

Higher Moments in Portfolio Optimization with Asian Hedge Funds

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Since the first introduction of the Polynomial Goal Programming (PGP) framework by Davies, Kat, and Lu (2004), this framework has not been discussed in any studies conducted for Asian hedge funds (AHFs) to the best of our knowledge. By employing the PGP method, this study attempts to examine if different optimal portfolios exist for AHF investors whose preferences over the four moments of a portfolio's return distribution are different. A sample of 95 AHFs with full monthly data during the period of 1st January 2000 – 15th June 2008 is selected. The omega ratio introduced by Keating and Shadwick (2002) is used to rank AHFs in the chosen sample. It is assumed that only a portfolio consisting of 15 AHFs with the highest omega ratios is in the investment interest of AHF investors. In addition, only five different distinctive groups of AHF investors who have five different sets of preferences over a portfolio's higher moments, i.e. mean, standard deviation, skewness, and kurtosis, are chosen. Results obtained from the study confirm that different optimal portfolio allocations exist for the five groups of AHF investors. The findings suggest that classifying investors into different groups based on their risk-return preferences is necessary as it will enable fund managers to tailor different sets of optimal portfolio allocations to meet individual AHF investors' specific investment objectives.

Keywords: Asian hedge funds, portfolio construction, Polynomial programming, optimal portfolio, non-normal distribution.

1. Introduction

Starting from the West back in the 1940s, the first hedge fund was introduced in the Asia Pacific region only around the early 1990s. Since then, the Asian hedge fund (AHF) industry has been growing rapidly at an estimated annual growing rate of 34%. This fast growing rate reflects the great interest that hedge fund investors have in the Asia Pacific region. However, the number of studies conducted for AHFs is very limited, especially in the area of portfolio construction. Thus, this study attempts to fill in this gap.

In this study, we attempt to answer the question of whether taking into account all the higher moments of a portfolio distribution is necessary in the case of AHFs.

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Employing a new optimization method introduced by Davies, Kat, and Lu (2004, 2009) - the polynomial goal programming (PGP) method -, the study attempts to examine if optimal portfolio allocation decisions should be made differently for AHF investors whose preferences over the four moments of a portfolio's return distribution are different. A sample of 95 AHFs with full monthly data during the period of 1st January 2000 – 15th June 2008 is selected. We employ a new performance measure named omega ratio (Keating and Shadwick, 2002) to evaluate the performance of individual AHFs in the sample. Based on each fund's computed omega ratio, only a portfolio consisting of 15 AHFs with the highest ratios is assumed to be in the investment interest of AHF investors. It is also assumed that there are five different distinctive groups of AHF investors who have five different sets of preferences over a portfolio's higher moments, i.e. mean, standard deviation, skewness, and kurtosis. Results obtained from the study confirm that the optimal portfolio allocations are different for each of the five groups of AHF investors. The findings suggest that classifying investors into different groups based on their risk-return preferences is necessary as it will enable fund managers to tailor different sets of optimal portfolio allocations to meet individual AHF investors' specific investment objectives.

The rest of the paper is organised as follows: literature review is presented in Section 2. Research methodology adopted in this study is discussed in Section 3. Findings are presented in Section 4. In the final section (Section 5), key conclusions and implications are given.

