A Heuristic Approach to
Asian Hedge Fund Allocation

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ABSTRACT

Unlike traditional investment vehicles, hedge funds seem to produce return distributions with significantly non-normal skewness and kurtosis. Hedge fund managers that apply mean-variance optimization approach to form optimal portfolio may find this approach no longer appropriate. Moreover, utilizing a portfolio optimizer to perform portfolio allocations will cause what is known as the 'butterfly effect', that is small changes in inputs especially mean returns, can cause large changes in the optimal asset weightings (see Nawrocki, 2000). This phenomenon, couple with the illiquidity of hedge funds, may prompt hedge fund managers to consider alternative approach in portfolio allocation.

In this study, we introduce a practical heuristic approach using the semi-variance (that better accounts for non-normality in hedge fund returns) as a measure for downside risk. This heuristic approach is able to provide better forecasts, stable portfolio allocations and more diversification than the optimization approach.

We find the 'butterfly effect' in our sample of Asian hedge funds when using portfolio optimizers resulting in dramatic changes in optimal weights over time. We also find that our risk-return heuristic approach recommend portfolio with higher returns when compared with optimizers. In risk-reward comparisons against the optimizers, the heuristic approach yields the highest return to standard deviation and return to semi-deviation ratio (trade-offs).

JEL Classification: G11, G15
Keywords: hedge funds, portfolio allocation, 'butterfly effect', heuristic approach.

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1. Introduction

Hedge funds are pooled investments that are privately organised and professionally managed by investment managers and they are not widely available to the public. Due to their private nature, hedge funds are not tightly regulated and there are no specific disclosure requirements. Hence, this allows hedge funds managers to follow investment strategies that may involve the use of leverage, short-selling and derivatives trading. These investment strategies are uncommon to the traditional and regulated vehicles such as mutual funds. Over the past decade, the hedge funds industry has grown at an extremely rapid rate. In 1990, it was estimated that the total fund value was about US$20 billion. By December 2004, the number of hedge funds has reached 7000 with an estimated value of US$830 billion. One reason for the rapid growth of the hedge funds industry has been the increased interest shown by high net worth investors as well as institutional investors.

Unlike traditional investment vehicles, hedge funds seem to produce return distributions with significantly non-normal skewness and kurtosis. Hedge fund managers that apply mean-variance optimization approach to form optimal portfolio may find this approach is no longer appropriate. Moreover, utilizing a portfolio optimizer to perform portfolio allocations will cause what is known as the ‘butterfly effect’, that is the optimal weights are sensitive to small changes in the input parameters viz., the mean returns (see Nawrocki, 2000). This phenomenon, couple with the illiquidity of hedge funds, may prompt hedge fund managers to consider alternative approach in portfolio allocation.

In this paper, we introduce a practical heuristic approach using the semi-variance (that better accounts for non-normality in hedge fund returns) as a measure for downside risk. This heuristic approach is able to provide better forecasts, stable portfolio allocations and more diversification than the optimization approach.

We organize our paper as follows: In Section 2 of this paper we present an overview of the current literature. Section 3 describes the risk measures and the methodology to generate optimal hedge fund portfolio. Specifically, we compare the optimization approach to a practical heuristic approach. The data employed are described and empirical results are presented in Section 4. Section 5 concludes.

2. Literature Review

Over the last decade, extensive academic research work had been carried out to question the integrity and persistence of hedge fund returns. In those studies, some authors advocate the persistence of hedge fund returns (for examples, Agarwal and Naik [1999, 2000], Fung and Hsieh [1997], Schneeweis [1998]) while others argue that the impressive risk-adjusted returns achieved by hedge funds in the 90s should be viewed with scepticism because of risk measurement biases. Research carried out by Asness et, al. (2001) and Getmansky et al. (2004) have cast doubt over the integrity of standard measures of hedge fund betas and alpha. Barry (2002) argued that the lack of integrity could be attributed to stale pricing or return smoothing by hedge funds.

To both academics and practitioners, one pressing issue requiring a satisfactory solution is the portfolio allocation to hedge funds, that includes how much to allocate to hedge funds as part of investors' existing portfolios as well as the selection of hedge funds to form a fund of hedge funds. Since the seminal work of Markowitz

(1952), the standard deviation has long been used as the “standard” measure for risk. The Markowitz model is based on the assumption that investors’ utility curves are a function of expected return and standard deviation of return only. Is the Markowitz model still valid when investors include hedge funds in their portfolio? In their study, Brooks and Kat (2002) found that hedge fund index returns are not normally distributed. Many of the hedge fund indices exhibit relatively negative skewness and high kurtosis. They document that investors are effectively receiving a better mean and a lower variance in return for more negative skewness and higher kurtosis. Hence, funds that exhibit low variance may indeed be more ‘risky’ where significant losses are more likely.

