	7.59	0.01	0.02	-0.01	-0.47	0.10	0.18
			(0.53)	(1.62)	(0.97)	(-0.21)	(1.61)	(0.25)	(0.72)	(-0.51)	(-2.60)	(0.81)	
1a-10c spread	0.06	7.06	0.54	0.36	0.16	-0.88	6.23	0.03	0.04	0.01	-0.77	0.23	0.10
			(0.59)	(1.23)	(0.50)	(-0.30)	(0.82)	(0.55)	(0.97)	(0.39)	(-2.12)	(0.96)	
1-2 spread	0.25	2.04	0.05	-0.06	0.09	1.00	0.82	-0.01	0.01	0.00	-0.10	0.10	-0.01
			(0.17)	(-0.72)	(0.82)	(0.92)	(0.34)	(-0.53)	(0.66)	(0.31)	(-0.99)	(1.43)	
9-10 spread	-0.34	1.82	-0.47	0.11	0.04	-1.61	1.50	0.00	0.00	-0.01	-0.09	-0.05	0.00
			(-2.11)	(1.10)	(0.49)	(-1.61)	(0.60)	(0.14)	(0.32)	(-1.07)	(-1.34)	(-0.84)	

For example, portfolios D1b, D1, D2, D3, D4, and D6 have positive alpha values that are significant at the 1% level. In addition, the portfolio of previous year's worst-performing funds (D10c) displays a very high alpha of 1.22%, which is significant at the 1% level. These results indicate that there is persistence in performance among most of the Asia-focused hedge funds during the first, bullish sub-period.

I then estimate the performance of these portfolios by applying the adjusted Teo's (2009) model, which is better suited for explaining the performance of Asia-focused hedge funds. This is immediately evident in the significantly higher values of adjusted R^2 that are obtained using this model, as shown in Table 6.5. As expected, most portfolios exhibit positive, significant exposure to the two Asian equity factors. Fund exposures to primitive trend-following strategies are negligible and mostly insignificant. Lower-decile funds have negative, significant exposure to the credit factor, while their exposure to the bond factor is low and insignificant. With the exception of portfolio D4, which manifests small, positive exposure to size, no portfolio displays significant loadings to that factor. Column 4 suggests that most portfolios exhibit persistence in performance. In fact, portfolios D1, D2, D3, D4, D6, and D8 have positive alphas that are statistically significant at the 1% level. Other portfolios have positive, significant alphas at the 5% level, while portfolios D10a and D10b are the only portfolios with positive but statistically insignificant alphas.

6.5.3 Persistence in One-Year Sorted Returns in Sub-period 2

Tables 6.6 and 6.7 display the results of the performance persistence analysis for Asia-focused hedge funds during the sub-period that encompasses the global financial crisis. Table 6.6 shows the performance results obtained using the Fung and Hsieh (2004a) model and Table 6.7 estimates hedge fund performance using the Teo's (2009) model.

The figures for monthly excess returns over the second sub-period reveal some interesting information. Somewhat surprisingly, the monthly excess return of portfolio D1 is the same as that for D10c, implying that previous year's best-performing funds (located in portfolio D1) had the same monthly excess returns as previous year's worst-performing funds. Cross-sectional variation in returns exhibits a pattern similar to that seen in sub-period 1, as it is considerably larger for the top- and bottom-decile funds than for middle-decile funds.

Table 6.6 Portfolios of hedge funds formed on lagged one-year returns, estimated using Fung and Hsieh (2004) model. February 2007 – December 2010

Hedge funds are ranked on January 1 each year according to their performance in the previous calendar year. The portfolios are equally weighted monthly so that the weights are readjusted whenever a fund disappears. Funds with the highest past annual performance comprise decile 1 and funds with the lowest comprise 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	-0.10	6.81	1.62	0.16	0.37	0.76	1.42	0.01	0.07	0.02	-0.00
			(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	0.00	0.02	-0.00	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	-0.00	0.04	-0.03	0.25
			(2.51)	(3.40)	(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	0.00	0.04	-0.00	0.14
			(3.13)	(2.42)	(1.90)	(0.08)	(0.18)	(0.20)	(1.77)	(-0.20)	
D2	0.03	4.99	0.92	0.36	0.15	-1.27	-1.42	0.01	0.03	-0.00	0.39
			(3.94)	(5.74)	(1.72)	(-1.02)	(-0.57)	(0.95)	(1.94)	(-0.20)	
D3	-0.13	4.23	0.69	0.23	0.20	-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	0.00	3.26	0.60	0.24	0.23	-1.34	-2.76	-0.00	0.01	0.01	0.44
			(2.93)	(5.62)	(3.73)	(-1.40)	(-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
			(2.30)	(6.15)	(2.74)	(-1.13)	(-0.59)	(-0.79)	(1.24)	(1.18)	
D6	0.45	2.78	0.50	0.29	0.14	0.06	-0.46	-0.00	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	3.30	0.54	0.38	0.12	-1.96	-3.99	0.02	-0.00	0.02	0.47
			(2.44)	(6.82)	(1.78)	(-1.32)	(-1.63)	(1.70)	(-0.30)	(1.28)	
D8	0.70	3.48	0.57	0.39	0.20	-0.89	-4.20	0.02	-0.01	0.00	0.49
			(2.23)	(7.17)	(2.80)	(-0.56)	(-1.54)	(1.43)	(-0.39)	(0.03)	
D9	0.61	4.28	0.59	0.39	0.17	-2.20	-7.92	0.00	0.02	0.00	0.43
			(1.90)	(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	0.00	0.02	0.02	0.36
			(2.34)	(3.92)	(1.66)	(-0.50)	(-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	0.00	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	0.00	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 spread	-0.61	6.46	0.03	-0.14	0.08	0.97	10.23	0.00	0.02	-0.02	0.04
			(0.07)	(-0.89)	(0.48)	(0.54)	(1.87)	(0.12)	(0.86)	(-0.92)	
1a-10c spread	-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 spread	-0.09	1.57	-0.00	-0.09	0.11	1.30	1.78	-0.01	0.02	-0.00	-0.03
			(-0.00)	(-1.11)	(1.06)	(1.26)	(0.69)	(-0.55)	(0.99)	(-0.08)	
9-10 spread	0.06	2.07	-0.51	-0.02	-0.01	-1.37	1.66	0.00	0.00	-0.01	-0.02
			-2.25	-0.28	-0.14	-1.36	0.58	0.05	0.08	-1.07	

Table 6.7 Portfolios of hedge funds formed on lagged one-year returns, estimated using adjusted Teo's (2009) model. February 2007 – December 2010

Hedge funds are ranked on January 1 each year according to their performance in the previous calendar year. The portfolios are equally weighted monthly so that the weights are readjusted whenever a fund disappears. Funds with the highest past annual performance comprise decile 1 and funds with the lowest comprise 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	Exc. return	St.dev.	α	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSCOM	PTFSFX	ASIA	Jap.	Adj. R^2
D1a	-0.10	6.81	-0.11	-0.07	-0.50	-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)	(-1.80)	(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)	(-0.50)	(-0.81)	(0.95)	(-1.00)	(3.61)	(1.14)	
D1c	0.29	4.85	0.20	-0.12	-0.24	-1.13	-0.63	-0.01	0.06	-0.04	0.44	0.16	0.66
			(0.50)	(-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	-1.60	-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)	(-1.40)	(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	-0.00	0.03	-0.03	0.37	0.14	0.81
			(-0.55)	(-1.04)	(-1.54)	(-0.66)	(-1.85)	(-0.08)	(1.10)	(-1.19)	(5.71)	(1.98)	
D4	0.00	3.26	0.08	0.02	-0.19	0.23	-1.28	0.00	0.01	-0.00	0.24	0.15	0.86
			(0.46)	(0.32)	(-2.13)	(0.30)	(-1.96)	(0.20)	(0.56)	(-0.08)	(6.52)	(2.54)	
D5	0.11	3.23	0.13	-0.03	-0.13	-0.36	-1.65	-0.00	0.01	-0.00	0.26	0.14	0.91
			(0.84)	(-0.65)	(-1.75)	(-0.51)	(-2.96)	(-0.24)	(0.65)	(-0.00)	(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	3.30	0.61	0.01	-0.02	2.38	-1.20	0.01	-0.04	0.03	0.31	0.01	0.76
			(2.58)	(0.11)	(-0.14)	(1.97)	(-1.10)	(0.54)	(-2.21)	(1.59)	(5.15)	(0.16)	
D8	0.70	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)	(-1.80)	(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)	(1.00)	(-1.69)	(1.33)	(3.45)	(0.65)	
D10	0.54	5.81	0.68	0.08	-0.00	3.64	-3.26	0.09	-0.13	0.09	0.39	0.09	0.63
			(1.26)	(0.50)	(-0.01)	(1.53)	(-1.24)	(1.77)	(-2.28)	(1.46)	(2.70)	(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)	(1.10)	(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)	(1.10)	(-1.91)	(2.60)	(-2.85)	(1.44)	(2.81)	(0.86)	
1-10 spread	-0.61	6.46	-0.95	-0.17	-0.36	-5.21	2.53	-0.11	0.18	-0.15	0.10	0.10	0.01
			(-1.03)	(-0.60)	(-0.73)	(-1.37)	(0.62)	(-1.32)	(2.08)	(-1.51)	(0.38)	(0.43)	
1a-10c spread	-0.04	8.16	-0.55	-0.04	-0.46	-6.40	5.94	-0.19	0.26	-0.19	-0.04	0.09	0.07
			(-0.49)	(-0.10)	(-0.70)	(-1.27)	(1.25)	(-1.84)	(2.61)	(-1.74)	(-0.14)	(0.31)	
1-2 spread	-0.09	1.57	-0.28	-0.01	-0.10	-1.14	0.06	-0.01	0.01	-0.01	0.07	0.01	0.01
			(-1.22)	(-0.14)	(-1.10)	(-1.42)	(0.10)	(-0.75)	(0.26)	(-0.83)	(1.24)	(0.17)	
9-10 spread	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)	(-0.20)	(-0.14)	(-1.46)	(1.13)	(-2.41)	(2.48)	(-1.51)	(-0.92)	(-0.44)	

Previous year's best-performing funds, which are grouped in portfolios D1a and D1b, delivered monthly excess returns of -0.10% and -0.37%, respectively, while the largest monthly excess returns were delivered by the so-called 'extreme-loser' portfolios D10a and D10b, which had monthly excess returns of 0.73% and 0.95%, respectively. This implies that, overall, previous year's worst-performing portfolios delivered the highest monthly excess returns. Portfolios in the middle decile exhibited solid positive monthly excess returns with a considerably lower standard deviation than in the top- and bottom-decile portfolios. Portfolios D3, D4, D5, and D8 display positive and significant (at 1%) exposure to the size factor, while the portfolios generally do not display any exposure to the bond and primitive trend-following factors. Portfolios D9, D10, and D10a show negative, significant exposure to the credit factor. Alphas estimated using the Fung and Hsieh (2004a) model are positive and significant in most cases, and the same is true for portfolio sensitivities to the equity factor. Portfolios D1b, D2, D3, D4, D6, and D10c display positive and significant alphas at the 1% level. Portfolios D9, D10a, and D10b exhibit positive but insignificant alphas, while the rest of the portfolios exhibit positive and significant alphas at the 5% level.

While Table 6.6 offers strong evidence of persistence in performance, the situation is significantly different when the adjusted Teo's (2009) model is used to estimate portfolio performance. Table 6.7 shows that only portfolios D6, D7, and D8 have positive, statistically significant alphas, indicating that the evidence of performance persistence is weak and that such evidence only applies to the middle-decile portfolio. Portfolios D6 and D8, which had positive, significant alphas in the first sub-period, managed to sustain persistence in performance during the financial crisis. The fact that these portfolios also had significant alphas in the first sub-period indicates that their superior performance was predictable irrespective of the market environment. Portfolio D6, which is the only portfolio to display a positive and significant alpha at the 1% level, also exhibits positive and significant (at 1%) exposure to the bond factor, and negative, high, and significant (at 1%) exposure to credit factor. Furthermore, portfolio D6 exhibits small, but significant, negative exposure to the primitive-trend following strategy on commodities and a small positive, but highly significant, exposure to the primitive trend-following strategy on foreign exchange. Finally, portfolio D6, for which the high adjusted R^2 of 93% indicates the ability of the adjusted Teo's (2009) model to almost fully explain the portfolio's returns, has positive exposure to the MSCI Asia ex Japan index that is highly significant at the 1% level. This portfolio has insignificant exposure to the Nikkei 225 index. I find no evidence of persistence in poor (negative) performance. Although portfolios D1a, D1b, D1, and D3 have negative alphas, they are insignificant.

6.6 Conclusion

The issue of persistence in hedge fund performance has been widely discussed in the academic literature, with widely differing and often conflicting results. From the perspective of the hedge fund investor, this issue is extremely important, as performance often serves as the basis for hedge fund investment decisions. Furthermore, Asia-focused hedge funds have grown rapidly over the last ten years in terms of the number of funds and the amount of assets under management.

The main goal of this chapter, therefore, has been to shed some light on this issue by investigating a relatively large database of Asia-focused hedge funds during the period January 2000 until December 2010, a period that encompasses the global financial crisis of 2007 to 2010. I follow Capocci et al. (2005) and divide the sample into two sub-periods in order to analyze persistence in hedge fund performance in two distinctively different market environments. The contribution of this chapter is that it examines the largest data sample of Asia-focused hedge funds over a period that includes both bullish and bearish market periods using a parametric methodology. Investors can take advantage of potential persistence in performance by replicating this strategy and investing in those hedge funds that exhibit potential persistence in performance.

This chapter investigates persistence at the annual horizon using the methodology previously used by Hendricks et al. (1993), Carhart (1997), and Capocci et al. (2005), in which 10 portfolios are constructed at the beginning of every year based on the funds' performance in the previous year. This procedure is then repeated for the whole time period, which subsequently yields a time series of portfolio returns. Portfolio returns are then estimated using two multi-factor performance measurement models: the Fung and Hsieh (2004a) model and an adjusted version of Teo's (2009) model.

Previous research has shown that survivorship and backfilling bias, as well as illiquidity-induced return smoothing, can influence the measure of performance persistence and overstate persistence. It would then be unclear whether persistence is a result of managerial skill or a result of these biases. To alleviate this threat, I account for the possibility of survivorship and backfilling bias. As the data sample covers the period from 2000 onwards, and as the Eurekahedge database includes both surviving and dissolved funds, survivorship bias should not significantly affect the results. To account for backfilling bias, I delete the first 12 months of returns for every hedge fund. Finally, to account for illiquidity-induced return smoothing, I follow Getmansky et al.'s (2004) desmoothing procedure, which was also used in Chapter 5.