2. Literature Review

In various studies, hedge fund data is found to exhibit a non-normal distribution (see Favre, Galeano, and Gibson, 2000; Davies, Kat, and Lu, 2004; Bergh and Rensburg, 2008; Chatterjee, 2008). Particularly, Chatterjee (2008) points out four drawbacks of the Modern Portfolio Theory (MPT) in dealing with the financial world today. Under MPT, the distribution of the entire asset is considered to be normal, with stable parameters, means and standard deviations. The assumption implies that returns as random numbers are generated from the same distribution moving forward in time. However, in reality, most financial assets are seldom or never following a normal distribution mentioned by the author. Regarding to the volatility, the author do not think that it is a good measure of risk, particularly for individual assets such as shares. The author believes that volatility varies from one period to another and thus cannot be anything more than a measure of risk in a historical period. The third drawback of MPT is the past correlations between assets. The author pointed that past correlations are a product of coincidence and may not hold in the future. Although Pearson's Correlation is the commonly accepted measure of dependence, its requirement is that all the distributions of the assets need to be normally distributed, which do not often occur in the case of asset returns. Finally, the author pointed out that the concept of the "efficient frontier" is not useful in practice as it seems to be no way of predicting in advance that what asset allocations would give a portfolio that lies on the curve although empirically it has been found that efficient frontiers do exist.

Therefore, a question on the application of the Mean–Variance (MV) optimization method to the portfolio construction for hedge funds is raised. Lhabitant and Learned

(2002) study the inter-temporal evolution of diversification effects on hedge funds by using a large database of hedge funds for a period of 1990 – 2001. The authors build equally weighted portfolios of randomly selected hedge funds, and repeat the process several times and study the characteristics of the resulting 50,000 portfolios. In their first finding, diversification seems to work well in a mean variance method as the number of hedge funds in a hedge fund portfolio increases, the portfolio's volatility decreases while maintaining its average return level. In addition, downside risk statistics such as maximum monthly loss, maximum drawdown, and value at risk, are also reduced in larger-size hedge fund portfolios. However, when taking into account additional factors such as skewness and kurtosis, diversification is far from being a "free lunch". The results show that for some strategies, diversification reduces positive skewness or creates negative skewness, and increases kurtosis, implying that there is a trade-off between reward (profit) and risk (probability of loss).

Brooks and Kat (2002) investigate the drawbacks of the MV method by using this method to construct two portfolios, of which one consists of the S&P 500, the Lehman Brothers bond index, and 48 different hedge fund indices and the other one consists of only hedge fund indices. Their sample period is from January 1995 to April 2001. Short selling and restriction on the allocation of hedge funds imposed by investors are excluded from the analysis. Their results show a very high allocation to hedge funds and a marked improvement in expected returns. The results are significantly different between strategies such as risk arbitrage, long/short equity, and equity market neutral. Moreover, the allocations vary quite significantly between categories. The authors also calculated the skewness and kurtosis of the constructed optimal portfolios. Their results show that the skewness of the hedge fund index is lower than that of the portfolio to which it is added (-0.66) and the skewness of the new portfolio tends to be less attractive than that of the original portfolio comprising only stocks and bonds. Most of hedge fund indices exhibit positive excess kurtosis while stocks and bonds do not and thus kurtosis of the portfolio that includes hedge funds is higher compared to that of the portfolio that does not include hedge funds. In addition, the authors find a strong relationship between their Sharpe ratio and their skewness and kurtosis properties, implying that it is not necessary that when returns increase, skewness and kurtosis would decrease. Their overall results suggest that Mean-Variance analysis is no longer sufficient as a portfolio decision-making tool.

Many researchers attempt to find an alternative portfolio construction method that can be used for a non-normally distributed portfolio of hedge funds. One of them is the Polynomial Goal Programming (PGP) optimisation model. To the best of our knowledge, the PGP approach was first introduced by Davies, Kat, and Lu (2004, 2009). According to Davies et al. (2004, 2009), the method incorporates investor preferences concerning a return distribution with higher moments. It allows multiple competing objectives to be solved within a mean-variance-skewness-kurtosis framework, where investors' utility will be augmented by a positive first moment (the expected return), a positive third moment (skewness), and a negative fourth moment (the kurtosis). Thus, PGP is expected to be more effective than MV because of its ability to tailor different optimal portfolio allocations to investors who possess different sets of preferences over the four moments of a portfolio's return distribution.

However, taking into account of the higher moments of a return distribution has not been discussed for hedge funds in general, especially for AHFs. Thus, it would be

very interesting to examine on whether the PGP method is effective in constructing an optimal portfolio of AHFs.

