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ABSTRACT

We employ the stochastic dominance approach that utilizes the entire return distribution to rank the performance of Asian hedge funds as traditional mean-variance and CAPM approaches could be inappropriate given the nature of non-normal returns. We find both first-order and higher-order stochastic dominance relationships amongst the funds and conclude that investors would be better off by investing in the first-order dominant funds to maximize their expected wealth. By investing in higher-order dominant funds, risk-averse investors can maximize their expected utilities but not their wealth. In addition, we find the common characteristic for most pairs of funds is that one fund is preferred to another in the negative domain whereas the preference reverses in the positive domain. We conclude that the stochastic dominance approach is more appropriate compared with traditional approaches as a filter in hedge fund selection. Compared with traditional approaches, the SD approach, not only is assumption free, but also provides greater insights to the performance and risk inherent in a hedge fund's track record.

JEL Classification: G11, G15

Key words: hedge funds, stochastic dominance, risk-averse investors, performance measurement.

1. INTRODUCTION

There is an increasing trend to include alternative investments in managed portfolios. An often cited reason is the diversification benefits obtained for doing so. Hedge funds as an alternative investment have become more popular among institutional investors. We have also seen financial institutions marketing hedge fund investments to retail investors. The hedge funds industry has experienced extraordinary growth over the last decade. Hedge funds that focus on investing in Asia have been established at an increasing pace. While, 30 new funds were established in 2000 and 20 in 2001, the Bank of Bermuda reported that 66 new hedge funds were started in Asia in 2002 and 90 in 2003. Most of the Asian hedge fund managers are located in Australia, Singapore, Hong Kong, and Japan, although several manage the Asian funds out of Europe or the U.S.

According to EurekaHedge, there are more than 520 hedge funds operating in Asia (including those in Japan and Australia), with assets under management estimated at more than US$15 billion as of end 2004. Due to its relative small size compared with the global hedge fund industry (with assets under management in excess of US$1 trillion), we expect strong growth of Asian hedge funds in the near future given the potential to provide diversification benefits along with strong growth in both the real and financial sectors in the Asian economies. This potential along with the general lack of transparency of hedge funds motivates us to understand Asian hedge funds performance, specifically to provide a methodology that is useful for investors to filter or rank potential investments based on their past performance. We note that future returns of hedge funds and their risk profile are not easily predicted using past data and as Kat and Menexe (2003) suggested, the benefit of a track record lies in the insights it provides in the performance on one fund’s risk relative to that of another.

Section 2 of this paper reviews the literature and motivates the analyses carried out. The data and methodologies employed are described in Section 3. Empirical results and their implications are presented in Section 4 and Section 5 concludes.

2. LITERATURE REVIEW AND MOTIVATION

Typically, hedge fund managers adopt investment strategies to provide absolute returns under different market conditions compared with traditional fund managers who manage relative to benchmarks. It is commonly believed that hedge funds can generate positive alphas and the returns provided are generally uncorrelated with the traditional asset classes. Hedge fund managers use a range of strategies to generate such returns. Fung and Hsieh (1999a) classified hedge fund strategies as directional (or market timing) and non-directional. The directional approach dynamically bets on the expected directions of the markets that fund managers will long or sell-short securities to capture gains from the advance and decline of their counterpart stocks or indices. In contrast, by exploiting structural anomalies in the financial market, the non-directional approach attempts to extract value from a set of embedded arbitrage opportunities within and across securities.

Comparing the performance of managed funds is not a straightforward task and the strategies employed by hedge fund managers have introduced new problems. Firstly, hedge funds including those that invest in Asia have low correlations with the traditional asset classes like stocks and bonds and attempt to offer protection in falling and/or volatile markets (Amenc et al., 2003). Hence, comparing hedge funds returns to standard market indices would be erroneous since hedge funds have an entirely different objective compared with traditional managed funds (Gregoriou et al., 2005). Contemporary finance advocates the use of the mean-variance (MV) criterion developed by Markowitz (1952) for portfolio construction and the capital asset pricing model (CAPM) statistics developed by Sharpe (1964), Treynor (1965) and Jensen (1969) for managed funds performance evaluation. Many of the studies using such traditional measures (see, for example, Ackerman et al., 1999; Liang, 1999) conclude that hedge funds generate superior results.

Over the last decade, extensive empirical analyses had been carried out to determine the statistical properties of hedge fund returns. The conclusion of these studies is that hedge fund returns are generally more skewed and leptokurtic than expected if the underlying distribution is normally distributed. Lavinio (2000) argued that many hedge funds have distributions with fat-tails, and so normality assumptions on the distribution of hedge fund returns are generally not correct. Fung and Hsieh (2000) documented that hedge funds have fat tails resulting in a greater number of extreme events than one would normally anticipate. Brooks and Kat (2002) found that hedge fund index returns are not normally distributed. They argued that while hedge funds may offer relatively high means and low variances, such funds give investors both third and fourth moments attribute that are exactly the opposite to those that are desirable.

As the return distributions of hedge funds are generally non-normal, the MV criterion and the CAPM statistics may not be appropriate to assess the relative performance of hedge funds. Fung and Hsieh (1997) documented that measures such as the Sharpe ratio could pose problems due to the option-like returns that hedge funds generate. Kat (2003) noted that modern portfolio theory is too simplistic to deal with hedge funds. He maintained that Sharpe ratios and standard alphas could be misleading in analyzing such investments. This makes the use of traditional performance measures questionable.

Investors who use volatility as the sole measure of the riskiness of hedge fund returns could also be misled. While some hedge funds may have low standard deviation, this does not mean that they are relatively riskless. They may well harbor skewness and kurtosis, which make them risky. Furthermore, traditional Sharpe ratios usually overestimate fund performance due to negative skewness and leptokurtic returns (Brooks and Kat, 2002). As a starting point, our study first employs the MV criterion and CAPM statistics to investigate the performance of Asian hedge funds and some market indices. One finding is that hedge funds do not dominate the market indices used or vice versa further motivating the need to explore other alternative approaches to determine the benefits (if any) of including hedge funds in managed portfolios.

Given that traditional performance measures could provide erroneous results, many approaches have been offered as alternatives to evaluate hedge fund performance. Edwards and Caglayan (2001) and Gregoriou et al. (2002) used multifactor models to examine hedge fund performance. However, as dynamic trading strategies are employed by hedge funds, exposure to market factors is unlikely to be stable overtime. Multifactor models possess low predictive power. Furthermore, hedge funds are known as absolute return vehicles and their aim is to provide superior performance with low volatility in both bull and bear markets as opposed to comparing their relative performance to traditional market indices (Brealey and Kaplanis, 2001).

Regardless of the ability of existing and frequently used models to explain hedge fund returns, the dynamic trading strategies employed along with skewed returns distribution remains a problem for hedge fund performance evaluation. Some have proposed the use of longitudinal analyses to better describe temporal features of hedge fund performance. Brown et al. (2001) applied survival analysis to estimate the lifetimes of hedge funds and found that these are affected by factors such as their size, their performance and their redemption period. Getmansky et al. (2004) examined the illiquidity exposure of hedge funds. Agarwal and Naik (2004) proposed a general asset class factor model comprising of option-based and buy-and-hold strategies to benchmark hedge fund performance.

On the other hand, studies have applied the Value-at-Risk (VaR) and conditional-VaR (CVaR) (see for example, Jorion, 2000; Rockafellar and Uryasev, 2000, 2002;

Alexander and Baptista, 2002, 2004) methodology to hedge funds. Lhabitant (2001) reported factor model-based VaR figures for some hedge funds. Gupta and Liang (2005) examined the risk characteristics and capital adequacy of hedge funds through the VaR approach. They showed that VaR-based measures are superior to traditional risk measures like standard deviation of returns and leverage ratios, in capturing hedge fund risk. However, Ogryczak and Ruszczynski (2002), Leitner (2005) and Ma and Wong (2006) noted that stochastic dominance (SD) approach is superior as whatever information obtained by applying VaR and CVaR could be obtained by the SD approach.