For the full sample period, I find only limited evidence of persistence in hedge fund performance. My analysis of the full sample period indicates that superior performance is more predictable among medium and poor performers. When using Teo’s (2009) model for the full sample period, I find positive, highly significant alphas (at 1%) only among the middle and bottom deciles. The same is true when the Fung and Hsieh (2004a) model is used. My results are similar to those of Capocci et al. (2005), as I also find that most of the persistence in performance is found in the first, bullish sub-period. Both performance measurement models indicate that most of the portfolios display positive performance persistence in the first sub-period. In the second sub-period, the results differ depending on the performance model used. When I use the Fung and Hsieh (2004a) model, I find that most of the portfolios exhibit positive, statistically significant persistence in performance. However, the situation changes significantly when I use Teo’s (2009) model to explain performance. In this case, only three portfolios, all of which are located in the middle decile, exhibit significant persistence in performance. As the adjusted Teo’s (2009) model is better for explaining Asia-focused hedge fund persistence, as proven by its considerably higher adjusted R^2 statistics, one can conclude that there is only weak evidence of performance persistence during the second sub-period.

Furthermore, I find no conclusive evidence of persistence in performance for the best- and worst-performing funds. One can explain this phenomenon in the following way: even though 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.

7. Survival analysis of Asia-focused hedge funds

7.1 Introduction

This main aim of this chapter is to analyze the survival of Asia-focused hedge funds using data included in the Eurekahedge database. I apply a survival analysis in an attempt to investigate whether hedge fund mortality can be predicted on the basis of certain hedge fund characteristics. The goal is to examine whether the survival time of individual Asia-focused hedge funds depends on fund characteristics, such as age, performance, standard deviation, size, leverage, lock-up period, and management fee. In line with previous studies of hedge fund survival, I apply a parametric probit regression method to model hedge fund survival status on several explanatory variables. I also use the less restrictive, semi-parametric Cox proportional hazard model to investigate the factors that affect the survival and mortality patterns of Asia-focused hedge funds.

Casey et al. (2006) find that institutional investors, such as endowments, foundations, and pension funds, have come to represent a much larger portion of hedge fund investor universe over time. Furthermore, owing to the illiquidity that often characterizes hedge funds, these institutional investors have a preference for investing on a long-term basis. The issue of hedge fund survival and mortality patterns is particularly relevant for hedge fund investors, as those investors constantly face a selection problem when trying to choose hedge funds in which to invest. If the probability of hedge fund death can be predicted on the basis of some explanatory variables, then the selection of hedge funds based on these variables should enhance future portfolio performance. In this respect, survival analysis may allow for the identification of hedge funds with a higher probability of survival and a good long-term outlook, thus limiting the liquidation risk and the associated loss of capital. The selection of a hedge fund with a higher chance of longevity can ease some investor concerns regarding the illiquidity they face when investing in hedge funds, especially those concerns related to redemption and lock-up provisions.

As discussed in Chapter 1, research on the sources of hedge fund returns can broadly be divided into two categories. The first category investigates the impact of macroeconomic factors (exposure to various asset classes) on the performance of hedge funds, while the second category focuses on the impact of microeconomic factors (firm-specific characteristics, such as fund age, size, fees, and lock-up periods) on fund performance. The first part of this dissertation focuses on the impact of macroeconomic factors on the performance of Asia-focused hedge funds. This chapter, in contrast, deals with the impact of microeconomic factors (firm-specific characteristics) on the probability of hedge fund survival.

The remainder of this chapter is structured as follows. Section 2 presents a review of the literature on the relationship between hedge fund performance and certain fund characteristics. The second part of the literature review focuses on the relationship between fund characteristics, hedge fund survival, and mortality patterns. Section 7.4 describes the methodology applied in this chapter. Section 7.5 reports and discusses the results. Section 7.6 concludes the chapter.

7.2 Literature Review

7.2.1 Fund Size

One strand of academic literature studies the relationship between hedge fund performance and certain hedge fund characteristics, such as fund size, age, fees, and lock-up periods. Hedge fund size and its potential impact on fund performance is one of the most studied relationships in the hedge fund literature. However, the academic research on the link between hedge fund size and performance has arrived at conflicting conclusions and indicates that the impact of hedge fund size on performance can be twofold.

From the perspective of the investor, the size of the hedge fund is one important characteristic to analyze before investing. From the point of the view of the hedge fund manager, the link between fund size and performance is important because the manager needs to make a decision regarding the optimal size of the fund. Larger hedge funds might enjoy economies of scale and hence have lower expenses than smaller funds. However, some authors argue that hedge funds that exceed a certain size become too large to be effectively managed. The ability of such funds to execute trades without moving the market diminishes and they may encounter problems in liquidating their positions in tough market conditions. Hence, the argument is that larger funds perform worse than smaller funds, as smaller funds are more agile and more liquid.

Research into the link between fund size and performance is rooted in the academic literature on mutual funds. Indro et al. (1999) use a sample of 683 US equity mutual funds from 1993 to 1995 to investigate the link between mutual fund size and performance. They find that fund size affects fund performance and that mutual funds need to achieve a minimum size in order to achieve sufficient returns to justify their costs of acquiring and trading on information. The authors also find evidence of a negative relationship between fund size and fund performance when the size of the fund exceeds the fund's optimal size. Furthermore, the authors show that 20% of the mutual funds in their sample were too small to reach the break-even point. Chen et al. (2004) also examine the effect of size on performance in the mutual fund industry and document that increasing mutual fund size decreases mutual fund performance. The authors do not ascribe this effect to the heterogeneity in fund styles, a correlation of fund size with other observable fund characteristics, or any type of survivorship bias. Instead, they find that the effect of fund size on mutual fund performance is most pronounced for funds that invest in stocks with a small market capitalization, implying that the liquidity factor is an important reason for why size erodes performance.

Harri and Brorsen (2004) investigate the impact of hedge fund size on hedge fund performance. They include the size of the fund as an explanatory variable when trying to identify the sources of hedge fund returns. The authors propose a hypothesis that states that the source of hedge fund returns is the existence of inefficiencies in the pricing of assets in the debt, equities, currency, and commodities markets. Hence, the authors suggest that if the size of a fund matters, the hypothesis that inefficiency exploitation is the source of hedge fund returns is supported. The authors explain that this is because hedge fund managers exploit market inefficiencies in the form of mispriced securities. As the size of these inefficiencies is fixed, an increase in the amount of money involved in exploiting a particular inefficiency would cause returns to decrease. The authors find a strong, negative relation between hedge fund size and returns, which leads them to conclude that their results are consistent with the hypothesis that hedge fund managers exploit market inefficiencies.

Gregoriou and Rouah (2002) investigate the link between the size of a fund and fund performance. The authors analyze 204 hedge funds using the Zurich Hedge Fund Universe and La Porte databases from 1994 to 1999. They define the size of the hedge fund as total asset under management at the beginning of the investigation period. The authors use a Pearson correlation and a Spearman rank correlation to test the link between hedge fund size and performance, where performance is measured using the geometric mean return, the Sharpe ratio, and the Treynor ratio. They find the correlations between fund size and fund performance to be statistically insignificant. The authors document that the size of the hedge fund has no impact on fund performance, and they suggest that the investigation of the relationship between hedge fund size and performance be carried out over a longer period.

Ammann and Moerth (2005) use the TASS database from January 1994 to April 2005 to investigate the impact of hedge fund size on fund performance. They analyze the impact of fund size with respect to hedge fund returns, standard deviations, Sharpe ratios, and alphas derived from multi-factor models. Using cross-sectional regression techniques, the authors find a negative relationship between fund size and returns. However, they also observe that funds at the low end of the size spectrum (very small funds) underperform on average. The authors conclude that the phenomenon of underperformance among very small funds can be explained by higher total expenses ratios. Similarly, Amenc et al. (2003) use several performance measurement models, such as the standard CAPM, a CAPM adjusted for the presence of stale prices, and an implicit factor model extracted from a principal component analysis, to analyze the effect of specific hedge fund characteristics on fund performance. The authors find that the mean alpha for large hedge funds exceeds the mean alpha for small funds. Furthermore, their results are statistically significant, indicating that large hedge funds outperform small funds on average.

Boyson (2003a) uses several theories of reputation to investigate how hedge fund managers' career concerns influence their decisions. After noting that a manager's compensation is linked to both fund performance and fund size, the author investigates the link between fund size and fund performance. She documents a positive relationship between hedge fund size and performance, as well as between hedge fund size and fund survival.

Getmansky (2005) uses the TASS database from January 1994 until December 2002 to investigate the relationship between industry- and fund-specific factors and the probability of hedge fund survival and performance. She finds a positive, concave relationship between past fund asset size and current fund performance, which implies that hedge funds have an optimal size and that exceeding that size has negative effects on performance. Furthermore, she finds that the performance-size relationship takes on different functional forms for different hedge fund categories. For instance, relatively more illiquid hedge fund strategies that are subject to limited opportunities, such as convertible arbitrage or emerging markets, are more likely to display a concave relationship between performance and fund size, and the optimal size for these funds can be calculated. The opposite is true for relatively more liquid hedge fund strategies, such as equity long/short or dedicated short bias.

Edwards and Caglayan (2001) use the MAR database over the period from January 1990 to August 1998 to investigate the relationship between individual funds' excess returns and certain fund characteristics. They estimate excess returns using a multi-factor model similar to that of Fama and French (1992; 1996). The authors document a positive relationship between size and hedge fund performance, indicating that hedge fund performance increases at a declining rate as fund size increases.

Herzberg and Mozes (2003) use a database containing approximately 3000 hedge funds to study the impact of various fund characteristics on the performance of hedge funds. The authors find that funds with smaller amount of assets under management outperform hedge funds with larger assets under management. However, the authors note that the difference in returns between the smaller and larger hedge funds is only marginally significant, while the difference in Sharpe ratios is highly significant. Along the same lines, Hedges (2004) analyzes the link between hedge fund size and performance using a data sample covering 268 hedge funds over the period from January 1995 to December 2002. The author finds evidence that smaller funds outperform larger funds. However, the author also finds that the mid-sized funds perform the worst. As a result, Hedge proposes the concept of the "mid-life crisis" of the hedge fund manager as an explanation. Koh et al. (2003) investigate the relationship between hedge fund size and performance in the Asian context. Applying the cross-sectional Fama and MacBeth (1973) framework, the authors regress monthly fund returns on stock characteristics in univariate and multivariate settings. The authors find only weak, statistically insignificant evidence of a relationship between hedge fund size and fund returns.

De Souza and Gokcan (2004) apply a logit model to examine how certain hedge fund characteristics predict hedge fund demise. They find that smaller funds are more likely to liquidate than larger funds. Similarly, Malkiel and Saha (2005) use probit regression analysis to examine the factors that contribute to the probability of a fund's demise. They find a negative, highly significant coefficient for hedge fund size, indicating that larger hedge funds have a higher probability of dissolution than smaller funds.

7.2.2 Fund Age

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

Howell (2001) uses the TASS database from 1994 until 2000 to study the relationship between hedge fund age and performance. The author defines young hedge funds as those with a track record of less than three years. Hedge funds are sorted into deciles according to their maturity. In terms of unadjusted returns, young hedge funds display a spread of 980 basis points over the whole sample median. However, these results do not take into account the potentially higher failure rate. In order to account for this possibility, the author adjusts the returns by applying the probability of a failure to report to the surviving funds. This gives the ex-post returns, which correspond to the true costs and benefits of investing in funds with different maturities. The author then adjusts the returns by applying the probability of future survival to the survivors' returns by age decile. This gives ex-ante returns, which are the expected returns from investing in hedge funds with different maturities. The author finds that hedge fund performance deteriorates over time, even when the risk of failure is taken into account.

Amenc et al. (2003) use several performance measurement models and find that the mean alpha for newer funds exceeds the mean alpha for older funds in all models. They define age as the length of time in operation prior to the beginning of their study. The significance of the relationship varies depending on which model is used, with the most significant results obtained with the CAPM and Explicit factor models.

Koh et al. (2003) find no relationship between hedge fund age and performance in their investigation, which uses a cross-sectional Fama and MacBeth (1973) framework. De Souza and Gokcan (2004) find that young funds with poor performance, minimal assets under management, short lock-up periods, short redemption notice periods, and no high-water marks are the funds that are most likely to liquidate. Edwards and Caglayan (2001) find a positive, statistically significant relationship between hedge fund age and performance for certain hedge fund strategies, such as global-macro funds, global funds, and market-neutral funds. Herzberg and Mozes (2003) document that younger hedge funds with limited experience display better returns than older hedge funds with more experience. However, the authors find that younger funds do not exhibit higher Sharpe ratios than older hedge funds. Getmansky (2005) documents that an increase in the age of hedge funds negatively affects fund flows.

Using a probit analysis of fund termination, Brown et al. (2001) analyze how certain hedge fund characteristics (absolute and relative performance, excess volatility, fund age) contribute to fund dissolution. They document that older hedge funds have a higher likelihood of survival. In a similar fashion, Liang (2000) conducts a probit regression analysis using hedge fund characteristics to determine the predictive power of those characteristics on fund dissolution. He finds that younger funds with poor performance and a small size have a higher chance of dissolution.

7.2.3 Performance Fees

Edwards and Caglayan (2001) document that hedge fund performance is positively related to the performance fee charged by the hedge fund. The authors note that this is consistent with the argument that fund managers' skills might explain some of the positive excess returns earned by hedge funds. Their results stand in stark contrast to the mutual fund literature, which finds a negative relationship between high fees charged by a fund and fund performance (Carhart, 1997b). Kazemi et al. (2002) also investigate the impact of performance fees on performance. They investigate the performance of hedge funds, and find a negative relationship between higher fees and hedge fund performance.

Amenc et al. (2003) investigate the impact of incentive fees paid to hedge fund managers on fund performance. The authors divide funds into two groups according to their incentive fees. The first group is composed of funds with incentive fees of 20% or more. The second group is composed of those hedge funds that charge an incentive fee lower than 20%. The authors use several methods to establish the relationship between incentive fees and hedge fund performance. Their results indicate that the mean alpha for funds in the first group exceeds the mean alpha for funds in the second group.