Several studies have attempted to explain why hedge fund returns are non-normal. Agarwal and Naik, (2004), Fung and Hsieh (2001) explain that option-like strategies implemented by hedge funds may account for the non-normality effect. They employ a dynamic asset class factor model combining option-based strategies and buy-and-hold strategies and find that the option-based factors significantly explain hedge fund returns. In a more recent study, Demaray and Luccioni (2003) employ a multi-linear regression model coupled with option-like functions to capture the non-linearity in returns. They find that this approach enhanced the predictive power of the regression and also captured the non-linearity associated with hedge fund returns.

In the literature to date, most academic researchers agree that traditional mean-variance approach cannot capture many of the risk exposures of hedge fund investments. The mean-variance approach, however, is still used by practitioners (see Amenc et. al., [2004]). In recent years, academic researchers have proposed alternative risk-measures (like VAR, downside risk, asymmetric volatility, semi-deviation, extreme value analysis etc.) to capture the risk exposure of hedge fund returns. We note that while alternative risk measures are useful in ranking hedge funds. However, the portfolio allocation problem (i.e., which funds and the weighting in each), like those faced by fund of hedge fund managers remains unresolved.

In a recent study by Cremers et. al (2005), they find that mean-variance optimization is not particular effective for identifying optimal hedge fund allocations if preferences are bilinear or S-shaped. While Nawrocki (2000) argues that managers that employ portfolio optimizers to perform portfolio allocations will experience what is known as the 'butterfly effect', that is a small change to an input works its way through the system of equations and results in a large change in allocations[1]. In other words, a small change in the market will result in large changes (sometimes negative) in the portfolio returns. To overcome this, he proposed an alternative approach known as portfolio heuristic approach. A portfolio heuristic is a solution algorithm used to determine 'an approximately good' solution given the same set of information inputs. Although a heuristic does not provide an optimal solution (unlike portfolio optimizers) it does provide a reasonably good one. The main advantage of heuristic approach is that it is cheaper, faster to use than an optimizer, and it is less sensitive to the 'butterfly effect' (Nawrocki, 2000).

3. Methodology

The problem of portfolio allocation is one of the crucial functions in funds management and has received the attention of academics over the last half century. Rachev, Menn and Fabozzi (2005) propose two main approaches to the portfolio

[1] See In his paper, Nawrocki (2000) also outlines the statistical problems with optimizers.

allocation. The first approach is based on utility theory which offers a rigorous mathematical optimization to the portfolio allocation problem. This approach is not popular with asset managers as it is often difficult to implement. This is because both the utility function and the distribution assumption are required for the utility maximization approach before deciding on the investment strategy. The other approach is the risk-reward analysis. In this approach, a portfolio choice is made with respect to two criteria: the expected portfolio return and portfolio risk. A portfolio is preferred to another if it has a higher expected return and lower risk.

Following Rachev, Menn and Fabozzi (2005)'s proposition and for comparison purposes, we evaluate both the optimization and heuristic approach to form portfolio of hedge funds. Our heuristic approach is a practical application using the risk-reward trade-off approach.[2]

In comparison of the investment performance between the optimizer and the heuristic approach, we use the return to standard deviation ratio (or Sharpe ratio) and return to standard semi-deviation ratio as our risk-reward ratios[3]. The Sharpe ratio is based on the mean-variance approach which is theoretically derived using utility maximization. While the return to standard semi-deviation ratio which takes into account of asset returns distributions that exhibit fat tails and skewness, provides a better risk-reward measures when the return distribution is non-normal.

We approach the portfolio allocation problem initially via the utility maximization approach based on mean-variance and mean-semi-deviation. The objective of analysis is two-fold. First, to examine whether any differences arise in portfolio formation (ie

[2] Research on the relationship between the two approaches is still on-going. (See Gasbarro,Wong and Zumwalt (2007) and Ogryyczak and Ruszczynski (2001).)
[3] There are various other risk-reward ratios that take into account of non-normal return distribution such as the MiniMax ratio, Sortino-Satchell ratio, and the Rachev Generalized ratio.

the concentration of hedge funds and weights) for the different optimizers where some return distributions of hedge funds display skewness and kurtosis. Second, to examine the extent of the ‘butterfly effect’ for each optimizer caused by a small change in input parameters. This is important as hedge fund investments are not liquid, with most funds allowing redemption once a month and a small number only once a quarter.

