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TIME SERIES RISK FACTORS OF HEDGE FUND INVESTMENT OBJECTIVES

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ABSTRACT OF THE MASTER'S THESIS

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Abstract

From this thesis, I find eight most important time series risk factors among all hedge fund investment objectives, including: equity market factor, equity size spread factor, bond credit spread factor, emerging market factor, equity trend following factor, Fama-French value factor, time series momentum factor and currency risk factor. The selected statistical model constructed from the eight risk factors provides higher adjusted R^2 and lower pricing errors than Fung-Hsieh model. In addition, I find that small hedge funds outperform large funds with alpha spread of 3.43 percent annually.

Keywords
Hedge fund, time series risk factor, capital constraints

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1. INTRODUCTION

Hedge funds have been experiencing rapid growth, becoming a popular investment vehicle for wealthy individuals and institution investors. Although investment requires good knowledge of asset's risk profile, understanding of hedge fund risk is difficult due to the lack of transparency and its possible complex trading strategies. Previous studies find hedge funds are exposed to many risk factors. Fung and Hsieh (2001, 2002, 2004a, 2004b) find two equity-based factors, two bond-based factor and three trend following factors. Agarwal and Naik (2004) discover four option based risk factors. Recent studies also prove hedge fund's exposure to time series momentum factor (Baltas & Kosowski 2012) and market liquidity factor (Sadka 2010). The increase of number of hedge fund risk factors raises the question of which factors are the most important.

The first research question of this thesis is "What are dominant risk factors among all hedge fund investment objectives?" I focus on hedge fund strategy level instead of individual funds because investors have a tendency to choose investment style first before picking individual funds (Barberis & Shleifer 2003). Additionally, hedge funds in the same strategies are likely to be affected by a number of dominant risk factors (Naik et al. 2007). My findings suggest that there are eight important risk factors including equity market factor, equity size spread factor, bond credit spread factor, emerging market factor, equity trend following factor, Fama-French value factor, time series momentum factor and currency risk factor. Compared with Fung-Hsieh model, the selected statistical model constructed from these eight factors has higher adjusted R^2 and is less rejected by the tests of jointly equal to zero of alphas, two indications of a better model. This conclusion asks for the improvement of model used to evaluate hedge fund performance. Finally, using the selected statistical model hedge fund's abnormal return measured by alpha becomes smaller than using the Fung-Hsieh model. This implies that the estimation of alpha can be sensitive to model selection. The combination of most important factors in a model yields alpha smaller. This result questions the existence of statistically significant positive hedge fund alpha. Hedge fund alpha or abnormal return may disappear once new risk factors are uncovered in the future.

By attracting more investment capital, small hedge funds grow to become large funds. The capital growth may cause hedge funds to face capital constraints. Berk and Green (2004) derive a rational model which proves that mutual fund returns decrease to scales when managers deploy their skills. To explain for this effect, the diseconomies of scale reasons that large funds may be forced to choose less profitable investment ideas, and encounter difficulty in implementation of large trade while small funds can bet all of money on its best investment ideas. In many previous research results, indicators of capital constraints such as capital inflow and fund size are negatively related to hedge fund performance: Naik et al. (2007), Fung et al. (2008) and Ramadorai (2011) find that the increase of capital inflow hurts both hedge fund future alphas and future returns; Jones (2007, 2009), Teo (2007), Ammann and Moerth (2008), and Joenväärä et al. (2012) find negative correlation between fund size and hedge fund returns. The conclusion about the relationship between capital constraints and hedge fund performance are still mixed since Baltas and Kosowski (2012) find lagged fund flows are not related to future fund performance for CTA hedge funds.

This thesis aims to investigate the existence of capital constraints in hedge funds by examining the relationship between fund size and performance. The second research question of this thesis is “Do small hedge funds outperform large funds?” Supporting the existence of capital constraints in hedge fund industry, this thesis finds small hedge funds outperform large hedge funds by at least 3.43 percent (5.27 percent) annually using equal weighted returns (value weighted returns). According to the risk return trade-off and the traditional capital asset pricing model by Sharpe (1964) higher returns should associates with higher risk because investors demand a higher payoff to compensate for more risky assets. Therefore it is expected that small funds generating higher return should load on more risk than large funds. However this thesis finds no clear evidence to support this hypothesis.

In addition to answering the primary research questions, this thesis also reports that statistically significant alphas or abnormal returns in nine out of thirteen hedge fund strategies including Emerging Markets, Event Driven, Long Only, Long/Short, Market Neutral, Multi-Strategy, Relative Value, Sector and Others. However, there are no statistically significant alphas for CTA, Fund of Funds and Short Bias. Global Macro strategy has significant alpha in equal weighted returns, but not in value weighted returns. Finally, hedge funds show a most statistically significant exposure to equity market factor, bond credit spread factor, emerging market factor and time series momentum factor.

Following Liang (1999), Agarwal & Naik (2000, 2004), and Titman & Tiu (2011) I use stepwise regression to address the two research questions. The advantage of this method is to give a parsimonious selection of explanatory variables for the model. On the other hand, it causes the over-fitting problem for the selected model. This means that the model may only work well in-sample data, but fails the out-of-sample data. However, this can be solved by additional robust tests using different data samples and various comparisons with the existing results. In this thesis I perform a robust check on an out-of-sample hedge fund database obtained from Edelman et al. (2013). The expected outcome of stepwise regression is a set of dominant risk factors which have the power to explain returns of the hedge fund strategies. The common factors are later used to construct the best statistical model in hedge fund performance evaluation. Of course, one can pool all factors in a combined model as done in Capocci and Hubner (2004). But with a large number of risk factors found in hedge fund literature, the model can be a burden to implement. Plus, many of these risk factors are highly correlated, and their effects may be diminished in the presence of each others. Therefore, for convenient use it is necessary to build a simple model with a limited number of risk factors.

I use the aggregate hedge fund database obtained from the paper Joenväärä et al. (2012), in which they merge five major databases: BarclayHedge, EurekaHedge, Hedge Fund Research, Morningstar and TASS. The time period is seventeen years from January 1995 to October 2011. The data consists of time series returns of hedge fund investment strategies categorized by size. Compared with the previous studies, which use smaller data sample, this thesis avoids the biased results driven by the incomplete database.

This thesis relates to earlier literature by employing the complete data and the use of time series analysis. Most previous studies focus on one specific strategy, or a group of similar strategies. The sample in this thesis covers all hedge fund investment strategies, providing a thorough look on the whole industry as well as allowing the comparison of performance between them. In addition, it examines a broad set of risk factors discovered in hedge fund literature and asset pricing. Finally, instead of using cross sectional analysis, a common approach to hedge fund in literature, this thesis employs time series analysis. The advantage of time series regression is the direct interpretation of coefficients, R^2 and alphas as measures of how sensitive hedge fund returns are to the risk factors and how well these factors capture the return variation and the cross-section of average returns (Fama & French 1993).

This thesis is organized as follows. Chapter 2 provides a short discussion about asset pricing model for hedge fund performance and review of hedge fund literature. Chapter 3 presents the data and methods employed in this thesis. Chapter 4 reports and discusses the empirical results. Chapter 5 performs a robust check for the results found in the previous chapter. Finally, chapter 6 drives to conclusions.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW OF HEDGE FUND

The first section of this chapter presents the asset pricing theory and multifactor model which are used to evaluate hedge fund performance. The second section defines hedge fund investment strategies and reviews recent studies on them. The third section provides a thorough review on risk factors which are potential candidates affecting hedge fund performance. Finally the last section discusses the performance of small funds versus large funds.

2.1 Asset pricing theory

Arbitrage pricing theory (APT) (Ross 1976) is applied widely in asset pricing empirical literature. The theory expresses asset expected return as a linear model of various macro-economic factors:

$$E(r_i) - r_f = b_{i1}RP_1 + b_{i2}RP_2 + \ldots + b_{in}RP_n \tag{1}$$

where

$E(r_i)$ is expected return on asset i,
r_f is risk free rate,
b_{ik} is the sensitivity of the ith asset to factor k; also called factor loadings,
RP_k is the risk premium of factor k.

For each asset i, the fact loadings b_k are estimated from the regression:

$$R_{i,t} - r_{ft} = \alpha_i + b_{i1}RP_{1,t} + b_{i2}RP_{2,t} + \ldots + b_{in}RP_{n,t} + \varepsilon_{it} \tag{2}$$

where

$R_{i,t}$ is return on asset i at time t,
$r_{f,t}$ is risk free rate at time t,
α_i is intercept of the regression,
$RP_{k,t}$ is the risk premium of factor k at time t,
$\varepsilon_{i,t}$ is asset i's idiosyncratic random shock with mean zero. (Fama & French 1996.)

The difference between (1) and (2) is the existence of intercept and the use of realized returns R_i instead of expected return $E(r_i)$. Model (2) is obtained from running regression on the data. Model (1) makes a clear implication on model (2) that the intercept should be equal to zero. It means that the excess returns on an asset should be totally explained by the set of risk factors. The intercept of the regression (2) is often interpreted as asset's abnormal return since it presents the part of returns which are not explained by risk factors. In evaluating hedge fund performance, alpha is understood as skills of managers. If fund alpha is positively significantly different from zero, meaning that the fund manager uses his talent to add value to his fund. Therefore, it is an important topic in hedge fund research to study whether hedge funds, on average, deliver abnormal risk adjusted returns.

Since APT theory does not identify which risk factors should be included in the model, it gives space for later research to find and develop a suitable set of factors tailored to a specific asset. For example Fama-French (1993) find three common factors market, size, and value among mutual funds. Although both mutual funds and hedge funds are two popular alternative investments, Fama-French model does not suit hedge fund because hedge funds may possibly employ dynamic trading strategies (Fung & Hsieh 1997a). In seeking for hedge fund risk factors, Fung and Hsieh (1997a) first use the principal component analysis to extract five most common components, then construct five style factors which are correlated with these components. These styles include system/opportunity, global/macro, value, system/trend following, and distressed style factors. Although these style factors capture most of the option-like features of hedge fund returns, they express a nonlinear relationship to the asset market (Fung & Hsieh 2001). To solve this issue, Fung and Hsieh (2001) construct a portfolio of look back straddles which model these common components. These portfolios are the trend following risk factors which resemble the returns of trend following hedge funds, providing a key link between hedge fund returns and market assets. In conclusion, hedge fund asset-based style factors can be found by two steps: first extract the common component among hedge funds, then link the components to the observable assets.

Using the above analysis, Fung and Hsieh (2004) construct a model of seven asset-based risk factors, including: equity market factor, size spread factor, bond market factor, credit spread factor, bond trend-following factor, currency trend-following factors, and commodity trend-following factor. Their model explains up to 80 percent of the variations in hedge fund's monthly returns (Fung & Hsieh 2004b). The Fung-Hsieh seven factor model becomes common to use in hedge fund performance evaluation. Applying the principal component analysis, Teo (2009) find two additional equity risk factors, which explain the returns of Asia portfolio fund returns. The augmented risk factors are the excess returns on Asia excluding Japan equity index and the excess returns on Japan equity index.