Finally, Koh et al. (2003) document that Asia-focused hedge funds with higher performance fees show lower post-fee returns than funds with lower performance fees.

7.2.4 Other Factors

Boyson (2003) studies the effect of manager's tenure on fund performance using a sample of 982 hedge funds in the TASS database covering the period from January 1994 until December 2000. Boyson's underlying hypothesis argues that career concerns increase over time and, as a result, hedge fund managers become more risk-averse as their career progresses. The author investigates whether risk-taking behavior differs systematically among managers with different levels of experience, measured in terms of manager tenure at the hedge fund. Boyson's (2003) results indicate that as managers age, their risk-taking behavior increases – they increase their volatility and herd less than less-experienced managers. The author finds evidence that the inclination of more experienced managers to accept more risk translates into higher returns for their funds. Boyson's results are in line with evidence from the mutual fund industry, and are consistent with theories regarding agency costs and career concerns of hedge fund managers.

Koh et al. (2003) investigate Asia-focused hedge funds' characteristics, such as redemption periods, size of holding companies, and size of minimum investment, and examine how these factors impact fund performance. They find that redemption period and size of the holding company have a positive, statistically significant relationship with the performance of Asia-focused hedge funds. The size of minimum investment, on the other hand, displays no significant relationship with fund performance.

De Souza and Gokcan (2004) find that investment of a manager's own capital in the fund, as well as the existence of lock-up and redemption periods, have positive impacts on hedge fund performance. Furthermore, Schneeweis et al. (2002) document that hedge funds adopting similar strategies and longer lock-up periods exhibit higher performance than the funds with shorter lock-up periods. This indicates that redemption periods affect hedge fund performance.

7.2.5 Hedge Fund Survival and Hedge Fund Characteristics

Several academic studies focus on the relationship between hedge fund characteristics and the probability of hedge fund demise. Using the TASS database, Liang (2000) applies a probit regression to analyze the reasons for hedge fund dissolutions. In particular, the author examines how certain hedge fund characteristics, such as average monthly returns, assets under management, managers' personal investments, incentive fees, management fees, fund age, and leverage ratios, affect the probability of hedge fund demise. Liang (2000) finds that younger funds with poor performance and relatively smaller assets under management are more likely to be dissolved. Furthermore, the author documents that all of the aforementioned variables, except management fees, are statistically significant, indicating that the probability of hedge fund demise is significantly related to fund characteristics. Similarly, Brown et al. (2001) analyze the effect of hedge fund characteristics on fund dissolution using the TASS database covering the period from period 1994 to 1998. The authors find that poor hedge fund performance relative to the high-water mark threshold and to industry benchmarks increases the probability of fund dissolution. For investors, this implies that hedge funds that underperform the industry average are more likely to be shut down. The authors also document that risk (measured in terms of the volatility of returns) and fund age have significant effects on hedge fund dissolution, with relatively riskier and younger hedge funds having a higher probability of dissolution.

Malkiel and Saha (2005) apply a probit analysis to the TASS dataset of hedge funds to study the relationship between fund characteristics and the probability of fund demise. The hedge fund characteristics examined in this context are past performance, risk, past performance relative to the industry, and fund size. Their results show that previous fund performance and risk are important determinants of the probability of a fund's demise. In addition, contrary to Liang’s (2000) finding that smaller funds have a higher probability of dissolution, Malkiel and Saha (2005) find that larger funds have a higher probability of dissolution. Furthermore, the authors show that riskier funds have a lower probability of survival, which is in line with the previous literature.

Baquero et al. (2005) apply the longitudinal probit method to model the liquidation process of hedge funds. Their empirical results show that historical performance is an important factor in explaining fund liquidation, as their analysis shows that funds with high returns are much less likely to liquidate than funds with low returns. In addition, their results indicate that smaller funds are much more likely to liquidate than larger funds. Furthermore, the authors find that fund age, investment style, and magnitude of incentive fees are also linked to hedge fund survival.

Finally, Xu et al. (2010) apply a probit analysis to the Center for International Securities and Derivatives Markets (CISDM) database in their investigation of how hedge fund characteristics influenced fund attrition during the period which includes the financial crisis of 2007-2009 . The impacts of several fund characteristics, including size, age, performance, risk, leverage, and the regularity of an audit, are examined. The authors find that older funds with better pre-crisis performance and regularly audited funds had a higher probability of surviving the financial crisis, and that leveraged funds were more likely to close down during the crisis.

Several studies apply the Cox (1972) proportional hazards model to study the effect of explanatory variables on hedge fund survival. Brown et al. (2001) were the first to use the Cox model to analyze hedge fund mortality. They arrive at the same result as with the probit model – younger hedge funds with low past returns are at a higher risk of failure. They also find a strong link between volatility and fund failure. 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 until 2001 to investigate whether some explanatory variables can predict hedge fund failure. The author uses several survival models, including the product-limit estimator, the life table method, the accelerated failure time model, and the semi-parametric Cox (1972) proportional hazards model. He finds that larger, low leveraged, better performing funds have a higher probability of survival. Furthermore, funds with a higher minimum investment requirement tend to die faster.

Boyson (2002) documents that manager attributes, such as age and education, are positively related to fund survival. Rouah (2005) analyzes hedge fund lifetimes by applying a multinomial logistic regression that allows for different types of fund exits. Similar to Getmansky, Lo, and Mei (2004), who propose the need to differentiate between hedge fund exits, Rouah (2005) notes that it is important to isolate liquidation from other forms of hedge fund exits that are of little relevance to hedge fund investors. The author documents that several variables, including past performance, risk (measured in standard deviation terms), average and standard deviations of fund size, and high-water mark provisions, explain the survival of hedge funds.

Baba and Goko (2006) apply a survival analysis to individual hedge funds in the TASS database. They use several methodologies, including a non-parametric survival analysis, the Cox (1972) proportional hazards model with shared frailty, and a logit analysis, to estimate the effect of fund characteristics and dynamic performance properties on the survival probabilities of hedge funds. The authors find that 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. They also find that funds with a longer redemption notice period and a lower redemption frequency have a higher probability of survival. Interestingly, Baba and Goko (2006) find that leverage does not significantly influence the probability of fund survival.

Gregoriou et al. (2009) study the survival of exchange-listed hedge funds. They compare survival times and characteristics of listed and non-listed hedge funds, and find that listed funds are larger and adopt more conservative investment strategies than non-listed funds. They also find that listed funds survive two years longer than non-listed funds, on average.

Liang and Park (2010) implement a survival analysis to investigate the determinants of hedge fund failure. The authors compare the effectiveness of various downside risk measures in predicting hedge fund attrition. They find that funds with high historical performance and high-water mark provisions are less likely to fail. The impact of other variables, such as age, size, and lock-up provisions, depends on how fund failure is defined.

7.3 Dataset

In order to examine the effect of the characteristics of Asia-focused hedge funds on the probability of fund demise, I use the same Eurekahedge dataset as in previous two chapters. For the purpose of this analysis, I select only those Asia-focused hedge funds that have complete monthly return data from January 2005 until January 2007, which represents the pre-crisis period. In choosing this pre-crisis investigation period, I follow 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.

The final dataset contains 497 hedge funds and includes information on such fund characteristics as: investment strategy, management fee, performance fee, redemption frequency, notification period, lock-up period, fund location, fund size, inception date, minimum investment, and use of leverage. Some of these fund idiosyncrasies, such as management fee, performance fee, lock-up period, minimum investment, and use of leverage, are recorded as of January 2007 and assumed to be constant over the sample period for the purpose of this analysis. Although this assumption is reasonable for the mentioned characteristics, it is not reasonable for the fund size characteristic. To account for the fact that hedge fund size varies over time, I use the average asset value of the fund in the pre-crisis period as a proxy for fund size.

The problem of survivorship bias is well documented in the hedge fund literature. Survivorship bias is most accentuated in hedge funds with returns prior to 1994. In order to minimize survivorship bias, I include both live and dissolved funds. Furthermore, the Eurekahedge dataset covers only hedge funds with returns from 2000 onwards, which also helps to address this bias. In addition, hedge funds often operate in illiquid markets, which can have an effect on reported returns. In order to account for this "illiquidity bias", I use returns that are desmoothed using the Getmansky et al. (2004) procedure.

Defining hedge fund dissolution is not simple because detailed information on defunct hedge funds is hard to obtain. Early studies of hedge fund dissolution make no distinction between failed and liquidated hedge funds. Fund liquidation does not necessarily mean fund failure, as successful funds can be liquidated voluntarily by hedge fund managers for a variety of reasons. A few recent articles have taken advantage of the level of detail provided in certain hedge fund databases to begin differentiating between fund failure and fund liquidation. Getmansky, Lo, and Mei (2004) use the status codes provided in the TASS database to differentiate between various reasons for fund exclusion from the database of live funds. In addition to fund liquidation, other reasons given for fund exclusion from the database are: stop reporting, unable to contact, closed to new investments, merged into another fund, and dormant fund.

Liang and Park (2009) discuss three possible reasons for why successful hedge funds might liquidate without being considered as failures. First, according to Liang and Park (2009), hedge funds that successfully liquidate in anticipation of a market crash should be regarded as liquidated, rather than failed, funds. Second, hedge fund managers could liquidate successful start-up funds after launching new funds. They could be motivated to do so by their desire to define the terms of new funds in a more beneficial way by adding lock-up periods or extending redemption frequency. Finally, Liang and Park (2009) suggest that some liquidated hedge funds have not failed terms of downside risk management and hence should not be considered as failed.

The level of detail in the Eurekahedge database does not allow for a distinction to be made with regard to the various reasons for fund liquidation. Therefore, I do not differentiate between hedge funds that are actually dissolved and hedge funds that, for whatever reason, stopped reporting information to data vendors. I regard all liquidated funds in my sample as failed funds.

7.4 Methodology

This section describes the methods used to analyze the relationship between the probability of hedge fund mortality and fund characteristics. The decision to use the probit model in this study is based on its widespread use in similar contexts in the academic literature on hedge funds. In addition to the probit model, I use the Cox semi-parametric hazard rate regression approach to increase the robustness of my results.

7.4.1 Probit Analysis

The probit model has been described as follows:

The probit model is a non linear (in the parameters) statistical model that achieves the objective of relating the choice probability P_i to explanatory factors in such a way that the probability remains in the (0,1) interval. (Griffiths et al., 1993)

In the context of hedge fund mortality, a probit model can be used to explain how various fund characteristics (independent variables) influence the dependent variable y_i. This dependent variable is binary in nature. In other words, it is constructed as dichotomous measure, where the occurrence of the dissolution of the hedge fund during the crisis is coded 1, while the absence of the dissolution event (survival) is coded 0.

From an econometric perspective, explaining a binary dependent variable, such as y_i, requires a special procedure. The easiest method of dealing with dichotomous dependent variables is the linear probability model, which is based on the assumption that the probability of an event occurring, Pi, is linearly associated with a set of independent variables x_{2i}, x_{3i}, …, $x_{4i.}$ The linear probability model is consistent with the way in which quantitative (continuous) outcome dependent variables are explained using linear regression analysis. While the linear probability model is simple to estimate and intuitive to interpret, the fitting of a binary dependent variable (y_i) to a set of explanatory variables using the linear regression framework is inappropriate because doing so generates fitted values that are not restricted to lying between 0 and 1, as is required by the definition of the dependent variable. A probit model overcomes this limitation by using a function that essentially transforms the regression model in a way that fitted values are bounded within the (0,1) interval. In this context, the cumulative distribution function is a probability transformation that achieves the objective of keeping the fitted values between 0 and 1. The probit model operates under the assumption that the probability of y_i being equal to 1 is given by:

$$\mathrm{P}(y_i = 1 \mid x_i, \beta) = \phi(x_i{}'\beta). \qquad (30)$$

The probability of y_i being equal to 0 is:

$$\mathrm{P}(y_i = 0 | x_i, \beta) = 1 - \phi(x_i{}'\beta), \tag{31}$$

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

$$E(y_i | x_i, \beta) = \phi(x_i{}'\beta). \tag{32}$$

One can also write the probit model in the form of the regression equation:

$$y_i = \phi(x'_i\, \beta) + \varepsilon_i, \tag{33}$$

where the residual (ε_i) represents the deviation of the dichotomous variable y_i from its conditional mean, x'_i are the variables that explain the probability of hedge fund death, and β are the parameters to be estimated.

Unlike the ordinary least square (OLS) regression, the methods used to estimate the parameters involve nonlinear approaches, such as maximum likelihood estimation procedures. Typically, given the assumption of random exogenous sampling, the parameters of the probit model are estimated by maximizing the log-likelihood function with respect to β:

$$\hat{\beta} = \sum_{i=1}^{N} [y_i \ln \phi(x'_i\, \beta) + (1 - y_i) \ln(1 - \phi(x'_i\, \beta))]. \tag{34}$$

The first-order conditions for the likelihood equation, which is obtained by maximizing the log-likelihood equation with respect to β, are nonlinear. Therefore, the parameter estimates are obtained by iterative solution. For the purpose of statistical inference, 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) .

As with the linear regression framework, there are several methods of testing the goodness of fit of the probit model. While the standard goodness of fit measures from the linear regression framework, such as RSS or R^2, are easily calculable, they would have no meaning in the nonlinear probit context. However, various other measures can be computed to assess the goodness of fit of the probit model. One of the measures is the percentage of y_i values correctly predicted by the model. This is defined as 100x the number of observations correctly predicted divided by the total number of observations (Brooks, 2008):

$$\text{Percent correct prediction} = \frac{100}{N}\sum_{i=1}^{N} y_i I(\hat{P}_i) + (1 - y_i)(1 - I(\hat{P}_i)),$$

where $I(yi)$=1 if $\hat{y}_i > \bar{y}$ and 0 otherwise . The higher this number, the better the fit of the model. Alternatively, one can use the "pseudo-R^2", a measure analogous to the R^2 in the linear regression framework. This measure is defined as:

$$\text{Pseudo- } R^2 = 1 - \frac{LLF}{LLF_0} \qquad (35)$$

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. Another property of pseudo-R^2 is that, as its value always lies between 0 and 1. Furthermore, while the pseudo-R^2 can be used to compare different specifications of the model, it is not good for comparing models with different sets of data.