Recently, Gregoriou et al. (2005)[1] applied data envelopment analysis (DEA) to evaluate the performance of different classes of hedge funds. It is a useful tool for ranking self appraised and peer group appraised hedge funds. Lee et al. (2006) introduced a practical non-linear approach based on first and cross-moments analyses in up and down markets to assess the risk and performance of Asian hedge funds. They found that while all funds provide diversification in the sense that they are not perfectly correlated with market index returns, few funds provide downside protection along with upside capture that is assumed to be preferred by investors. They found that funds having these preferred attributes provided returns that are not, on average, significantly less than those that do not provide such preferred attributes. The same data sample was used in our paper. We have found that selected funds provide both stochastic dominating returns as well as funds that provide upside capture and downside protection, as well as stability in volatile condition at insignificant cost.

The search for performance measures for hedge funds is an on-going process. We recommend the SD approach that allows investors to appropriately rank fund performance without the need for strong assumptions on investors' utility function or the return distribution of asset returns. SD rules offer superior criteria on which to base

[1] Gregoriou et al., (2005) provided a detailed literature review of hedge fund performance measures.

investment decisions compared with the traditional MV and CAPM analysis because the assumptions underlying SD are less restrictive. Taylor and Yoder (1999) argued that SD incorporates information on the entire distribution, rather than the first two moments and requires no precise assessment as to the specific form of investors' risk preference or utility function.

The SD approach had been used in the evaluation of performance of mutual funds since the 1970s (Levy and Sarnat, 1970; Porter, 1973). Recently, Taylor and Yoder (1999) used the SD approach to compare the performance between load and no-load funds during the 1987 crash. Kjetsaa and Kieff (2003) documented that the SD approach provides a collateral and feasible strategy to reveal relative investment preferences by discriminating among and parsing the universe of mutual fund opportunities. More recently, Gasbarro et al. (2007) utilized both the SD approach and the CAPM criterion to compare the performance of 18 country market indices (iShares) and found that SD appears to be both more robust and discriminating than the CAPM in the ranking of iShares.

In this paper, we use the Davidson and Duclos (DD, 2000) or DD test to determine if the difference in the cumulative density functions of the returns of two hedge funds are statistically significant. The SD tests developed by Barrett and Donald (BD, 2003) and Linton et al. (LMW, 2005) are computed for comparison.

We use the DD test to determine if SD occurred among the 70 individual Asian hedge funds during our sample period. We find that over the sample period (January 2000 to December 2004), some hedge funds dominate others. Conversely, some funds do not dominate any other hedge funds, but they themselves are not dominated by other hedge funds as well. Surprisingly, for the two equity market indices being examined, viz. MSAUCPI (Morgan Stanley Pacific Index) and S&P 500 are dominated by 21 and 15 other indices/funds respectively at the first-order. In addition, we find the common characteristic for most pairs of funds is that one fund is preferred to another in the negative domain or bear markets whereas the preference reverses in the positive domain or bull runs.[2] Our suggested methodology can be a useful filter for fund selection for different levels of risk aversion among investors to maximize their expected wealth and/or utilities along with the usually skewed and non-normal characteristics of hedge fund returns.

3. DATA AND METHODOLOGY

The data analyzed in this study are the monthly returns of the 70 Asian hedge funds reported by the EurekaHedge database for the sample period from January 2000 to December 2004. For completeness, we include the EurekaHedge Asia Ex-Japan (IX1), Eureka Hedge Japan (IX2) and EurekaHedge Asian Hedge Fund (IX3) indices. We also carry out our analysis on two traditional equity market indices, viz. the Morgan Stanley Pacific Index (MSAUCPI)[3] (IX4) and the S&P500 index (IX5). We include the S&P 500 in our study as traditional U.S. based fund managers and investors may use the S&P 500 as the equity benchmark. If they are investing internationally, diversification benefits can be measured relative to a regional benchmark constructed by Morgan Stanley, like the MSAUCPI. The 3-month U.S. T-bill rate and the Morgan Stanley Capital International Global index (MSCI) proxy the risk-free rate and the global market index respectively are used for CAPM statistics.

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[2] Post and Levy (2005) studied the dominance of assets in the negative and positive domains and concluded that investors are risk-averse in bear markets and risk-seeking in bull markets. We agree with Post and Levy that investors could make inference in bear (bull) markets when examining negative (positive) domain though bear (bull) markets are not exactly equal to negative (positive) domain of the returns.

[3] The MSAUCPI is a free-float-adjusted market capitalization index that is designed to measure the equity market performance in the Australasian region. It includes 12 emerging and developed market countries: viz. Australia, China, Hong Kong, Indonesia, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Taiwan and Thailand.

The MV criterion and CAPM statistics are commonly used for mutual funds performance evaluation. The MV criterion (Markowitz, 1952; Tobin, 1958) states that, for the returns of any two funds Y and Z with means μ_y and μ_z and standard deviations, σ_y and σ_z respectively, Y is said to dominate Z if $\mu_y \geq \mu_z$ and $\sigma_y \leq \sigma_z$.[4] The CAPM risk-adjusted performance measures developed by Sharpe (1964), Treynor (1965) and Jensen (1969) are the Sharpe ratio, Treynor's index and Jensen (alpha) index.[5] However, both the MV criterion and CAPM measures are derived assuming the Von Neumann-Morgenstern (1944) quadratic utility function and that returns are normally distributed (Feldstein, 1969; Hanoch and Levy, 1969). Thus, the reliability of performance comparisons using the MV criterion and CAPM analysis depends on the degree of non-normality of the returns data and the nature of the (non-quadratic) utility functions (Fung and Hsieh, 1999b).

Essentially, the most commonly-used SD rules that correspond with three broadly defined utility functions are first-, second- and third-order SD for risk averters, denoted by FSD, SSD and TSD respectively. Formally, we let F and G be the cumulative distribution functions (CDFs) and f and g are the corresponding probability density functions (PDFs) of the returns for two funds Y and Z respectively with common support of $[a, b]$ $(a < b)$. Define

$$H_0 = h \text{ and } H_j(x) = \int_a^x H_{j-1}(t)\,dt \text{ for } h = f, g \text{ , } H = F, G \text{ and } j = 1, 2, 3 .\quad (1)$$[6]

Fund Y would dominate Fund Z by FSD if and only if $F_1(x) \leq G_1(x)$; by SSD if and only if $F_2(x) \leq G_2(x)$; and finally, by TSD if and only if $F_3(x) \leq G_3(x)$ for all x, and

[4] Refer to Meyer (1987), Wong (2007) and Wong and Ma (2007) on the relation between stochastic dominance and mean-variance rules.

[5] Readers may refer to Sharpe (1964), Treynor (1965) and Jensen (1969) for the details and discussions of these statistics.

[6] Refer to Wong and Li (1999), Anderson (2004) and Wong and Chan (2007) for the discussions on the definitions.

the strict inequality holds for at least one value of x ; and Y has higher expected return than Z.

The existence of FSD (SSD, TSD) implies that the expected wealth (utilities) of investors are always higher when holding the dominant fund than holding the dominated fund and, consequently, the dominated fund should not be chosen. Investors exhibit non-satiation (more is preferred to less) under FSD; non-satiation and risk aversion under SSD; and non-satiation, risk aversion, and decreasing absolute risk aversion (DARA) under TSD. We note that hierarchical relationship exists in SD (Levy 1992, 1998): FSD implies SSD, which in turn implies TSD. However, the converse is not true. Thus, only the lowest dominance order of SD is reported in practice.