3. Research Methodology

3.1 Sample and Study Period

From the Eurekahedge database, a sample of 95 AHFs with full monthly return data during the period of 1st January 2000 – 15th June 2008 is selected for this study. The top 15 performing funds of this sample are identified based on a risk adjusted performance measure - omega ratio - that was introduced by Keating and Shadwick (2002). The use of the omega ratio is believed to help overcome the possibly ambiguous results produced by the Sharpe ratio (Ackermann et al., 1999; and Do et al., 2005).

According to Keating and Shadwick (2002), the Omega ratio takes into account the entire distribution of the returns for individual hedge funds. Thus, it allows possible comparisons among hedge funds with different risk-return tradeoffs, so that no estimation of their return distributions is needed at any moment. Thus, the omega ratio is perceived to be extremely useful for alternative investments in which the return distribution is not a normal distribution.

The formula for the Omega ratio at the threshold of “r” percent is given below:

$$\Omega(r) = \frac{\int_r^b (1 - F(x)) dx}{\int_a^r F(x) dx}$$

The above Omega function for the distribution F(x) is obtained by taking all possible returns, r, between two boundaries of “a” and “b”. This function is mathematically equivalent to the distribution itself as it contains all of the information entailed. The interpretation for an Omega ratio is quite straightforward. At a given threshold of “r” percent, a hedge fund with a higher Omega ratio is preferred over a hedge fund with a lower Omega ratio. A flatter Omega curve implies a higher risk. In this study, Omega ratios for all AHFs in the sample are computed at a chosen threshold of zero percent based on the assumption that the targeted minimum return ought to be a positive return. Our study is considered to be the first study that employs the Omega ratio as a performance measure for AHFs.

3.2 Optimisation Method

Employing the polynomial goal programming (PGP) method introduced by Davies, Kat, and Lu (2004 and 2009) for a sample of AHFs for the first time in this study, multiple objective programming problems in this study are stated below:

$$\text{Maximise } Z_1 = X^T \tilde{R}_1 \quad (\text{Equation 1})$$

$$\text{Maximise } Z_3 = \frac{T}{(T-1)(T-2)} \sum \left(\frac{X^T (\tilde{R}_1 - \bar{R})}{\sqrt{X^T V X}} \right)_3 \quad (\text{Equation 2})$$

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$$\text{Minimise } Z_4 = \left\{ \frac{T(T+1)}{(T-1)(T-2)(T-3)} \sum \left(\frac{X^T(\bar{R}_i - \bar{R})}{\sqrt{X^T V X}} \right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)} \right\} \quad (\text{Equation 3})$$

$$\text{Subject to } X^T V X = A; \quad (\text{Equation 4})$$

$$x_i \geq 0; \quad (\text{Equation 5})$$

$$\sum_{i=1}^{15} x_i = 1 \quad (\text{Equation 6})$$

Where:

$X = (x_1, x_2, \dots, x_n)$, where x_i represents the percentage of wealth invested in the i^{th} AHF;

N is the number of AHFs in a portfolio;

15 is the specific number of AHFs that investors plan to invest in;

\bar{R}_i is the return of AHF i^{th} in the portfolio ($\bar{R} = \bar{R}_1, \bar{R}_2, \dots, \bar{R}_n$);

\bar{R} is the mean return of a portfolio of AHFs;

V is a positive definite $n \times n$ variance-covariance matrix V ;

T superscript denotes the transpose of the array in a matrix formula;

t is the number of observations in the time series;

Z_1 , Z_3 , and Z_4 are the formulas for portfolio mean return, skewness, and excess kurtosis, respectively;

A denotes the level of variance pre-specified in the optimization ($A = 1^2, 2^2, \dots, 10^2$);

$X^T V X$ is portfolio variance.