Agarwal and Naik (2004) find that hedge funds exhibit non-normal payoffs due to their use of options and option-like trading strategies. To replicate the non-linear payoff, they specify a piecewise linear form using call and put options on the market index (Glosten & Jagannathan 1994):

$$R\_p = \alpha + \beta\_1 \, R\_m + \beta\_2 \, max(R\_m - k\_1,0) + \beta\_3 \, (R\_m - k\_2,0) + \beta\_4 \, max(k\_1 - R\_m, 0) + \beta\_5 \, max(k\_2 - R\_m, 0) + \varepsilon \tag{3}$$

where

R_p is return on portfolio,

α_i is intercept of the regression,

β is the sensitivity of the portfolio to factor; also called factor loadings

R_m is excess return on market

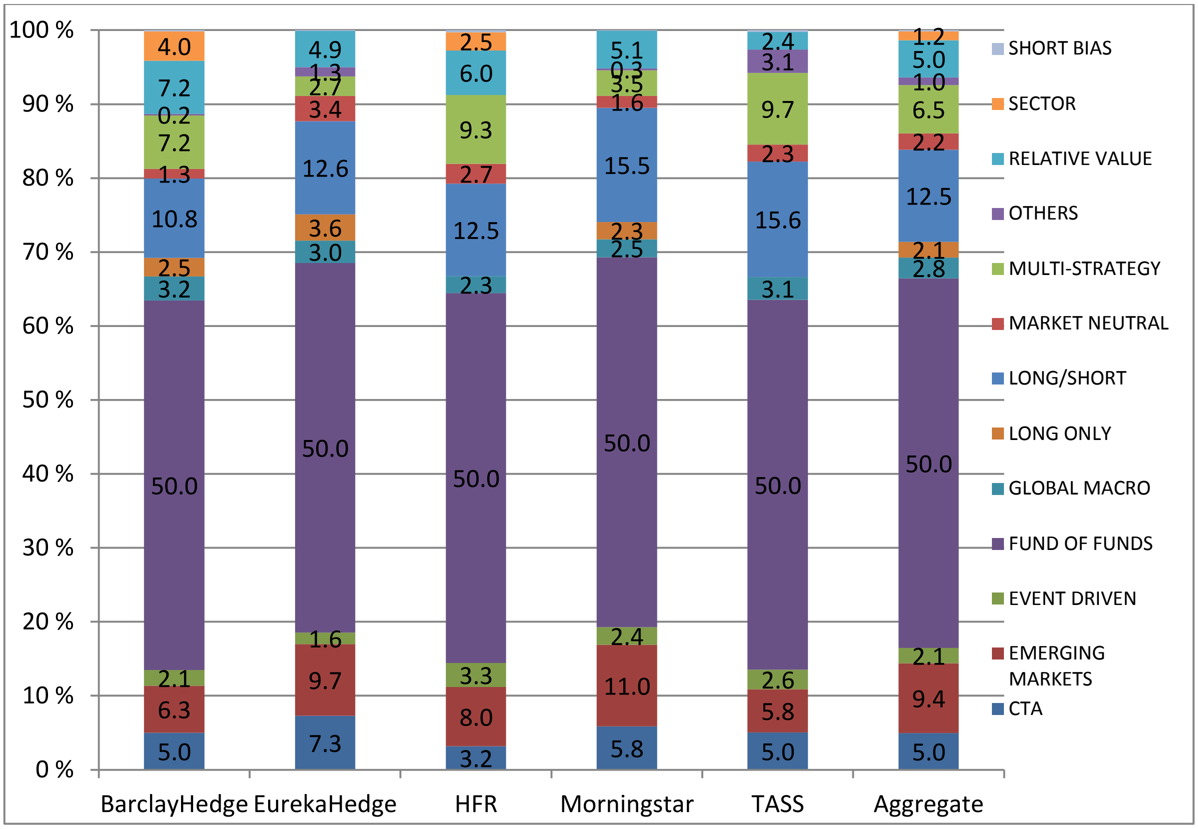
$\max(R_m\text{-}k)$ and $\max(k\text{-}R_m)$ are payoffs on call and put options.

The augmentation of the linear factor model using option based risk factors aims to improve the accuracy of performance evaluation of hedge fund. This thesis uses the multifactor model as the APT theory proposes to evaluate hedge fund performance with the employment of a variety of risk factors, including both linear and non-linear factors.

2.2 Hedge fund investment objectives

Hedge funds are categorized by their investment strategies. In this thesis I use the hedge fund categorization proposed by Joenväärä et al. (2012) in which they classify hedge fund into 13 categories: CTA, Emerging Markets, Event Driven, Global Macro, Fund of Funds, Long Only, Long/Short, Market Neutral, Multi-Strategy, Relative Value, Short Bias, Sector and Others. Figure 1 shows the proportion of hedge funds investment objectives in each database at the end of 2011. The aggregate data is constructed from the five databases: BarclayHedge, Morning star, Hedge Fund Research, Morningstar and TASS. By the end of 2011, Fund of Funds has grown to become the largest category of all strategies. The smallest category is Short Bias strategy. The following paragraphs will discuss these strategies in details.

Figure 1. Proportion of hedge fund strategies in different databases



Source Joenväärä et al. (2012)

CTA, standing for Commodity Trade Advisors, are hedge funds which mainly invest in commodity and financial instrument markets using technical trading strategies. CTA differ themselves from other types of hedge fund strategies by its obligation to register with Commodity Future Trading Commission (CFTC) (Liang 2004). Fung and Hsieh (1997b) find that CTA funds implement the trend follow strategy which uses technical analysis to make profit from long, medium, or short term moves. Liang states that correlations between CTA and other hedge fund strategies are zero or negative, which makes CTA a good hedge against downside risk in a hedge fund portfolio. Jeanneret et al. (2010) show that investors get higher returns and a better downside protection using commodity hedge funds instead of the traditional long-only index. They explain these benefits as the results of the large investment choices and dynamic trading strategies used by commodity hedge funds.

Emerging Markets invest in developing markets such as Asia, Latin America, and Eastern Europe, which are less developed compared with American or Western European markets: lack of advanced investment tools such as short sell and derivatives, and highly illiquid. In such markets hedge fund's trading dynamics is hard to implement. Most Emerging Market hedge funds tend to follow the primarily long strategies. Before 2007 Emerging Market funds behave more similarly to mutual funds than hedge funds. This is proved by their large exposure to the dominant asset classes such as "emerging market equities", non-US equities", and "emerging market bonds" before 2007. (Abugri & Dutta 2009.)

Event Driven Funds exploit profits by focusing on company's special events such as mergers, acquisitions, restructures, or bankruptcies (Jorion 2008). When companies are in these special situations, their stock prices are very likely to be undervalued. By investing with cheap price, hedge funds can make significant profits. However, these events are very uncertain: a merger or acquisition may fail even after announcement. Jorion points out that the uncertainties in discontinuous and asymmetric pay offs from these investments, and in the historical price movement is irrelevant to risk measurement of the strategy.

Fund of Funds invests in other hedge funds, which help diversify the fund specific risk. While hedge funds usually require high initial investments, Fund of fund is affordable for small investors because it allows low investments. (Liang 2004.) Since Fund of funds invests in other hedge funds, it has different fee structure compared with other hedge funds. When investing in fund of funds, investors actually pay double fee: first for the underlying hedge funds, second for the fund of funds. Investors are willing to invest in funds of funds because it brings the diversification benefit and has a lower capital investment requirement. Therefore, the number of Fund of Funds has grown to be the largest, taking up about 50 percent of total funds in all five hedge fund databases (figure 1).

Long Only hedge funds take long positions with possible use of leverage. It may be common to employ this strategy in emerging market where short sell is not allowed. At these markets fund managers mainly implement the buy and hold strategy. When funds do not use short sale, they do not hedge against risks for their portfolios. Probably the lack of flexibility in implementing investment prevents the growth of this strategy. There is none of Long Only funds in the HFR and TASS databases. It is largest in Eureka Hedge with 322 funds, taking up 3.6 percent of total fund in the database. Because of small quantity studies have not focused on Long Only strategy. To solve the investment restriction in investment, a variation of Long Only called 130/30 funds appear in market (Lo and Patel 2008). The 130/30 holds 130 percent of its capital in long position and 30 percent in short position.

Long/Short is the oldest hedge fund strategy applied by the father of this industry A.W. Jones in 1949. The main characteristic of this trading style is employing two important investment toolkits short sale and leverage (Fung & Hsieh 2004a). Not only being the oldest strategy, Long/Short is also the second largest hedge fund style after Fund of Funds. Without counting Fund of Funds, in TASS, the number of Long/Short hedge funds takes up to 36 percent of total funds, 35 percent for Morning star, 30 percent for Hedge Fund Research, 31 percent for EurekaHedge, and 22 percent for BarclayHedge (Joenväärä et al. 2012). Fung and Hsieh (2004a) extract the Long/Short alphas after adjusted for equity market factor and equity size spread factor and find that the strategy offers significant alphas even in the stressed market condition. Fung and Hsieh (2011) find more than 80 percent of Long/Short funds deliver significant alphas, and the alphas are positively related to market activities and negatively related to short term interest.

Market Neutral funds aim to eliminate major equity market risks by combining long and short positions in related securities (Patton 2009). At the same time they also take bet on relative price movements of these securities (Fung & Hsieh 1999). The clear benefit of investing in market neutral hedge fund is being able to avoid the fluctuations in equity market. Both Patton (2009) and Ribeiro and Machado-Santos (2011) seek to answer the question whether Market Neural hedge funds actually employ 'market neutral' strategy. Both studies share a common conclusion that many market neutral funds have significant exposure to market risks, suggesting that a lot of Market Neural funds do not neutralize market risks as they claims.

Multi-strategy funds flexibly apply several investment strategies. Typically, these funds are owned by large investment firms which pursue different strategies. At the beginning history, Multi-strategy funds follow quite similar strategies. Nowadays they become more diverse to compete with Fund of Funds. This change makes Multi-strategy become more comparable to its competitor. One clear characteristic to distinguish Multi-strategy from Fund of Funds is the single layer of fee charged to investors. (Scott 2006.) Another difference is Multi-Strategy is more flexible in relocating capital among investment strategies (Reddy et al. 2007). Agrawal and Kale (2007) find that Multi-Strategy funds statistically outperform Fund of Funds on a risk-adjusted basis by 2.6 percent to 4.8 percent per year in gross-of-fees alphas and by 3.0 percent to 3.6 percent in net-of-fees alpha. They explain the superior performance of Multi-Strategy funds by better managers of these funds compared with Fund of Funds. However Reddy et al. (2007) criticize Agrawal and Kale's study in term of its small data sample, which may create a biased result toward the superior performance of Multi-Strategy. They prove that Multi-

Strategy do not bring benefits as Fund of Funds due to the limitation in manager selection.

Relative Value hedge funds refer to arbitrage strategy where hedge funds simultaneously buy and sell two related securities which, in trader's opinion, are not at their true value. On market there are highly correlated securities which have similar price movements. Traders will profit from trading these securities when there is a price discrepancy between them. This strategy is also called as 'pairs' trading because the trading is often done on a pair of similar securities.

Sector hedge funds focus their investments in a specific sector of the economy (Fung & Hsieh 1999). Relying on in-depth bottom up research approach, managers of Sector funds often have profound sector knowledge and good industry connections. Many sector funds concentrate on high-tech industries which require large R&D investments such as Technology, Biotech, Cleantech and Telecom. Sector funds are reported in two databases BarclayHedge and Hedge Fund Research with a small proportion 4 percent and 2.5 percent of total funds, but not reported in three databases TASS, Eureka Hedge, and Morning star.

Short Bias hedge funds use short sale as their main investment tool to make profits (Fung & Hsieh 1999). Short Bias is the smallest category of all hedge fund strategies. In all five database BarclayHedge, Morning star, Hedge Fund Research, Morningstar and TASS, less than 1 percent of funds are Short Bias (Joenväärä et al. 2012). Due to its small quantity, not much research has investigated this style. However after the strong fall of market during the financial crisis 2007-2008 which is a favorable trading condition for short selling, this strategy attracts more research attentions. Connolly and Hutchinson (2011) use three different models to estimate alpha of this strategy. They find that Short Bias deliver significant alphas in both the no-crisis and crisis periods.

Therefore, they recommend this strategy as an excellent diversification instrument and a great protection against market downturns.

Other category includes all hedge funds which have other investment strategies other than above discussed ones.

2.3 Risk factors and hedge fund returns

Since hedge funds implement dynamic trading strategies and use derivatives, the Sharpe's asset class factor model, which are commonly used for mutual funds, do not succeed in explaining hedge fund returns (Fung & Hsieh 1997a). This motivates research on the performance evaluation model for hedge fund returns. Fung and Hsieh (2004b) successfully build the first model with seven asset based factors, which is widely used nowadays. The seven factors include two equity risk factors (equity market factor and size spread factor) (Fung & Hsieh 2004a), two bond risk factors (bond market factor and credit spread factor) (Fung & Hsieh 2002), and three trend following risk factors (bond trend-following factor, currency trend-following factor, and commodity trend-following factor) (Fung & Hsieh 1997a, 2001). Later Edelman et al. (2012) add the Emerging market index as the eighth factor to the model.

Agarwal and Naik (2004) argue that hedge fund can present the nonlinear option like payoffs because it is common for hedge funds to use derivatives such as options or to implement option-like dynamic trading strategies. Therefore, besides using the asset based risk factors, they add four option based risk factors, including at-the-money (ATM) and out-of-the-money (OTM) European call and put options. They construct the option based risk factors by buying and selling the call/put options on the S&P 500 index at the beginning of each month, creating the monthly time series returns. Their results show a significant exposure of many different hedge fund strategies to these option based risk factors.

Besides the Fung-Hsieh model, studies (Bali et al. 2011, 2012, Fung & Hsieh 2004a) also use the Fama-French-Carhart (1993,1997) four factor model to explain hedge funds' returns. This model includes four factors: market risk factor, size factor, value factor, and momentum factor. Originally Fama and French (1996) build the three factors model from the first three risk factors to explain the cross sectional difference in stock returns. Carhart (1997) extends the three factor model by adding momentum as the fourth risk factor when evaluating mutual fund's performance.

Recent studies find different asset classes such as stock, bond, and currency are exposed to the same risk factors. These risk factors include global value risk factor, global momentum risk factor, time series momentum risk factor, currency risk factor, carry trade risk factor, and liquidity risk factor. Since hedge funds invest in the asset classes, they may be also exposed to the same set of risk factors. Following this spirit I will test hedge fund's exposure to the six common risk factors. Since these risk factors are recently discovered, they require more attention to explain.

