Literature Overview Of The Hedge Fund Industry

Introduction

The last 15 years witnessed a remarkable increasing investors' interest in alternative investments that leads the hedge fund industry to one of the fastest growing sectors in term of asset under management (AuM) and in term of number of funds in the whole financial industry. Credit Suisse/Tremont Index estimates the total industry AuM at $1.5 trillion as of March 2010 .Hedgefundresearch estimated the total number of hedge funds at about 9000 in mid-2009. According to the management consultant firm Casey Quirk, the industry AuM expended at more than 20% per year between 2000 and mid-2008 but suffered significant outflows during the financial crisis. Casey Quirk forecasts that hedge fund assets will attain almost $2.6 trillion by the end of 2013, after reaching their low point during the subprime crisis in 2009.

Besides the possible historical and demographic factors , the reasons behind this outstanding evolution lie in the specific risk-return characteristics and investment opportunities of hedge funds returns. With higher risk-adjusted returns and lower correlation with "traditional" asset classes (Agarwal and Naik [2000b]; Brown et al. [1999]; Capocci and Hübner [2004]), hedge funds give investors the possibility to increase their return on investment and diversify their portfolio. These characteristics attracted always more and more institutional and private investors looking for news investment opportunities with lower systematic risks, higher returns or diversification potential. Big incentive-based fees on returns have attracted brilliant managers with superior stock picking skills and many hedge funds are built around financial geniuses working in an environment in which they can prosper (Agarwal and Naik [2000a] and [2000b], or Brown and Goetzmann [2003]). Indeed, hedge funds usually benefit from favorable tax legislation and are located in "tax heavens" countries (Brown et al. [1999]). Moreover, because many regulators do not allow hedge funds to advertise (Brown et al. [1999]), investors often decide to invest in a certain hedge fund by looking at the past performance and assuming that this is an good indicator for outstanding manager and superior future returns (Schaub [2008]). High and stable performance is therefore extremely important for managers to assure the durability of their funds.

With trillions of dollars invested in this industry during the last decade, one may suppose that investments opportunities for managers become rare and that the alpha production is subject to decreasing returns to scale. "As new money flows into the hedge fund industry and more hedge funds are built, managers might be forced not only to invest into the most profitable strategies but to opt for less attractive investments or diversify to other strategies, where their knowledge and experience might be limited" . These declining returns to scale are often interpreted as evidence of capacity constraints in the hedge fund industry. The capacity constraint is agreed for mutual funds (Clark [2003];

Hedges [2003]; Herzberg and Mozes [2003]) but less established within the hedge fund industry. There exists nowadays a contradiction concerning the evolution of hedge fund performances over time. Some recent studies suggest that hedge fund alpha has decreased while others put forward that alpha is stable and do not find evidence of a capacity constraint in the hedge fund industry. In particular, two main studies disagree regarding their conclusion. By analyzing the distribution of individual hedge funds alpha, Zhong [2008] finds that not only the average alpha has decreased over time. They observe that the number of funds generating a positive alpha is lower over time whereas the number of funds generating negative alpha is stable. On the contrary, Ammann, Huber and Schmid [2009] cannot confirm based on their own multifactor models a systematic decrease of the alpha over time. Breaking down the relationship between fund flows and alpha, they cannot confirm the existence of capacity constraints in the hedge fund industry. The objective of this master thesis is to investigate where these divergences in evolution of hedge fund alphas come from. Both papers are based on different methodologies, models and databases that could explain such disparities in conclusion. My suggestion is first to replicate both studies to apply methodologies and characteristics of one paper separately on the other to isolate the possible reasons explaining the different findings, and vice versa.

The rest of the thesis is structured as follows. Section 2 gives a brief overview of hedge fund history and characteristics. Section 3 describes the literature overview concerning the hedge fund industry. Section 4 and section 5 presents the methodologies and the replications of Zhong [2008] and Ammann, Huber and Schmid [2009] respectively. Section XXX presents the impact of databases, period of time, biases on hedge fund performances. Section XXX presents the difference in databases that could explain the contradiction. Section XXX concludes this master thesis with …