We then employ a practical risk-reward heuristic approach (similar to Nawrocki (2000)’s heuristic approach) using the semi-variance as a measure for downside risk. We show that this heuristic approach provides a better investment performance than the optimization approach over one-year investment horizon. In this approach we evaluate the hedge funds portfolio formation based on the full hedge funds as well as hedge funds whose return distributions exhibit negative skewness only (ie. $\frac{SV^-}{SV^+} > 1$). The reason to include the latter as part of the evaluation is to examine whether investors are effectively receiving a better mean and a lower variance in return for more negatively skewed hedge funds (see Brook and Kat 2002).

For completeness, we describe our risk measures, portfolio optimization and heuristic approach in the following sub-sections.

3.1 Risk Measures

In our analysis, we include variance and semi-variance as risk measures in our optimization approach.

Variance and volatility (standard deviation)

A variance is a statistical measure of the average squared deviation from the mean return and the standard deviation of return which is the square root of variance is the most traditional statistical measure for risk. It corresponds to the dispersion of the return around the mean-return. The mean and variance return can be summarized as follows:

$$Mean = E(R) = \frac{1}{N}\left(\sum_{i=1}^{N} R_i\right)$$

$$S\tan dard\ \ Deviation = \left[\frac{1}{N-1}\sum_{i=1}^{N} R_i - \bar{R})^2\right]^{1/2}$$

Where R is the return of the risky asset

Semi-variance and semi-deviation

This risk measure was originally discussed by Markowitz (1959). Investors are primarily concerned with downside risk and not so of the upside volatility. Lhabitant (2004) cited two reasons why investors are interested in minimizing downside risk: (i) only downside risk or safety first is relevant to an investor, (ii) security return distribution may not be normally distributed, so the variance is no longer a good measure of risk. Hence a downside risk measures by semi-variance would help investors to make proper decisions when faced with non-normal security return distribution.

The calculation of this mean-semi-variance is similar to the computation of mean-variance. The difference between each return (R_i) and the mean return /target return ($\bar{R}$) is computed from a sample of returns. The differences are then squared and average. This gives the downside variance and by taking the square root yields the downside risk.

Mathematically the downside risk can be represented as follows:

$$Downside \ \ \mathrm{var} iance = \frac{1}{N}\sum[\max(0, \bar{R} - R_i)]^2$$

$$Downside \ \ risk = [downside \ \ \mathrm{var} iance]^{0.5}$$

Where $\bar{R}$ is the mean return.

3.2 Portfolio Optimization and Heuristic Algorithms

<u>Optimization algorithm</u>

To determine the optimal allocation weights in the mean-variance optimizer, the following optimization equation is used:

$$\text{Minimize} \quad V = \frac{1}{N}\sum(R_p - \overline{R}_p)^2$$

$$\text{Subject to} \quad \sum w_i = 1, \quad 0 \le w_i \le 1$$

Where V is the portfolio variance, $\bar{R}_p$ is the mean portfolio return, R_p is portfolio return and w_i is the weight. The optimal portfolios are those that yield the highest expected return for a given level of risk (or standard deviation).

While to determine the optimal allocation weights in the semi-variance optimizer, the following optimization equation is used:

$$\text{Min} \qquad SV^- = \frac{1}{N}\sum[\max(0, \bar{R}_p - R_p)]^2$$

Subject to $\sum w_i = 1$

$0 \le w_i \le 1$

Where SV^- is the downside portfolio semi-variance.

Heuristic algorithm

We compute the portfolio allocation based on the heuristic algorithm as follows: First, we specify the number of hedge funds (let's say 10 funds) that will be included in the portfolio. Next, the return to standard semi-deviation ratio is computed for each hedge fund using the following formula:

$$R_{hf} / SSD \ ratio = (R_{hf} - R_{TB}) / \sqrt{SV^-}$$

where R_{hf} is the hedge fund return, R_{TB} is the Treasury bill return, SV^- is the downside semi-variance and *SSD* is the standard semi-deviation.

In our analysis, we assume that investor's objective is to avoid losing money hence R_{TB} (the Treasury bill return) is zero.

The funds are then ranked from the highest $R_{hf} / SSD \ ratio$ to the lowest ratio value. A priori, if we decide to have 10 funds in our portfolio, then the top 10 funds are selected based on their $R_{hf} / SSD \ ratio$.

The portfolio weights are determined by dividing each fund's $R_{hf} / SSD \ ratio$ by the sum of $R_{hf} / SSD \ ratio$ of the 10 funds.