Combining all the objective functions in Equation (1), (2), and (3), the PGP method is re-stated as follows:

$$\text{Minimize } Z = (1 + d_1)^\alpha + (1 + d_3)^\beta + (1 - d_4)^\gamma \quad (\text{Equation 7})$$

Subject to:

$$X^T \bar{R} + d_1 = Z_1^* \quad (\text{Equation 8})$$

$$\frac{t}{(t-1)(t-2)} \sum \frac{X^T(\bar{R} - \bar{R})^3}{\sqrt{X^T V X}} + d_3 = Z_3^* \quad (\text{Equation 9})$$

$$\left\{ \frac{t(t+1)}{(t-1)(t-2)(t-3)} \sum \left(\frac{X^T(\bar{R} - \bar{R})}{\sqrt{X^T V X}} \right)^4 - \frac{3(t-1)^2}{(t-2)(t-3)} \right\} + d_4 = Z_4^* \quad (\text{Equation 10})$$

$$d_1, d_3 \geq 0 \quad (\text{Equation 11})$$

$$d_4 \leq 0 \quad (\text{Equation 12})$$

$$X^T V X = A; \quad (\text{Equation 13})$$

$$x_i \geq 0; \quad (\text{Equation 14})$$

$$\sum_{i=1}^{15} x_i = 1 \quad (\text{Equation 15})$$

Where:

$Z_1^* = \text{Max}\{Z_1 | X^T V X = A\}$ is the mean return for the optimal mean – variance portfolio with a specified variance

$$; \quad (\text{Equation 16})$$

$$Z_3^* = \text{Max}\{Z_3 | X^T V X = A\} \text{ is the skewness value of the optimal skewness - variance portfolio with a specified variance} \quad ; \quad (\text{Equation 17})$$

$$Z_4^* = \text{Min}\{Z_4 | X^T V X = A\} \text{ is the kurtosis value of the optimal kurtosis - variance portfolio with a specified variance} \quad (\text{Equation 18})$$

Z is the total deviations of a constructed portfolio's expected return, skewness, and kurtosis from the portfolio's optimal values, i.e. maximum return, maximum skewness, and minimum kurtosis.

α , β , and γ represent subjective and non-negative preferences of an AHF investor for the expected return, skewness, and kurtosis of a return distribution.

The optimal amount of investments allocated to each AHF in a portfolio is depicted by the weight vector, i.e. $X = (x_1, x_2, \dots, x_{15})$, where each weight must be positive and the total weights for the 15 AHFs equals 1.

For comparison purposes, each portfolio of AHFs will be optimized at 10 possible discrete levels of standard deviation, ranging from 1 to 10. In other words, the 10 levels of variance (A) in this study are $1^2, 2^2, \dots, 10^2$. The value of d_1 denotes the deviation of the expected return of a portfolio from its optimal value, denoted as Z_1^* (Equation 16). The value of d_2 denotes the deviation of the expected skewness of a portfolio from its optimal value, denoted as Z_3^* (Equation 17). Similarly, the value of d_4 denotes the deviation of the expected kurtosis of a portfolio from its optimal value, denoted as Z_4^* (Equation 18).

Similar to the assumption made in Davies et al (2004 and 2009), AHFs' investors are also assumed to prefer maximizing the first and third moments (mean and skewness) and minimizing the second and fourth moments (variance and kurtosis). In other words, AHFs' investors are assumed to aim for maximum expected return (mean), maximum positive skewness, minimum volatility (standard deviation), and minimum kurtosis in this study. Thus, optimal portfolios of AHFs constructed from the PGP are expected to have a lower mean return, lower skewness, and higher kurtosis than those obtained from (1) optimal mean – variance portfolios, (2) optimal skewness – variance portfolios, and (3) optimal kurtosis – variance portfolios. Thus, d_1 and d_3 represent positive deviations from Z_1^* and Z_3^* , while d_4 represents a negative deviation from Z_4^* . The goal of the Equation 7 is to minimise the total deviations (Z) of a constructed portfolio's expected return, skewness, and kurtosis from the portfolio's optimal values, i.e. maximum return, maximum skewness, and minimum kurtosis.