7.4.2 Cox semi-parametric Hazard Rate Regression Approach

The Cox model is a regression-based model used in survival studies to estimate the relationship between multiple explanatory variables and the survival times of the subject. The main goal of survival analyses is to model time to event data, whereby event is considered death and is operationalized through dichotomous variable. An idiosyncratic feature of these analyses, which are longitudinal in nature, is the fact that they allow for the effect of censoring and the dependency of survival times on explanatory variables. This statistical approach was originally developed in the medical and biological sciences but is now extensively applied in the social and economic sciences. In the context of hedge funds, survival analysis translates into estimating how is the duration of life time of Asia-focused hedge funds influenced by explanatory variables (covariates), such as the funds' past monthly returns, volatility, age, size, management fees, use of leverage, and lock-up periods. In essence, survival analysis allows one to investigate the probability of a hedge fund failure given some explanatory variables.

Conventional statistical models, such as multiple linear regression, are inappropriate for analyzing survival data because of censoring and non-normality, both of which are characteristic of survival data. A standard normal distribution, which is symmetrical by nature, includes both positive and negative values. Survival data (duration), on the other hand, by definition only assumes positive values and hence violates the normality assumption of the regression models. In fact, Timmermann et al. (1999) argue that probit analysis is too restrictive due to strong distributional assumptions. They suggest the use of a less restrictive, semi-parametric method – the Cox hazard rate regression approach. Unlike the parametric models, for the Cox method to work, the exact nature of the survival function does not need to be known. However, the Cox method does have some intrinsic features that might be problematic for researchers. These include the restrictive assumption of proportional hazards for explanatory variable effects and the "loss" (non-estimation) of the baseline hazard function induced by conditioning on event times (Royston, 2001).

Censoring is another characteristic of survival data that multiple regression methods are unable to take into account. The Eurekahedge databases include censored funds because it includes both dead and live funds. In general, censored observations occur whenever the dependent variable of interest exemplifies the time to the terminal event (fund dissolution in this case) and the duration of the study is limited. Hence, the event of interest is very rarely observed in all subjects. The most common form of censoring is right-censoring, which occurs if the period of observation expires or the subject is removed from the study before the event of interest occurs. In the context of survival analysis of Asia-focused hedge funds, censoring arises because I examine hedge funds that came to existence from January 2000 onwards and monitor their development until December 2010. Some hedge funds die during the observed period which is immediately registered in the database together with the time of death, hence making the lifetimes of these hedge funds fully transparent. However, those funds that are still alive and operating at the end of the observation period are censored because the exact time of their death is unknown. Given that the lifetimes of censored funds also provide important relevant information regarding overall hedge fund survival, not including these censored funds in the analysis would generate a downward bias of the sample's survival time.

Following Gregoriou (2002), I define hedge fund's survival time or duration, as a random variable denoted by T whereby T>0.. Date of entrance of hedge fund to the database is denoted as zero. Finally, the survival function, denoted as S(t), represents the probability that the hedge fund will survive longer than time t:

$$S(t) = P(T > t). \tag{36}$$

Another important component of the survival model is the hazard rate, which is denoted as $\lambda_i(t)$. In the hedge fund context, hazard function is defined as the rate of hedge fund failure at time T=t, conditional upon fund's survival up to time t. More formally, the hazard function can be estimated using the following equation:

$$\lambda(\mathrm{t}) = \lim_{\Delta t \to 0} \frac{P\left[(t \leq T < t + \Delta t \middle| T \geq t)\right]}{\Delta t} = \frac{f(t)}{S(t)}. \tag{37}$$

The hazard function is the derivative of the survival function. Hence, these functions can be converted into each other. The essence of this survival study is the estimation of the hazard function $\lambda_i(t)$ using the semi-parametric Cox regression approach. Cox's method resembles the multiple regression approach except that the dependent variable (Y) is the hazard function at a given time:

$$\begin{aligned}\lambda(\mathrm{t}) = \lambda_0(t)\exp(& age\beta_1 + perf\,\beta_2 + stdev\beta_3 + size\beta_4 + lev\beta_5 + mnfee\beta_6 \\ & + perffee\beta_7 + hwm\beta_8 + redfreq\beta_9 + lockup\beta_{10} + mininv\beta_{11} + listed\,\beta_{12}),\end{aligned} \tag{38}$$

where the quantity $\lambda_0(t)$ is the baseline (underlying) hazard function and is equal to the probability of fund dissolution when all of the covariates are zero. The value of the hazard function corresponds to the product of the baseline hazard and a covariate effect (Norusis, 2004). The baseline hazard function is analogous to the intercept in an ordinary multiple regression. While the baseline hazard is dependent upon time, the covariate effect is the same for all time points. Thus, the ratio of the hazards for any two cases at any point in time is the ratio of their covariate effects. The regression coefficients β_1 to β_7 show the proportional change that can be expected in the hazard related to changes in the explanatory variables. The assumption of a constant relationship between the dependent variable and the explanatory variables is called proportional hazards and is a prerequisite assumption in order for the Cox model to work.

As Gregoriou (2002) note, the main goal of the Cox model is not to retrieve actual estimates of survival times but rather to determine the relative influence of explanatory variables on survival. This assessment is made in the form of hazard ratios. Hazard ratios greater than one indicate a decrease in survival (an increase in the hazard rate). The magnitude, significance and direction of each beta indicate the strength of the relationship between the explanatory variable and the dependent variable.

7.4.3 Explanatory Variables

As mentioned earlier, the main goal of this chapter is to conduct an empirical investigation of the extent to which certain hedge fund characteristics explain the survival of hedge funds. This section describes the explanatory variables used in this analysis and the motivation for including them in this analysis. Whereas the motivation for the inclusion of some variables is evident, for others it might be less clear.

Previous academic literature suggests that the following characteristics affect the attrition of hedge funds: performance, risk, fund size (assets under management), age, leverage, fees, high-water marks, lock-up provisions, minimum investment size, and listing on an exchange. The motivations for the inclusion of performance and risk as explanatory variables of hedge fund attrition are straightforward. Previous empirical studies have shown that funds with better performance and lower risk are less likely to shut down (see Liang, 2000; Brown et al., 2001; and Malkiel and Saha, 2005). The performance of the hedge fund is proxied by mean monthly returns during the period under investigation, while the risk is represented as the standard deviation of the returns over the sample period. The influence of fund size on the survival of the hedge fund is more ambiguous, as discussed in the literature review. On the one hand, size may be an advantage when it comes to fund survival due to the larger, more stable asset base. On the other hand, as Malkiel and Saha (2005) show, smaller, nimbler hedge funds are more likely to survive. In terms of size, hedge fund assets under management are recorded in December 2011 and treated as a fixed variable over the period under investigation.

Leverage is another important hedge fund characteristic often mentioned in the context of fund survival. As Baba and Goko (2006) note, there is a widespread perception that hedge fund returns are very volatile due to hedge funds' extensive use of leverage. Hence, hedge funds that use leverage will be at a higher risk of liquidation than those funds that do not. The Eurekahedge database contains a binary variable for leverage (yes/no). Therefore, leverage is treated as a fixed binary variable in this analysis, with 1 indicating the use of leverage and 0 indicating no use of leverage.

As the literature review shows, the age of the hedge fund can also be viewed as an explanatory variable in the survival analysis of hedge funds.

In order to analyze the impact of the incentive structure on the liquidation probability of hedge funds, I use the following explanatory variables: management fee, performance fee, and high-water mark. While management fee is a characteristic shared by almost all professional asset managers, the performance fee is an idiosyncratic feature of the hedge fund industry. There are two predominant ways to think about the impact of performance fees on the probability of hedge fund liquidation. Market participants often argue that high performance fees are associated with more risk taking by fund managers due to the convexity in compensation it creates for fund managers (see Panageas and Westerfield, 2009). Taken to its logical conclusion, this argument implies that high performance fees increase the risk associated with hedge funds and, hence, increase the probability of liquidation.

The high-water mark is another distinctive characteristic of the hedge fund industry. It is designed to protect the investor, as it conditions the potential payout of the performance fee to the manager upon the share price exceeding its previous highest value. If the investment drops in value, then the manager is obliged to bring the value back above the previous level before he or she can receive the performance fees. High-water mark provisions can have ambiguous effects on the liquidation probability of hedge funds. On the one hand, they increase the risk-taking behavior of managers, thus leading to an increased probability of liquidation. On the other hand, high-water mark provisions provide fund managers with an incentive to apply a more prudent approach in fund management. Panageas and Westerfield (2009) study the portfolio choices of hedge funds which include the high-water mark provision. They find that the risk-taking behavior of these managers depends on the time horizon they have. Provided that the time horizon is infinite or indefinite, Panageas and Westerfield's (2009) model predicts less risk-taking behavior, while it predicts more risk-taking behavior if the manager has a finite time horizon. The effect of the high-water mark on the probability of hedge fund survival is ascertained empirically in this study.

Furthermore, I investigate the impact of lock-up period and redemption frequency on hedge fund survival. These two variables characterize the liquidity constraint aspect of hedge fund investments. Investors care about these two features, as the presence of a lock-up period and a lower redemption frequency indicate a lower liquidity for investment. Two competing hypotheses attempt to explain the impact of lock-up periods and redemption frequencies on the survival of hedge funds. According to the first hypothesis, hedge funds with lock-up provisions and longer redemption frequencies have more control over unforeseen outflows that could have a destabilizing effect on the survival of the fund. The second hypothesis argues that lock-up provisions and long redemption periods prevent fund managers from growing their assets under management, as investors refuse to invest in funds with such liquidity constraints.

The minimum required investment is also considered in this analysis as one factor that contributes to hedge fund dissolution. Baba and Goko (2006) provide two hypothesizes regarding the impact of minimum investment requirement on the performance of hedge funds. On the one hand, hedge funds with a higher minimum investment amount are more likely to experience larger outflows, thereby destabilizing funds' operations. On the other hand however, funds with smaller minimum investment amounts are more likely to have smaller outflows and more risk-averse investors.

Finally, I assess whether being listed on an exchange has any impact on the survival of hedge funds. A status of being exchange listed offers some important advantages for hedge fund managers. For example, in listed hedge funds, investor capital is tied up with no risk of fund withdrawal at unfavorable times. Gregoriou et al. (2009) examine the relationship between exchange listing and hedge fund survival by studying the Barclay Hedge database for the period from 2000 until 2007. They find that listed hedge funds tend to survive approximately two years longer on average than non-listed funds and that their failure rates are lower than those of non-listed funds. Hence, I expect the dichotomous variable corresponding to whether a fund is listed or not to have a positive effect on the survival of Asia-focused hedge funds.

7.5 Empirical Results

The probit method models the chances of hedge fund dissolution as a function of specified idiosyncratic fund characteristics. The dependent variable in the probit model is binary, taking a value of 0 if the fund is still alive or 1 if the fund is defunct. A negative coefficient for an explanatory variable indicates that a higher value of that variable decreases the odds of fund dissolution. Coefficients for the probit model are estimated via the maximum likelihood method. Timmermann et al. (1999) argue in favor of using the Cox semi-parametric hazard model to analyze the failure of funds. They argue that the probit model is too restrictive due to its strong distributional assumptions. The following sections report the results obtained using the probit regression and the Cox semi-parametric proportional hazard model.

7.5.1 Probit Regression Analysis

Table 7.1 reports the results obtained through the probit regression analysis. The coefficient estimate for age is negative and statistically significant at 1%, indicating that older Asia-focused hedge funds have a higher probability of survival. Likewise, the coefficients for fund size and mean of returns are negative and significant at 1%, indicating that larger funds with better performance have a higher probability of survival. Interestingly, the coefficients for standard deviation and leverage are negative and statistically significant at 5%, indicating that funds that employ leverage and have highly volatile returns are more likely to survive. These results initially seem counter-intuitive, as many recent hedge fund failures have been associated with a high amount of leverage and volatility in returns.[14] Hence, the effect of leverage and standard deviation are discussed in more details in the next section.

The empirical results show that the coefficient for redemption frequency is positive and significant at 5%, indicating that funds with lower redemption frequency have a higher probability of survival. Finally, the coefficient for whether the fund is listed or not is positive and significant at 1%, implying that listed Asia-focused hedge funds have a lower probability of survival. This result contradicts Gregoriou et al. (2009), who found that listed hedge funds have a lower probability of liquidation. The estimated coefficients for management fee, performance fee, and high-water mark – the explanatory variables that characterize the incentive structure aspect of hedge fund investing – are insignificant.

[14] See LTCM debacle, Amaranth collapse.

Furthermore, the lock-up and minimum investment variables also yield insignificant coefficient estimates. Table 7.1 reports the parameter estimates and pseudo-R^2 from the probit regression of Asia-focused hedge fund failures.

Table 7.1 Probit analysis

Variable	Coefficient	Std. Error	Z-statistic	Prob.
Intercept	0.39	0.26	1.53	0.13
Age	**-0.01**	0.00	**-5.42**	0.00
Mean return	**-0.39**	0.06	**-6.43**	0.00
Standard deviation	-0.03	0.02	-2.05	0.04
AUM	**0.00**	0.00	**-3.95**	0.00
Leverage	-0.19	0.08	-2.22	0.03
Management fee	-0.15	0.10	-1.50	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	**0.00**	0.00	**2.74**	0.01
Lock-up	-0.20	0.14	-1.47	0.14
Minimum investment	0.00	0.00	-0.25	0.81
Listed	**0.35**	0.09	**3.84**	0.00
Pseudo-R^2 (%)	17.00			

7.5.2 Cox-regression Analysis

Table 7.2 presents the results of fitting the Cox semi-parametric proportional hazard model to the Asia-focused hedge fund lifetime data. The results of this model are consistent with the results obtained when using the probit regression model. The explained variable in the Cox model is the hazard rate. Therefore, the negative estimated coefficient for that variable implies that the variable reduces the hazard rate. The estimated coefficient for the mean of fund returns is negative and highly significant, indicating that mean returns are a statistically significant predictor of the likelihood of fund failure at 1%. This suggests that higher fund returns lead to a lower probability of fund dissolution. Consistent with the results from the probit model, the estimated coefficient for standard deviation is negative and statistically significant at 1%, implying that a higher level of standard deviation leads to a lower likelihood of fund dissolution. This result is in contrast to that found in previous literature. I discuss the possible reasons for this result in the final sub-section of this chapter.