Our heuristic approach attempts to improve on mean-variance and mean-semi-variance optimization by providing a ‘better’ solution that overcomes the pitfalls like the ‘butterfly effect’.

4. Data Description and Analysis

We focus on a relatively new, but high potential Asian hedge fund industry. While hedge funds are well established in the United States and Europe, hedge funds in Asia are growing at a very fast pace from a much later start. According to the Bank of Bermuda, there were 30 hedge funds established in Asia (including those in Japan and Australia) in year 2000. By 2003, the number of hedge funds has reached 90 with an estimated value of over US$15 billion. It is expected that hedge fund investments in Asia will continue to grow. There are several factors supporting this view. First, Asian hedge funds currently account for a tiny slice of the global hedge fund pie and a mere trickle of the total financial wealth of high net worth individuals in Asia. Second, the growth in Asian hedge funds requires a better understanding of their performance and risk, specifically the impact when such funds are included in the investors’ portfolios.

In our analysis, we only included funds that have completed five years of data from January 2000 to December 2004. As a result, 70 Asian hedge funds are included in the sample. These hedge funds are sourced from Eureka Hedge. Of the hedge funds included in the Asia Hedge Fund Directory of Eureka Hedge, 57% are domiciled in Cayman Islands, while 15% are situated in the British Virgin Islands. The estimated geographical distribution of the Asian hedge funds is shown in Exhibit 1. Most of the decision-makers of the funds are located in a number of Asian cities, with Australia, Singapore, and increasingly China being the preferred locations. Depending on their investment strategies, hedge fund managers may concentrate on one financial market, or a couple of the most liquid markets.

Exhibit 1. Geographical Distribution of Asian Hedge Funds Managers

Country	Distribution (%)
Australia	15
Hong Kong	16
Japan	9
Korea	1
Malaysia	1
Singapore	11
Thailand	1
United Kingdom	23
United States	18

Source: Eurekahedge, 31 December 2004

Exhibit 2 shows the distribution of hedge fund strategies that employed by the 70 hedge funds that have been in existence from January 2000 to December 2004. There are 42 hedge funds in the long-short equities strategy which account for 60% of the total hedge funds under study. This suggests that the long-short equities strategy is the most common strategy used by Asian hedge funds in our sample. These funds maintain a long position in equities that perceived to be undervalued and hedged these positions by selling stocks that perceived to be overvalued or neutral valued. Sometimes the hedge funds managers may employ leverage in order to enhance the expected returns.

Exhibit 2. Strategy Classification of Asian Hedge Funds Managers For period January 2000 to December 2004

Strategy Classification	Number of Hedge fund managers
Convertible Arbitrage	1
CTA	3
Distressed Debt	5
Event Driven	1
Fixed Income	2
Long/Short Equities	42
Macro	3
Multi Strategy	7
Relative Value	5
Others	1

Source: Eurekahedge, 31 December 2004

Exhibit 3 shows the hedge funds performance characteristics for period from January 2000 to December 2003. Of the 70 hedge funds, 30 (43%) are found to exhibit non-normality using the JB test at the 5% significance level. The presence of non-normality in many of the hedge funds means that the standard deviation is an unreliable measure of downside risk. Another way to measure asymmetry of the hedge funds return distribution is to compute the semi-variance ratio, SVR. If SVR ratio is greater than one, the return distribution is non-normal. Hence, the more this ratio exceeds one, the less reliable results one will obtain by implementing Markowitz mean-variance model. Last column of exhibit 3 shows that SVR ratio exceeds one in all cases where the skew measure is negative.