Recent advances in SD empirical techniques allow the statistical significance of SD to be determined. To date, the SD tests for risk averters have been well developed, for example, see McFadden (1989), Klecan et al. (1991), Kaur et al. (1994), Anderson (1996, 2004), Davidson and Duclos (DD, 2000), Barrett and Donald (BD, 2003) and Linton et al. (LMW, 2005). The DD test has been found to be one of the most powerful, but yet less conservative in size (Wei and Zhang, 2003; Tse and Zhang, 2004 and Lean et al., 2007); while the BD test is another powerful test instrument and the LMW is useful as it is extended from Kolmogorov-Smirnov test for FSD and SSD by relaxing the iid assumption. We report the results of the DD test and skip reporting those of BD and LMW tests as the former is the only SD statistics that test the SD relationship up to the third-order and the results of both BD and LMW tests are consistent with those of the DD test.

For any two funds Y and Z with CDFs F and G respectively and for a grid of pre-selected points $x_1, x_2 \ldots x_k$, the order-j DD test statistics, $T_j(x)$ (j = 1, 2 and 3), is:

$$T_j(x) = \frac{\hat{F}_j(x) - \hat{G}_j(x)}{\sqrt{\hat{V}_j(x)}}, \quad (2)$$

where $\hat{V}_j(x) = \hat{V}_Y^j(x) + \hat{V}_Z^j(x) - 2\hat{V}_{Y,Z}^j(x)$,

$$\hat{H}_j(x) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(x-h_i)_+^{j-1},$$

$$\hat{V}_H^j(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x-h_i)_+^{2(j-1)} - \hat{H}_j(x)^2\right], H = F, G; h = y, z;$$

$$\hat{V}_{Y,Z}^j(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x-y_i)_+^{j-1}\left(x-z_i\right)_+^{j-1} - \hat{F}_j(x)\hat{G}_j(x)\right];$$

in which F_j and G_j are defined in (1).

It is empirically impossible to test the null hypothesis for the full support of the distributions. Thus, Bishop et al. (1992) proposed to test the null hypothesis for a pre-designed finite number of x. Specifically, the following hypotheses are tested:

$H_0 : F_j(x_i) = G_j(x_i)$, for all x_i, $i = 1, 2, ..., k$;
$H_A : F_j(x_i) \neq G_j(x_i)$ for some x_i ;
$H_{A1} : F_j\left(x_i\right) \leq G_j\left(x_i\right)$ for all $x_i, F_j\left(x_i\right) < G_j\left(x_i\right)$ for some x_i;
$H_{A2} : F_j\left(x_i\right) \geq G_j\left(x_i\right)$ for all $x_i, F_j\left(x_i\right) > G_j\left(x_i\right)$ for some x_i.

We note that in the above hypotheses, H_A is set to be exclusive of both H_{A1} and H_{A2}, which means that if either H_{A1} or H_{A2} is accepted, we will not say H_A is accepted. Under the null hypothesis, DD showed that $T_j\left(x\right)$ is asymptotically distributed as the Studentized Maximum Modulus (SMM) distribution (Richmond, 1982) to account for joint test size. To implement the DD test, the test statistic at each grid point is computed and the null hypothesis, H_0, is rejected if the test statistic is significant at any grid point. The SMM distribution with k and infinite degrees of freedom, denoted by $M_{\infty,\alpha}^k$, is used to control for the probability of rejecting the overall null hypotheses. The following decision rules are adopted based on 1-α percentile of $M_{\infty,\alpha}^k$ tabulated by Stoline and Ury (1979):

If $\left|T_j\ (x_i)\right| < M_{\infty,\alpha}^k$ for $i = 1,...,k,$ accept H_0;
if $T_j\ (x_i) < M_{\infty,\alpha}^k$ for all i and $-T_j\ (x_i) > M_{\infty,\alpha}^k$ for some i, accept H_{A1};
if $-T_j\ (x_i) < M_{\infty,\alpha}^k$ for all i and $T_j\ (x_i) > M_{\infty,\alpha}^k$ for some i, accept H_{A2}; and
if $T_j\ (x_i) > M_{\infty,\alpha}^k$ for some i and $-T_j\ (x_i) > M_{\infty,\alpha}^k$ for some i, accept H_A.

Accepting either H_0 or H_A implies non-existence of any SD relationship, non-existence of any arbitrage opportunity between these two hedge funds and neither of these two hedge funds are preferred to one another. However, if H_{A1} or H_{A2} of order one is accepted, a particular hedge fund stochastically dominates another hedge fund at first-order. In this situation, any non-satiated investor will increase her/his expected wealth if s/he switches from the dominated hedge fund to the dominant one.[7] On the other hand, if H_{A1} or H_{A2} is accepted for order two or three, a particular hedge fund stochastically dominates the other at second- or third-order. In this situation, arbitrage opportunity does not exist and switching from one hedge fund to another will only increase investors' expected utilities, but not expected wealth.

The DD test compares the distributions at a finite number of grid points. Various studies examine the choice of grid points. For example, Tse and Zhang (2004) showed that an appropriate choice of k for reasonably large samples ranges from 6 to 15. Too few grids will miss information of the distributions between any two consecutive grids (Barrett and Donald, 2003) and too many grids will violate the independence assumption required by the SMM distribution (Richmond, 1982). To make more detailed comparisons without violating the independence assumption, we follow Fong et al. (2005) and Gasbarro et al. (2007) to make 10 major partitions with 10 minor partitions within any two consecutive major partitions in each comparison and to make the statistical inference based on the SMM distribution for k=10 and infinite degrees of

[7] Refer to our conclusion for the discussions.

freedom[8]. This allows the examination of the consistency of both magnitudes and signs of the DD statistics between any two consecutive major partitions without violating the independent assumption.

4. EMPIRICAL FINDINGS AND IMPLICATIONS

4.1 MV Criterion and CAPM Statistics Results

We begin our empirical analysis of the Asian hedge funds using the MV criterion. The means and the standard deviations of the returns for all 70 Asian hedge funds studied are plotted and shown in Figure 1. The figure reveals that in general the means and standard deviations move together and thus the results are consistent with modern portfolio theory that higher mean accompanies higher risk. We depict in Figure 2 the risks versus returns trade-off and the corresponding efficient frontier for the 70 funds. We find that most of the funds are not in the efficient frontier. We exhibit in Table 1 the summary statistics of the five indices (IX1 to IX5) and the four 'most outstanding funds' (AHF01, AHF18, AHF39 and AHF47) with largest or smallest means, standard deviations or Sharpe ratios.[9] Interestingly, we find that the most outstanding funds reported in Table 1 adopt different investment strategies: AHF01 is Distressed Debt, AHF18 is Long/Short Equities, AHF39 is Multi-Strategy and AHF47 is Macro.[10] From Table 1, the average monthly mean return of the 70 Asian hedge funds is observed to be

[8] Refer to Lean et al (2007) for the reasons. Critical values are: 3.691, 3.254 and 3.043 for 1%, 5% and 10% level of significance tabulated in Stoline and Ury (1979).

[9] Refer to Table 1 for the full names of IX1-IX5, AHF01, AHF18, AHF39 and AHF47 and the characteristics of the funds.