The coefficient for size is negative and significant at 1%, indicating that Asia-focused hedge funds with larger assets under management have a lower probability of failure. The estimated coefficient for redemption frequency is positive and significant at 5%, implying that funds with a higher redemption frequency face a higher probability of failure. Table 7.2 also shows that the estimated coefficient for leverage is negative but statistically insignificant. The coefficients for management and performance fees, high-water mark, lock-up, minimum investment, and the exchange-listed variable are not statistically significant. The estimated coefficient for redemption frequency is statistically significant and positive, indicating that higher redemption frequency is detrimental for the survival probability of hedge funds.

The hazard ratio in the Cox proportional hazard model allows for a comparison of survival between different levels of explanatory variables. A hazard ratio higher than 1 indicates that the explanatory variables have a negative effect on survival time or that a higher value of the explanatory variable will lead to a shorter survival time. On the other hand, a hazard ratio lower than 1 implies a positive effect on survival time – a higher value of an explanatory variable indicates a longer survival time. Hazard ratios for funds' mean returns, sizes, and standard deviations are all lower than one, while the hazard ratio for redemption frequency is higher than one. These hazard ratios are as expected for all variables except standard deviation, which in the extant literature assumes a value higher than 1, indicating that higher volatility is detrimental for fund survival.

Table 7.2 Cox proportional- hazards regression analysis

Variables	Estimate of regression coefficient	Standard errors	Wald	Sig.	Hazard ratio
Mean return	**-0.65**	0.04	266.83	**0.00**	0.52
St. dev. return	**-0.14**	0.02	46.68	**0.00**	0.87
AUM	**-0.01**	0.00	59.66	**0.00**	0.99
Leverage	-0.10	0.09	1.26	0.26	0.90
Management fee	0.18	0.12	2.12	0.15	1.19
Performance fee	0.02	0.01	2.73	0.10	1.02
High-water mark	0.09	0.17	0.28	0.60	1.09
Redemption freq.	**0.00**	0.00	4.27	**0.04**	1.00
Lock-up	0.11	0.16	0.47	0.49	1.12
Minimum investment	0.00	0.00	0.88	0.35	1.00
Listed	0.04	0.10	0.19	0.66	1.05

7.5.3 Discussion

The empirical results presented in this chapter confirm the results presented in most academic studies on hedge funds – better performing hedge funds have a lower probability of liquidation. While this result is expected and intuitive, the finding that fund volatility, measured in terms of the standard deviation of its returns, positively affects the chances of fund survival is less understandable. Market participants often associate higher volatility with a higher, not lower, probability of closure. Furthermore, the finding that a higher standard deviation increases the chances of fund survival, which is obtained when using both the probit and the Cox models, contradicts most of the literature on hedge fund survival. One possible explanation for this result lies in the nature of the Eurekahedge database. The group of surviving funds in my sample has a higher standard deviation, calculated over the full sample period, than the group of defunct funds. This gives rise to some possible problems of interpretation. For example, if one were to measures risk in terms of standard deviation, then one might be tempted to conclude that defunct hedge funds are less risky than surviving hedge funds, which clearly cannot be true.

In order to further analyze this result, I break the full sample period into two parts, with the breakpoint set as the start of the financial crisis in February 2007 (Xu et al., 2010).

I calculate the standard deviation for both the living and defunct hedge funds. I find that the pre-crisis average standard deviation is lower for surviving funds than for the dead funds. However, during the crisis period, the standard deviation for surviving funds is higher than for the defunct funds. After carefully examining the database, I noted that most of the dead funds in the Eurekahedge database do not have returns from 2007 to 2010, a period characterized by a highly volatile investment climate. The fact that most of the dead funds in the database do not have returns during that period explains why their volatility is lower than the surviving funds, which were active during the crisis period. In fact, when the probit model is re-run on the pre-crisis period alone (January 2000 to February 2017), the coefficient for standard deviation loses its statistical significance.

The probit model yields a negative significant estimated coefficient for leveraging, indicating that funds that employ leverage have a higher probability of survival. This result is somewhat surprising, as one would expect highly leveraged funds to have a higher likelihood of dissolution. The Eurekahedge database provides information on whether the fund employs leverage but the database does not specify the amount of leverage. Hence, the leverage measures reported in the Eurekahedge database may not be appropriate for detecting any destabilizing effects of high leverage. The Cox model shows that the leverage variable has no significant effect on liquidation hazard ratios.

Both of the models employed here demonstrate that the incentive structure of Asia-focused hedge funds has no effect on the mortality rates of the respective funds. The probit and the Cox models yield insignificant estimated coefficients for management fees, performance fees, and high-water mark policies. The variable acting as a proxy for minimum investments is also insignificant in both models.

Consistent with Baba and Goko (2006), I find that lower redemption frequency decreases the probability of hedge fund dissolution. These results support the hypothesis that that lower liquidity contributes to fund survival.

7.6 Conclusion

Recent evidence suggests that institutional investors have come to represent a significant proportion of hedge fund investors in recent years. As these investors invest in hedge funds on a long-term horizon, the issue of hedge fund survival is of crucial interest for them, as it is inextricably linked to their capital preservation/loss. Therefore, for these institutional investors it is of great importance to select those hedge funds that are most likely to produce consistent returns and remain in operation for a long time.

While Chapter 6 focused on the issue of how to select hedge funds that produce persistent returns, this chapter focuses on selecting hedge funds with the highest chances of survival. In this chapter, I investigated the survival of Asia-focused hedge funds from January 2000 until December 2010. Although several prior studies investigate the issue of hedge fund survival, no previous article discusses this issue in the context of Asia-focused hedge funds.

I apply the parametric probit regression model and the less restrictive semi-parametric Cox proportional hazard model to investigate the factors that affect the survival and mortality patterns of Asia-focused hedge funds. Consistent with previous literature, I find that larger, better performing funds with lower redemption frequency have a higher likelihood of survival. Surprisingly, I also find that higher standard deviation has a positive effect on survival in Asia-focused hedge funds. This result can most likely be attributed to the structure of the Eurekahedge database, where most of the defunct funds died before the global financial crisis began in 2007. Therefore, the group of surviving hedge funds has a higher standard deviation than the group of defunct funds. The incentive structure of hedge funds (management fees, incentive fees, and lock-up provisions) does seem not to have an effect on fund survival. Finally, I find that two models disagree on the impact of leverage on hedge fund survival – the probit model indicates that higher leverage is beneficial for fund survival, while the Cox model indicates that leverage has no effect on hedge fund survival.

8. Conclusion

8.1 Summary of Findings

Over the last two decades, alternative asset classes in general and hedge funds in particular have become increasingly popular among investors, who have channeled enormous amount of capital into these investment vehicles. According to estimates from Hedge Fund Research (HFR) indicate that global assets under management grew from US $491 billion in 2000 to a peak of US $1.9 trillion in December 2010, implying a compounded annual growth rate of 14%.15 While the typical investor in a hedge fund in 1990 was a high-net-worth individual, today institutional investors, such as endowments, foundations, and pension funds, represent a much larger portion of the hedge fund investor universe (Casey et al., 2006).

Hedge funds focused on Asia have been one particularly nimble and dynamic sector of the global hedge fund industry. Eurekahedge estimates that the Asian hedge fund industry grew from approximately US $30 billion in 2000 to US $125 billion in December 2010 in terms of assets under management, implying a compounded annual growth of roughly 15%. The growth rate in the Asian hedge fund industry, therefore, has outpaced that of global hedge fund industry. Most academic research on hedge funds focuses on US- and Europe-centric funds. However, given the growing importance of the Asian hedge fund sector, I have focused my research on three specific aspects of Asian-focused hedge funds.

The first of these three aspects deals with the risk-adjusted performance of hedge funds, i.e., alpha creation. In the context of rapidly increasing inflows the issue of the sustainability of hedge fund alpha has become more relevant. Although much of the earlier research on hedge fund performance documents that hedge funds typically produce positive and significant alpha (Fung and Hsieh, 2004, Kosowski et al., 2007, Titman and Tiu, 2008), some studies find that hedge fund alphas have been declining (Fung et al. 2008; Zhong 2008).

I use three multi-factor performance measurement models encompassing both linear and non-linear risk factors to analyze Asia-focused hedge funds ‘monthly returns in the period from January 2000 until December 2010. My data set is derived from the Eurekahedge database. To account for the possibility of structural breaks in my data, which are particularly relevant because the sample includes the global financial crisis of 2007-2010, I

[15] http://www.reuters.com/article/2011/01/19/us-hedgefunds-assets-idUSTRE70I6JY20110119

conduct Chow's (1960) breakpoint test, which reveals a structural break in February 2007, corresponding to the beginning of global financial crisis. Hence, in addition to analyzing hedge fund performance over the full data sample, I analyze two sub-periods: the period before the beginning of the financial crisis and the period of the crisis. My results, which are derived using Teo's (2009) adjusted model and the step-wise regression Asia model, indicate that Asian hedge funds, as a group, produced statistically significant alpha over the full sample period. However, in terms of risk-adjusted performance during the second sub-period, which encompasses the global financial crisis of 2007-2010, I find that Asia-focused hedge funds did not produce significant alphas on average. These results are in line with extant research. Eling and Faust (2010) examine the performance of emerging markets hedge funds and find significant alphas during the whole sample period from January 1996 to August 2008, but find insignificant hedge fund alphas for the sub-period from January 2007 to August 2008. Xu et al. (2010) investigate the risk-adjusted performance of hedge funds and document the lack of statistically significant hedge fund alphas during the crisis period from February 2007 through December 2008.

The second aspect deals with an important question from the perspective of hedge fund investors, who constantly face selection problems when trying to choose hedge funds in which to invest: Provided that Asia-focused hedge funds show significant risk-adjusted performance (alpha), do their alphas reflect managerial skill or chance? The answer to this question is important because if performance in hedge fund returns persists, active selection is likely to increase the expected return because one superior average return period is likely to be followed by another superior average return period (Capocci et al., 2005). The academic literature offers little consensus on the issue of performance persistence.

Following Capocci et al. (2005), I divide the sample into two sub-periods in order to analyze persistence in Asia-focused hedge fund performance in two distinctively different market environments. I apply the methodology used by Hendricks et al. (1993), Carhart (1997), and Capocci et al. (2005) in which 10 portfolios are constructed at the beginning of every year based on the funds' performance in the previous year. This procedure is then repeated for the whole time period, which subsequently yields a time series of portfolio returns. Portfolio returns are then estimated using two multi-factor performance measurement models: the Fung and Hsieh (2004a) model and an adjusted version of Teo's adjusted (2009) model.

I find only limited evidence of persistence in hedge fund performance over the full sample period from January 2000 until December 2010. My analysis of the full sample period indicates that superior performance is more predictable among medium and poor performers. When using Teo's adjusted (2009) model for the full sample period, I find positive, highly significant alphas (at 1%) only among the middle and bottom deciles. My results are similar to those of Capocci et al. (2005), as I also find that most of the persistence in performance is evident in the first, bullish sub-period. For the second sub-period, which encompasses the global financial crisis of 2007-2010, I find only weak evidence of performance persistence using Teo's adjusted (2009) model. In this respect, only three portfolios, all of which are located in the middle decile, exhibit significant persistence in performance. Finally, I find no conclusive evidence of persistence in performance for the best- or worst-performing funds.

Third, this research focuses on the relationship between hedge fund characteristics and the probability of their survival. In light of recent evidence showing that institutional investors now represent a significant proportion of hedge fund investors (see Casey et al., 2006), the question of hedge fund survival is of crucial interest, as survival is inextricably linked to capital preservation/loss among institutional investors. Despite the growing importance of Asia-focused hedge funds in the global hedge fund industry, no previous academic study deals with the issue of hedge fund survival in this context.

I therefore examine whether Asia-focused hedge fund mortality can be predicted on the basis of certain hedge fund characteristics: age, performance, standard deviation, size, 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. In order to analyze how hedge funds' characteristics influence their chances of survival, I apply both the parametric probit regression and the semi-parametric Cox proportional hazards analysis. Consistent with previous research, I find that larger, better performing funds with lower redemption frequencies are more likely to survive.

8.2 Contribution to Academic Research

This dissertation contributes to the academic literature on hedge funds in several ways. First, using three multi-factor performance measurement models, it analyzes the performance of a large sample of Asia-focused hedge funds over a ten-year period that encompasses the global financial crisis of 2007-2010. Previous studies on the performance of Asia-focused hedge funds covered shorter time periods and excluded periods in which global markets declined. Subsequently, the large sample, the relatively long period under consideration (10 years), and the inclusion of the global financial crisis of 2007-2010 all contribute to the robustness of my results. Second, this dissertation expands the work of Koh et al. (2003), who analyze the performance persistence of Asia-focused hedge funds using non-parametric methods. I adopt an approach similar to that used by Capocci et al. (2005) in that I use a parametric methodology to examine the largest data sample of Asia-focused hedge funds over a period that includes both bullish and bearish market periods. Finally, this study closes the gap in the academic literature on the relationship between Asia-focused hedge fund characteristics and the probability of hedge fund survival.

8.3 Limitations and Areas for Future Research

The limitations of this dissertation are related to data availability, the assumptions made, and the inherent constraints in the applied methodologies. In the first part of this dissertation, I use regression-based, parametric, multi-factor models in order to investigate hedge fund performance. Some authors (Fung and Hsieh, 2001; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004) note that hedge fund performance measures do not always follow parametric normal distributions. Hence, future research could apply methodologies that avoid the assumption that hedge fund performance is normally distributed, such as the bootstrap and Bayesian methodologies used by Kosowski et al. (2007).

Furthermore, I analyze the performance persistence of Asia-focused hedge funds over 12-month time horizons. However, in light of redemption periods, future research could examine long-term performance persistence over time horizons of 12 to 36 months.

In terms of data availability, when analyzing the survival of Asia-focused hedge funds, I have treated all hedge fund exits as a single group and have not tried to distinguish among various types of exits. However, given the voluntary nature of inclusion in the Eurekahedge database, the group of failed hedge funds does not necessarily consist solely of funds that were liquidated. For example, some funds may have exited the database because they were closed to new investments. Such funds could have better returns than liquidated funds. Unlike the TASS database, which provides seven distinct reasons for why hedge funds enter the graveyard group, the Eurekahedge database does not distinguish among various exit types. As all exits are treated as liquidations in this study, the strength of the relationships between covariates and the probability of fund survival might be biased. Hence, one could improve this study by collecting data on the reasons for Asia-focused hedge funds' exits and then re-running the analysis, allowing for multiple exit types (see Rouah, 2005; Liang and Park, 2009).