Exhibit 3 Hedge Fund Performance Characteristics, 2000-2003

Strategy	Hedge Fund	Mean return	Std. dev	Skew	Kurtosis	JB test	SV-	SV+	SV-/SV+
Convertible Arbitrage	HF26	0.78%	1.50%	0.569	1.286	4.56*	0.0097	0.0112	0.75
CTA	HF07	0.95%	4.43%	0.287	-0.073	0.69	0.0296	0.0323	0.84
	HF13	1.68%	12.15%	2.419	9.662	190.53*	0.062	0.103	0.37
	HF22	0.98%	2.86%	0.572	-0.131	2.58	0.018	0.0218	0.68
Distressed Debt	HF01	1.24%	1.31%	0.046	-0.662	1.04	0.009	0.009	0.951
	HF03	1.01%	2.99%	-0.614	1.387	5.53*	0.023	0.019	1.429
	HF08	1.90%	2.95%	-0.223	0.132	0.374	0.022	0.020	1.225
	HF10	1.24%	2.08%	-0.326	0.088	0.8	0.015	0.014	1.254
	HF21	1.28%	2.23%	1.155	3.572	29.09*	0.013	0.018	0.579
Event Driven	HF04	0.63%	1.52%	-0.933	2.302	14.1*	0.012	0.009	1.618
Fixed Income	HF14	0.35%	7.15%	-0.672	0.886	4.3*	0.054	0.0459	1.368
	HF48	0.52%	2.31%	2.629	10.129	213.2*	0.011	0.020	0.313
Macro	HF31	-0.36%	7.32%	0.474	0.761	22.31*	0.047	0.055	0.737
	HF47	3.95%	20.18%	1.121	0.957	10.52*	0.114	0.164	0.490
	HF54	2.51%	6.64%	0.262	0.383	0.615	0.046	0.047	0.935
Relative Value	HF28	0.92%	1.53%	-0.589	-0.027	2.65*	0.012	0.010	1.439
	HF32	0.58%	1.65%	0.129	-0.364	0.53	0.011	0.012	0.951
	HF40	0.11%	5.54%	-0.360	0.108	0.97	0.041	0.036	1.263
	HF41	0.21%	3.86%	-0.321	-0.090	0.85	0.028	0.026	1.152
	HF67	-0.01%	8.89%	1.016	8.038	108.6*	0.059	0.065	0.818
Long/short									

Equities									
	HF02	2.31%	4.92%	0.116	-0.315	0.43	0.034	0.035	0.958
	HF06	0.25%	4.75%	-0.360	1.670	4.77*	0.035	0.031	1.251
	HF09	1.77%	8.94%	2.857	13.804	363*	0.046	0.076	0.368
	HF11	1.06%	4.28%	-0.099	-0.122	0.18	0.030	0.030	1.036
	HF15	1.29%	7.62%	-0.026	-0.254	0.25	0.054	0.052	1.089
	HF18	-0.60%	3.25%	-1.918	8.338	136*	0.026	0.019	1.995
	HF19	-0.09%	2.33%	-0.577	-0.061	2.56*	0.018	0.015	1.411
	HF23	1.65%	4.13%	1.518	4.282	45.07*	0.023	0.034	0.474
	HF24	0.34%	1.85%	-0.829	2.615	15.08*	0.014	0.011	1.545
	HF25	2.91%	11.52%	0.814	0.459	5.13*	0.070	0.090	0.615
	HF29	2.35%	7.17%	0.147	-0.531	0.88	0.049	0.052	0.884
	HF33	1.13%	6.02%	0.338	2.398	9.12*	0.040	0.044	0.844
	HF34	1.35%	4.93%	0.099	0.990	1.25	0.034	0.035	0.957
	HF35	1.99%	5.48%	-0.451	1.051	2.88	0.040	0.037	1.162
	HF36	-0.13%	8.44%	-0.384	0.370	1.2	0.062	0.056	1.250
	HF37	1.50%	5.10%	0.247	2.845	12.31*	0.035	0.036	0.921
	HF38	1.12%	5.55%	0.261	-0.366	0.91	0.037	0.041	0.841
	HF42	0.08%	1.75%	0.770	5.311	47.7*	0.012	0.013	0.795
	HF43	-0.16%	3.96%	-0.930	1.184	8.25*	0.031	0.024	1.773
	HF44	1.34%	1.83%	2.086	6.664	101.5*	0.009	0.015	0.374
	HF45	0.24%	3.02%	0.571	0.289	2.48	0.019	0.023	0.723
	HF46	0.80%	3.58%	0.225	0.330	0.44	0.024	0.026	0.886
	HF49	0.17%	4.02%	-0.191	-0.683	1.35	0.029	0.027	1.153
	HF50	0.53%	5.16%	-0.380	-0.609	1.98	0.038	0.034	1.260
	HF51	1.28%	7.85%	0.364	0.463	1.16	0.053	0.057	0.844
	HF52	0.99%	4.33%	-0.071	0.052	0.05	0.030	0.030	0.996
	HF53	1.20%	4.13%	-0.292	-0.544	1.39	0.030	0.028	1.209
	HF55	1.29%	3.79%	0.924	3.747	27.47*	0.024	0.029	0.658
	HF56	0.78%	4.15%	-0.024	0.403	0.12	0.029	0.030	0.935
	HF57	0.03%	4.02%	0.512	0.843	2.77	0.026	0.030	0.794
	HF58	0.87%	2.83%	0.631	2.779	14.27*	0.018	0.021	0.727
	HF59	0.33%	2.27%	0.222	-0.811	1.82	0.015	0.017	0.828
	HF60	1.01%	5.31%	0.235	-0.281	0.69	0.035	0.039	0.815