Overview of the hedge fund industry

To identify why the development of this industry has been so tremendous, one needs to define the characteristics of hedge funds. The first hedge fund was created by Alfred Winslow Jones in 1949 (Loomis [1966]). He raised $100’000 and founded an equity long/short fund as a general partnership to avoid the SEC regulation and maximize its portfolio’s investments flexibility. Making huge profits, his approach was reproduced by other hedge fund managers who built new investment strategies depending on bull or bear market environments. After a slowdown in the 1970s and early 1980s, the popularity of hedge funds was revived in 1986 by an article in Institutional Investor (Rohrer [1986]) about the terrific performance of Julian Robertson’s Tiger Fund . The remarkable development of this alternative investment class started in mid-1990 with the so-called “golden age” of global-macro funds and their aggressive and market directional bets without specific hedging strategies. Some of these hedge funds emerged as major players in financial markets and attracted widespread media attention. Their managers take extremely aggressive positions to increase the profits, contributing to financial instability like the George Soros’s Quantum Fund and the depreciation of the British pounds in 1992. Compared with the 600 hedge funds worldwide and the less than $ 20 billion of asset under management in 1990, the evolution represents according to Casey Quirk a little more than 24% of implied annual growth during the last 20 years.

The lack of precise legal definition for “hedge fund” can lead to contradictions and misinterpretations. To understand the reasons why Zhong [2008] and Ammann et al. [2009] apply some specific methods, one needs to distinguish hedge funds from other mutual or common investment funds. According to Lhabitant [2002], the term “hedge fund” only describes an investment structure or style. We can define common characteristics shared by hedge funds and specific to this industry . First, hedge funds are actively managed. This means that managers seek to add value through active management and skill-based strategies. They do not try to replicate a particular benchmark like mutual fund managers but instead seek absolute returns. Second, hedge funds are securitized trading floor not very different than traditional trading floor of investment banks. Third, hedge funds have flexible investment policies. To achieve higher returns and profit from arbitrage opportunities, hedge funds managers are given greater option regarding the methods, investment techniques and asset classes they can use. This is not uncommon to see hedge funds employing high leverage, derivatives, buying on margin and/or short selling. Fourth, hedge funds use unusual legal structures to avoid regulations and minimize their tax bills. There are often limited partnerships and offshore companies established in tax-favorable jurisdictions. Fifth, hedge funds have limited liquidity. Fund managers generally limit the subscription and redemption possibilities to investors and set a minimum period investment to avoid big liquidity buffer and focus their investments on illiquid assets and mispricing. Sixth, hedge funds charge performance fees and target absolute returns. In opposite to traditional funds, hedge funds charge not solely a management fee (generally between 1% and 3% of the asset under management) but also an incentive fee from 15% to 25% of the annual realized performance that aims at encouraging managers to achieve maximum returns. Moreover, this aligns their interests with investors. Seventh, hedge fund managers are partners and not employees. They generally share both upside and downside risks with investors by investing their personal stake in the fund and reducing agency problems. Eighth, hedge funds have limited transparency. It is difficult to get a precise overview of their investments behind the net asset value. The particular legal structure and offshore registration restrict access to their investment policies and fund managers keep the secrets about their specific positions and strategies. Finally ninth, hedge funds cater specific investors like high net worth private investors and institutional investors with large minimum capital investment and complex investment strategies. These investors are supposed to be well-informed enough to assess their own investments’ risks. Lhabitant [2002] does not claim that this list of characteristics fully describes hedge funds but it gives us an excellent definition of this industry. Moreover, it gives us a large description of the specific hedge funds returns pattern that helps us to understand why hedge funds studies contain specific characteristics.

Literature Overview

The hedge fund industry is based on the search for alpha, the excess risk-adjusted return. To assess the foundation and check the robustness of our both studies, one needs to review the recent academic literature on hedge funds. Because of their various specific characteristics and the increasing interest for alternative investments, hedge fund research has been an extremely popular topic among academic scholars and investment banks during the last decade. There exists a vast literature on hedge fund performance and alpha based on different factor models.