The global value and global momentum risk factors are comprehensively studied among many asset classes by Asness et al. (2012). These two factors come from the two most famous anomalies in finance: 'value' and 'momentum' effects. The value anomaly refers to phenomenon where higher asset returns associates with relatively higher book/market value. The momentum anomaly is presented when in a short period of time, less than a year, high return assets continue to have high returns and low return assets continue to have low returns. Instead of constructing the factor mimicking portfolios based on the US data done before by Fama-French (1993) and Carhart (1997), Asness et al. (2012) extend the data to global level which include most common assets such as stocks, bonds, currency, and commodity futures across many different markets US, UK, European, and Asia. Their results are striking when many assets show the exposure to the global value and momentum factors. Furthermore, they test the hedge fund's exposure to the global momentum and value momentum risk factors. They find that their three factor model of market risk factor, global momentum, and value momentum risk factor outperform CAPM and Fama-French models in terms of pricing error.

Time series momentum factor is the phenomenon where asset returns are consistent over short time periods. It is different from the momentum effect by Carhart (1997), which focuses on the cross sectional approach, obtaining from performance comparison between different assets: winners continue to be winners, and losers continue to be losers in short run. In contrast, the time series momentum focuses on an asset's own past returns. Because both cross sectional momentum and the time series momentum are driven by positive auto-covariance, they are found to be highly correlated. It is shown that time series momentum captures cross sectional momentum. Time series momentum is first documented in equity index, currency, commodity, and bond futures. Applying time series momentum strategy on a diversified portfolio of these assets yields a Sharpe ratio of 2.5 times greater than equity market portfolio (Moskowitz et al. 2012.)

Extending the paper Moskowitz et al. (2012), Baltas and Kosowski (2012) construct the time series momentum factor using a more extensive database. They add 13 more future contracts and extend the research period from 1974 to 2012. Consistent with previous finding, they find the time series momentum create high Sharpe ratio of above 1.2. They also show a significant explanation power of time series momentum to CTA's time series returns. More interestingly, when including the time series momentum to the Fung-Hsieh seven factor model, some trend following risk factors loose its significance.

Currency risk factor and carry trade risk factor are constructed by Lustig et al. (2011). From the currency exchange rate data of 35 different countries, they build six sorted portfolios by their forward discount rates. Using principal component analysis and checking correlation, they are able to identify two common components among all currency portfolios.

The first component is the average return of a portfolio of all foreign currencies available on forward market, which is driven by the value fluctuations of a domestic currency against a broad portfolio of foreign currencies. This component is called currency risk factors, whose risk premium compensates for the home country risk. Currency risk factor does not explain the variations in average excess return across all these currency portfolios, in other word all portfolios load on the same amount of the currency risk factor. Instead, currency factor explains the average level of excess returns (Lustig et al. 2011).

The second principal component is the difference between returns of the portfolio with highest forward discount rate and the portfolio with lowest forward discount rate. This factor is carry trade risk factor, whose risk premium compensates for global or common risk. When investors borrow money from countries with lower interest rates, and invest in countries with higher interest rates (for example buy high yield bonds in foreign countries), carry returns are made. However, this is not arbitrage because the investors have to bear the risk of exchange rate fluctuations. We often see during economic crises currencies with high interest rates tend to depreciate and vice versa. As a result, there is a trade-off between return and risk: currencies with high interest rates (or high forward discount) load more on the carry trade risk factor because these currencies offer higher return compared with low interest rate currencies. Therefore carry trade risk factor explains the variations in average excess return among currencies. (Lustig et al. 2011.)

Liquidity risk factor is the risk that investors cannot quickly sell their assets or have to sell them at very low prices. When assets are illiquid, investors require a risk premium to compensate for the risk. Pastor and Stambaugh (2003) find that expected returns on stocks are higher when stocks are more sensitive to liquidity even after adjusted for value, size, and momentum factors. They also state that liquidity should be included in the asset pricing model as an important risk factor since it lowers the stock's abnormal return or alpha by 1.5 percent. Sadka (2010) also tests the influence of market-wide liquidity risk on hedge fund's performance. By measuring liquidity as the covariance of fund returns with unexpected change in aggregate liquidity, his result shows that hedge funds with high exposure to high liquidity risk outperform hedge funds with low exposure by 6 percent annually. From this impressive result he concludes that liquidity risk should be included in hedge fund performance evaluation.

2.4 Capital constraints

There have been two opposite arguments about the relationship between fund size and performance. The first group states that large funds could have advantage of scale over small funds by exploiting larger research resources and lower expense ratios. On the other hand the second one believes while small funds can easily bet all of its money in its best investment ideas, large funds with its large capital have to invest in even not-so-good ideas causing performance erosion. (Chen et al. 2004.) This is called diseconomies of scale. Berk and Green (2004) derive a model of active portfolio management and prove that mangers face decreasing returns to scales in deploying their skills. As a result, alpha and persistence will disappear in equilibrium.

Evidences are found among mutual funds. Both Yan (2008) and Chen et al. (2004) find that an inverse relation between fund size and performance in mutual funds, and this phenomenon is stronger among illiquid funds which tend to hold small and less liquid stocks. Therefore liquidity is the reason behind the diseconomies of scale in mutual funds. Turning to our main research objective, hedge funds are different from mutual funds because of their dynamic trading on more complex and illiquid assets. As a result it is interesting to investigate how the diseconomies of scale present in hedge funds?

Jones (2007) tests whether smaller and younger funds outperform larger and older funds. Combining data from HFR, HedgeFund.net, Alvest from InvestorForce and Barclay Global HedgeSource, he constructs indices for small, medium, and large funds. The small fund index has annualized return of 12.5 percent, medium fund index 5.89 percent, and large fund index 2.8 percent. The result is repeated when using the Monte Carlo simulations. Based on the study he suggests that investors should seek for smaller funds to maximize return and look for larger funds to maximize capital preservation. There are many reasons to explain for the outperformance of small funds over large funds: small funds can select best investment ideas; with smaller trading positions and easily maneuver without much attention, small funds can exploit market inefficiency and opportunities. Meanwhile, large funds with large capital have to look outside of their best investment ideas and their expertise; keep a large amount of fund in cash to provide liquidity to investors; have to please conservative institution investors who are more risk averse (Jones 2009).

Teo (2007) examines how the fund size affects the cross-sectional future performance of many hedge fund strategies. Using both Fama-MacBeth regression and portfolio sort methods the results show a negative relationship between fund size and future performance. Overall he finds that small funds outperform large funds by 2.75 percent annually after adjusted for risk. He also finds the phenomenon is pervasive among all hedge fund strategies, however the variation is substantial. In more details the alpha spread between small funds and large funds for Emerging Market is 6.75 percent while they are smaller for Relative Value (1.29 percent) and Global funds (2.06 percent). He attributes this occurrence to large price impact created by large funds when they implement large trading on the market. It is more difficult to execute large trades than small trades due to market impact and transaction size, therefore large size erodes performance (Perold & Salomon 1991). This effect is also stronger among funds which hold more illiquid securities such as Emerging Market funds. Again, liquidity plays an important role in deciding the impact of size on fund performance.

Ammann and Moerth (2008) also have supporting evidence about the negative relationship between size and fund performance. They find that large fund cannot take advantage of economies of scales. They use TASS and CISDM databases and eliminate the Fund of Funds, resulting 4699 hedge funds and 2718 CTAs for the research period January 1994 to April 2005. By sorting funds in percentile, they find that fund performance negatively relate to fund size even after adjusted for risk. Alphas of small funds tend to be higher than the alphas of large funds.

Studies show that capital constraints negatively relate to both hedge fund future alpha and future returns. Fung et al. (2008) investigate the influence of capital inflow on hedge funds' ability to deliver alpha in the future. After separate Fund of Funds data in two groups: have-alpha funds and beta-only fund, they continue to divide the have-alpha funds into two groups: above-medium capital inflow and below-medium capital inflow. They find that the have-alpha funds with higher capital inflow have lower probabilities to deliver alpha in the future, while those with lower capital inflow have better chance of offering alpha in the next time periods. The capital constraints also affect the information ratios funds because funds with higher capital inflow have lower t-statistic of alpha in the future and vice versa. Using new data on hedge fund investor interest Ramadorai (2011) explores the effect of capital constraints on hedge fund future returns and finds that both capital inflow and fund size negatively forecast hedge fund returns.

Consistent with studies by Teo (2007) and Ammann & Moerth (2008) Joenväärä et al. (2012) also find that small funds deliver superior performance over large funds. Using Fung-Hsieh seven factor model to evaluate hedge fund performance, they find that ten out of twelve investment strategies in which small funds have higher alpha than large funds. In detail, the hedge funds with asset under management less than 10 million dollars has alpha of 7.25 percent annually. Since the average alpha is impossibly large and statistically highly significant, they claim small funds' superior performance as a result of data bias.

Fund of funds is different from other categories. Large Fund of funds can take more advantage of large scale by using more resources to do due diligence than small funds. Therefore, studies (Getmansky 2004, Xiong et al. 2009) have found positive relationship between fund size and performance. However, the relationship is also concave, meaning that fund performance increases with size to a certain point, and then start to decrease. In addition, using the Fund of Funds data from TASS and Morning star databases, Xiong et al. (2009) find that the relationship between fund size and standard deviation is negative. It means that small funds are more volatile than large funds.

This thesis aims to investigate the relationship between size and performance in hedge fund industry. By dividing hedge funds in three groups: small, medium, and large, I can compare the performance between them. Consistently with previous studies, I also find that small funds outperform large funds in term of risk adjusted returns or alpha. However, due to scope of my research, this thesis does not seek for the reasons behind the negative relation between hedge fund performance and size.

3. DATA AND METHODOLOGY

This chapter presents data and methodology. The data consists of the hedge fund aggregate and the risk factor databases. They are monthly excess return observations from January 1995 to October 2011. The main method is stepwise regression, which allows hedge funds flexibly choose their risk exposures. As the results, stepwise regression finds the most important risk factors for each hedge fund time series return. This also implies that alpha is “cleaner” since many of fund’s possible risk exposure is taken into account when estimating fund alpha. In other words, alpha becomes smaller, which shows an accurate measure of skill of fund managers. In addition, two statistics tests Wald and Gibbons- Ross-Shanken (GRS) are used to test the hypothesis of jointly equal to zero of alphas. GRS test is different from Wald test because it takes into consideration of factor’s covariance and model’s residuals. The purpose of using the two tests in this thesis is to compare the performance of different models.

3.1 Data

3.1.1 Hedge fund aggregate data

Most of previous hedge fund studies have their limitation in small database. Since hedge funds are not compulsory to report their performance to any regulatory authors, hedge fund data were not extensively collected until late 90s. Previous research often chooses one or two databases out of the five largest hedge fund data supply: BarclayHedge, EurekaHedge, Hedge Fund Research, Morningstar and TASS. Joenväärä et al. (2012) find that there is a significant difference between these databases, which may drive research results. Therefore they suggest using hedge fund aggregate dataset, which is constructed from merging all of these five largest databases. Of course the work of combining the databases is not easy. However a thorough hedge fund database is the first important step to have a better understanding about hedge funds. This thesis distinct itself from previous studies by using the extensive aggregate data obtained from Joenväärä et al. (2012).

By merging the five largest hedge fund databases (BarclayHedge, EurekaHedge, Hedge Fund Research, Morningstar and TASS), there are 25 522 unique hedge funds at the end of October 2011. These hedge funds are categorized by their investment objective and size. Table 1 provides details on the number of funds in each strategy in different databases at the end of research period. Using monthly returns of these hedge funds, Joenväärä et al. (2012) construct equally weighted portfolio and value weighted portfolios. Since there are 13 investment objectives, and each has 3 sizes (large, medium and small), totally 39 portfolios are made. The “All” portfolio is the aggregate data for a whole strategy. The research period is from January 1995 to October 2011.

Table 2 reports the summary statistics of the hedge fund portfolio returns after fee by strategy and size. In panel A of Table 2, equal weighted returns on Sector, Emerging Market, and Long Only have the highest annual mean (10.48 percent, 9.79 percent, and 9.14 percent in order). However investment objectives have the highest annual Sharpe ratios are Market Neutral, Event Driven, and Relative Value (1.17 percent, 1.11 percent and 1.04 percent, in order). Two strategies have the lowest mean returns are Short Bias (0.6 percent annually) and Fund of Funds (3.5 percent annually). Fund of Funds has much lower returns probably because of an additional fee layer charged to investors.

When looking at the investment objectives by sizes, most categories present a clear trend: small hedge fund portfolios have higher mean returns and Sharp ratios than the large funds. It means small funds outperform the large funds. Since the Sharpe ratios also follow this pattern, it proves that small hedge funds outperform large ones not by increasing volatility. Out of all strategies, small funds of Emerging Market (13.12

percent), Long Only (12.25 percent) and Sector (11.75 percent) have the highest mean annual returns over the research period. Short Bias and Fund of Funds are two outcasts which do not follow this trend. For Short Bias, the quality of data collected may affect this result. Large funds in the Fund of Funds strategy have more advantage over small funds because they benefit from economies of scales.