[10] Macro Strategy: A Macro fund aims to profit from changes in global economies, typically brought about by shifts in government policy that impact interest rates, in turn affecting currency, stock, and bond markets; Participates in all major markets - equities, bonds, currencies and commodities - though not always at the same time. Uses leverage and derivatives to accentuate the impact of market moves. Utilizes hedging, but the leveraged directional investments tend to make the largest impact on performance. (http://www.magnum.com/hedgefunds/abouthedgefunds.asp).

higher than the monthly mean returns of the market indices except AA EH Asia ex Japan Index whereas the average standard deviation of monthly returns of the 70 Asian hedge funds is larger than the standard deviations of the market indices except MSAUCPI, inferring that hedge funds, in general, produce higher return but generate higher risk.

The means and standard deviations vary widely across Asian hedge funds. For example, AHF47 possesses the largest monthly mean return (0.03648) and the largest standard deviation (0.1941) among the 70 hedge funds and the five market indices while both AHF18 and AHF39 exhibit the lowest monthly mean returns (-0.0069) and smallest standard deviation (0.00787) respectively. Interestingly, using the MV criterion, we have found a fund, AHF47, possessing the largest mean that does not dominate any other fund, including AHF18 and AHF39. Thus, we conclude that, using the MV criterion, a fund with the largest mean return may not be a good investment choice. On the other hand, AHF01 and AHF39 are found to have significant higher means and smaller standard deviations (not significant) than AHF18. Therefore, both AHF01 and AHF39 dominate AHF18 by the MV criterion.

Insert Tables 1 and 2, Figures 1 and 2 here

Next, we investigate the CAPM measures for all indices and funds.[11] From Table 1, AHF01 exhibits the largest Sharpe ratio (0.83995) while AHF18 has the lowest (-0.2948). Furthermore, AHF39 possesses the highest Treynor (0.7199) while AHF47 obtains the highest Jensen (0.0369) measures. A summary of dominance results among the 4 most outstanding Asian hedge funds and the 5 indices measured by the MV criterion and all the CAPM statistics are presented in Table 2.[12] From the table, we find that sometimes a fund dominates another fund by a CAPM statistic but the dominance relation can be reverse if measured by other CAPM statistic(s). For example, AHF39 dominates AHF01 by Treynor index whereas AHF01 dominates AHF39 by both Sharpe

[11] We only report the most important results in Table 1. Other results are available upon request.

[12] Refer to the note in Table 2 on how to read the table.

ratio and Jensen index. Thus, we conclude that, in general, different funds are chosen using different CAPM measures. In addition, our results show that some of the return distributions are non-normal and exhibit both negative skewness and excess kurtosis. Specifically, 19 skewness, 26 kurtosis and 27 Jarque-Bera measures are significant at the 0.05 level,[13] highlighting the non-normality feature for the returns of these hedge funds. As noted by Kat (2003) and Kooli et al. (2005), the modern portfolio theory is too simplistic to deal with hedge funds. Furthermore, Gregoriou et al. (2005) pointed out that CAPM measures will usually overestimate and miscalculate hedge funds performance. Therefore, the results drawn by both the MV and CAPM statistics can be misleading.

Nonetheless, from our analysis using the MV criterion and CAPM statistics, we observe some consistent outcomes. We find, for example, that both AHF01 (fund with the largest Sharpe ratio) and AHF39 (fund with the smallest standard deviation) dominate AHF18 (the fund with the smallest Sharpe ratio) across most of the MV and CAPM statistics. Thus, one may ask whether the fund with the largest Sharpe ratio and the fund with the smallest standard deviation are the best choices while the fund with the smallest Sharpe ratio is the worst choice. To explore this question and to examine alternative measures to choose funds, we utilize the SD approach.

4.2 Stochastic Dominance Results

DD stated that the null hypothesis of equal distribution could be rejected if any value of the test statistic, T_j ($j=1,2,3;$ see eqn (2)), is significant. In order to minimize the Type II error and to accommodate the effect of almost SD (Leshno and Levy, 2002), we follow Gasbarro et al. (2007) to use a conservative 5% cut-off point for the proportion of test statistics in statistical inference. Using a 5% cut-off point, we conclude fund Y dominates fund Z if we find at least 5% of T_j to be significantly

[13] The results are partially displayed in Table 1. Detailed results are available upon request.

negative and no portion of T_j is significantly positive. The reverse holds if the fund *Z* dominates fund *Y*.

Insert Tables 3 and 4 here

We depict in Table 3 the DD test statistics for the pair-wise comparison of the 5 market indices and the 4 most outstanding Asian hedge funds and display in Table 4 the summary of their DD dominance results. From the tables[14], we first find that in general one could not conclude that funds will always outperform indices and vice versa because there exist FSD relationships from funds to indices as well as from indices to funds. In addition, we conclude that risk averters may not always prefer investing in funds than indices and vice versa because there exist SSD relationships from funds to indices as well as from indices to funds.

Secondly, we find that in our sample period AA EH Japan Index is the most favorable index and MSAUCPI is the least favorable index as the former dominates 11 (23) other indices/funds at first (second) order but is dominated only by AHF01 at SSD whereas the latter is dominated by 21 (19) indices/funds at first (second) order but dominates only 2 indices/funds at second order. On the other hand, AHF01 is the most favorable fund as it dominates 16 (38) other indices/funds at first (second) order and is not dominated by any other index/fund. Similarly, from the tables, one could conclude that AHF39 is the second most favorable fund. The two least favorable funds are AHF47 and AHF18. The former is dominated by 63 indices/funds at second order but does not dominate any index/fund while the latter is dominated by 17 (4) indices/funds at first (second) order and dominates two other indices/funds. Between AHF47 and AHF18, though the former is dominated by more indices/funds, AHF18 is the least favorable as it gets the largest number of indices/funds dominating it at first order, this

[14] One may refer to the notes in the tables on how to read the tables.

means that investors will increase their expected wealth by selling AHF18 and longing any fund, say for example, AHF01, dominating it. However, when selling AHF47 and buying any fund dominating it could only increase one's expected utility, not expected wealth. Thus, we conclude that AHF18 is the least favorable one.

Now, we come back to our conclusion drawn using the MV criterion and CAPM statistics where we find that AHF01 and AHF39 are the most favorable funds while AHF18 is the least favorable fund. Using the SD approach, we demonstrate that AHF01 (AHF39) is the (second) most favorable fund whereas AHF18 (AHF47) is the (second) least favorable fund. This finding leads us to conjecture that the SD approach could exploit more information to decide on fund choice than its MV and CAPM counterparts. Based on this conjecture, we further investigate whether we can acquire additional information by adopting the SD approach to obtain the percentage of significant DD statistics for pairs of these funds in details, namely, AHF47 (largest mean) versus AHF18 (smallest mean), AHF39 (smallest standard deviation) versus AHF47 (largest standard deviation), AHF01 (largest Sharpe ratio) versus AHF18 (smallest Sharpe ratio), AHF01 (the most favorable fund under SD) versus AHF39 (the second most favorable fund under SD). In addition, we include the comparisons of AHF01-AHF47 and AHF39-AHF18 in our study because these comparisons exhibit FSD relations that seldom occur empirically. The results are reported in Table 5. We note that our paper is the first paper to systematically and empirically study first order stochastic domination in the literature.

Insert Table 5 here

In Table 5, we apply equation (2) with the preferable fund being the first variable (*F*) and the less preferable fund being the second variable (*G*) in the equation. If the results behave as expected, there will exist $j(j=1,2,3)$ such that there will not be any significantly positive T_j but there will exist some significantly negative T_j. For example, as investors are risk-averse, we expect the fund with the smallest standard deviation (AHF39) will be preferred to the fund with the largest standard deviation (AHF47). Thus, we place AHF39 as the first variable and AHF47 as the second variable in equation (2). The DD results displayed in Table 2 show that there are 22(11) percentage of T_1 to be significantly positive (negative), indicating that AHF39 and AHF47 do not dominate each other at first order. However, we find that all values of $T_2(T_3)$ are non-positive with 15(19) percentage of them to be significantly negative, implying AHF39 dominates AHF47 at second (third) order SD as expected.