In this study, it is assumed that in the AHF world, there are five different groups of AHF investors with five different sets of preferences over the four moments of an AHF's return distribution (see Table 1), i.e. the first moment (mean), the second moment (standard deviation), the third moment (skewness), and the fourth moment (kurtosis).

Unlike Davies et al. (2004 and 2009)'s, in this study, four different levels of preferences are standardized at each level of standard deviation for mean, skewness, and kurtosis for each type of investors. These preferences are set as follows: 0 refers to "None", 1 refers to "Low", 2 refers to "Medium", and 3 refers to "High".

Given a choice, a risk-averse AHF investor would desire to achieve a distribution of returns with the highest mean, the highest skewness, the lowest standard deviation, and the lowest kurtosis. To reflect this reality of choice made by risk-averse investors, only two preferences over the fourth moment (kurtosis) are assumed to exist for all AHF investors, namely "None" and "Low".

Table 1: Investors' Preferences over the Four Moments of a Return Distribution for AHFs in the Study

Risk Preference	Investor#1	Investor#2	Investor#3	Investor#4	Investor#5
Mean	1	3	1	3	2
Skewness	3	1	0	2	3
Kurtosis	0	0	3	1	1

Note: 0 refers to "None", 1 refers to "Low", 2 refers to "Medium", and 3 refers to "High"

As shown in *Table 1*, Investor#1 has a preference of low mean, the highest skewness, and no kurtosis. Investor#2 prefers the highest mean, low skewness, and no kurtosis. Investor#3 prefers low mean, no skewness, and the highest kurtosis. Investor#4 prefers the highest mean, medium skewness, and low kurtosis. Investor#5 prefers medium mean, the highest skewness, and low kurtosis.

The above PGP method is carried out according to a two-step procedure. Firstly, the optimal values for Z_1^* , Z_3^* , and Z_4^* at each pre-specified level of variance are estimated by using *Equation 16*, *Equation 17*, and *Equation 18*. Then, these optimal values are substituted into the constraints as shown in *Equation 8*, *Equation 9*, and *Equation 10* in order to find the minimum value for the objective function as shown in *Equation 7*.

4. Findings

4.1 Descriptive Statistics of the Sample of 15 AHFs

As presented in *Table 2*, 15 AHFs in the sample are arranged according to a descending order based on their omega ratios. Omega ratios of the 15 AHFs are ranging from 2.09 to 5.8. These omega ratios are computed based on the entire return distributions of individual AHFs in the sample. By taking into all higher moments (mean, standard deviation, skewness, and kurtosis) of a return distribution, the omega ratio is therefore perceived to be a more accurate performance measure as compared to the Sharpe ratio. Therefore, a fund with a low Sharpe ratio may not be necessarily considered to be a bad performing fund. This can be seen from *Table 2*. Although AHF#9 has the lowest Sharpe ratio, its omega ratio is much higher as compared to other five AHFs in the sample, i.e. AHF#11, AHF#12, AHF#13,

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AHF#14, and AHF#15. The higher omega ratio of AHF#9 implies that AHF#9 has a higher probability of having positive returns to probability of having negative returns ratio as compared to those of other AHFs. This result strongly supports the similar claims made by Ackermann et al. (1999) and Do et al (2005) for their hedge fund samples.

Table 2: Descriptive Statistics of the 15 AHFs

In this table, five descriptive statistics, i.e. mean, standard deviation, skewness, and kurtosis, mean to standard deviation ratio, and omega ratio for 15 Asian hedge funds are provided.