The first studies on hedge funds such as Schneeweis [1996] and Fung and Hsieh [1996] emphasized that hedge funds and Commodity Trading Advisors have diverse investment pattern and opportunities than mutual and traditional stock and bond funds. Fung and Hsieh [1997] built one of the first multi-factor models to benchmark and identify hedge fund performances. Based on Sharpe [1992] asset class factor model for mutual funds' performance attribution, they found "five main investment styles in hedge funds, which when added to Sharpe's [1992] factor model can provide an integrated framework for style analysis of both buy-and-hold and dynamic trading strategies" . The proposal that hedge fund returns can be evaluated with multiple factor models was therefore extended during the last decade. Schneeweis and Spurgin [1998] built one of the first asset class multi-factor models based on passive positions in the commodity, fixed income, equity and currency markets to benchmark hedge fund returns. Agarwal and Naik [1999] find that simple option long and short strategies can explain a significant part of variation in hedge fund returns. They propose an asset class multi-factor model based on stepwise regression techniques to reflect the dynamic trading strategies of hedge funds incorporating exposure to equities, bonds, currencies and commodities. They found low correlation between hedge fund returns and traditional asset classes suggesting that a certain level of diversification is conceivable for investors exploiting a combination of alternative and passive investment strategies. These approaches differ from funds comparison used by Ackermann, McEnally and Ravenscraft [1999] who compared hedge fund performances to market indices and classified mutual funds. They notice that hedge funds have higher Sharpe ratios (Sharpe [1994]) than mutual funds but not necessarily than market indices. Liang [1999] also finds than hedge funds outperform mutual funds in term of Sharpe ratios and show positive abnormal returns for the late nineties. Brown, Goetzmann and Ibbotson [1999] examined the performance of hedge fund industry and its persistence during the nineties. They found low correlation with the U.S. stock market, high attrition rates of funds and persistence in risk-adjusted returns over time. Schneeweis, Kazemi and Martin [2003] compare multiple factor models and single factor model and find out that hedge fund performance is sensitive to the choice of model. They conclude that multi-factor models that capture return variations may be superior to other approaches.

The proposal that hedge fund returns exhibit non-linear payoffs was developed by Fung and Hsieh [1997] and [2000a]. They observe that hedge fund returns occur from three factors: (1) Trading strategy factors which show the non-linear option-like exposures to bond, equity, commodity and currency classes; (2) Location factors which show payoffs from Buy-and-Hold strategies; and (3) Leverage factors. Agarwal and Naik [2000] propose "a general asset class factor model including excess returns on option-based strategies and on buy-and-hold strategies to benchmark the performance of hedge funds" . Interestingly, they find that only 38% of hedge funds have added value in the first part of the nineties whereas only 28% in the second part of the nineties suggesting a possible decline of hedge fund performances over time. Mitchell and Pulvino [2001] study hedge fund returns and claim that analysis including the non-linearity in payoffs gives a more accurate description of the risk-adjusted returns. Fung and Hsieh [2004] reject conventional models and propose an APT-like factor model with time-varying betas that capture dynamic risk factors in hedge funds, using the asset-based style (ABS) factors in Fund and Hsieh [2002b]. The seven factors explain a significant part of the systematic variation of hedge fund returns with up to 90% R-squared. A more accurate description of the model is given in the next section as we will apply it in the empirical results section to replicate Zhong [2008]. They find a change in magnitude and significance of hedge fund alphas depending on bull or bear market, signifying an evolution of hedge fund performances over time.

Concerning a possible capacity constraint within the industry, Liang [1999] finds a positive relationship between monthly returns and fund assets under management. He notices a negative relationship with fund age, funds with short history outperforming funds with longer history. Edwards and Caglayan [2001] analyze hedge fund risk-adjusted returns with respect to fund sizes from January 1990 to August 1998. They find on average a positive significant alpha and evidence of persistence for positive and negative excess returns at a declining rate as fund sizes increase, suggesting a probable capacity constraint within the industry. Gregoriou and Rouah [2003] study the link between the size of hedge funds and their risk-adjusted performances. Using the geometric mean, the Sharpe [1994] ratio and the Treynor [1965] ratio, they do not find a positive or negative correlation between hedge fund sizes and returns. They conclude that fund size has no impact on its performance. Kazemi and Schneeweis [2003] show that in average, larger funds underperform smaller funds on return perspectives, have lower risk, and lower risk-adjusted returns. The results can differ depending on the strategies with positive correlation between funds size and performances for merger arbitrage funds for example. Ammann and Moerth [2005] analyze the impact of fund sizes on hedge fund returns, alphas and Sharpe ratios. Employing cross-sectional regressions, they find a negative relationship between fund sizes and returns except for extreme small funds. Ammann and Moerth [2008] refined their study about the possible impact of hedge fund sizes on performances with a percentiles-based methodology. They use an asset class factors model to explain hedge fund performances. Their empirical results suggest that smaller hedge funds outperform bigger funds, with a coefficient of the variable "size" significant at a 1% significance level. In contrast, larger hedge funds have on average lower Sharpe ratios and lower variability. Moreover, Ammann and Moerth [2008] investigate the relationship between fund flows and performances. They found that large inflows in hedge funds are followed by lower performances of these funds in the following 12-month period than hedge funds witnessing weaker inflows or outflows. They suggest that hedge funds are subject to capacity constraint whereas strong asset growth has a negative impact on future fund performance. Fung, Hsieh, Naik and Ramadorai [2008] investigate if the performances, risk and capital formation of funds-of-hedge funds have varied over time. Using robust bootstrap methodologies, they came to the conclusion that on average only 22% of funds-of-hedge funds deliver positive and significant alpha for the period 1995 to 2004. They find strong evidence that hedge funds capital inflows affect negatively the future production of alpha. Funds with high inflows have lower chance to deliver alpha in the future, suggesting a capacity constraint. Teo [2009] investigates the capacity constraint within the hedge fund industry. He finds that hedge funds are subject to diseconomies of scale. Larger hedge funds underperform ex-post smaller funds and the capacity constraints are persistent and significant across the industry.