Insert Figure 3 here

So far, all comparisons behave as expected except the pair AHF47-AHF18. As AHF47 possesses the highest mean while AHF18 attains the smallest mean and it is a common sense that all non-satiated investors prefer more to less, we expect AHF47 to be preferred to AHF18. However, their DD results shown in Table 5 reveal that all $T_2(T_3)$ are non-negative with 11(9) percentage of $T_2(T_3)$ to be significantly positive, implying that, contradict to the common belief, the fund, AHF18, with the smallest mean dominates the fund, AHF47, with the largest mean at second (third) order SD. Hence, we confirm that risk averters and risk-averse investors with DARA who make portfolio choice on the basis of expected-utility maximization will unambiguously prefer AHF18 to AHF47 to maximize their expected utilities.

We recall that the MV and CAPM criteria show that AHF18 does not dominate AHF47 whereas AHF47 dominates AHF18 by Sharpe Ratio, Jensen index and Treynor index. As AHF47 possesses an insignificantly larger mean but significantly larger standard deviation than AHF18, one should not be surprised that our SD results reveal that AHF18 dominates AHF47 at second and third order. This result is consistent with Markowitz (1991) that investors, especially risk-averse investors, worry more about downside risk than upside profit. In addition, together with Figure 3, the results from

Table 5 show that 9% of T_1 is significantly positive in the negative domain whereas 22% of T_1 is significantly negative in the positive domain. All these SD information implies that actually AHF47 and AHF18 do not outperform each other. AHF18 is preferable in the negative domain whereas AHF47 is preferable in the positive domain and, overall, risk averters prefer to invest in AHF18 than AHF47. All these information revealed by utilizing SD could not be obtained by adopting the MV or CAPM counterparts.

We note that most of the SD comparisons for assets in the literature behave as in the above comparison: one asset dominates another asset at SSD or TSD (see for example, Seyhun, 1993). Applying the DD technique, we could obtain more information than the usual SD comparison as we state in the above example: one asset dominates another asset on the downside while the reverse dominance relationship can be found on the upside. This finding is in line with the direction of research in Post and Levy (2005) who investigate the behaviors of investors in bull and bear markets..

4.3 FSD Results and Discussions

We next explore the FSD relationship in our empirical findings. We find three FSD relationships: AHF01-AHF18, AHF01-AHF39 and AHF39-AHF18. For illustration, we only discuss AHF01-AHF18 and AHF01-AHF39 in details. [15] The first pair is interesting as we compare the fund with the largest Sharpe ratio (AHF01) versus the fund with the smallest Sharpe ratio. The second is also interesting as AHF01 is the most preferable fund and AHF39 is the second most preferable fund under SD in our study and thus one may be surprised that the former first-order stochastically dominates the latter.

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[15] We skip the discussion of AHF39-AHF18 as it is similar to that of AHF01-AHF18.

Insert Figures 4 and 5 here

Table 5 shows that, for AHF01-AHF18, none of T_1 is significantly positive with 21% of it to be significantly negative. Similarly, the table displays that for AHF01-AHF39, none of T_1 is significantly positive with 27% of it to be significantly negative. These results imply that AHF01 stochastically dominates both AHF18 and AHF39 at first order and thus investors will increase their expected wealth if they shift their investment from AHF18 and/or AHF39 to AHF01.

Recently, using the same dataset, Lee et al. (2006) found that some of the Asian hedge funds provide upside capture, downside protection, low volatility in down markets and high volatility in up-markets. Our findings, when comparing the CDF of AHF01 with that of AHF18 or AHF39, first support the findings of Lee et al. that AHF01 possesses lower volatility in down markets (and thus provides downside protection)[16] and possesses high volatility in up-markets (and thus provides upside capture)[17]. In addition to standard information (such as non-satiated investors will attain higher expected wealth by investing in AHF01) obtained by the SD approach. Using SD, we can provide additional to investors. For example, it is shown in Figure 5, that AHF01 possesses higher volatility on return from 0.02 to 0.04 whereas AHF39 has zero probability to obtain return greater 0.02. Thus, we claim that SD approach is more informative than the approach used by Lee et al.

Many studies, for example, Jarrow (1986) and Falk and Levy (1989) claim that if FSD exists, under certain conditions arbitrage opportunity exist and investors will

[16] It is because CDF of AHF01 lies below that of AHF18 and AHF39 statistically in the negative domain and thus AHF01 possesses smaller probability on the downside.

[17] It is because probability on the upside is equal to one minus probability on the downside and because CDF of AHF01 lies below that of AHF18 and AHF39 statistically. One may draw PDFs of these funds to reveal a clear picture for the issue.

increase their wealth and expected utilities if they shift from holding the dominated hedge fund to the dominant one. In this paper, we claim that if FSD exists statistically, arbitrage opportunity may not exist but investors could increase their expected wealth as well as their expected utilities if they shift from holding the dominated hedge fund to the dominant one. We explain our claim by these examples. Refer to Figure 4 (5), the two CDFs do cross and thus the CDF of the dominant fund does not totally lie below that of the dominated one. Thus, the values of T_1 are not totally non-positive in both figures: there is a positive portion of T_1 in the positive (negative) domain in Figure 4 (5), though these positive values are not significant. This shows that AHF18 (AHF39) does dominate AHF01 in this small portion of the positive (negative) domain or in a small part of bull run (bear market) though this domination is not statistically significant. In other words, AHF01 dominates both AHF18 and AHF39 statistically but not mathematically. Hence, arbitrage opportunity may not exist but investors can still increase their expected wealth as well as their expected utilities but not their wealth if they shift their investment from AHF18 and/or AHF39 to AHF01. In addition, even if one fund dominates another fund at first order mathematically, we claim that arbitrage opportunity may not exist also as arbitrage opportunity in FSD exists only if the market is 'complete'. If the market is not 'complete', even FSD exists, investors may not be able to exploit any arbitrage opportunity there.[18]

In addition, if the test detect the first-order dominance of a particular fund over another but the dominance does not last for a long period, these results cannot be used to reject market efficiency or market rationality.[19] In general, the first-order dominance

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[18] See Jarrow (1986), Falk and Levy (1989) and Wong and Chan (2007) for more discussions. For example, Jarrow (1986) discovered the existence of the arbitrage opportunities by SD rules. He defined a 'complete' market as 'an economy where all contingent claims on the primary assets trade.' His Arbitrage versus SD theorem says that when the market is complete, X stochastically dominates Y in the sense of FSD if and only if there is an arbitrage opportunity between X and Y.

[19] See Falk and Levy (1989), Bernard and Seyhun (1997) and Larsen and Resnick (1999) for more

should not last for a long period of time because market forces cause adjustment to a condition of no FSD if the market is rational and efficient. For example, if fund A dominates fund B at FSD, then all investors would buy fund A and sell fund B. This will continue, driving up the price of fund A relative to fund B, until the market price of fund A relative to fund B is high enough to make the marginal investor indifferent between A and B. In this situation, we infer that the market is still efficient and rational. In the conventional theories of market efficiency, if one is able to earn an abnormal return for a considerable length of time, the market is considered inefficient. If new information is either quickly made public or anticipated, the opportunity to use the new information to earn an abnormal return is of limited value. On the other hand, in the situation that the first-order dominance holds for a long time and all investors increase their expected wealth by switching their asset choice, we claim that the market is neither efficient nor rational. Another possibility for the existence of FSD to be held for a long period is that investors do no realize such dominance exists. It would be interesting to find out if FSD relationships among some funds would disappear over time. If it does not, then it would be considered a financial anomaly.[20]

5. CONCLUSION

Hedge funds differ from traditional investments in many respects including benchmarks, investment processes, fees, and regulatory environment. With its absolute return strategies and non-normality returns distribution, additional investor skill is required to evaluate the quality of hedge funds and how a hedge fund fits into an investor's portfolio. Consistent with other studies, we find that sometimes the traditional MV criterion and CAPM statistics are ambiguous in their evaluation of the Asian hedge

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discussions.