One assumption behind the semi-parametric Cox proportional-hazards model applied in this study is that covariates are not time dependent. A similar model has been applied in several articles in the context of hedge fund survival (see Gregoriou, 2002; Grecu et al., 2007; Gregoriou et al., 2009). However, some authors (Rouah, 2005) propose using the Cox model, which allows for time-dependent covariates. Future research could explore the applicability of this approach.

Finally, this dissertation examines the performance and survival of Asia-focused hedge funds using quantitative approach. Future research could explore the qualitative aspect of hedge fund investing in Asian regions in order to shed more light on investment strategies employed, structure of portfolio, hedge fund managers and their backgrounds fund manager's attitude towards risk.

9. References

Abugri, B. A., & Dutta, S. (2009). Emerging market hedge funds : Do they perform like regular hedge funds ? *Journal of International Financial Markets, Institutions and Money*, *19*(5), 834–849. Elsevier.

Ackermann, C., McEnally, R., & Ravenscraft, D. (1999). The performance of hedge funds: Risk, return, and incentives. *The Journal of Finance*, *54*(3), 833–874. John Wiley & Sons.

Admati, A. R., & Ross, S. A. (1985). Measuring investment performance in a rational expectations equilibrium model. *The Journal of Business*, *58*(1), 1–26. JSTOR.

Agarwal, V., & Naik, N. Y. (2000a). Multi-period performance persistence analysis of hedge funds. *Journal of Financial and Quantitative Analysis*, *35*(3), 327–342. Cambridge University Press.

Agarwal, V., & Naik, N. Y. (2000b). Generalised Style Analysis of Hedge Funds. *Journal of Asset Management*, *1*(1), 93-109.

Agarwal, V., & Naik, N. Y. (2004). Risks and Portfolio Decisions Involving Hedge Funds. *Review of Financial Studies*, *17*(1), 63-98.

Agarwal, V., & Naik, N. Y. (2005). Hedge funds: are they appropriate for your portfolio? *Foundations and Trends in Finance*, *1*(2), 103-169.

Agarwal, V., Daniel, N. D., & Naik, N. Y. (2009). Role of Managerial Incentives and Discretion in Hedge Fund Performance. *The Journal of Finance*, *64*(5), 2221-2256.

Agarwal, V., Fung, W., Loon, Y. C., & Naik, N. Y. (2005). Risks in hedge fund strategies: Case of convertible arbitrage. *Working Paper, Georgia State University and London Business School, 2005.*

Amenc, N, Curtis, S., & Martellini, L. (2003). The alpha and omega of hedge fund performance measurement. *Workign paper Edhec*, *33*(0), 0-35.

Amenc, Noel, El Bied, S., & Martellini, L. (2003). Predictability in Hedge Fund Returns. *Financial Analysts Journal*, (213), 32–46. JSTOR.

Amin, G. S., & Kat, H. M. (2003). Hedge fund performance 1990–2000: do the “money machines” really add value? *Journal of Financial and Quantitative Analysis*, *38*(02), 251–274. Cambridge Univ Press.

Ammann, M., & Moerth, P. (2005). Impact of fund size on hedge fund performance. *Journal of Asset Management*, *6*(3), 219-238.

Ammann, M., Huber, O. R., & Schmid, M. M. (2009). Has Hedge Fund Alpha Disappeared? *papers.ssrn.com*, (September).

Ammann, M., Huber, O. R., & Schmid, M. M. (2010a). Hedge Fund Characteristics and Performance Persistence. *European Financial Management*, *49*(August). Wiley Online Library.

Ammann, M., Huber, O. R., & Schmid, M. M. (2010b). Benchmarking Hedge Funds: The Choice of the Factor Model. *Working Paper, University of St.Gallen.*.

Anderson, S., Born, J., & Schnusenberg, O. (2010). Closed-End Funds, Exchange-Traded Funds, and Hedge Funds. *Innovations in Financial Markets and Institutions*, *18*, 87-103. Boston, MA: Springer US.

Asness, C. S., Krail, R. J., & Liew, J. M. (2001a). Do Hedge Funds Hedge? *SSRN Electronic Journal*.

Asness, C. S., Krail, R. J., & Liew, J. M. (2001b). Do Hedge Funds Hedge? *The Journal of Portfolio Management*, *28*(1), 6-19.

Baba, N., & Goko, H. (2006). Survival analysis of hedge funds. *Institute for Monetary and Economic Studies and Financial Markets Department*, (06).

Baquero, G., Horst, J., & Verbeek, M. (2005). Survival , Look-Ahead Bias , and Persistence in Hedge Fund Performance. *Journal of Financial and Quantitative Analysis*, *40*(3).

Bares, P.-antoine, Gibson, R., & Gyger, S. (2003). Performance in the Hedge Fund Industry. *Journal of Alternative Investments*, *6*(3), 25-41.

Barry, R. (2002). Hedge funds: a walk through the graveyard. *Working Paper, Ross Barry Macquaire Applied Finance Center*.

Bentz, V. M., & Shapiro, J. J. (1998). *Mindful inquiry in social research*. Sage Publications, Inc.

Berk, J. B., & Green, R. C. (2004). Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy*, *112*(6), 1269-1295.

Black, T. R. (1999). *Doing quantitative research in the social sciences: An integrated approach to research design, measurement and statistics*. *Europe*. Sage Publications Ltd.

Bodie, Z., Kane, A., & Marcus, A. J. (2005). *Investments*. McGraw-Hill.

Bookstaber, R. (2003). Hedge fund existential. *Financial Analysts Journal*, *59*(5), 19–23. JSTOR.

Boyson, N. (2002). How Are Hedge Fund Manager Characteristics Related to Performance, Volatility and Survival? *Unpublished working paper, Ohio State University, Fisher College of Business*, *4*(2), 57–60. Institutional Investor Journals.

Boyson, NM. (2003a). Why do experienced hedge fund managers have lower returns. *Purdue University*.

Boyson, NM. (2008). Hedge Fund Performance Persistence: A New Approach. *Financial Analysts Journal*, *64*(6), 27-44. doi:10.2469/faj.v64.n6.6

Boyson, NM, & Cooper, M. J. (2004). Do hedge funds exhibit performance persistence? A new approach. *Forthcoming to Financial Analysts Journal*, (765).

Boyson, NM. (2003b). Why do experienced hedge fund managers have lower returns ? *Working Paper*, (765).

Brooks, C. (2008). *Introductory econometrics for finance*. *International Journal*. Cambridge University Press.

Brown, S. J., & Goetzmann, W. N. (1995). Performance persistence. *Journal of finance*, *50*(2), 679–698. JSTOR.

Brown, S. J., & Goetzmann, W. N. (2003). Hedge Funds With Style. *Journal of Political Economy*, *29*(2), 101-112.

Brown, S. J., Goetzmann, W. N., & Ibbotson, R. G. (1999a). Offshore Hedge Funds: Survival and Performance, 1989–95. *The Journal of Business*, *72*(1), 91-117.

Brown, S. J., Goetzmann, W. N., & Ibbotson, R. G. (1999b). Offshore Hedge Funds: Survival and Performance, 1989–95. *The Journal of Business*, *72*(1), 91-117.

Brown, S. J., Goetzmann, W. N., & Park, J. M. (2001). Careers and survival: Competition and risk in the hedge fund and CTA industry. *The Journal of Finance*, *56*(5), 1869–1886. John Wiley & Sons.

Capocci, D., & Huebner, G. (2004). Analysis of hedge fund performance. *Journal of Empirical Finance*, *11*(1), 55–89.

Capocci, D., Corhay, A., & Huber, O. R. (2005). Hedge fund performance and persistence in bull and bear markets. *The European Journal of Finance*, *11*(5), 361–392. Routledge.

Capon, N., Fitzsimons, G. J., & Alan Prince, R. (1996). An individual level analysis of the mutual fund investment decision. *Journal of Financial Services Research*, *10*(1), 59–82. Springer.

Carhart, M. M. (1997a). On persistence in mutual fund performance. *Journal of finance*.

Carhart, M. M. (1997b). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57.

Carpenter, J., & Lynch, A. (1999). Survivorship bias and attrition effects in measures of performance persistence. *Journal of financial economics*, *54*(3), 337-374.

Casey, Q. & A. and the B. of N. Y. (2006). Acito: Institutional Demand for Hedge Funds: New Opportunities and New Standards. *New York*.

Chen, J., Hong, H., & Huang, M. (2004). Does fund size erode mutual fund performance? The role of liquidity and organization. *The American Economic*, 74–87. JSTOR. doi:10.2139/ssrn.372721

Chen, K., & Passow, A. (2003). Quantitative selection of long-short hedge funds. *FAME, Research Paper*, *94*(July).

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, *28*(3), 591–605. JSTOR.

Coldwell, T., & Kirkpatrick, T. (1995). A primer on hedge funds. *courtesy of Lookout Mountain Capital, Inc.* Elsevier.

Cook, T. D., & Campbell, D. T. (1976). The design and conduct of quasi-experiments and true experiments in field settings. *Handbook of industrial and organizational psychology*, *223*, 336. Chicago: Rand MacNally.

Cooper, D. R., & Schindler, P. (2002). *Business Research Methods*. McGraw-Hill.

Couillard, M. (2005). A comment on measuring the Hurst exponent of financial time series. *Physica A: Statistical Mechanics and its*, *348*, 404-418.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, *34*(2), 187–220. JSTOR.

De Souza, C., & Gokcan, S. (2004). Hedge Fund Investing: A Quantitative Approach to Hedge Fund Manager Selection and De-Selection. *The Journal of Wealth Management*, *6*(4), 52-73.

Edwards, F., & Caglayan, M. (2001). Hedge fund performance and manager skill. *Journal of Futures Markets*, *21*(11), 1003–1028. John Wiley & Sons.

Eling, M. (2009a). Does Hedge Fund Performance Persist? Overview and New Empirical Evidence. *European Financial Management*, *15*(2), 362-401. doi:10.1111/j.1468-036X.2008.00471.x

Eling, M. (2009b). Does hedge fund performance persist? Overview and new empirical evidence. *European Financial Management*, *15*(2), 362-401.

Eling, M., & Faust, R. (2010). The performance of hedge funds and mutual funds in emerging markets. *Journal of Banking & Finance*, *34*(8), 1993-2009. Elsevier B.V. doi:10.1016/j.jbankfin.2010.01.008

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of finance*, *47*(2), 427–465. JSTOR.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, *51*(1), 55–84. JSTOR.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 607–636. JSTOR.

Fung, W., & Hsieh, D. (1997). Empirical characteristics of dynamic trading strategies: the case of hedge funds. *Review of Financial Studies*, *10*(2), 275-302. doi:10.1093/rfs/10.2.275

Fung, W., & Hsieh, D. (2000). Performance Characteristics of Hedge Funds and Commodity Funds : Natural vs . Spurious Biases. *The Journal of Financial and Quantitative Analysis*, *35*(3), 291-307.

Fung, W., & Hsieh, D. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies*, *14*(2), 313. Soc Financial Studies. doi:10.1093/rfs/14.2.313

Fung, W., & Hsieh, D. (2002a). Asset-based style factors for hedge funds. *Financial Analysts Journal*, *58*(5), 16-27.

Fung, W., & Hsieh, D. (2002b). Risk in fixed-income hedge fund styles. *The Journal of Fixed Income*, *12*(2), 1-21.

Fung, W., & Hsieh, D. (2004a). Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal*, *60*(5), 65-80.

Fung, W., & Hsieh, D. (2004b). Extracting portable alphas from equity long-short hedge funds. *Journal of Investment Management*, *2*(4), 1–19.

Fung, W., Hsieh, D., Naik, N. Y., & Ramadorai, T. (2008a). Hedge funds: Performance, risk, and capital formation. *The Journal of Finance*, *63*(4), 1777–1803. John Wiley & Sons.

Fung, W., Hsieh, D., Naik, N. Y., & Ramadorai, T. (2008b). Hedge Funds: Performance, Risk, and Capital Formation. *The Journal of Finance*, *63*(4), 1777-1803.

Garbaravicius, T., & Dierick, F. (2005). Hedge funds and their implications for financial stability. *European Central Bank*.

Getmansky, M. (2005). The life cycle of hedge funds: Fund flows, size and performance. *UMASS, Amherst working paper, Amherst, MA*, *1708*(617).

Getmansky, M., Lo, A. W., & Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics*, *74*(3), 529–609. Elsevier.

Getmansky, M., Lo, A. W., & Mei, S. X. (2004). Sifting through the wreckage: Lessons from recent hedge-fund liquidations. *Journal of Investment Management*, *2*(4), 6-38. World Scientific Pub Co Inc.

Grecu, A., Malkiel, B. G., & Saha, A. (2007). Why Do Hedge Funds Stop Reporting Performance? *The Journal of Portfolio Management*, *34*(1), 119–126. Institutional Investor Journals.

Greene, W. H., & Zhang, C. (2003). *Econometric analysis*. *International Journal* (Vol. 5). Prentice hall New Jersey.

Gregoriou, G. N. (2002). Hedge fund survival lifetimes. *Journal of Asset Management*, *3*(3), 237–252. Palgrave Macmillan.

Gregoriou, G. N., & Duffy, N. E. (2006). Hedge funds: A summary of the literature. *Pensions: An International Journal*, *12*(1), 24-32.

Gregoriou, G. N., & Rouah, F. (2001). Last Year's Winning Hedge Fund as this Year's Selection: A Simple Trading Strategy. *Derivatives Use, Trading & Regulation*, *7*(3), 269–274. Proquest ABI/INFORM.

Gregoriou, G. N., & Rouah, F. (2002). Large versus Small Hedge Funds. *The Journal of Alternative Investments*, *5*(3), 75–77. Institutional Investor Journals.

Gregoriou, G. N., Lhabitant, F., & Rouah, F. D. (2009). The Survival of Exchange-Listed Hedge Funds. *Journal of Applied Research in Accounting and Finance*, *4*(2), 2–11.

Griffiths, W., Hill, R., & Judge, G. (1993). Learning and practicing econometrics.

Grinblatt, M., & Titman, S. (1992). The persistence of mutual fund performance. *Journal of Finance*, 1977–1984. JSTOR.

Géhin, W. (2004). A Survey of the Literature on Hedge Fund Performance. *EDHEC*, *33*(October).

Hakamada, T., Takahashi, A., & Yamamoto, K. (2007). Selection and Performance Analysis of Asia-Pacific Hedge Funds. *The Journal of Alternative Investments*, *10*(3), 7-29.