	HF61	0.53%	6.32%	0.185	0.124	0.25	0.043	0.046	0.881
	HF62	1.17%	4.55%	0.018	0.303	0.05	0.032	0.032	0.965
	HF63	2.48%	8.07%	0.296	-0.649	1.65	0.053	0.059	0.807
	HF64	0.27%	3.83%	-0.738	5.969	59.04*	0.029	0.025	1.361
	HF65	-0.58%	4.23%	-0.902	1.349	8.48*	0.033	0.026	1.646
	HF66	0.97%	3.75%	1.733	5.246	64.7*	0.021	0.031	0.449
	HF68	2.81%	4.92%	-0.092	0.242	0.08	0.035	0.034	1.076
	HF69	0.85%	8.58%	0.169	-0.430	0.73	0.059	0.061	0.917
	HF70	1.94%	3.21%	-0.232	-0.512	1.08	0.023	0.022	1.177
Multi Strategies	HF05	0.74%	3.42%	0.439	0.045	1.46	0.023	0.025	0.796
	HF16	0.71%	5.64%	-0.009	-0.873	1.65	0.039	0.040	0.981
	HF17	0.41%	2.78%	-1.686	5.050	60.34*	0.023	0.016	2.085
	HF20	1.01%	4.26%	0.274	-0.399	1.02	0.029	0.031	0.873
	HF27	0.66%	9.94%	-0.642	0.992	4.27	0.074	0.065	1.314
	HF30	1.57%	5.44%	0.529	2.120	8.46*	0.036	0.040	0.801
	HF39	0.65%	0.77%	-0.457	0.532	1.82	0.006	0.005	1.250
Others	HF12	0.28%	17.56%	0.266	0.045	0.55	0.119	0.126	0.892

* indicates statistically significant at 5% level. SV- and SV+ are the downside and upside semi-variance measures and SV-/SV+ denotes their ratio.

4. Empirical results

Exhibit 4

The 'butterfly effect' of hedge funds allocations employing optimization approach with variance and semi-variance as risk measures

	Mean-Variance Optimizer (Weight in %)			**Mean-Semi-variance Optimizer (Weight in %)**			
Hedge Funds	Jan 2000- Dec 2003	Feb 2000- Jan 2004	Mar 2000 – Feb 2004	Hedge Funds	Jan 2000- Dec 2003	Feb 2000- Jan 2004	Mar 2000 – Feb 2004
HF01	10.31%	15.69%	12.56%	HF01	5.24%	8.43%	10.45%
HF03	1.19%	0.94%	1.20%	HF04	0.82%	0.49%	0.70%
HF09	0.07%	0.26%	1.78%	HF24	0.60%	0.14%	0.04%
HF18	3.36%	3.95%	2.46%	HF26	4.45%	5.71%	7.31%
HF20	0.42%	1.28%	-	HF32	9.33%	8.88%	9.07%
HF22	3.26%	4.37%	2.77%	HF39	69.54%	62.71%	63.92%
HF24	2.12%	1.27%	0.59%	HF42	6.66%	4.93%	5.82%
HF26	1.00%	1.88%	3.28%	HF48	3.36%	1.46%	1.03%
HF28	16.21%	16.92%	17.85%	HF28	-	7.26%	1.68%
HF30	1.20%	0.53%	2.32%				
HF32	7.13%	7.01%	7.17%				
HF33	0.96%	0.68%	-				
HF34	1.70%	1.83%	1.65%				
HF37	3.07%	2.85%	1.32%				
HF39	31.63%	26.46%	28.79%				
HF41	1.44%	1.37%	1.06%				
HF42	9.17%	8.22%	8.83%				
HF48	2.65%	1.79%	1.56%				
HF51	1.61%	1.61%	1.26%				
HF56	1.22%	1.10%	2.13%				
HF10			1.44%				
Expected mean return	0.72%	0.73%	0.75%		0.63%	0.67%	0.68
Std. dev	0.40%	0.39%	0.37%		0.52%	0.52%	0.52%

Exhibit 4 shows the 'butterfly effect' of hedge fund allocations employing the optimization approach. The implication is clear. If the optimization approach is employed to decide on the optimal investment allocation, then a small change in the input, especially mean returns will result large changes in the optimal hedge funds weightings and these optimal weights will change over time. In some cases, one needs to sell one hedge fund and buy back another hedge fund (see column 'Mar 2000- Feb 2004' of mean-variance optimizer) to optimize the portfolio allocations.