The value weighted returns in panel B show a similar pattern as the equal weighted returns. Sector, Emerging Market, and Long Only still have the highest annual mean returns (in order 13.36 percent, 10.34 percent, and 9.02 percent). Small funds also have higher mean returns and Sharpe ratios than large funds, except for Fund of Funds strategy. Overall value weighted returns show a higher average returns for all hedge fund investment objectives and all sizes compared with equal weighted returns.

Following Teo (2007) and Edelman et al. (2013) I construct three portfolios of hedge funds based on size using above aggregate data. Three portfolios are named Large Medium and Small groups. Table 3 reports the summary statistics of these portfolios. It is not a surprise to see the Small group shows higher average return compared with the Medium and Large groups because this is the aggregate data from Table 2. The spread mean returns between the Small group and the Large group is 3.43 percent (4.82 percent) annually in equal weighted returns (value weighted returns). The Small group also has higher annual Sharpe ratio than the Large group with the spread is 0.46 (0.69) in equal weighted returns (value weighted returns).

3.1.2 Risk factors

There are 22 risk factors with monthly observations from January 1995 to October 2011. Table 4 provides the description of these risk factors. Table 5 reports the summary statistics of the factors during the research period.

Table 1. Number of hedge funds in each strategy in different databases at the end of October 2011

MainStrategy/Database	Barclay Hedge	Eureka Hedge	HFR	Morningstar	TASS	Aggregate
CTA	398	657	257	438	342	1265
EMERGING MARKETS	503	875	652	828	397	2405
EVENT DRIVEN	168	140	266	179	179	528
FUND OF FUNDS	3969	4510	4065	3747	3394	12761
GLOBAL MACRO	256	270	186	184	210	713
LONG ONLY	199	322	0	173	0	546
LONG/SHORT	854	1136	1017	1159	1060	3180
MARKET NEUTRAL	101	306	219	120	155	564
MULTI-STRATEGY	575	240	757	259	659	1665
OTHERS	17	115	0	19	213	262
RELATIVE VALUE	570	439	487	384	164	1286
SECTOR	317	0	201	0	0	306
SHORT BIAS	11	10	23	4	15	41
TOTAL	7938	9020	8130	7494	6788	25522

Table 2. Summary statistics of hedge fund aggregate data by strategy and size

A. Equal weighted returns

Group	Mean (% pa)	Std(%pa)	Sharpe (pa)	Skew	Kurtosis
			CTA		
Large	4,12	7,42	0,56	0,35	0,09
Medium	5,99	7,77	0,77	0,57	0,33
Small	9,19	6,72	1,37	0,36	0,49
All	6,43	6,97	0,92	0,4	-0,04
			EMERGING MARKETS		
Large	6,23	16,33	0,38	-1,59	6,72
Medium	10,02	16,77	0,60	-1,19	4,61
Small	13,12	17,43	0,75	-0,43	1,47
All	9,79	16,47	0,59	-1,05	3,67
			EVENT DRIVEN		
Large	5,82	6,52	0,89	-2,13	8,89
Medium	7,07	6,4	1,10	-1,73	6,97
Small	9,27	7,61	1,22	-0,75	2,8
All	7,39	6,63	1,11	-1,55	5,6
			FUND OF FUNDS		
Large	4,07	7,17	0,57	-1,09	4,42
Medium	3,39	7,07	0,48	-1,06	4,15
Small	3,04	7,39	0,41	-0,73	3,06
All	3,5	7,16	0,49	-0,97	3,89
			GLOBAL MACRO		
Large	4,59	5,86	0,78	0,16	0,61
Medium	4,8	5,82	0,82	0,12	0,93
Small	6,62	5,71	1,16	0,16	0,19
All	5,33	5,2	1,03	0,18	0,41
			LONG ONLY		
Large	6,53	12,58	0,52	-0,97	3,58
Medium	8,64	13,27	0,65	-0,85	3,79
Small	12,25	12,34	0,99	-0,6	1,84
All	9,14	12,24	0,75	-0,93	3,38
			LONG/SHORT		
Large	6,26	10,18	0,61	-0,55	2,44
Medium	8,1	10,07	0,80	-0,53	1,75
Small	10,48	11,31	0,93	-0,17	1,62
All	8,28	10,43	0,79	-0,41	1,85

Group	Mean (% pa)	Std (%pa)	Sharpe (pa)	Skew	Kurtosis
			MARKET NEUTRAL		
Large	3,9	4,5	0,87	-0,49	3,07
Medium	3,9	4,39	0,89	-0,63	3,28
Small	6,54	4,28	1,53	-0,28	1,09
All	4,78	4,1	1,17	-0,63	2,91
			MULTI-STRATEGY		
Large	5,78	6,85	0,84	-0,24	1
Medium	6,58	7,68	0,86	0,13	0,07
Small	8,19	8,91	0,92	0,31	-0,1
All	6,85	7,6	0,90	0,14	-0,11
			OTHERS		
Large	4,96	5,99	0,83	-0,81	5,2
Medium	6,68	8,37	0,80	-0,72	4,46
Small	9,28	8,59	1,08	-0,08	2,48
All	6,98	7,24	0,96	-0,64	4,24
			RELATIVE VALUE		
Large	4,56	5,64	0,81	-3,4	24,61
Medium	4,2	5,45	0,77	-2,59	15,73
Small	7,91	5,57	1,42	-3,13	19,77
All	5,56	5,35	1,04	-3,28	22,7
			SECTOR		
Large	8,54	13,09	0,65	-0,28	3,47
Medium	11,14	13,98	0,80	-0,15	2,29
Small	11,75	16,09	0,73	-0,32	2,33
All	10,48	13,98	0,75	-0,34	2,37
			SHORT BIAS		
Large	-1,55	14,63	-0,11	0,49	3,06
Medium	2,58	16,77	0,15	0,56	2,46
Small	0,76	15,5	0,05	0,8	4,34
All	0,6	14,32	0,04	0,85	3,16

A. Value weighted returns

Group	Mean (% pa)	Std (% pa)	Sharpe (pa)	Skew	Kurtosis
			CTA		
Large	5,96	8,91	0,67	0,15	-0,31
Medium	7,32	7,37	0,99	0,62	0,46
Small	9,7	9,02	1,08	-0,32	3,69
All	6,16	8,8	0,70	0,17	-0,35
			EMERGING MARKETS		
Large	8,74	16,11	0,54	-0,93	3,98
Medium	15,39	16,74	0,92	-0,48	2,46
Small	17,69	16,9	1,05	0,53	2,98
All	10,34	15,8	0,65	-0,79	3,48
			EVENT DRIVEN		
Large	8,09	6,64	1,22	-1,85	6,91
Medium	8,64	5,98	1,44	-1,02	3,61
Small	11,16	7,15	1,56	-0,4	2,9
All	8,24	6,48	1,27	-1,79	6,33
			FUND OF FUNDS		
Large	5,43	7,85	0,69	-0,64	2,73
Medium	4,49	6,84	0,66	-0,83	3,3
Small	5,1	7,32	0,70	-0,4	2,56
All	5,36	7,63	0,70	-0,69	2,83
			GLOBAL MACRO		
Large	8,14	9,01	0,90	0,05	4,13
Medium	7,08	5,56	1,27	0,46	0,63
Small	8,18	5,62	1,46	-0,01	0,57
All	8,28	8,84	0,94	0,12	4,1
			LONG ONLY		
Large	8,45	12,39	0,68	-0,82	1,63
Medium	10,19	12,06	0,84	-0,81	4,05
Small	14,38	12,87	1,12	-0,54	2,9
All	9,02	12,17	0,74	-0,85	1,86
			LONG/SHORT		
Large	7,92	10,02	0,79	-0,14	2,83
Medium	11,45	10,03	1,14	0,14	3,09
Small	14,76	11,54	1,28	0,85	4,71
All	8,69	9,9	0,88	-0,27	2,27

Group	Mean (% pa)	Std (%pa)	Sharpe (pa)	Skew
		MARKET NEUTRAL		
Large	3,65	4,78	0,76	-1,27
Medium	5,73	4,38	1,31	-0,45
Small	6,65	4,03	1,65	-0,22
All	4,34	4,66	0,93	-0,63
		MULTI-STRATEGY		
Large	7,18	6,63	1,08	0,03
Medium	8,86	7,47	1,19	0,4
Small	9,77	9,29	1,05	0,6
All	7,34	6,61	1,11	0,06
		OTHERS		
Large	4,44	4,98	0,89	0,52
Medium	9,93	8,62	1,15	1,03
Small	16,28	9,62	1,69	1,87
All	5,44	5,4	1,01	0,65
		RELATIVE VALUE		
Large	5,06	5,74	0,88	-2,37
Medium	6,14	4,47	1,37	-0,81
Small	9,63	4,61	2,09	-0,75
All	5,42	5,48	0,99	-1,97
		SECTOR		
Large	12,12	12,14	1,00	0,58
Medium	15,98	14,09	1,13	0,99
Small	17,77	16,35	1,09	0,69
All	13,36	12,38	1,08	0,73
		SHORT BIAS		
Large	1,17	11,94	0,10	0,8
Medium	7,84	17,46	0,45	0,54
Small	7,84	13,82	0,57	0,78
All	2,46	11,95	0,21	0,98

Table 3. Summary statistics of hedge fund aggregate data by size

A. Equal weighted returns

Group	Mean (%pa)	Std (%pa)	Sharpe (pa)	Skew	Kurtosis
Large	4,91	5,85	0,84	-1,15	4,44
Medium	6,39	6,14	1,04	-0,75	2,98
Small	8,34	6,39	1,31	-0,49	3,11

B. Value weighted returns

Group	Mean (%pa)	Std (%pa)	Sharpe (pa)	Skew	Kurtosis
Large	6,64	5,89	1,13	-0,61	2,25
Medium	9,16	5,94	1,54	-0,17	1,79
Small	11,46	6,31	1,82	0,33	2,95

Table 4. Descriptions of risk factors

Risk factor	Descriptions
SPRF	Monthly return of the S&P 500 stock market index minus Risk-free rate[1]
RLSP	Monthly return of the Russell 2000 stock market index return minus Monthly return of the S&P 500 stock market index return
TYRF	Monthly return of the FRB 10Y constant maturity bond minus Risk-free rate
BAATY	Monthly return of Moody's Baa bond minus Monthly return of FRB 10Y constant maturity bond
MSEMKFRF	Monthly return of MSCI Emerging Market index minus Risk-free rate
PTFSBDRF	Monthly return of the PTFS Bond lookback straddle factor minus Risk-free rate
PTFSFXRF	Monthly return of the PTFS Currency lookback straddle factor minus Risk-free rate
PTFSCOMRF	Monthly return of the PTFS Commodity lookback straddle factor minus Risk-free rate
PTFSIRRF	Monthly return of the PTFS Short-Term Interest Rate lookback straddle factor minus Risk-free rate
PTFSSTKRF	Monthly return of the PTFS Stock Market lookback straddle factor minus Risk-free rate
SMB	Small minus big factor[2]
HML	High minus low factor
VAL	Global Value factor [3]
MOM	Global Momentum factor
TMOM	Time Series Momentum factor [4]
LIQ	Liquidity risk factor[5]
RX	Currency risk factor[6]
Carry	Carry Trade risk factor
ATM Call	At-the-money European Call [7]
OTM Call	Out-of-the-money European Call
ATM Put	At-the-money European Put
OTM Put	Out-of-the-money European Put.

[1] The first ten risk factors is from the website https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

[2] The SMB and HML data is from the website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[3] The VAL and MOM data is from http://faculty.chicagobooth.edu/tobias.moskowitz/research/data.html

[4] The data is from the website http://faculty.chicagobooth.edu/tobias.moskowitz/research/data.html

[5] The data is from the website http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2012.txt

[6] The RX and Carry data is from the website http://web.mit.edu/adrienv/www/Data.html

[7] The data is provided by Vikas Agarwal.