Fund	Mean	Standard Deviation	Skewness	Kurtosis	Sharpe Ratio (R_f=0)	Omega ratio
AHF # 1	1.10	1.25	-0.35	1.14	0.88	5.80
AHF # 2	1.01	1.22	-0.39	1.25	0.83	5.38
AHF # 3	0.91	1.31	-0.50	0.63	0.69	5.00
AHF # 4	0.88	1.47	-0.85	2.26	0.60	5.00
AHF # 5	0.90	1.31	-0.51	0.56	0.69	4.67
AHF # 6	1.18	2.62	0.23	4.42	0.45	3.25
AHF # 7	1.43	3.20	-0.74	0.96	0.45	2.64
AHF # 8	1.23	2.80	-0.40	0.37	0.44	2.52
AHF # 9	0.93	3.51	-1.04	3.43	0.26	2.52
AHF # 10	2.08	5.11	-0.40	0.73	0.41	2.52
AHF # 11	1.17	3.80	-0.00	2.78	0.31	2.40
AHF # 12	2.49	7.64	1.14	2.31	0.33	2.40
AHF # 13	0.82	2.70	0.07	2.93	0.30	2.29
AHF # 14	1.98	5.13	0.58	0.79	0.39	2.19
AHF # 15	1.11	3.06	0.21	1.27	0.36	2.09

4.2 Performance of the Constructed Portfolios of AHFs

Results of the constructed portfolios of AHFs in the sample are shown in *Table 3*, *Table 4*, *Table 5*, *Table 6*, and *Table 7*.

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As shown in the above tables, descriptive statistics of the optimal portfolios constructed for Investor#1, Investor#2, Investor#3, Investor#4, and Investor#5 seem satisfying risk and return trade-off preferences made by the five types of investors as indicated in *Table 1*. This suggests that PGP is effective in tailoring individual portfolios for the five types of investors.

In terms of fund-selection and portfolio-allocation decisions made for the five types of investors, different results are found at only standard deviations of 2 and above, in this study.

As shown in Panel A of *Table 3*, at the standard deviation of 1, similar performances in terms of omega ratio are found for all portfolios constructed for the five types of investors. In addition, fund selection is also found to be the same for all the five types of investors. As shown in Panel A of *Table 3*, the same set of funds, i.e. AHF#2, AHF#4, AHF#5, AHF#6, AHF#9, and AHF#15, is selected to be in the optimal portfolios constructed for the five types of investors.

This finding may shed lights on the issue of why the Mean-Variance method might be still employed by many fund managers as its primary objective is to construct an optimal portfolio with lowest risk (standard deviation) at a given level of return (mean). Since the performance of portfolios constructed for the five investors cannot be differentiated at the lowest standard deviation, i.e. 1, in this study, the distinction between the MV and the PGP methods cannot be seen in terms of the omega ratios of their constructed portfolios. However, one fact that cannot be denied is that the MV method fails to classify investors according to their individual preferences over the four moments of a return distribution, while the PGP method does. As seen in Panel A of *Table 3*, evidences of different portfolio-allocation decisions made for the five types of investors are found, although heavy weights seem to be always given to AHF#2, AHF#4, and AHF#5, and lighter weights are always given to AHF#6, AHF#9, and AHF#15. This suggests that funds with higher omega ratios, i.e. AHF#2, AHF#4, and AHF#5, are given higher allocation weights under PGP. This implies that investing more in good performing funds will help to enhance the overall performance of a portfolio of AHFs.

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Table 3: Portfolio Allocations Made for the Five Groups of Investors at Standard Deviation Levels of 1 and 2