According to Kallberg and Zeimba (1984) and Adler (1987), the instability of optimal weights over time in optimization approach is the direct result of making estimation errors when used in forecasting.

Exhibit 5

Hedge Funds Allocations based on Optimization and Heuristic Approach
Based on sample period from January 2000 to December 2003

Hedge Funds	**Mean-Variance Optimizer**	**Hedge Funds**	**Mean-semi Variance Optimizer**	**Hedge Funds**	**Risk-Return Heuristic-All Funds**	**Hedge Funds**	**Risk-return Heuristic—Negatively skewed funds**
HF01	10.31%	HF01	5.24%	HF44	14.47%	HF39	17.36%
HF03	1.19%	HF04	0.82%	HF01	14.0%	HF08	13.38%
HF09	0.07%	HF24	0.60%	HF39	11.62%	HF70	12.68%
HF18	3.63%	HF26	4.45%	HF21	9.79%	HF10	12.30%
HF20	0.42%	HF32	9.33%	HF08	8.98%	HF28	12.13%
HF22	3.26%	HF39	69.54%	HF70	8.49%	HF04	8.07%
HF24	2.12%	HF42	6.66%	HF10	8.23%	HF35	7.62%
HF26	1.00%	HF48	3.36%	HF68	8.17%	HF03	6.75%
HF28	16.21%			HF26	8.14%	HF53	6.07%
HF30	1.20%			HF28	8.12%	HF24	3.64%
HF32	7.13%						
HF33	0.96%						
HF34	1.70%						
HF37	3.07%						
HF39	31.63%						
HF41	1.44%						
HF42	9.17%						
HF48	2.65%						
HF51	1.61%						
HF56	1.22%						

In exhibit 5, it is clear that in both optimizers, the optimal hedge fund portfolios are essentially formed by a few dominant hedge funds. HF39 dominates both hedge fund portfolios with over 31% of the portfolio allocation in mean-variance optimizer and over 69% of the portfolio allocation in mean-semi-variance optimizer. Other dominating funds that form the optimal hedge fund portfolio in the mean-variance optimizer are HF01 (10.31%) and HF28 (16.21%). On the other hand, the risk-return heuristic approach distributes the allocations among 10 funds with the largest allocation to HF44 of 14.47% in all funds and to HF39 of 17.36% in negatively skewed hedge funds. The allocations are smoothly distributed down to 8.12% to HF28 and 3.64% to HF24 in all hedge funds and negatively skewed funds respectively.

Exhibit 6

Historical Performance of Hedge Funds Portfolios based on Optimization and Heuristic Approach for sample period from January 2000 to December 2003

	Mean-Variance Optimizer	**Mean-Semi-variance Optimizer**	**Risk-Return Heuristic-All Funds**	**Risk-Return Heuristic- Only Negatively Skewed Funds**
Annualized return	8.99%	7.83%	17.74%	15.80%
Monthly Mean return	0.72%	0.63%	1.37%	1.23%
Standard Deviation	0.42%	0.56%	1.17%	1.36%
Std. Semi-deviation	0.77%	0.52%	1.06%	1.27%
R/SD Ratio	1.809	1.125	1.17	0.91
R/SSD Ratio	0.938	1.211	1.30	1.213

Note: R/SD ratio = (return of fund-T/B rate)/Standard deviation
R/SSD ratio = (return of funds-T/B rate)/Std. semi-deviation
In this study, we assume that investor's objective is to avoid losing money, hence T/B rate =0.

The objective of the mean-variance optimizer is to minimize the portfolio variance such that the portfolio return is optimal therefore we expect the fund portfolio variance to be lower than other approaches. In exhibit 6, the results show that the fund portfolio has the lowest standard deviation (0.42%) than the mean-semi-variance optimizer portfolio (0.56%) and risk-return heuristic portfolios (1.17% and 1.36%). Similarly, the mean-semi-variance optimizer is to minimize the portfolio semi-variance hence it also has the lowest standard semi-deviation (0.52%) than the mean-variance optimizer (0.77%) and the risk-return heuristic portfolios (1.06% and 1.27%).