Table 5. Summary statistics of risk factors

	Mean (% pm)	STD (% pm)	Min (% pm)	Max (% pm)	Skew	Kurtosis
SPRF	0,50	4,61	-16,88	10,93	-0,63	0,86
RLSP	0,07	3,55	-16,38	18,41	0,26	4,45
TYRF	0,36	2,24	-7,57	9,42	0,04	1,44
BAATY	0,20	2,10	-14,37	8,11	-1,31	13,21
MSEMKFRF	0,56	7,16	-29,34	17,14	-0,77	1,84
PTFSBDRF	-1,88	14,71	-25,60	68,43	1,46	3,00
PTFSFXRF	0,14	19,22	-30,15	89,81	1,42	2,97
PTFSCOMRF	-0,13	14,05	-23,44	64,36	1,15	2,13
PTFSIRRF	1,87	28,48	-30,92	221,50	4,14	23,65
PTFSSTKRF	-5,02	13,07	-30,59	45,72	1,11	2,28
SMB	0,02	3,70	-22,06	13,74	-1,13	7,63
HML	0,37	3,49	-9,93	13,88	0,42	2,43
VAL	0,21	1,45	-7,64	4,89	-0,68	5,12
MOM	0,35	1,79	-4,66	5,58	-0,15	0,61
TMOM	1,46	3,85	-9,40	11,74	-0,31	0,08
LIQ	0,78	4,13	-10,52	21,22	0,59	2,74
RX	0,15	1,87	-6,86	4,69	-0,32	1,19
Carry	0,80	2,57	-7,43	8,84	-0,30	0,73
ATM Call	-3,63	76,73	-99,18	216,91	0,64	-0,54
OTM Call	-5,76	82,03	-99,12	246,85	0,78	-0,33
ATM Put	-19,27	87,68	-95,76	386,02	1,83	3,48
OTM Put	-21,88	90,43	-96,46	400,33	1,99	4,14

3.2 Method

3.2.1 Stepwise regression

With 22 risk factors I would like to test which are the most important for hedge funds. Since hedge funds follow different investment strategies, they should not have the same exposure to these risk factors. However, they should share their exposure to a few common risk factors. My research interest is to identify these dominant factors. Ideally, I would like to find the eight most important risk factors to build the best statistical model which explain return of hedge fund strategies. I choose eight factor model because I want to compare my model with Fung-Hsieh model.

Following Agarwal and Naik (2004), I use the stepwise regression method to identify the dominant risk factors among hedge fund investment objectives. Stepwise procedure is used to select the explanatory variables based on Akaike Information. Furthermore, only the factors, which achieve significant level of at least 95 percent, stay in the selected model. As stated by Agarwal and Naik, the advantage of this method is its parsimonious selection of variables. This stingy choice of explanatory variables can cause the selected statistical model over-fits the in-sample data, which is a shortcoming of stepwise method. However, this should not be a large concern in this thesis since the results is checked by a robust test, in which the selected model is tested on the out-of-sample data to see whether it consistently outperforms the Fung-Hsieh model.

3.2.2 Wald test and GRS test

Wald and Gibbons- Ross-Shanken (GRS) tests are used to test whether all pricing errors or alpha are jointly equal to zero. The Wald test uses the chi-square distribution which assumes alphas are normally distributed, but no assumption about the regression residuals (Wald 1943). On the other hand, the GRS test uses F-test which requires the regressions residual are normal, uncorrelated and homoscedastic. The normal regression residuals result in normal alphas and independent residual covariance matrix. The difference of two tests is shown in their formulas. (Cochrane 2005.) Using both tests in my thesis is to make sure that the results are robust.

Given an asset pricing model:

$$R_t^{ei} = \alpha_i + \beta_i f_t + \varepsilon_t^i$$

where R_t^{ei} is asset i's excess return at time t,

α_i is regression intercept of asset i,

β_i is the factor f's coefficient and

ε_t^i is residual of asset i at time t.

The model works well when the regression intercept or pricing error is equal to zero. We can test the hypothesis that the pricing error is equal to zero for each asset. However in reality we often test one model on many assets at same time, therefore we are also interested to know if all assets' pricing errors are jointly equal to zero. If the test result cannot reject the hypothesis of joint equality to zero, we can say that the model is sufficient. In contrast, if the null hypothesis is highly rejected, it means that the pricing errors of the model are not equal to zero; therefore, the explanatory variables cannot explain the dependent variable. In this thesis, I use the results from the Wald and GRS tests to compare the Fung-Hsieh model and the selected statistical model. The higher the values of the tests are, the more rejected the null hypotheses are. In other word, the models with higher test values underperform the models with lower values.

The Wald test has the following formula:

$$W = \hat{\alpha}'\left[Var[\hat{\alpha}]\right]^{-1}\hat{\alpha} \sim X^2(J)$$

where $\hat{\alpha}$ is a vector of the estimated intercepts and

X^2 (J) is chi-square distribution with J degree of freedom. (Greene 2011.)

The GRS has the formula:

$$GRS = \frac{T-N-K}{N}\left(1 + E_T(f)'\hat{\Omega}^{-1}E_T(f)\right)^{-1}\hat{\alpha}'\hat{\sum}^{-1}\hat{\alpha} \sim F_{N,T-N-K}$$

where N is the number of assets,

K is number of factor,

E_T (f) is sample mean,

$\hat{\alpha}$ is a vector of the estimated intercepts and

$\hat{\Sigma}$ is the residual covariance matrix.

$$\hat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t'$$

$$\hat{\Omega} = \frac{1}{T}\sum_{t=1}^{T}[f_t - E_T(f)][f_t - E_T(f)]'$$. (Cochrane 2005.)

Both the Wald and GRS tests check the validity of the null hypothesis H_0: $\alpha_i = 0$. Wald test uses only alphas and its covariance matrix in formula, without assumptions about the regression residuals. In opposite, the GRS test uses both alphas and regression residuals.

4. EMPIRICAL RESULTS

This chapter reports the empirical results by applying the above methodology. The first important result is gained from the stepwise regression. I find eight dominant risk factors among all of the strategies of hedge fund aggregate data, including equity risk factor SPRF, equity size spread factor RLSP, bond credit spread factor BAATY, emerging market factor MSEMKFRF, Fama-French value factor HML, equity trendfollowing factor PTFSSTKRF, time series momentum factor TMOM and currency risk factor RX. The regression also indicates that ten (nine) out of thirteen strategies provide significant alphas using equal weighted returns (value weighted returns). Sector strategy has the highest alpha of 12.27 percent (13.87 percent) annually using equal weighted returns (value weighted returns). Market neutral and Multi-Strategy have the lowest annual alphas with a little more than 3.9 percent (2.5 percent) using equal weighted returns (value weighted returns). Finally, the result shows a monotonic relationship between fund performance and size. The alpha spread between small funds and large funds are impressively high with a value of at least 3.43 percent (5.27 percent) using equal weighted returns (value weighted returns). However, it is not clear whether small funds load more on certain risk factors than large funds.

This chapter is organized as follows. The first section discusses the result of stepwise regression reported in Table 6. This section is in turn divided into two parts. The first part, looking from hedge fund strategy's perspective, discusses the risk exposure of each hedge fund investment objective. The second part, looking from risk factor's perspective, discusses the dominant factors among hedge fund strategies. Finally the second section of this chapter discusses the result of time series regression of three size hedge fund portfolios using Fung-Hsieh model and the selected statistical model.

4.1 Result from stepwise regression

4.1.1 Risk exposure of hedge fund investment objectives

Table 6 presents the result of the stepwise regression of 13 hedge fund investment objectives' monthly returns on 22 risk factors. Panel A reports the result for equal weighted returns, and panel B is for value weighted returns. The overall results show that except for CTA, Fund of Funds, and Short Bias all other strategies have statistically significant alphas, ranging from 3.93 percent (Multi-strategy) to 12.27 percent (Sector) annually in equal weighted returns; from 2.78 percent (Market Neutral) to 13.87 percent (Sector) annually in value weighted returns. Global Macro has significant alpha of 4.04 percent annually when using equal weighted returns but has no significant alpha using value weighted returns. We are provided with the equal weighted alpha by investing the equal amount of capital to each hedge fund, in opposite to the value weighted alpha by weighting holdings in each fund by the asset under management of the fund. Overall, the results in table 6 confirm the high values of both types of alphas in the hedge fund industry. The adjusted R^2 values are in general high for both types of data; however they are impressively high for equal weighted returns ranging between 0.49-0.88. For value weighted returns the values are lower, staying between 0.32-0.82. The high adjusted R^2 results show that these risk factors have significant explanatory power over hedge fund strategies' returns. The next paragraphs discuss risk exposure of thirteen strategies in detail.

CTA is significantly expose to bond trend following risk factor PTFSBDRF, currency trend following risk factor PTFSFXRF, Fama-French value factor HML, momentum time series momentum factor TMOM, and currency risk factor RX in both panel A and B. This is consistent with previous studies: Fung and Hsieh (1997b) find CTA implement trend following strategies; Baltas and Kosowski (2012) find that time series momentum factor have significant explanatory power over CTA returns. CTA has an insignificant alpha of 1.9 percent (t-value 1.3)/-1.3 percent (t-value -0.6) using equal weighted returns/ value weighted returns.

Emerging Market is exposed to the least number of factors, four in panel A and five in panel B. It has the largest exposure to emerging market factor MSEMKFRF, next to cross sectional momentum factor MOM, bond credit spread factor BAATY, and negative exposure to currency factor. It has statistically high alphas of 5.44 percent (t-value 2.8)/7.8 percent (t-value 4.0) using equal weighted returns/value weighted returns. The adjusted R^2 is high, more than 0.8, meaning that the set of risk factors explains very well the variations of returns.

Event Driven is exposed to many factors, in which bond credit spread factor BAATY, equity market factor SPRF, and equity size spread RLSP have the highest coefficients. The result from the equal weighted returns is not consistent with the value weighted returns. Although the results in panel A shows that the strategy is significantly exposed to two equity factors SPRF and RLSP, the values are not significant in panel B. The strategy has high significant alphas, 5.31 percent (t-value 5.6)/6.38 percent (t-value 6.4) in panel A/ panel B.

Fund of Funds is also exposed to a large number of factors, ten in panel A and nine in panel B, mainly to bond credit spread factor BAATY, emerging market risk factor MSEMKFRF, and time series momentum factor TMOM. The large number of risk factors of Fund of Funds is due to the fact that the strategy invests in other individual hedge funds across several strategies. Fund of Funds and Event Driven are only two strategies which show significant exposure to option based factors although the coefficients are very small. Different from Even Driven, Fund of Funds do not deliver significant abnormal returns because the alphas in both panels are insignificantly differently from zero.

Global Macro is exposed to bond market factor TYRF, bond credit spread factor BAATY, emerging market factor MSEMKFRF, and time series momentum factor TMOM. The strategy shows a conflicting result of estimated alpha when using two types of returns. The equal weighted returns shows that the strategy has a significant alpha of 4.04 percent (t-value) and an adjusted R^2 of 0.61 while the value weighted returns shows small and statistically insignificant alpha of 1.41 percent (t-value 0.6), and a lower adjusted R^2 of 0.35. This means that the risk factors do a very good job of explaining variations in equally weighted returns but not value weighted returns.

Long Only and Long/Short are both exposed to equity market factor SPRF, equity size spread factor RLSP, bond credit market factor BAATY, and emerging market factor MSEMKFRF. In addition, Long Only is exposed to currency factor RX while Long/Short is to momentum factor MOM. Both strategies offer high alpha, only lower than Sector strategy. Long Only has alphas of 7.49 percent (t-value 4.1)/5.65 percent (t-value 6.2) in panel A/panel B. Long/Short has alphas of 8.36 percent (t-value 7.0)/ 7.53 percent (t-value 5.6) in panel A/panel B. The regressions on two strategies also have highest adjusted R^2, over 0.8.

Market Neutral is exposed to currency factor RX and momentum factor MOM. The number of risk factors in panel A is higher than that in panel B. Also, the adjusted R^2 in panel A is 0.56, higher in panel B with 0.32. Therefore, risk factors explain the equal weighted returns better than the value weighted returns. The strategy offers alphas of 3.96 percent (t-value 5.5)/ 2.78 percent (t-value 2.8).

Multi-Strategy, similar to Fund of Funds, is exposed to a large number of risk factors, in which the largest coefficients belong to time series momentum factor TMOM, bond credit spread factor BAATY, bond market factor TYRF, and emerging market factor MSEMKFRF. The similarity in risk exposure between two strategies is an evidence to show that Multi-Strategy is evolving to compete with Fund of Funds. However, Multi-Strategy seems to be more attractive, at least from this regression result, because it offer significant alphas of around 3 percent annually meanwhile Fund of Funds have no significant alphas.

Relative Value has the largest exposure to bond credit spread factor BAATY, currency factor RX, and equity market factor SPRF. In addition, it has significantly negative exposure to global value factor VAL. The adjusted R^2 is quite high, 0.78 in panel A and 0.74 in panel B. The strategy has high alpha of 4.13 percent (t-value 6.0)/4.9 percent (t-value 6.3) using equally weighted returns/value weighted returns.

Sector has the largest exposure to equity market factor SPRF and equity size spread factor RLSP. Interestingly, the strategy has statistically significant negative exposure to Fama-French size SMB and value HML. The adjusted R^2 is high in both panel, 0.84 in panel A and 0.77 in panel B. Sector proves to be the best strategy with the largest alpha of around 13 percent annually.

Short Bias shows the largest negative exposure to equity market factor SPRF and equity size spread factor RLSP. In addition, it is positively exposed to bond credit spread factor BAATY, Fama-French value factor HML and currency factor RX. The adjusted R^2 is high in both panels, 0.79 in panel A and 0.73 in panel B. The strategy does not deliver significant alpha using both types of returns. However, similar to Sector, the number of Short Bias funds in aggregate data is very small, only 41 funds. Therefore, it may affect the result.