As we can see, there exist among scholars contradictions on capacity constrain arguments in the hedge fund industry. The question remains whether the hedge fund industry witnessed a decline in performance these last decades due to its extraordinary expansion. Naik, Ramadorai and Stromqvist [2006] use the seven-factor model of Fung and Hsieh [2004] to show that hedge funds alpha has decreased significantly during the period early 2000 to end of 2004 in comparison to the 1990s. Interestingly, they find a higher flow means for the period with the lowest alphas and conclude that capacity constraints may be the reason for the decline in alpha. Fung et al. [2008] analyzed and divided the evolution of the alpha of an own index of funds of funds into three distinct sub-periods. They find a positive alpha only in the short second period from October 1998 to March 2000 but a significant decline during the period from April 2000 to December 2004.

Zhong [2008]

The two main studies on evolution of hedge fund performance over time are the essays “Why does Hedge Fund Alpha decrease over time? Evidence from Individual Hedge Funds” of Z. K. Zhong [2008] and “Has Hedge Fund Alpha disappeared?” of M. Ammann, O. Huber, and M. Schmid [2009]. The first paper mentions that due do the decline in the proportion of funds delivering positive alpha, the average alpha has decreased over time. Based on their own strategy indices, Ammann et al. [2009] do not find a significant alphas’ decline over time. In the two following sections, we will present and replicate both papers in order to isolate the possible reasons behind these differences in conclusions. As a first stage, we will focus our analysis on the evolution of equally-weighted strategy indices alphas applying the respective methodologies. The second part of this thesis will investigate the evolution of individual hedge fund alphas and its distribution over time. Zhong [2008] investigate the sustainability of single hedge fund alphas and equally-weighted indices over the period 1994 to 2005. He tries to explain if and why the performance of individual funds has decreased. Based on the 7-factors model of Fung and Hsieh [2004], he finds that on average alphas have declined significantly during the period, especially during the last sub-period. Moreover, adapting the kernel density estimator of Rosenblatt [1956], he analyses the distribution of individual hedge fund alphas and find that the difference of performance between the best and the worst funds has become less significant over time and a decreasing number of fund capable to deliver positive alphas. In this section, we will therefore use the same data and methodologies and replicate his study on equally-weighted indices.

Data

Zhong used the CISDM data covering the period from January 1994 to December 2005. Writing this master thesis two years later, we logically include the turbulent time during the financial crisis and use a broader period of time from January 1994 to January 2009. The database gathers information for over 12950 hedge funds, funds-of-funds and CTAs . The choice of January 1994 is deliberate since the CISDM started reporting information on dead funds only after 1993. We therefore reduce the survivorship bias including both lived and defunct funds. To reduce other possible bias, we follow Zhong's methodology and impose some filters to get a representative sample: (1) We include only funds with both monthly return and AUM data available; (2) We include only funds that report monthly; (3) We include only funds without evident irregularity in return or AUM time-series; (4) To be included in our analysis, we impose a fund at least 24 monthly consecutive observations; (5) Since managed futures and CTA have no clear distinction in the CISDM database and are not always considered as pure hedge fund strategies, we do not take them into consideration. Our sample may suffer from backfilling (or incubation) bias since Zhong does not require non-backfilled returns observations . To control for it and check the robustness of our findings, we delete the first twelve months of each fund and repeat the analysis in the robustness section; (6) To be included into the equally-weighed indices, we require a fund's AuM to exceed at least once during its life $5 million or its exchange value for not-USD denominated funds . To control for small funds bias, we repeat our analysis with a sample excluding funds with AuM of less than $10 million. After all these readjustment, our final sample contains 5768 hedge funds for the analyses of equally-weighted indices and 6069 hedge funds for the analyses of individual performances divided into 20 different strategies.