Though the risk-return heuristic hedge funds portfolios are not optimal, in exhibit 6, the results show that they have higher returns, but higher standard deviation and standard semi-deviation than the two optimizers. The monthly mean returns of hedge fund portfolios are 1.37% for the all hedge fund portfolio and 1.23% for the negatively skewed hedge fund portfolio. In terms of return per unit risk which measures by R/SD and R/SSD ratios, the heuristic hedge fund portfolios (all hedge funds and negatively skewed hedge funds) have higher R/SSD ratios than the two optimizers. However, the negatively skewed fund portfolio has a lower R/SD ratio than the two optimizers, while the all hedge fund portfolio has a lower R/SD ratio than that of the mean-variance optimizer.

Exhibit 7

Holding Period Performance of Hedge Funds Portfolios based on Optimization and Heuristic Approach for period from January 2004 to December 2004

	Mean-Variance Optimizer	**Mean-Semi-variance Optimizer**	**Risk-Return Heuristic-All Funds**	**Risk-Return Heuristic- Only Negatively Skewed Funds**
Annualized return	7.19%	6.17%	11.09%	14.71%
Monthly Mean return	0.58%	0.50%	0.88%	1.15%
Standard Deviation	0.57%	0.64%	0.76%	0.86%
Std. Semi-deviation	0.61%	0.55%	0.74%	0.88%
R/SD Ratio	1.024	0.776	1.163	1.304
R/SSD Ratio	0.954	0.90	1.195	1.340

Using the holding period from January 2004 to December 2004, exhibit 7 shows the performance of hedge funds portfolios based on the optimization and heuristic approach. It is clear that the risk-return heuristic approach out-performed the two optimizers. The mean-semi-variance optimizer portfolio seems to have performed the worst with the lowest annualized portfolio return of 6.17%. In terms of risk-return performance, it has the lowest R/SD and R/SSD ratio with values 0.776 and 0.9 respectively. The mean-variance optimizer hedge fund portfolio has the second lowest return with an annualized portfolio return of 7.19%. Its risk-reward performance is relative higher than that of mean-semi-variance optimizer. The R/SD and R/SSD ratios of mean-variance optimizer are 1.024% and 0.95% respectively.

On the other hand, the risk-return heuristic has the higher returns relative to the two optimizers especially the negatively skewed hedge funds with an annualized portfolio return of 14.71%. It exhibits higher standard deviation and standard semi-deviation relative to the two optimizers but it has the highest R/SD and R/SSD ratios. The all hedge fund portfolio has R/SD and R/SSD ratio of 1.163% and 1.195% respectively. While the negatively skewed hedge fund portfolio has R/SD and R/SSD ratio of 1.304% and 1.340 % respectively. It is clear that the risk-return heuristic approach has a better forecasting performance than the optimization approach, specifically when investors select hedge funds that produce return distributions with significantly negative skewness. Our findings are consistent with Brooks and Kat's study that hedge fund index returns are not normally distributed and investors are effectively receiving a better mean and a lower variance in return for more negative skewness and higher kurtosis. Our findings also imply that practitioners who employ optimizers to form optimal portfolio that includes portfolio allocation to hedge funds need to be aware of the ‘butterfly effect’ and illiquidity of hedge funds.

5. Conclusions

The key to a successful portfolio allocation decision is to have very good estimates for risk and return. The make up of the portfolio can be determined heuristically through risk-return ratios at the general asset class level, at the mutual fund level and at the individual stock level, and running an optimizer to determine asset allocation (strategic or tactical) by itself does not add value to a portfolio. It is the selection of assets and the careful determination of risk and return measure that the managers input to the optimization or the heuristic algorithm decision that provides the value adding (Nawrocki, 2000).

In this connection, in our study we have examined the statistical properties of the 70 Asian hedge funds and showed the inappropriateness of traditional mean-variance optimizer to form optimal hedge fund portfolios. In addition, we have introduced a practical heuristic approach using the semi-variance (that better accounts for non-normality in hedge fund returns) as a measure for downside risk.

Our conclusions are as follows:

- Many Asian hedge fund return distributions are not normal and exhibit negative skewness and leptokurtosis (fat-tails).

- There is significant ‘butterfly effect’ when using the mean-variance and mean-semi-variance optimizers, viz. the optimal weights change dramatically over time for small changes in input values.
- The mean-semi-variance optimizer portfolio is the most concentrated portfolio (more than 69% of optimal weight in HF39) and performs the worst in terms of annualized return and risk-return (measures by R/SD and R/SSD ratio).
- The risk-return heuristic has the higher returns relative to the two optimizers especially the negatively skewed hedge funds with an annualized portfolio return of 14.71%. In terms of the risk-reward performance, the heuristic approach yields the highest R/SD and R/SSD ratio.
- The results suggest that the heuristic approach has better forecasting performance, provides stable portfolio allocations and allows greater diversification than optimizers.

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