The Other category is exposed to equity market factor SPRF, equity size spread factor RLSP, cross sectional momentum factor MOM, bond credit spread factor BAATY, and emerging market factor MSEMKFRF. The regression has high adjusted R^2, 0.78 in panel A and 0.63 in panel B. It has high alpha of over 5 percent annually.

4.1.2 Dominant risk factors among hedge fund investment objectives

Panel A of Table 6 reports out of 22 factors there are four risk factors to which no strategies have significant exposure: liquidity factor LIQ, At-the-money European call option ATM Call, Out-of-the-money European call option OTM Call, and Out-of-the-money European put option OTM Put. Therefore, they are not included in the result of panel A. At-the-money European put option ATM Put and carry trade factors are significant to only one category with very low coefficients (-0.003 and 0.08). In panel B commodity trend following factor PTFSCOMRF, liquidity factor LIQ, At-the-money European put option ATM Put, and Out-of-the-money European put option OTM Put factors have no significant explanatory power to any hedge fund strategy's returns. As a result, they are not included in panel B as well. Carry trade factor and OTM Put significantly explain only for CTA and Fund of Funds. ATM Call has only three significant coefficients. Although the four option- based risk factors are found significant to explain hedge fund returns using Hedge Fund Research database (Agarwal & Naik 2004), they do not have explanatory power over hedge fund aggregate data in both equal weighted and value weighted returns. Liquidity factor LIQ, carry trade factor Carry, and commodity trend following factor PTFSCOMRF are not dominant as well. Since our purpose is to identify the dominant factors among all investment objectives, these risk factors are out of our interest. The following paragraphs will discuss how the remaining factors influence across strategies.

Fung-Hsieh factors. Six out of ten Fung-Hsieh factors have strong explanatory power over many hedge fund strategies: equity market factor SPRF, equity size spread factor RLSP, bond credit spread factor BAATY, emerging market factor MSEMKFRF, short term interest trend following factor PTFSIRRF, and equity trendfollowing factor PTFSSTKRF. It is not a surprise that most of equity funds such as Long Only, Long/Short, Short Bias, and Sector have exposure to the equity market factor SPRF and the equity size spread factor RLSP. Meanwhile ten (nine) of out thirteen strategies for equal weighted returns (value weighted returns) are exposed to the credit spread factor BAATY; the emerging market factor MSEMKFRF also explains for most strategies (11 for equal weighted returns, 10 for value weighted returns). Two trend following factors PTFSIRRF and PTFSSTKRF show influence on more strategies for equal weighted returns in panel A (10 and 8 significant coefficients) than for value weighted returns in panel B (6 significant coefficients for both factors). It is worth to notice that the PTFSIRRF behaves peculiarly when all of its coefficients have similar value of -0.01 in both panel A and B. Four Fung-Hsieh factors: bond market factor TYRF, bond trend following factor PTFSBDRF, currency trend following factor PTFSFXRF and commodity trend following factor PTFSCOMRF do not offer significant explanations to many strategies.

Fama-Frech factors. The Fama-French size factor SMB has significant coefficients for Long/Short, Market Neutral, Sector, and Short Bias in panel A. However it loses the significance when using value weighted returns in panel B. The Fama-French value factor HML consistently shows influence in both panel A and panel B for CTA, Fund of Funds, Long Only, Multi-Strategy, Sector and Short Bias.

Similar to SMB, Global Value factor VAL also has more significant coefficients in equal weighted returns (5 significant coefficients) than value weighted returns (3 significant coefficients). Nevertheless, it should not be a dominant factor considering its uncommonness among all strategies. In contrast, the Global Momentum factor MOM gains more popularity when using value weighted returns. It consistently affects Emerging Market, Long/Short, Market Neutral, and Others in both panels. The time series momentum factor TMOM has quite similar behavior in both panel except it loses one significant coefficient in panel B. Consistent with study of Baltas and Kosowski (2012), I find significant exposure of CTA hedge fund to TMOM in both types of data. The Currency risk factor RX significantly explains for CTA, Emerging Market, Long Only, Market Neutral, Relative Value, and Short Bias in both panels.

In conclusion there are ten dominant factors among all hedge fund strategies: equity market factor SPRF, equity size spread factor RLSP, bond credit spread factor BAATY, emerging market factor MSEMKFRF, short term interest rate trend following factor PTFSIRRF, equity trendfollowing factor PTFSSTKRF, Fama-French value factor HML, cross sectional momentum factor MOM, time series momentum factor TMOM, and currency factor RX. Until now I have addressed the first research question of identifying important risk factors. I would like to further develop this research by building up an asset pricing model for hedge funds using these dominant risk factors. To evaluate how well the selected statistical model performs, I need benchmark models to compare with. I choose Fung-Hsieh seven factor model and its augmented eight factor model. To make a fair and compatible comparison, I will select eight factors out of the ten dominant factors to construct the best statistical model. SPRF, RLSP, BAATY, MSEMKFRF, HML, PTFSSTKRF and RX are first candidates because they have dominant numbers of significant coefficients. PTFSIRRF also has a large number of significant coefficients but it has an odd behavior when all of its coefficient values are the same in both types of returns. The difficult choice is between MOM and TMOM since none of them shows a clear outweigh in the number of coefficients. I made a decision of choosing TMOM since TMOM captures MOM (Moskowitz et al. 2012). The next chapter presents the results of comparing the selected statistical model and Fung-Hsieh model.

Table 6. Result of stepwise regression

A. Equal weighted returns

Strategy/ Factors	CTA	EMERGING MARKETS	EVENT DRIVEN	FUND OF FUNDS	GLOBAL MACRO	LONG ONLY	LONG/ SHORT	MARKET NEUTRAL	MULTI-STRATEG	OTHERS	RELATIVE VALUE	SECTOR	SHORT BIAS
α (%pa)	1,90 (1,3)	5,44 (2,8)	5,31 (5,6)	1,41 (1,3)	4,04 (4,0)	7,49 (6,2)	8,36 (7,0)	3,96 (5,5)	3,93 (2,4)	5,26 (5,1)	4,13 (6,0)	12,27 (7,3)	1,90 (1,0)
SPRF			0,16			0,39	0,32	0,09		0,19	0,06	0,45	-0,64
RLSP			0,13			0,18	0,33			0,12		0,56	-0,62
TYRF	0,13				0,14				0,19		0,06		
BAATY		0,17	0,25	0,19	0,12	0,19		0,09	0,22	0,11	0,34		0,19
MSEMKFRF	0,07	0,62	0,06	0,14	0,13	0,13	0,16		0,11	0,10	0,05	0,11	
PTFSBDRF	0,03		-0,02						0,04				
PTFSFXRF	0,04			0,01	0,01				0,03	0,01			
PTFSCOMRF					0,01				0,03				
PTFSIRRF			-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	
PTFSSTKRF			0,01	0,02	0,02	0,02	0,03	0,01	0,03			0,02	
SMB							-0,12	-0,03				-0,25	0,17
HML	0,06			0,06			-0,12		0,09		0,04	-0,37	0,46
VAL				-0,26		-0,22				-0,23	-0,16	-0,45	
MOM		0,24					0,23	0,22		0,15			
TMOM	0,18		0,04	0,10	0,07				0,18				
RX	0,22	-0,26		0,13		0,25		0,21			0,11		0,25
Carry							-0,08						
ATM Put				-0,003									
Adj R^2	0,49	0,82	0,79	0,79	0,61	0,88	0,87	0,56	0,55	0,78	0,78	0,84	0,79

B. Value weighted returns

Strategy/ Factor	CTA	EMERGING MARKETS	EVENT DRIVEN	FUND OF FUNDS	GLOBAL MACRO	LONG ONLY	LONG/ SHORT	MARKET NEUTRAL	MULTI-STRATEGY	OTHERS	RELATIVE VALUE	SECTOR	SHORT BIAS
α (%pa)	-1,30	7,80	6,38	2,28	1,41	5,65	7,53	2,78	2,84	5,09	4,90	13,87	3,10
	(-0,6)	(4,0)	(6,4)	(1,7)	(0,6)	(4,1)	(5,6)	(2,8)	(2,0)	(5,0)	(6,3)	(7,6)	(1,8)
SPRF						0,28	0,28	0,12		0,10	0,06	0,33	-0,57
RLSP						0,14	0,15	-0,06		0,17		0,66	-0,40
TYRF				0,11	0,31				0,14				
BAATY		0,23	0,27	0,22	0,37	0,15			0,16	0,12	0,36		0,27
MSEMKFRF		0,60	0,10	0,15	0,10	0,18	0,17		0,07	0,07	0,03	0,12	
PTFSBDRF	0,03		-0,02						0,03				
PTFSFXRF	0,04			0,01	0,02				0,02				
PTFSIRRF			-0,01	-0,01			-0,01			-0,01	-0,01	-0,01	
PTFSSTKRF		0,04					0,03		0,02	0,02	0,01	0,04	
SMB										-0,16		-0,44	
HML	0,08			0,05	0,11	0,09			0,06	-0,10		-0,33	0,32
VAL				-0,28			-0,20				-0,18		
MOM		0,33	0,16				0,35	0,18		0,25		0,38	
TMOM	0,27			0,14	0,24				0,23				
RX	0,35	-0,31			-0,33	0,16		0,19	0,16		0,12		0,28
Carry	0,16												
ATM Call			0,004		0,01	0,01							
OTM Call				0,005									
Adj R^2	0,41	0,82	0,66	0,69	0,35	0,81	0,81	0,32	0,53	0,63	0,74	0,77	0,73

This table shows the results of stepwise regression $R_t^{ei} = \alpha_i + \sum_{k=1}^{K} \beta_k^i F_{k,t} + \varepsilon_t^i$ for thirteen hedge fund investment objectives during the full sample period from January 1995 to October 2011. The table shows the intercept (α) with t-statistics in parentheses, statistically significant (at the 5 percent level) slope coefficient on 22 risk factors and adjusted R^2 (Adj R^2). The risk factors include Monthly return of the S&P 500 stock market index minus Risk-free rate (SPRF), Monthly return of the Russell 2000 stock market index return minus Monthly return of the S&P 500 stock market index return (RLSP), Monthly return of the FRB 10Y constant maturity bond minus Risk-free rate (TYRF), Monthly return of Moody's Baa bond minus Monthly return of FRB 10Y constant maturity bond (BAATY), Monthly return of MSCI Emerging Market index minus Risk-free rate (MSEMKFRF), Monthly return of the PTFS Bond lookback straddle factor minus Risk-free rate (PTFSBDRF), Monthly return of the PTFS Currency lookback straddle factor minus Risk-free rate (PTFSFXRF), Monthly return of the PTFS Commodity lookback straddle factor minus Risk-free rate (PTFSCOMRF), Monthly return of the PTFS Short-Term Interest Rate lookback straddle factor minus Risk-free rate (PTFSIRRF), Monthly return of the PTFS Stock Market lookback straddle factor minus Risk-free rate (PTFSSTKRF), Small minus big factor (SMB), High minus low factor (HML), Global Value factor (VAL), Global Momentum factor (MOM), Time Series Momentum factor (TMOM), Liquidity risk factor (LIQ), Currency risk factor (RX), Carry Trade risk factor (Carry), At-the-money European Call (ATM Call), Out-of-the-money European Call (OTM Call), At-the-money European Put (ATM Put), Out-of-the-money European Put (OTM Put). In panel A no strategies have significant exposure to four risk factors LIQ, ATM Call, OTM Call, and OTM Put .Therefore they are not included in the result of panel A. In panel B no strategies have significant exposure to four risk factors PTFSCOMRF, LIQ, ATM Put, and OTM Put .Therefore they are not included in panel B.

4.2 The selected statistical model and Fung-Hsieh model

Table 7 shows three main results. First, the selected statistical model (hereafter selected model) outperforms Fung-Hsieh model based on the indicators average R^2, average alpha, Wald test, and GRS test. Second, hedge funds deliver statistically high abnormal returns even after adjusted for risks with average returns between 3.1 percent- 6.93 percent annually. Third, the small hedge fund group outperforms the large group with significant difference of greater than 3.4 percent between alphas of two groups. The next paragraphs will discuss these results in detail.

We see from Table 7 the selected model performs better than Fung-Hsieh model based on three indicators: average adjusted R^2, Wald test and GRS test using both equal weighted returns and value weighted returns. In panel A, the average adjusted R^2 is highest 0.79 for the selected model, 0.73 for Fung-Hsieh eight factors model and lowest with 0.59 for Fung-Hsieh seven factors model. The pattern is consistent in panel B. This shows that the risk factors used in the selected model explain better the variations of returns between three groups. Although both Wald test and GRS test show rejection for null hypotheses in all three models because of small p-values and Chi-Square test, the levels of rejection are different between them. The Wald test shows a largest rejection for Fung-Hsieh eight factor model with a value of 88.96, next is the Fung-Hsieh seven factor model with 56.6. The selected model is least rejected with a value of 52.35. Again, the result is consistent in panel B as well. The GRS test, as the last indicator, also favors the selected model over the other two with smaller value of 21.59 / 30.16in panel A/ panel B.