[20] We note that there are some financial anomalies do not disappear after discovered. For example, Jegadeesh and Titman (1993) first documented the momentum profit in stock markets that for longer holding period former winners are still winners and former losers are still losers. After many years, many studies, for example, Chan et al (2000) still found momentum profits empirically.

funds some of the time. At other times, though some of MV and CAPM measures can identify the dominant funds, they fail to provide detailed information of the dominance relationship nor on the preferences of investors.

This paper introduces a powerful SD test to present a more complete picture for hedge fund performance appraisal and to draw inference on the preference of investors on the funds. The SD approach that is basically free of assumption is used to investigate the characteristics of the entire distribution of returns and test whether rational investors benefit from any hedge fund to maximize their expected utilities and/or expected wealth. An advantage of this approach is that it alleviates the problems that can arise if hedge fund returns are non-normally distributed. Our approach also allows for a meaningful economic interpretation of the results. Based on a sample of the 70 individual Asian hedge funds from the EurekaHedge database, we find the existence of first-order SD relationship among some hedge funds in the entire sample period; suggesting that all non-satiated investors could increase their expected wealth as well as their expected utilities by investing in the Asian hedge funds to explore these opportunities by shifting their investments from the dominated funds to the dominant funds. We also find the existence of second-order SD relationship among other funds/indices; indicating that the non-satiated and risk-averse investors would maximize their expected utilities, but not their expected wealth by switching from the SSD dominated hedge funds to their corresponding SSD dominant ones. In addition, by applying the DD technique, we also discover that in most SD relationships, one fund dominates another fund in the negative domain while the reverse dominance relationship can be found in the positive domain. Beside, the normality assumption in the traditional measures, the difference may also come from the traditional measures definition of an abnormal return as an excess return adjusted to some risk measures, while the SD tests employ the whole distribution of returns. The SD measure is an alternative that is superior to the traditional measures to help investors and fund managers in managing their investment portfolios.

We note that while some hedge funds are dominated by others, other issues may need to be considered before implementing the SD methodology in the selection of hedge funds. One issue is that Asian hedge funds may have different redemption timing, ranging from daily to once a year in rare cases. Hence, investors may prefer funds with high redemption frequency. We also note that while AHF01 dominates AHF47, investors can only redeem AHF01 quarterly, while the redemption timing for AFH47 is once a month. Secondly, entry and exit into hedge funds can be costly. These include search and assessment costs considerable due diligence is often advised for hedge fund investors. Further, a “hidden” transaction cost may arise in the way hedge fund managers are rewarded using a performance related fee. Lee et al. (2004) showed that this fee structure can penalize investors who transact frequently due to the free-rider and claw-back problems.

Some authors propose using higher order (higher than three) SD in empirical application. For example, Vinod (2004) recommended employing fourth order SD to choose investment prospects amongst 1281 mutual funds. We, however, would like to note that the first three orders are the most commonly-used orders in empirical work on SD, regardless whether the analyses are simple or complicated. We would also like to note that a hierarchy exists in SD relationships whereby findings of the first-order SD implies the second-order SD which in turn implies the third-order SD and the fourth order SD and so on (Levy 1992, 1998). We thus stopped at third order in this paper. In addition, we note that Post and Versijp (2007) have developed a new SD test for multiple comparisons. The advantage of this approach is that they could make multiple SD comparisons while we ranked the funds pair-wise. As we explore pair-wise comparison in the domination, we do not apply their test in this study.

Lastly, we find results that are consistent with Kat (2003), Kooli et al. (2005), Gregoriou et al. (2005) and many others who claim that if the normality assumption fails, the results drawn using the MV criterion and CAPM statistics can be misleading. We point out that unlike the SD approach that is consistent with utility maximisation the dominance findings using the MV and CAPM measures may only be consistent with utility maximization, if the assets returns are not normally distributed, under very specific conditions. For example, Meyer (1987), Wong (2007) and Wong and Ma (2007) show that that if the returns of two assets follow the same location-scale family, then a MV domination could infer preferences by risk averters on the dominant fund to the dominated one. Furthermore, if all the regularity conditions are satisfied (for example, assets follow normality assumption), the MV and CAPM measures be consistent if asset returns possess second order SD preference characteristic. However, even if all the regularity conditions are satisfied, the MV and CAPM measures cannot identify the situations in which one fund dominates another one at first or third order SD. Thus, the SD approach allows better assessments for assets, regardless whether whose returns are normally or non-normally distributed.

We conclude that the stochastic dominance approach is more appropriate as a filter in the hedge fund selection process. Compared with the traditional approaches, the SD approach is more informative, providing greater insights and hence, allowing for better comparison in the performance and risk inherent in a hedge fund's track record relative to that of another.

Table 1: Summary Statistics of the Asian Hedge Funds and the Five Market Indices

	Mean	Std Dev	Sharpe Ratio	Skewness	Kurtosis	JB
AA EH Asia ex Japan Index (IX1)	0.01074	0.02474	0.3446	-0.1268	-0.6269	1.1437
AA EH Japan Index (IX2)	0.00779	0.01753	0.3179	0.8404*	1.2776	11.1446**
AA EH Index (IX3)	0.00839	0.01692	0.3647	-0.1265	-0.5447	0.9019
MSAUCPI (IX4)	-0.00259	0.04950	-0.0970	-0.0782	-1.0969	3.0693
S&P 500 (IX5)	-0.00211	0.04708	-0.0917	-0.1031	-0.2931	0.3213
Average (Hedge Funds)	0.00913	0.04784	0.1830	0.2232	1.9470**	41.3997**
Maximum (Hedge Funds)	0.03648	0.19413	0.8399	3.0663**	16.4066**	766.96**
Minimum (Hedge Funds)	-0.00690	0.00787	-0.2948	-1.6243**	-1.0969	0.0718
AHF01 (ADM Galleus Fund)	0.01267	0.01245	**0.8399**	-0.1083	-0.4376	0.5961
AHF18 (Furinkazan Fund USD)	**-0.00690**	0.03092	**-0.2948**	-1.5567**	7.8761**	179.32**
AHF39 (LIM Asia Arbitrage Fund)	0.00601	**0.00787**	0.4824	-0.4813	0.1959	2.4124
AHF47 (Pacific-Asset Alpha Fund)	**0.03648**	**0.19413**	0.1765	1.2334**	1.2206	18.9381**

Note: AHF01, AHF18, AHF39 and AHF47 are the 'most outstanding funds' in which AHF47 possesses the largest monthly mean return (0.03648) and the largest standard deviation (0.1941); AHF18 exhibits the lowest monthly mean return and the smallest Sharpe ratio (-0.2948); AHF39 exhibits the smallest standard deviation (0.00787); AHF01 exhibits the largest Sharpe ratio (0.83995); AHF39 possesses the highest Treynor (0.7199) and AHF47 obtains the highest Jensen (0.0369) measures. Results in bold are extreme values.

* $p < 0.05$, $^{**}p < 0.01$.