Harri, A., & Brorsen, B. W. (2004). Performance persistence and the source of returns for hedge funds. *Applied Financial Economics*, *14*(2), 131–141. Taylor & Francis.

Hasanhodzic, J., & Lo, A. W. (2007). Can hedge-fund returns be replicated?: The linear case. *Journal of Investment Management*, *5*(2), 5-45.

Hedges, J. (2004). Size vs. performance in the hedge fund industry. *Journal of Financial Transformation*, *10*, 14-17.

Hendricks, D., Patel, J., & Zeckhauser, R. (1993). Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988. *Journal of Finance*.

Herzberg, M., & Mozes, H. (2003). The Persistence of Hedge Fund Risk: Evidence and Implications for Investors. *Journal of Alternative Investments*, *6*(2), 22-42.

Indro, D., Jiang, C., & Hu, M. (1999). Mutual fund performance: does fund size matter? *Financial Analysts Journal*, *55*(3), 74-87.

Ineichen, A. M. (2003). *Absolute Returns – Risk and Opportunities of Hedge Fund Investing*. Wiley.

Ineichen, A. M. (2008). AIMA'S Roadmap to Hedge Funds. *Management*.

Jagannathan, R., Malakhov, A., & Novikov, D. (2010). Do hot hands exist among hedge fund managers? An empirical evaluation. *The Journal of Finance*, *65*(1), 217–255. Wiley Online Library.

Kat, H., & Menexe, F. (2003). Persistence in hedge fund performance: The true value of a track record. *Journal of Alternative Investments2*, *5*(4), 66-72.

Kazemi, H., Martin, G., & Schneeweis, T. (2002). Understanding Hedge Fund Performance: Research Issues Revisited-Part I. *Journal of Alternative Investments*, 313-315.

Kerlinger, F. N., & Lee, H. B. (1964). *Foundations of behavioral research: Educational and psychological inquiry*. *America*. Holt, Rinehart and Winston New York.

Khandani, A., & Lo, A. W. (2008). What happened to the quants in August 2007?: evidence from factors and transactions data. *Electrical Engineering*. National Bureau of Economic Research Cambridge, Mass., USA.

Koh, F., Koh, W., & Teo, M. (2003). Asian hedge funds: Return persistence, style, and fund characteristics. *papers.ssrn.com*.

Kosowski, R., Naik, N. Y., & Teo, M. (2007). Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. *Journal of Financial Economics*, *84*(1), 229-264.

Kouwenberg, R. (2003). Do hedge funds add value to a passive portfolio? Correcting for non-normal returns and disappearing funds. *Journal of Asset Management*, *3*(4), 361–382. Palgrave Macmillan.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *Journal of finance*, *31*(4), 1085–1100. JSTOR.

Leavens, D. H. (1945). Diversification of Investments. *Trusts and Estates*, *80*, 469-473.

Lhabitant, F.-S. (2004). Hedge Funds: Quantitative Insights. *The Wiley Finance Series*.

Lhabitant, F.-S. (2006). *Handbook of hedge funds* (Vol. 332). John Wiley & Sons Inc.

Liang, B. (2000). Hedge funds: The living and the dead. *Journal of Financial and Quantitative Analysis*, *35*(03), 309–326. Cambridge Univ Press.

Liang, B., & Park, H. (2007). Risk Measures for Hedge Funds: a Cross-sectional Approach. *European Financial Management*, *13*(2), 333-370.

Liang, B., & Park, H. (2009a). Predicting Hedge Fund Failure: A Comparison of Risk Measures. *Journal of Financial and Quantitative Analysis*, *45*(01), 199.

Liang, B., & Park, H. (2009b). Predicting Hedge Fund Failure: A Comparison of Risk Measures. *Journal of Financial and Quantitative Analysis*, *45*(01), 199.

Liang, B., & Park, H. (2010). Predicting hedge fund failure: A comparison of risk measures. *Journal of Financial and Quantitative Analysis*, *45*(1), 199–222. Cambridge Univ Press.

Lo, A. W. (2001). Risk management for hedge funds: Introduction and overview. *Financial Analysts Journal*, *57*(6), 16–33. JSTOR.

Lowenstein, R. (2000). *When genius failed*. Random house publishing.

Malkiel, B., & Saha, A. (2005). Hedge Funds: Risk and Return. *Financial Analysts Journal*, *61*(6), 80-88.

Markowitz, H. M. (1952). Portfolio selection: Efficient diversification of investments, *7*(1), 77-91. Wiley.

Markowitz, H. M. (1959). *Portfolio selection: Efficient diversification of investments*. Wiley.

McGrath, J. (1982). The study of research choices and dilemmas. *Judgement Calls in Research. Beverly Hills: Sage*, *2*.

Mitchell, M., & Pulvino, T. (2001). Characteristics of risk and return in risk arbitrage. *The Journal of Finance*, *56*(6), 2135-2175.

Naik, N. Y., Ramadorai, T., & Strömqvist, M. (2007). Capacity constraints and hedge fund strategy returns. *European Financial Management*, *13*(2), 239–256. Wiley Online Library.

Navone, M., & Belleri, M. (2007). Hedge Funds: Ability Persistence and Style Bias. *Working Paper, Bocconi University*.

Norusis, M. J. (2004). *SPSS 13.0 Advanced Statistical Procedures Companion*. *Cycle* (Upper Sadd.).

Panageas, S., & Westerfield, M. M. (2009). High-Water Marks : High Risk Appetites ? Convex Compensation , Long Horizons , and Portfolio Choice. *Journal of Finance*, *LXIV*(1).

Park, J. M., & Staum, J. C. (1998). Performance persistence in the alternative investment industry. *Working Paper (Long Island University and Columbia University)*, *10017*(212).

Preqin Research. (2009). *Overview of the Global Hedge Fund Institutional Investor Universe: 2009*. *Institutional Investor*.

Rouah. (2005). Competing risks in hedge fund survival. *Working Paper*, (November).

Royston, P. (2001). Flexible parametric alternatives to the Cox model, and more. *Stata Journal*.

Sackett, P., & Larsson, J. (1990). Research strategies and tactics in industrial and organizational psychology. *Outlook*, (33), 1-10.

Sancetta, A., & Satchell, S. E. (2005). New Test Statistics for Market Timing with Application to Emerging markets. *European Journal of Finance2*, *11*(5), 419-443. UNIVERSITY OF CAMBRIDGE.

Scandura, T., & Williams, E. (2000). Research methodology in management: Current practices, trends, and implications for future research. *Academy of Management journal*.

Schneeweis, T., & Spurgin, R. B. (1998). Multifactor analysis of hedge fund, managed futures, and mutual fund return and risk characteristics. *The Journal of Alternative Investments*, *1*(2), 1–24. Institutional Investor Journals.

Schneeweis, T., Kazemi, H. B., & Martin, G. a. (2002). Understanding Hedge Fund Performance. *The Journal of Alternative Investments*, *5*(3), 6-22.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of finance*, *19*(3), 425–442. JSTOR.

Sharpe, W. F. (1992). Asset allocation: Management style and performance measurement. *The Journal of Portfolio Management*, *21*(1), 49-58.

Sirri, E. R., & Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance*, *53*(5), 1589–1622. Wiley Online Library.

Strauss, A. L., & Corbin, J. (1990). *Basics of qualitative research*. *Methodology* (pp. 84-94). Sage Newbury Park, CA.

Struggles, H. (2010). Fund Industry Trends 2010, *2010*, 1-14.

Strömqvist, M. (2007). Should You Invest in Emerging Market Hedge Funds? *papers.ssrn.com*, (September).

Strömqvist, M. (2009). Hedge Funds and Financial Crises. *papers.ssrn.com*, (2007), 87-106.

Stulz, R. M. (2007). Hedge Funds: Past, Present, and Future. *Journal of Economic Perspectives*, *21*(2), 175-194.

Sun, Z., Wang, A., & Zheng, L. (2009). The road less traveled: Strategy distinctiveness and hedge fund performance. *Working Paper, University of California Irvine*, 1-48.

Sy, M., Nguyen, L., Yu, C., & Hossain, S. (2007). Hedge Fund Performance Persistence: A Multinomial Approach Application to Asian Hedge Funds. *papers.ssrn.com*, 1-38.

Teo, M. (2009). The geography of hedge funds. *Review of Financial Studies*, *22*(9), 3531.

Timmermann, A., Lunde, & Blake. (1999). The Hazards of Mutual Fund Underperformance: A Cox Regression Analysis. *Journal of Empirical Finance*, *6*, 121-152.

Titman, Sheridan, & Tiu, C. I. (2008). Do the Best Hedge Funds Hedge? *Working Paper, University of Texas Austin*.

Tobin, J. (1958). Liquidity Preference as Behavior Towards Risk. *The Review of Economic Studies*, *25*(2), 65.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, *48*(4), 817–838. JSTOR.

Williams, J. B. (1938). *The Theory of Investment Value*. Harvard University Press.

Xu, X. E., Liu, J., & Loviscek, A. (2010). Hedge Fund Attrition, Survivorship Bias, and Performance: Perspectives from the Global Financial Crisis. *papers.ssrn.com*, (973).

Zhong, Z. (2008). Why does hedge fund alpha decrease over time? Evidence from individual hedge funds. *Working Paper, Penn State University*, (January).

10. Appendix

Appendix – 1: Alphas of equally weighted hedge fund strategy indices

(January 2000 to January 2007)

	FH			Teo			SW Asia		
	α	*t*	Adj. R^2	α	*t*	Adj. R^2	α	*t*	Adj. R^2
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equity long/short	0.62	3.98	0.43	0.58	5.27	0.73	0,55	5,20	0,77
Relative value	0.62	3.01	0.30	0.52	3.02	0.52	0,49	3,32	0,59
Event driven	0.75	3.86	0.06	0.68	3.88	0.24	0,61	3,50	0,27
Macro	0.79	1.29	0.38	0.58	1.09	0.52	0,74	1,46	0,63
Directional	0.82	2.50	0.54	0.70	3.40	0.85	0,65	3,56	0,85
Fixed income	0.80	4.67	0.46	0.79	4.43	0.46	0,82	5,83	0,41
CTA	0.29	0.43	-0.01	0.19	0.28	-0.02	-0,29	-0,47	0,09
Others	0.59	3.45	0.52	0.53	4.19	0.75	0,65	4,34	0,76
Average	0.66	2.90	0.34	0.57	3.19	0.51	0,53	3,34	0,55

Appendix – 2: Period January 2000 to January 2007

Hedge fund portfolio performance is estimated relative to Fung and Hsieh's (2004) model for Asia-focused hedge fund strategies. The factors are: S&P 500 return minus the risk-free rate (*SNPMRF*), Russell 2000 minus the S&P 500 return (*SCMLC*), the change in the constant maturity yield of the US ten-year Treasury bond adjusted for the duration of the ten-year bond (*BD10RET*), the change in the spread of Moody's BAA bond over the ten-year Treasury bond (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), and commodities PTFS (*PTFSCOM*). The sample period is from January 2000 to January 2007.

Strategy	α	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSCOM	PTFSFX
Equity long/short	0.62	0.24	0.08	-0.87	-2.47	0.01	0.03	0.00
	(3.98)	(6.84)	(2.61)	(-1.09)	(-1.53)	(1.16)	(2.36)	(0.28)
Relative value	0.62	0.21	-0.03	-2.75	-6.97	0.00	0.01	0.02
	(3.01)	(4.60)	(-0.48)	(-2.42)	(-3.33)	(0.09)	(0.40)	(1.52)
Event driven	0.75	0.09	0.02	-0.61	-2.48	0.02	0.01	-0.02
	(3.86)	(1.57)	(0.52)	(-0.62)	(-1.18)	(1.66)	(0.59)	(-1.54)
Macro	0.79	0.75	0.22	2.29	-3.97	0.05	-0.07	-0.06
	(1.29)	(5.51)	(1.66)	(0.54)	(-0.69)	(0.83)	(-1.49)	(-2.48)
Directional	0.82	0.64	0.08	-3.51	-8.43	0.04	0.04	-0.00
	(2.50)	(7.85)	(0.90)	(-2.05)	(-2.61)	(1.74)	(1.90)	(-0.27)
Fixed income	0.80	0.18	0.02	-3.88	-4.46	0.03	0.01	0.01
	(4.67)	(3.64)	(0.24)	(-4.68)	(-2.69)	(2.40)	(0.76)	(1.00)
CTA	0.29	0.15	0.21	0.99	-1.02	0.05	0.03	0.03
	(0.43)	(0.68)	(1.24)	(0.31)	(-0.17)	(0.76)	(0.86)	(1.04)
Others	0.59	0.27	0.12	-0.60	-2.79	-0.00	0.03	0.00
	(3.45)	(6.98)	(2.95)	(-0.71)	(-1.92)	(-0.11)	(2.62)	(0.19)

Appendix – 3: Period January 2000 to January 2007

Hedge fund portfolio performance is estimated relative to Teo's (2009) adjusted model for Asia-focused hedge fund strategies. The factors are: S&P 500 return minus the risk-free rate (*SNPMRF*), Russell 2000 minus the S&P 500 return (*SCMLC*), the change in the constant maturity yield of the US ten-year Treasury bond adjusted for the duration of the ten-year bond (*BD10RET*), the change in the spread of Moody’s BAA bond over ten-year Treasury bond (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), commodities PTFS (*PTFSCOM*), MSCI Asia ex Japan index return minus the risk-free rate (*ASIAMRF*), and Nikkei 225 index return minus the risk-free rate (*JAPMRF*). The sample period is from January 2000 to January 2007