The alphas estimated for hedge fund size groups are significantly different in three models using both equal weighted returns and value weighted returns. Overall the average alpha is smaller in selected model compared with Fung-Hsieh model. The difference is significant because average alpha in the selected model is 3.1 percent annually, 1 percent less than the Fung-Hsieh seven factor model, and 1.12 percent in the

Fung-Hsieh eight factor model. The value weighted returns in panel B presents much higher average alphas for all three models but with the similar pattern. The selected model still has the lowest average annual alpha of 5.51 percent, compared with 6.81 percent for the Fung-Hsieh seven factors model, and 6.93 percent for the Fung-Hsieh eight factors model. Looking closely at each hedge fund group size, all alphas estimated in the selected model is smaller than these of Fung-Hsieh model in both panel A and panel B. More interestingly the alpha of the large group estimated by the selected model in Panel A is statistically insignificant with 1.38 percent (t-value 1.76). This is to say the factors included in the selected model do a good job in explaining the hedge fund return. The hedge fund abnormal return is diminished once time series momentum factor TMOM and currency factor RX are included in the model.

Of all eight factors chosen for the selected model, equity market factor SPRF, equity size spread factor RLSP, bond credit spread factor BAATY, emerging market factor MSEMKFRF, time series momentum factor TMOM, and currency factors RX are consistently influential factors with statistically significant coefficients. BAATY and MSEMKFRF are consistently significant at 99.9 percent confidence level in both Fung-Hsieh model and the selected model in panel A (t-value for BAATY is a little less in panel B). SPRF also proves to be an important factor in all three models with at least 95 percent confidence level across all three hedge fund groups in both panels. RLSP is significant in Fung-Hsieh seven factors model, but its coefficients becomes smaller and less significant when MSEMKFRF is added to the Fung-Hsieh eight factors model; finally, in the selected model RLSP coefficients loses its significance in the large hedge fund group with coefficient value of 0.03 (t-value 1.49)/ 0.02 (t-value 1.22) in panel A/ panel B.

Time series momentum factor TMOM and currency factor RX draw our attention when they have high coefficient values with statistical significance of 99.9 percent confidence level across all three hedge fund groups. TMOM shows the largest influence on the large group with coefficient of 0.12 (t-value 7.8) /0.15 (t-value 9.1) using equal weighted returns/value weighted returns, meaning one percent increase in TMOM factor causing

0.12 percent/0.15 percent increase in hedge fund return. This result is consistent with study of Baltas and Kosowski (2012) in which the CTA hedge funds has a coefficient of 0.19 using value weighted returns. RX is even more impressive when its coefficients are very high. It is highest for Medium hedge fund group with a value of 0.21(t-value 5.8) / 0.19 (t-value 4.9) using equal weighted returns/value weighted returns. However the result is contradicted with Lustig et al. (2011) in which they state that assets should be exposed to carry trade factor instead of currency factors.

Equity trendfollowing factor PTFSSTKRF and Fama-French value factor HLM show an inconsistence when using two types of returns. HML has no significant effect on any hedge fund groups when using equal weighted returns, but appears significant when using value weighted returns although it affects only the large and medium groups with 95 percent confidence level. The similar pattern happens to PTFSSTKRF when its coefficient is more significant in panel B than in panel A. The coefficient values of these two factors are quite small, largest for HML with 0.03 (t-value 1.75)/ 0.04 (t-value 2.44) using equal weighted returns/value weighted returns. PTFSSTKRF behaves oddly when all of its coefficients are 0.01 for all groups in both panel A and panel B.

4.3 Performance of small fund vs. large funds

Table 7 reports the performance of large, medium, and small hedge funds. Overall hedge funds deliver abnormal returns after adjusted for risk. The large group has the lowest annual alpha of 2.42 percent (t-value 2.47) /2.54 percent (t-value 3.15) in Fung-Hsieh seven factors model/ Fung-Hsieh eight factors model using equally weighted value. Using value weighted returns they are higher with values of 4.11 percent (t-value 3.97)/4.22 percent (t-value 4.72). Large funds even have insignificant alphas in the selected model with a value of 1.38 (t-value 1.76). The medium group has highest alphas of 4.13 percent (t-value 5.05) in Fung-Hsieh eight factor model, 4.01 percent (t-value 4.01) in Fung-Hsieh seven factors model and lowest in the selected model with 2.82 percent (t-value 3.53) in panel A. These numbers are much higher in panel B with value weighted returns: 6.96 percent (t-value 6.67), 7.08 percent (t-value 8.05) and 5.61

percent (t-value 6.59) orderly in three models. The small group is the most impressive with highest alphas in all three models. In panel A, they are all greater than 5 percent and high t-value statistics, indeed 5.86 percent (t-value 5.87)/5.99 percent (t-value 7.31)/5.1 percent (t-value 6.07) in Fung-Hsieh seven factors model/Fung-Hsieh eight factors model/ the selected model with eight factors.

Fung-Hsieh model and the selected model show a consistent result: small funds outperform large funds. The abnormal returns or alphas are decreasing with hedge fund size. The alpha spread between the small group and large group are 3.43 percent/3.44 percent/3.72 percent in Fung-Hsieh seven factors model/ Fung-Hsieh eight factors model/ the selected model using equal weighted returns. This result is consistent with study done by Teo (2007). He constructs two equally weighted portfolios of small funds and large funds, and find that the small fund portfolio outperforms the large fund portfolio by 2.75 percent annually after adjusted for seven Fung-Hsieh risk factors. The difference is even larger when using value weighted returns: 5.27 percent for both of Fung-Hsieh models and 5.3 percent for the selected model with eight factors.

What drive small funds' high alphas? According to risk-return trade off theory, we may suspect that small funds' larger exposure to risk factors may be the source of their high alphas. However the results do not show very clear evidence that small funds are exposed more to risk than large funds in all three models. The result is mixed when equal weighted returns shows that small funds are exposed to more risk factors than large funds meanwhile value weighted returns shows the opposite evidence. For example in panel A using Fung-Hsieh seven factors model, small funds significantly are exposed to five risk factors meanwhile large funds are exposed to four risk factors; using Fung-Hsieh eight factors model both groups are exposed to six risk factors; using the selected model the small group is exposed to seven while the large group does to five factors. However in panel B with value weighted returns, the number of risk factors for the small group is four, and for the large group is five using the Fung-Hsieh seven factors model; Again the number of significant factors for both groups are five and seven when using the Fung-Hsieh eight factors model and the selected model. Although these mixed results cannot help to make any final conclusion, it is worth to mention that Joenväärä et al. (2012) find no greater risk exposure of small funds compared with large funds.

In conclusion the superior performance of small hedge funds over large hedge funds has been confirmed by all three models. The eight dominant factors selected in the previous section to build the statistical model have proved better than Fung-Hsieh model. Since one disadvantage of stepwise regression is over-fitting data, meaning the result may be valid only within the sample data, it is necessary to perform a robust check using different data sample. The next chapter will discuss this robustness of the research result.

Table 7. Regression of Fung-Hsieh model and the selected statistical model on large, medium, and small hedge fund portfolios

A. Equal weighted returns

	Fung-Hsieh 7 factor model			Fung-Hsieh 8 factor model			Selected statistical model with 8 factors		
	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small
α (% pa)	2,42 **	4,01 ***	5,86 ***	2,54 **	4,13 ***	5,99 ***	1,38 percent	2,82 ***	5,10 ***
	(2,47)	(4,01)	(5,87)	(3,15)	(5,05)	(7,31)	(1,76)	(3,53)	(6,07)
SPRF	0,20**	0,23***	0,24***	0,05***	0,08***	0,09***	0,05*	0,08***	0,09***
	(2,91)	(3,99)	(4,35)	(10,36)	(11,72)	(12,29)	(2,49)	(3,64)	(4,15)
RLSP	0,10***	0,11***	0,14***	0,04*	0,06**	0,08***	0,03	0,04*	0,07***
	(4,23)	(4,82)	(5,99)	(2,11)	(2,78)	(4,15)	(1,49)	(2,21)	(3,64)
TYRF	0,09*	0,07	0,08*	0,10***	0,08**	0,10***			
	(2,31)	(1,68)	(2,09)	(3,29)	(2,54)	(3,04)			
BAATY	0,26***	0,24***	0,25***	0,17***	0,15***	0,16***	0,18***	0,14***	0,16***
	(5,84)	(5,28)	(5,51)	(4,59)	(3,92)	(4,19)	(5,46)	(4,25)	(4,6)
PTFSBDRF	-0,01	-0,002	0,001	-0,01	-0,001	0,003			
	(-1,61)	(-0,45)	(0,27)	(-1,63)	(-0,21)	(0,67)			
PTFSFXRF	0,01	0,01**	0,01*	0,01*	0,01***	0,01**			
	(1,62)	(2,62)	(2,24)	(1,99)	(3,22)	(2,74)			
PTFSCOMRF	0,01	0,01	0,004	0,01	0,01	0,004			
	(1,35)	(1,37)	(0,76)	(1,62)	(1,65)	(0,91)			
MSEMKFRF				0,14***	0,15***	0,15***	0,12***	0,12***	0,12***
				(9,69)	(9,83)	(9,81)	(8,59)	(8,28)	(8,25)
PTFSSTKRF							0,01	0,01	0,01*
							(1,78)	(1,66)	(2,33)
HML							0,03	0,03	0,01
							(1,54)	(1,75)	(0,82)
TMOM							0,12***	0,11***	0,10***
							(7,86)	(7,15)	(6,46)
RX							0,16***	0,21***	0,16***
							(4,63)	(5,82)	(4,1)
Adj R^2	0,57	0,59	0,62	0,71	0,73	0,75	0,78	0,79	0,79
Average α (% pa)	4,10			4,22			3,10		
Average Adj R^2	0,59			0,73			0,79		
Wald test	56,6			88,98			52,35		
Pr>ChiSq	<0.0001			<0.0001			<0.0001		
GRS test	26,97			31,08			21,59		
p-value	($1,32e^{-14}$)			($2,08e^{-16}$)			($4,34e^{-12}$)		

B. Value weighted returns

	Fung-Hsieh 7 factor model			Fung-Hsieh 8 factor model			Selected statistical model with 8 factors		
	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small
α (%pa)	4,11*** (3,97)	6,96*** (6,67)	9,38*** (8,43)	4,22*** (4,72)	7,08*** (8,05)	9,49*** (9,75)	2,81*** (3,31)	5,61*** (6,59)	8,12*** (8,49)
SPRF	0,20*** (9,74)	0,21*** (10,12)	0,22*** (10,29)	0,06* (2,56)	0,06** (2,57)	0,08*** (3,2)	0,06** (3,11)	0,06** (2,87)	0,08*** (3,5)
RLSP	0,09*** (3,85)	0,12*** (4,95)	0,15*** (5,62)	0,04 (1,89)	0,06** (3,02)	0,09*** (3,89)	0,02 (1,22)	0,05** (2,6)	0,08*** (3,76)
TYRF	0,10* (2,56)	0,06 (1,5)	0,05 (1,19)	0,12*** (3,38)	0,08* (2,22)	0,07 (1,74)			
BAATY	0,24*** (5,25)	0,20*** (4,23)	0,18*** (3,66)	0,16*** (3,95)	0,11** (2,74)	0,10* (2,21)	0,18*** (5,05)	0,11*** (3,24)	0,12** (3,1)
PTFSBDRF	-0,01 (-1,7)	-0,004 (-,75)	0,002 (0,4)	0,14 (-1,69)	0,15 (-0,58)	0,14 (0,72)			
PTFSFXRF	0,01* (2,01)	0,01** (2,8)	0,01* (2,02)	-0,01* (2,34)	-0,003*** (3,33)	0,004* (2,32)			
PTFSCOMRF	0,01 (1,58)	0,01 (1,57)	0,01 (1,1)	0,01 (1,81)	0,01 (1,85)	0,01 (1,24)			
MSEMKFRF				0,01*** (8,19)	0,01*** (8,93)	0,01*** (7,75)	0,12*** (7,76)	0,12*** (7,79)	0,11*** (6,57)
PTFSSTKRF							0,01* (2,56)	0,01* (2,25)	0,01** (2,64)
HML							0,04* (2,44)	0,04* (1,99)	-0,01 (-0,35)
TMOM							0,15*** (9,19)	0,13*** (8,0)	0,14*** (7,56)
RX							0,11** (2,94)	0,19*** (4,92)	0,15*** (3,52)
Adj R^2	0,52	0,52	0,52	0,64	0,66	0,63	0,75	0,75	0,72
Average α (%pa)	6,81			6,93			5,51		
Average Adj R^2	0,52			0,65			0,74		
Wald test Pr>ChiSq	131,36 <0.0001			182,12 <0.0001			126,44 <0.0001		
GRS test p-value	35,91 ($1{,}79e^{-18}$)			41,7 ($8{,}9e^{-21}$)			30,16 ($5{,}2e^{-16}$)		