Table 2: Pair-wise Comparison among the Asian Hedge Funds by the MV and CAPM Measures

	IX1	IX2	IX3	IX4	IX5	AHF01	AHF18	AHF39	AHF47
IX1		S,J	J	S,T,J,M	S,T,J,M	J	S,J,M	J	S
IX2	T		T	S,T,J,M	S,T,J,M		S,T,J,M	J	S
IX3	S,T	S,J,M		S,T,J,M	S,T,J,M		S,J,M	J	S
IX4							S,J		
IX5				S,T,J,M			S,J		
AHF01	M	M	M	M	M		S,T,M	S,J	S,T
AHF18						N		N	N
AHF39				M	M	T	S,T,J,M		S,T
AHF47						J	S,T,J	J	

M, S, T and J indicate dominance by MV criterion, Sharpe ratio, Treynor index, and Jensen index respectively. N denotes no dominance by MV, Sharpe ratio, Treynor index and Jensen index. In the table, the rows indicate whether the fund in the leftmost column dominates any of the funds in the top row while the columns show whether the fund in the top row is being dominated by any of the funds in the leftmost column. For example, the cells in the first row AHF01 and the second column AHF18 means that AHF01 dominates AHF18 by Sharpe ratio, Treynor index and MV criterion. The five indices IX1 – IX5 and the "four most outstanding funds", AHF01, AHF18, AHF39 and AHF47, are defined in Table 1.

Table 3: Pair-wise Comparison of the Asian Hedge Funds by the Davidson-Duclos (DD) Tests

	IX1	IX2	IX3	IX4	IX5	AHF01	AHF18	AHF39	AHF47	Dominates
IX1		ND	ND	FSD	FSD	ND	SSD	ND	SSD	4
IX2	ND		ND	SSD	FSD	ND	FSD	ND	SSD	4
IX3	ND	ND		SSD	SSD	ND	FSD	ND	SSD	4
IX4	ND	ND	ND		ND	ND	ND	ND	SSD	1
IX5	ND	ND	ND	ND		ND	ND	ND	SSD	1
AHF01	FSD	SSD	ND	SSD	SSD		FSD	FSD	SSD	7
AHF18	ND	ND	ND	ND	ND	ND		ND	SSD	1
AHF39	SSD	ND	ND	SSD	SSD	ND	FSD		SSD	5
AHF47	ND	ND	ND	ND	ND	ND	ND	ND		0
Dominated by	2	1	0	5	5	0	5	1	8	

The results in this table are read based on rows-versus-column basis. For example, the cell in the first row IX1 and the forth column IX4 tells us that IX1 stochastically dominates IX4 at first-order while the cell in the second row IX2 and the first column IX1 inform readers that IX2 does not stochastically dominate IX1. Alternatively, reading along the row IX1, it can be seen that IX1 dominates 4 other indices/funds while reading down the IX1 column shows that IX1 is dominated by 2 other indices/funds. The five indices IX1 – IX5 and the "four most outstanding funds", AHF01, AHF18, AHF39 and AHF47, are defined in Table 1.

Table 4: Summary of the Davidson-Duclos (DD) Test Statistics

	Dominates			Dominated By		
Index / Fund	FSD	SSD	TOTAL	FSD	SSD	TOTAL
AA EH Asia ex Japan Index	5	19	24	2	1	3
AA EH Japan Index	11	23	34	0	1	1
AA EH Index	7	28	35	2	0	2
MSAUCPI	0	2	2	21	19	40
S&P 500	0	2	2	15	12	27
AHF47	0	0	0	0	63	63
AHF18	0	2	2	17	4	21
AHF39	1	46	47	4	0	4
AHF01	16	38	54	0	0	0

The values indicate the number of indices/funds for each index/fund dominates or the number of indices/funds that it is dominated by. Note that in the table the reported number of SSD excludes the number of FSD. As hierarchical relationship exists in SD, FSD implies SSD. Thus, the total number of SSD (inclusive of FSD) is the sum of FSD and SSD (exclusive of FSD). For example, AA EH Asia ex Japan Index dominates 5 indices/funds at FSD, dominates 19 indices/funds at SSD (excluding FSD) and thus it dominates 24 indices/funds (including both FSD and SSD) totally. On the other hand, it is dominated by 2 other indices/funds at FSD, dominated by one index/fund at SSD (excluding FSD), and thus it dominated by 3 indices/funds (including both FSD and SSD) totally.

Table 5: Results of Davidson-Duclos (DD) Test for Risk Averters

Sample	FSD		SSD		TSD	
	$\%T_1>0$	$\%T_1<0$	$\%T_2>0$	$\%T_2<0$	$\%T_3>0$	$\%T_3<0$
AHF47 - AHF18	9	22	**11**	**0**	**9**	**0**
AHF39 - AHF47	22	11	**0**	**15**	**0**	**19**
AHF39 - AHF18	**0**	**17**	**0**	**27**	**0**	**5**
AHF01 - AHF18	**0**	**21**	**0**	**32**	**0**	**12**
AHF01 – AHF39	**0**	**27**	**0**	**27**	**0**	**0**
AHF01 – AHF47	**21**	**12**	**0**	**16**	**0**	**22**

Note: DD test statistics are computed over a grid of 100 on monthly Asian hedge fund returns. The table reports the percentage of DD statistics which is significantly negative or positive at the 5% significance level, based on the asymptotic critical value of 3.254 of the studentized maximum modulus (SMM) distribution. T_j is the Davidson and Duclos (DD) statistic for risk averters with *j =1, 2* and *3* defined in equation (2) with F to be the first fund and G to be the second fund stated in the first column. The five indices IX1 – IX5 and the "four most outstanding funds", AHF01, AHF18, AHF39 and AHF47, are defined in Table 1.