Strategy	α	*SNPMRF*	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSBD	PTFSCOM	ASIAMRF	JAPMRF
Equity long/short	0.58	-0.03	0.05	0.10	0.12	-0.00	0.01	0.01	0.20	0.16
	(5.27)	(-0.69)	(1.40)	(0.16)	(0.09)	(-0.58)	(2.01)	(1.36)	(5.81)	(5.74)
Relative value	0.52	-0.08	-0.04	-1.36	-3.43	-0.01	0.00	0.02	0.31	0.03
	(3.02)	(-1.33)	(-0.96)	(-1.50)	(-1.99)	(-0.84)	(0.14)	(1.67)	(6.18)	(0.69)
Event driven	0.68	-0.14	0.00	0.43	0.18	0.01	0.00	-0.01	0.23	0.06
	(3.88)	(-2.18)	(0.09)	(0.43)	(0.09)	(1.14)	(0.14)	(-1.55)	(3.59)	(1.27)
Macro	0.58	0.06	0.16	5.34	3.92	0.01	-0.09	-0.05	0.67	0.19
	(1.09)	(0.30)	(1.43)	(1.22)	(0.67)	(0.27)	(-2.31)	(-2.15)	(3.69)	(1.42)
Directional	0.70	0.02	-0.01	-1.18	-2.22	0.01	0.01	0.01	0.49	0.34
	(3.40)	(0.28)	(-0.10)	(-1.04)	(-0.98)	(0.53)	(1.12)	(0.89)	(7.90)	(7.18)
Fixed income	0.79	0.13	0.01	-3.67	-3.92	0.03	0.00	0.01	0.04	0.02
	(4.43)	(1.84)	(0.15)	(-4.58)	(-2.34)	(2.14)	(0.53)	(1.08)	(1.11)	(0.73)
CTA	0.19	-0.00	0.22	2.02	1.51	0.04	0.04	0.03	0.25	-0.09
	(0.28)	(-0.01)	(1.28)	(0.56)	(0.24)	(0.65)	(0.95)	(0.86)	(0.79)	(-0.54)
Others	0.53	-0.00	0.09	0.49	0.08	-0.02	0.02	0.01	0.23	0.13
	(4.19)	(-0.08)	(1.71)	(0.82)	(0.07)	(-1.90)	(2.39)	(0.97)	(6.13)	(4.69)

Appendix – 4: Decomposing Asia-focused hedge fund returns: stepwise Asia model (January 2000 to January 2007)

Equity long/short			**Relative value**		
Adj. R^2	0,77		Adj. R^2	0,59	
α	0,55	(5,20)	α	0,49	(3,32)
MSCEI Asia ex. Japan	0,20	(7,10)	MSCEI Asia ex. Japan	0,28	(9,95)
Nikkei 225	0,16	(6,45)	MSCEI World ex. US	0,09	(2,25)
Momentum	0,06	(2,87)	PTFSIR	-0,01	(-2,14)
Silver	0,03	(1,98)	HML	0,08	(2,57)
			JPM Japan govt. bond	0,12	(2,08)
			Oil	(0,02)	(1,75)
Event Driven			**Macro**		
Adj. R^2	0,27		Adj. R^2	0,63	
α	0,61	(3,50)	α	0,74	(1,46)
PTFSIR	0,22	(3,56)	MSCEI Asia ex. Japan	0,80	(7,58)
Nikkei 225	-0,01	(-0,96)	S&P REIT	-0,41	(-4,00)
Market	0,07	(1,52)	YEN/USD	0,40	(3,19)
			PTFSSTK	-0,09	(-2,64)
			Momentum	-0,16	(-1,92)
			SMB	0,18	(1,92)
			ML High Yield Index	-0,46	(-2,01)
Directional			**Fixed income**		
Adj. R^2	0,85		Adj. R^2	0,41	
α	0,65	(3,56)	α	0,82	(5,83)
MSCEI Asia ex. Japan	0,50	(10,42)	MSCEI Asia ex. Japan	0,10	(2,41)
Nikkei 225	0,35	(7,65)	JPM US govt. bond	0,45	(4,62)
Gold	0,05	(1,47)	Credit	-0,92	(-0,49)
			Market	0,14	(2,33)
			PTFSIR	-0,00	(-0,66)
			YEN/USD	-0,10	(-1,85)
CTA			**Others**		
Adj. R^2	0,09		Adj. R^2	0,76	
α	-0,29	(-0,47)	α	0,65	(4,34)
Oil	0,14	(2,29)	MSCEI Asia ex. Japan	0,26	(8,13)
Citigroup Bond Index	1,24	(1,51)	Nikkei 225	0,13	(5,10)
			Silver	0,03	(1,54)
			Momentum	0,06	(2,68)
			S&P REIT	-0,07	(-1,74)
			MSCEI World ex. US	0,08	(2,51)

Appendix – 5: Factors considered for the stepwise regression model

- **Equity indices**: Market Proxy (the value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks), Nikkei 225, MSCEI Asia excluding Japan, MSCI World, MSCI World ex. US, Russel 3000

- **Bond indices**: Bond factor (the monthly change in the 10-year treasury constant maturity yield), Credit (the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield), Citigroup World Broad Investment Grade Bond Index, J.P. Morgan Emerging Local Markets Index Asia, J.P. Morgan Global Government Bond Index, J.P. Morgan Japan Government Bond Index, J.P. Morgan US Government Bond Index , Merrill Lynch High Yield Cash Pay Index

- **Currencies**: Federal Reserve Traded Weighted Index of the US Dollar (USD), Japanese Yen Trade Weighted Index

- **Commodities**: Gold, Silver, Oil

- **Real estate**: S&P Developed REIT

- **Dynamic trading strategies**: Momentum, HML, SMB[16], Size, Primitive trend following strategies on bonds (PTFSBD), commodities (PTFSCOM), currencies (PTFSFX), short term interest rate (PTFSIR) and stock index (PTFSSTK)[17]

[16] Data on Market proxy, Momentum, HML and SMB obtained from the website of Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)
[17] Data on primitive trend following strategies obtained from the homepage of David Hsieh (http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm)

Appendix – 6: Correlation between passive investment strategies

This table reports the correlation coefficient between passive investment strategies which I included in the Stepwise selection procedure. The period for which the correlation was calculated is from January 2000 until December 2010. 1= Bond factor (the monthly change in the 10-year treasury constant maturity yield), 2= Citigroup World Broad Investment Grade Bond Index, 3= Credit (the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield), 4= Gold, 5= HML, 6= J.P. Morgan Emerging Local Markets Index Asia, 7= J.P. Morgan Global Government Bond Index, 8= J.P. Morgan Japan Government Bond Index, 9= J.P. Morgan US Government Bond Index, 10= Market Proxy (the value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks), 11= Merrill Lynch High Yield Cash Pay Index, 12= Momentum, 13= MSCEI Asia excluding Japan, 14= MSCI World, 15= Nikkei 225, 16= Oil, 17= PTFSBD, 18= PTFSCOM, 19= PTFSFX, 20= PTFSIR, 21= PTFSSTK, 22= PTFSSTK, 23= Russell 3000, 24= S&P Developed REIT, 25= Silver, 26= Size, 27= SMB, 28= Federal Reserve Traded Weighted Index of the US Dollar (USD), 29= Japanese Yen Trade Weighted Index

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1	1.00																												
2	-0.58	1.00																											
3	-0.49	0.09	1.00																										
4	-0.13	0.04	-0.13	1.00																									
5	-0.06	-0.03	-0.00	-0.08	1.00																								
6	0.16	0.12	-0.30	-0.01	0.03	1.00																							
7	-0.48	0.11	0.14	0.42	0.08	-0.04	1.00																						
8	-0.24	0.35	0.13	0.05	-0.00	0.39	0.15	1.00																					
9	-0.65	0.02	0.34	0.20	0.05	-0.20	0.68	0.05	1.00																				
10	0.13	0.08	-0.38	0.06	-0.12	0.01	0.03	-0.22	-0.27	1.00																			
11	0.31	0.13	-0.72	0.18	0.13	0.46	-0.11	-0.09	-0.33	0.21	1.00																		
12	-0.11	-0.07	0.18	0.17	-0.09	-0.06	0.00	0.12	0.16	-0.41	-0.12	1.00																	
13	0.09	0.17	-0.41	0.21	-0.10	0.07	0.15	-0.11	-0.19	0.82	0.21	-0.35	1.00																
14	0.33	-0.05	-0.62	0.05	0.19	0.61	-0.14	0.02	-0.34	0.26	0.69	-0.23	0.25	1.00															
15	0.16	-0.01	-0.41	0.09	-0.11	0.05	-0.10	-0.13	-0.20	0.67	0.17	-0.19	0.70	0.26	1.00														
16	0.27	0.02	-0.43	0.20	-0.13	0.13	-0.06	-0.16	-0.20	0.22	0.41	-0.05	0.31	0.29	0.30	1.00													
17	-0.16	0.05	0.21	0.07	-0.10	-0.17	0.23	0.09	0.24	-0.16	-0.30	-0.02	-0.08	-0.21	-0.05	-0.11	1.00												
18	-0.05	0.03	0.20	0.22	-0.08	0.01	0.12	0.13	0.09	-0.14	-0.04	0.23	-0.12	-0.08	-0.08	0.02	0.20	1.00											
19	-0.15	-0.04	0.31	0.04	0.02	0.05	0.27	0.17	0.16	-0.24	-0.11	0.18	-0.22	-0.09	-0.27	-0.11	0.25	0.43	1.00										
20	-0.14	0.01	0.43	-0.10	-0.06	-0.11	-0.03	0.11	0.06	-0.32	-0.26	0.01	-0.42	-0.25	-0.36	-0.25	0.20	0.39	0.30	1.00									
21	-0.20	-0.01	0.29	0.03	0.14	0.07	0.24	0.17	0.17	-0.29	-0.15	0.05	-0.24	-0.12	-0.24	-0.24	0.09	0.13	0.25	0.38	1.00								
22	0.31	-0.07	-0.58	0.06	0.19	0.54	-0.19	-0.01	-0.32	0.23	0.68	-0.21	0.20	0.97	0.23	0.27	-0.20	-0.07	-0.11	-0.23	-0.11	1.00							
23	-0.11	0.19	-0.37	0.15	0.34	0.08	0.22	-0.14	-0.08	0.67	0.29	-0.36	0.61	0.38	0.46	0.10	-0.14	-0.16	-0.19	-0.29	-0.13	0.35	1.00						
24	-0.01	0.13	-0.23	0.73	-0.05	0.10	0.26	0.01	-0.00	0.18	0.25	-0.03	0.32	0.13	0.19	0.25	-0.03	0.10	-0.00	-0.21	-0.03	0.11	0.25	1.00					
25	-0.01	0.05	-0.20	0.11	-0.15	-0.04	-0.07	-0.12	-0.11	0.26	0.13	0.15	0.23	0.15	0.31	0.10	-0.03	0.01	0.02	-0.11	-0.19	0.18	0.32	0.03	1.00				
26	0.04	0.03	-0.23	0.07	-0.38	-0.05	-0.07	-0.13	-0.10	0.27	0.09	0.13	0.26	0.12	0.33	0.15	0.01	0.01	0.00	-0.09	-0.21	0.14	0.21	0.01	0.93	1.00			
27	-0.14	0.07	-0.08	0.71	0.06	-0.16	0.37	-0.07	0.21	0.18	0.05	0.10	0.31	-0.07	0.22	0.23	0.17	0.14	0.00	-0.16	-0.10	-0.06	0.21	0.54	0.08	-0.00	1.00		
28	-0.05	0.29	-0.27	-0.06	-0.04	0.64	0.09	0.32	-0.13	0.18	0.28	-0.12	0.24	0.45	0.12	0.12	-0.19	-0.12	-0.06	-0.09	-0.00	0.31	0.20	0.01	0.02	0.08	-0.15	1.00	
29	0.18	-0.36	-0.11	-0.03	0.01	-0.38	-0.11	-0.90	0.02	0.22	0.06	-0.16	0.10	-0.05	0.11	0.13	-0.07	-0.10	-0.18	-0.08	-0.17	-0.02	0.14	-0.01	0.15	0.16	0.07	-0.29	1.00

Curriculum Vitae

Mato Njavro
Nationality: Croatian,
Birth date: 16.02.1986
Phone: +41786961731
Email: mato.njavro@unisg.ch

Education

02/2009 – 09/2012	**Universität St. Gallen, Switzerland, PhD in International Business,** St.Gallen, Switzerland
09/2007 – 09/2008	**SDA Bocconi, Master in Corporate Finance**, Milan, Italy
09/2004 – 09/2008	**Università Commerciale Luigi Bocconi**, Milan, Italy Bachelor Degree in International Economics and Management
07/2007 – 08/2007	**London School of Economics**, London, Analysis and Management of Financial Risk
10/2006 – 02/2007	**Universität St. Gallen, St. Gallen,** Switzerland International Exchange Programme, Erasmus Circuit
06/2005 – 08/2005	**University of Pennsylvania, Wharton Business School**, Philadelphia, USA, Summer Institute in Business and Technology
06/2004 – 09/2004	**Harvard University,** Summer School, Boston USA Introduction to International Relations International Law: War Crimes, Genocide and Justice
06/2003 – 09/2003	**Harvard University,** Summer School, Boston USA - Principles of Economics
09/2000 – 06/2004	**(V.) Fifth High School**, Zagreb, Croatia Curriculum with heavy focus on Mathematics and Computer Sciences

Professional experience

02/2009 - 09/2012	**Universität St. Gallen**, Research Assistant, Asia Research Centre
06/2009 – 09/2009	**Nomura Holdings Inc**, Debt Capital Market, summer internship, London, UK
06/2009 – 09/2009	**Lehman Brothers**, M&A Technology group, summer internship, London, UK

Skills

Languages	Croatian (mother tongue), English (fluent), Italian (fluent), German (fluent), French (intermediate)
Computer skills	European Computer Driving License (ECDL) , MS Office, Bloomberg, Eviews

Conferences, Teaching, Travels

09/2008 – present	**Zagreb School of Economics and Management**, Zagreb, Croatia, Visiting Lecturer
October 2011	Speaker, AIESEC Emerge Conference - BRIC , University of St.Gallen
November 2010	Visiting Lecturer, Bandung Institute of Technology, SEED program, Indonesia
06/2010 - 08/2010	Visiting Lecturer, University Malaysia Kelantan, Social Enterprise for Economic Development (SEED), Malaysia
January 2010, 2011, 2012	Confederation of Indian Industry Reception at the World Economic Forum, Davos, Switzerland
April 2009	Organised study trip to India for 20 bachelor students, site visits to Infosys, ABB, Bosch, METRO, Nranga Rao and Sons
December 2006	Study Trip to China (Shanghai), site visits to ABB China, Volkswagen Shanghai
April 2006	Study Trip to Japan (Tokyo, Kyoto, Hiroshima, Yokohama…) Site visits to Panasonic factory in Yokohama, Tokyo Stock Exchange
March 2006	University of Dayton, Dayton, USA, Redefining Investment Strategy Education Forum, Student panelist

Sports

May 2008	Member of SDA Bocconi Football team, participated at the MBAT tournament in Paris (HEC Business School)
August 2002	**Croatian National Snowboard Team Member**, World Junior Championship in New Zealand, seventh place in the Olympic discipline – boarder cross