We follow Zhong's procedure and divide our sample into 5 evenly-spaced sub-periods in order to investigate the evolution of hedge fund performances over time. With each 36 monthly returns, this method enables us to distinguish pattern and draw conclusion. Moreover, to conduct our analysis linked to hedge fund strategies, we follow Zhong's methodology and divide the 20 hedge fund strategies into eight categories according to the classification criteria in Agarwal et al. [2007]: Directional Trading, Emerging Markets, Global Macro, Multi-Process, Others, Relative Value, Securities Selection, and Fund of Funds (see Appendix A). We use these eight categories to compute the strategies' average alpha but we analyze the 20 strategies separately.

Methodology

To estimate the risk-adjusted performance, Zhong [2008] uses the APT-like seven factors model of Fung and Hsieh [2004]. To avoid biases present in databases, the model benchmarks hedge fund returns with risk asset-based factors build on Fung and Hsieh [2002b] instead of hedge fund return-based factors. Regressing the hedge funds' return in excess of the risk-free rate on the seven factors, the model split the hedge fund return into two categories of risk: idiosyncratic and systemic. Like an APT model, the resulting alphas of the regression represent the estimates for the hedge fund strategy performance.

Fung and Hsieh [2002b; 2004] extracted standard sources of risk in hedge fund returns with principal components analysis and link them to observable prices in market. They explicitly identify the risk loadings with marketable risk factors depending on hedge fund strategies. (1) Trend-following strategies are characterized by approaches betting on big up or down movements. Their payoffs look like long volatility investors payoffs, namely option buyers. To replicate it, Fung and Hsieh [2004] constructed five portfolios of lookback options from exchange-traded options and showed the great similarity in term of returns or correlation with trend-following funds. (2) Merger Arbitrage Funds (or Risk Arbitrage) bet on merger completion, buying the target stock and shorting the acquirer. Components are based on Mitchell and Pulvino [2001] that show that returns on risk arbitrage have high correlation with the S&P 500 only in case of large market declines. Put another way, merger arbitrageurs face the same risk than short option sellers of out-of-the-money put options on the S&P 500. Betting on merger or acquisition completions, the lost arises when more transactions failed at the same time, during bear market notably. (3) Fung and Hsieh [2002a] found that Fixed-Income hedge funds show exposure to interest rate spreads, betting on a tightening credit spread, shorting high credit rating treasuries and buying low rating or illiquid fixed income instruments. They include the credit spread in their model with the difference between the yield on Moody's Baa bonds and the yield on the ten-year constant maturity treasury. (4) Fung and Hsieh [2003] found that Equity Long/Short funds and Equity Market Neutral funds are exposed to stock market and the difference between small minus large cap stocks. They tend to decrease their correlation to the market risk, being long small capitalization stocks and short on large capitalization stocks. Their model therefore includes the S&P 500 and the difference between the Wilshire 1750 Small Cap index (SC) and the Wilshire 750 Large Cap Index (LC). The Fung and Hsieh [2004] seven-factor model is therefore composed of two Equity factors (S&P 500, SC-LC spread), two Fixed Income factors (the change in 10-year treasury yield and spread between 10-year treasury and Moody's Baa bonds) and three Trend-Following factors (lookback options on bonds, currencies and commodities) .

In an attempt to compare both papers, we complete our analysis by using the same procedure than Ammann et al. [2009] and build our own model in which the risk factors are chosen by stepwise regression. Like Ammann et al. [2009], we begin with the same 23 risk factors (see Appendix B) of the following asset classes: equities, bonds and credit, interest rates, currencies, options, volatility, convertible bonds, dynamic trading strategies, real estate and commodities. Moreover, Ammann et al. include option-based factors like call and put options on the S&P 500 (Agarwal and Naik [2004]) and lookback option straddles suggested by Fung and Hsieh [2004] to account for non-linear payoffs. We use the same iterative procedure of forward-stepwise selection based on the t-values of the factors coefficients. Following Ammann et al. [2009], we add a factor if its coefficient is significant at a 95% level and drop all others which are not at the same time significant at a 90% level. We then regress returns of an equally-weighted index on the returns of the significant factors and repeat the method until either we get a maximum of seven factors for each strategy or no other factors are significant .