Figure 1: Means and Standard Deviations of the 70 Asian Hedge Funds

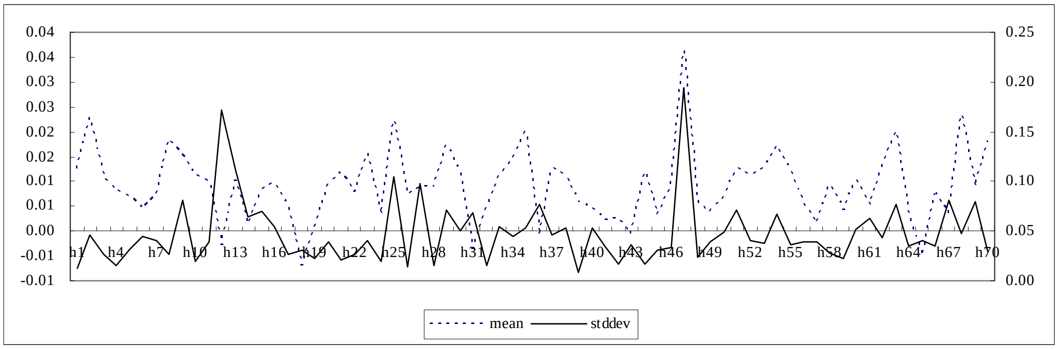
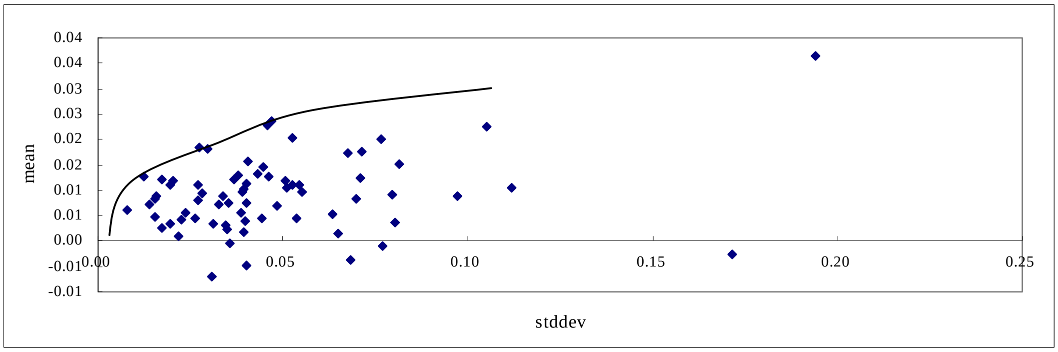
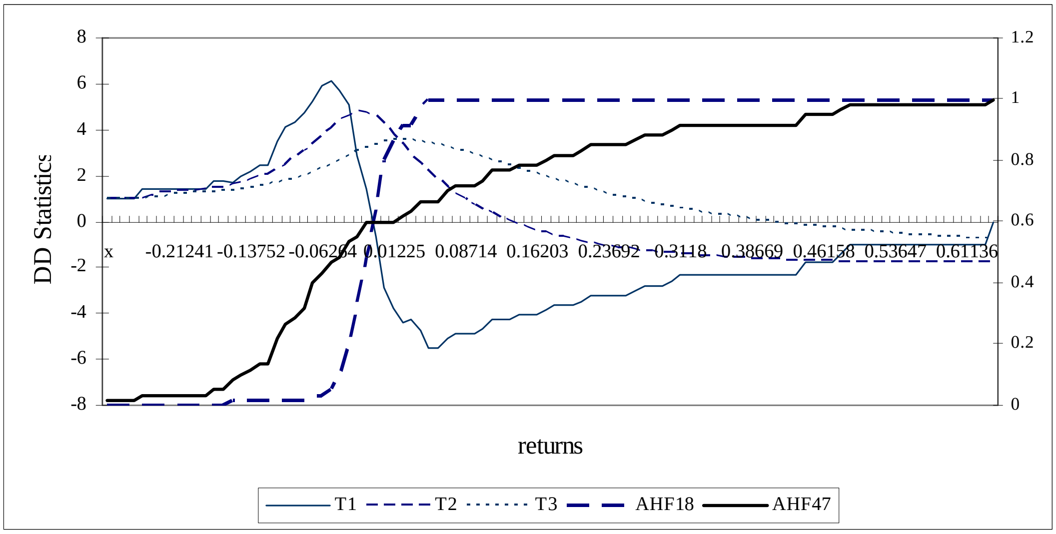


Figure 2: Plot of Risks versus Returns among the 70 Asian Hedge Funds



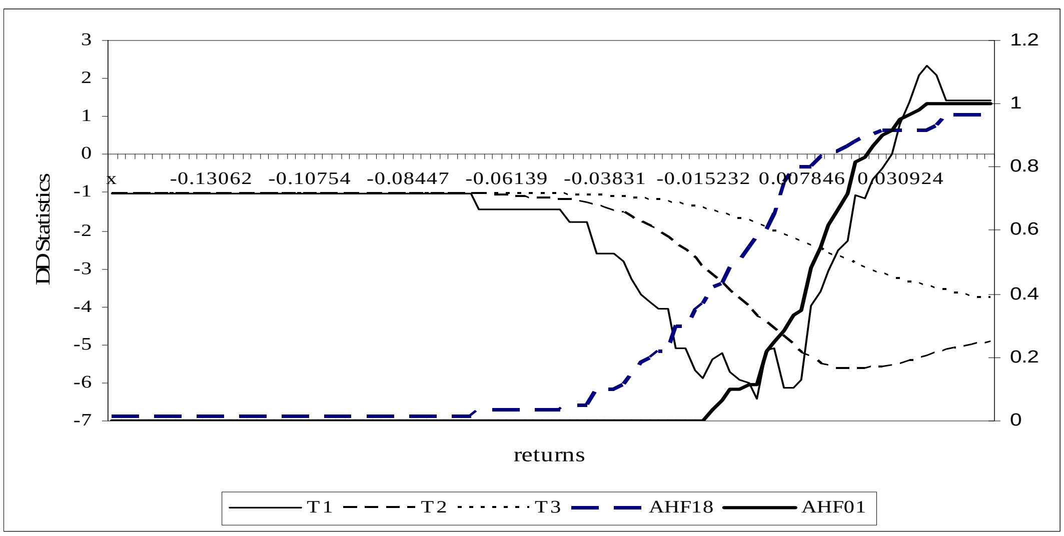
——— efficient frontier

Figure 3: DD Statistics of AHF47 - AHF18 and their Cumulative Distribution Functions



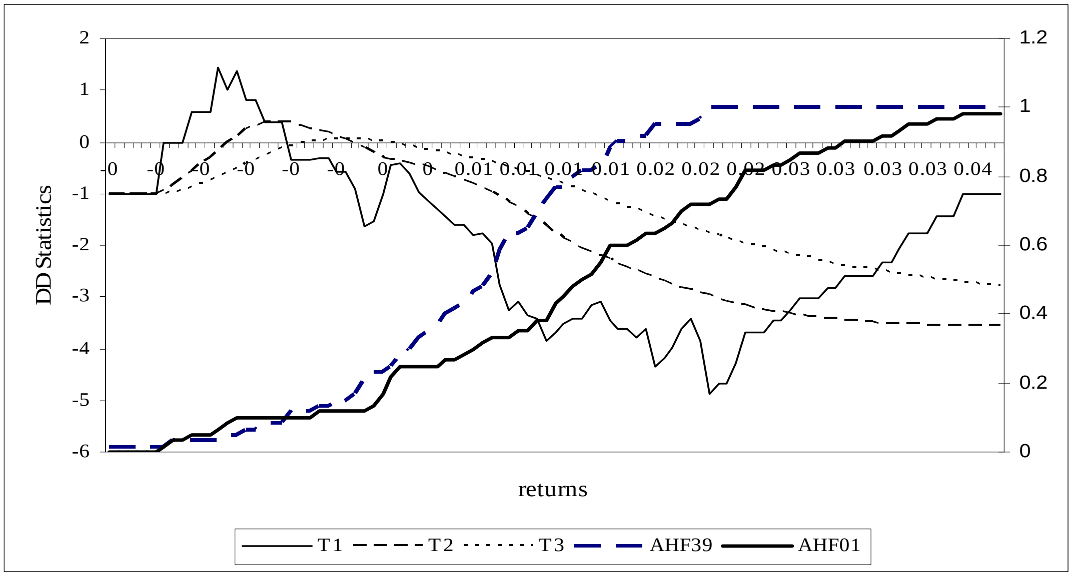
Note: T_j is the Davidson and Duclos (DD) statistic for risk averters with j =*1*, *2* and *3* defined in equation (2) with F = AHF47 and G = AHF18. AHF47 (AHF18) refers to the cumulative distribution function of AHF47 (AHF18).

Figure 4: DD Statistics of AHF01 – AHF18 and their Cumulative Distribution Functions



Note : T_j is the Davidson and Duclos (DD) statistic for risk averters with j =*1*, *2* and *3* defined in equation (2) with F = AHF01 and G = AHF18. AHF01 (AHF18) refers to the cumulative distribution function of AHF01 (AHF18).

Figure 5: DD Statistics of AHF01 – AHF39 and their Cumulative Distribution Functions



Note: T_j is the Davidson and Duclos (DD) statistic for risk averters with j =*1*, *2* and *3* defined in equation (2) with F = AHF01 and G = AHF39.. AHF01 (AHF39) refers to the cumulative distribution function of AHF01 (AHF39).

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