This table shows the results of the regression of three models on three hedge fund size groups. Three models are Fung-Hsieh seven factors model, Fung-Hsieh eight factors model and the selected statistical model with eight factors. The aggregate hedge fund size group data is constructed by putting all hedge fund strategy of the same size in one portfolio. The sample period is from January 1995 to October 2011. The table shows the annual intercept (α), slope coefficient on risk factors and adjusted R^2 (Adj R^2). Values of t-statistics are reported in parentheses. Average alpha and average adjusted R^2 (average adj R^2) are calculated for three size groups in each model. Wald test and GRS test are used to test the jointly equal to zero of alphas of three size groups. The p-values are provided for the tests. The Fung-Hsieh seven factors model includes seven risk factors Monthly return of the S&P 500 stock market index minus Risk-free rate (SPRF), Monthly return of the Russell 2000 stock market index return minus Monthly return of the S&P 500 stock market index return (RLSP), Monthly return of the FRB 10Y constant maturity bond minus Risk-free rate (TYRF), Monthly return of Moody's Baa bond minus Monthly return of FRB 10Y constant maturity bond (BAATY), Monthly return of the PTFS Bond lookback straddle factor minus Risk-free rate (PTFSBDRF), Monthly return of the PTFS Currency lookback straddle factor minus Risk-free rate (PTFSFXRF), Monthly return of the PTFS Commodity lookback straddle factor minus Risk-free rate (PTFSCOMRF). The Fung-Hsieh eight factors model includes above seven factor and Monthly return of MSCI Emerging Market index minus Risk-free rate (MSEMKFRF). The selected statistical model include eight factors SPRF, RLSP, BAATY, MSEMKFRF, Monthly return of the PTFS Stock Market lookback straddle factor minus Risk-free rate (PTFSSTKRF), High minus low factor (HML), Time Series Momentum factor (TMOM) and Currency risk factor (RX). *Significant at 5 percent level; **significant at 1 percent level;***significant at 0.1 percent level.

5. ROBUSTNESS CHECK

Purpose of the robust check is to see if the results found in the empirical part are still valid when using different data. Therefore the robust test should answer two questions: Does the selected statistical model still perform better than Fung-Hsieh model? Do small hedge funds outperform large hedge funds? The overall robust check result shows that the selected model is still better than Fung-Hsieh model. Although equity trendfollowing factor PTFSSTKRF, Fama-French value factor HML, and currency factor RX lose their significance when using out-of-sample data, the selected model remains higher adjusted R^2 and lower alphas than its competitors. Using the database in the robust test which is divided into two separated portfolios of small funds and large funds, the small fund portfolio continues to beat the large fund portfolio with spread alpha of at least 0.52 percent.

I perform the robust test on the data constructed by Edelman et al. (2013)[1]. The reason I choose this data is its compatibility with the sample data constructed by Joenväärä et al. (2012). First, this is a merged aggregate data from three large commercial databases Barclay Hedge, Hedge Fund Research, and TASS. Second, hedge funds are divided in two groups: small hedge funds and large hedge funds, which is convenient to compare the performance between them.

Edelman et al. (2013) define the large funds (small funds) are those with asset under management more than (less than) the smallest firm in the *Institutional Investor* "Hedge Fund100 List" and the *Absolute Return+Alpha* "Billion Dollar Club" list. Equally weighted portfolios of two funds groups are formed and rebalanced at the end of each sample year. Although the value weighted returns are available for the large group, it is

[1] Data is from https://faculty.fuqua.duke.edu/~dah7/MegaHF_Data.htm

not for the small group. Therefore I perform the test on only equal weighted returns. The time period is from January 2002 to December 2010, shorter than the sample data used in this thesis.

To answer the two questions mentioned at the beginning of this chapter, I estimate the large and small groups' performance using Fung-Hsieh seven factors model, Fung-Hsieh eight factors model, and the selected statistical model with eight factors. Average alpha and adjusted R^2 of two groups are calculated for each model. Table 8 reports the regression results.

The overall results show that the selected statistical model is better than Fung-Hsieh model based on the average alpha and adjusted R^2. The small hedge funds consistently deliver statistically significant alpha, and outperform the large funds with the spread alpha of more than 0.52 percent annually. This number is smaller than 3.43 percent found in the previous chapter. Because hedge funds are divided into two portfolios of small and large funds in this robust database while they are divided into three portfolio of large, medium and small funds in the database of Joenväärä et al. (2012), the alpha spread between the small portfolio and large portfolio in the robust check should be smaller than the one in the previous chapter.

Consistent with the result of the empirical part, the selected statistical model has the highest average adjusted R^2 with the impressive value of 0.85. For Fung-Hsieh eight factors model it is 0.82, and for Fung-Hsieh seven factors model it is lowest with 0.66. These values are higher than the values in the panel A of Table 7. It means that all three models do a good job in explanation the hedge fund groups' returns, and the selected model still keeps the leading role.

The superior performance may be supported by the time series momentum factor TMOM since it continues to show its significance in the out-of-sample data. Its coefficients with the Large group is 0.1 (t-value 5.51), and with the Small group is 0.7 (t-value 4.68). Currency factor RX loses its significance in this data sample with small coefficients and low t-statistics.

Alphas are smaller in the out-of-sample data compared with the one used in the empirical part. For the small group, although it is still very high with 4.45 percent annually (t-value 3.58) using the Fung-Hsieh seven factors model, it becomes much smaller when using Fung-Hsieh eight factor model and the selected model (2.27 percent with t-value 2.61 and 1.69 percent with t-value 1.99). For the large group, alphas become insignificant when using the Fung-Hsieh eight factors model and the selected model. One possible reason for the diminishing of alphas is the time period of these hedge funds returns are recent and short.

Table 8 reports interesting evidence about risk exposure of two groups. It is clear that the small group is significantly exposed to a greater number of risk factors than the large group in all three models. For example, in Fung-Hsieh seven factors model beside sharing two factors equity market factor SPRF and bond credit spread factor BAATY with the large group, the small group load on the third factor equity size spread factor RLSP with coefficient 0.09 (t-value 2.48). In the Fung-Hsieh eight factors model, the small group even load on three more factors (equity market factor SPRF, equity size spread factor RLSP, currency trend following factor PTFSFXRF) than the large group. Finally in the selected model it loads on two more factors (SPRF, RLSP). This result supports the trade-off theory, which explains the higher alpha in small funds compared with large funds.

Table 8. Regression of Fung-Hsieh model and the selected statistical model on large hedge fund portfolio and small fund portfolio

	Fung-Hsieh 7 factors model		Fung-Hsieh 8 factors model		Selected statistical model with 8 factors	
	Large	Small	Large	Small	Large	Small
α (%pa)	3,85** (2,79)	4,45*** (3,58)	1,75 (1,60)	2,27** (2,61)	0,61 (0,59)	1,69* (1,99)
SPRF	0,17*** (6,06)	0,26*** (10,33)	-0,02 (-0,56)	0,07** (2,65)	0,02 (0,64)	0,09*** (3,98)
RLSP	0,03 (0,76)	0,09* (2,48)	0,01 (0,27)	0,07** (2,70)	0,01 (0,31)	0,08*** (3,52)
TYRF	0,002 (0,05)	-0,01 (-0,32)	-0,02 (-0,61)	-0,04 (-1,35)		
BAATY	0,25*** (5,11)	0,21*** (4,75)	0,14*** (3,60)	0,10** (3,14)	0,18*** (5,10)	0,11*** (3,93)
PTFSBDRF	-0,01 (-1,04)	-0,004 (-0,44)	-0,01 (-1,11)	-0,002 (-0,34)		
PTFSFXRF	0,01 (0,81)	0,01 (1,83)	0,004 (0,72)	0,01* (2,25)		
PTFSCOMRF	0,003 (0,31)	0,01 (0,68)	-0,001 (-0,16)	0,001 (0,26)		
MSEMKFRF			0,18*** (8,25)	0,18*** (10,83)	0,16*** (7,39)	0,17*** (9,56)
PTFSSTKRF					0,0004 (0,06)	0,01 (1,25)
HML					-0,02 (-0,60)	-0,04 (-1,59)
TMOM					0,10*** (5,51)	0,07*** (4,68)
RX					0,002 (0,04)	0,01 (0,21)
Adj R^2	0,58	0,74	0,75	0,88	0,81	0,90
Average α (%pa)	4,15		2,01		1,15	
Average Adj R^2	0,66		0,82		0,85	

This table shows the results of the regression of Fung-Hsieh seven factors model, its augmented version with eighth factor and the selected statistical model with eight factors on large hedge fund portfolio and small hedge fund portfolio. The aggregate hedge fund size group data is constructed by putting all hedge fund strategy of the same size in one portfolio. The sample period is from January 2002 to December 2010. The table shows the annual intercept (α), slope coefficient on risk factors and adjusted R^2 (Adj R^2). Values of t-statistics are reported in parentheses. Average alpha and average adjusted R^2 (average adj R^2) are calculated for three size groups in each model. The Fung-Hsieh seven factors model includes seven risk factors Monthly return of the S&P 500 stock market index minus Risk-free rate (SPRF), Monthly return of the Russell 2000 stock market index return minus Monthly return of the S&P 500 stock market index return (RLSP), Monthly return of the FRB 10Y constant maturity bond minus Risk-free rate (TYRF), Monthly return of Moody's Baa bond minus Monthly return of FRB 10Y constant maturity bond (BAATY), Monthly return of the PTFS Bond lookback straddle factor minus Risk-free rate (PTFSBDRF), Monthly return of the PTFS Currency lookback straddle factor minus Risk-free rate (PTFSFXRF), Monthly return of the PTFS Commodity lookback straddle factor minus Risk-free rate (PTFSCOMRF). The Fung-Hsieh eight factors model includes above seven factor and Monthly return of MSCI Emerging Market index minus Risk-free rate (MSEMKFRF). The selected statistical model include eight factors SPRF, RLSP, BAATY, MSEMKFRF, Monthly return of the PTFS Stock Market lookback straddle factor minus Risk-free rate (PTFSSTKRF), High minus low factor (HML), Time Series Momentum factor (TMOM) and Currency risk factor (RX). *Significant at 5 percent level; **significant at 1 percent level;***significant at 0.1 percent level.

6. CONCLUSION

This thesis aims to answer two questions: what are common risk factors among all hedge funds strategies? Do small hedge funds outperform large hedge funds? This thesis employs an extensive aggregate hedge fund database from January 1995 to October 2011. The data is constructed as portfolios of hedge fund strategies and sizes. Examination of hedge funds by strategy and size helps understand better the characteristics and the source of high returns in this industry. This thesis differs itself from previous studies by examining hedge fund return's exposure to a large number of risk factors. These twenty two risk factors include ten well-known Fung-Hsieh factors, two Fama-French factors, four option based factors, and newly discovered factors such as global cross sectional momentum factor MOM, time series momentum factor TMOM, global value factor VAL, market liquidity factor LIQ, currency factor RX, and carry trade risk factor.

Using the stepwise regression method, I have identified eight dominant risk factors for all thirteen hedge fund investment objectives, including five Fung-Hsieh factors (equity market factor SPRF, equity size spread factor RLSP, bond credit spread factor BAATY, emerging market factor MSEMKFRF, equity trendfollowing factor PTFSSTKRF), Fama-French value factor HML, time series momentum factor TMOM, and currency risk factor RX. I use these eight factors to build a statistical model to evaluate hedge funds, and compare its performance with Fung-Hsieh model. I find that the selected statistical model is a better tool to evaluate hedge fund performance. The selected model provides higher adjusted R^2 and lower alpha than its competitors. This result questions the choice of Fung-Hsieh model as a common tool to evaluate hedge fund performance in recent research literature.

By dividing hedge funds in three groups large, medium and small, and then evaluating their performance this thesis shows that small hedge fund group outperforms the large group both on average mean return and abnormal return. The spread mean return between two groups is 3.43 percent (4.82 percent) annually using equal weighted returns (value weighted returns). Using three different models to estimate alpha for three different hedge fund groups, the result shows that the small group has higher alpha than the large group by at least 3.43 percent (5.27 percent) annually using equal weighted returns (value weighted returns). The results are robust even when using a different data sample. The result has validated the previous studies about the superior performance of small funds over large funds and the negative relation between capital constraints and hedge fund performance. My study has meaningful applications to hedge fund investors: to achieve higher return, investors should target small funds. However this thesis does not address the source of higher returns of small funds. Do small funds load on more risk than large funds? Or are managers of small funds more skilled? This requires further studies in the future.

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