Panel A: Standard Deviation = 1

Groups of Investors	1	2	3	4	5
Mean	0.97	0.97	0.98	0.97	0.97
Standard Deviation	1.00	1.00	1.00	1.00	1.00
Skewness	-0.53	-0.57	-0.57	-0.55	-0.55
Kurtosis	1.09	0.97	0.97	0.99	1.00
Omega Ratio	6.29	5.80	6.29	6.29	6.29
Portfolio Allocation (Weight)					
AHF # 1	0.00	0.00	0.08	0.00	0.00
AHF # 2	0.45	0.43	0.33	0.44	0.44
AHF # 3	0.00	0.00	0.13	0.00	0.00
AHF # 4	0.21	0.24	0.24	0.22	0.22
AHF # 5	0.21	0.19	0.07	0.20	0.20
AHF # 6	0.05	0.05	0.05	0.05	0.05
AHF # 7	0.00	0.00	0.00	0.00	0.00
AHF # 8	0.00	0.00	0.00	0.00	0.00
AHF # 9	0.01	0.02	0.02	0.02	0.02
AHF # 10	0.00	0.00	0.00	0.00	0.00
AHF # 11	0.00	0.00	0.00	0.00	0.00
AHF # 12	0.00	0.00	0.00	0.00	0.00
AHF # 13	0.00	0.00	0.00	0.00	0.00
AHF # 14	0.00	0.00	0.00	0.00	0.00
AHF # 15	0.06	0.08	0.07	0.07	0.07
Total Allocation	1.00	1.00	1.00	1.00	1.00

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Panel B: Standard Deviation = 2

Groups of Investors	1	2	3	4	5
Mean	1.46	1.49	1.18	1.44	1.40
Standard Deviation	2.00	2.00	2.00	2.00	2.00
Skewness	0.57	0.52	0.34	0.25	0.46
Kurtosis	1.72	1.77	2.80	0.27	0.45
Omega Ratio	3.43	3.25	3.43	2.78	3.64
Portfolio Allocation (Weight)					
AHF # 1	0.55	0.56	0.00	0.34	0.45
AHF # 2	0.00	0.00	0.00	0.00	0.00
AHF # 3	0.00	0.00	0.00	0.00	0.00
AHF # 4	0.01	0.00	0.00	0.00	0.00
AHF # 5	0.00	0.00	0.00	0.00	0.00
AHF # 6	0.00	0.00	0.71	0.00	0.00
AHF # 7	0.00	0.00	0.01	0.00	0.00
AHF # 8	0.02	0.04	0.00	0.18	0.26
AHF # 9	0.07	0.01	0.00	0.00	0.00
AHF # 10	0.00	0.00	0.01	0.00	0.00
AHF # 11	0.00	0.00	0.00	0.00	0.00
AHF # 12	0.19	0.17	0.00	0.06	0.20
AHF # 13	0.03	0.00	0.00	0.00	0.06
AHF # 14	0.13	0.17	0.01	0.26	0.00
AHF # 15	0.00	0.04	0.25	0.15	0.03
Total Allocation	1.00	1.00	1.00	1.00	1.00

As the standard deviation gets larger than 1, i.e. 2 (see *Table 3*, Panel B), optimal portfolios constructed for the five investors deviate from each other in terms of their omega ratios, fund-selection and fund-allocation decisions. In terms of fund-selection decision, different funds are selected for each optimal portfolio constructed for each type of investor. As the standard deviation of a portfolio is increased, the number of funds that are commonly selected for optimal portfolios constructed for the five types of investors is reduced. For instance, at standard deviation 2, AHFs that are commonly chosen under PGP for 4 out of 5 types of investors are AHF#1, AHF#8, AHF#12, AHF#14, and AHF#15. However, at two standard deviations, i.e. 3 and 4 (see *Table 4*), only two funds, i.e. AHF#1 and AHF#12 are commonly chosen for all types of investors. At other higher levels of standard deviations, i.e. 5, 6, and 7, only AHF#12 remains in all optimal portfolios constructed for all the five types of investors. This might be due to the fact that AHF#12 has the highest mean and skewness depicted among all the 15 AHFs in the sample, which may help to offset the high level of standard deviation designed for a portfolio of AHFs.

Moreover, it is also found that at a higher level of standard deviation, more funds with high skewness are selected to be in a portfolio under the PGP method. This important finding may suggest that funds with high skewness are likely to be chosen for an optimal portfolio under PGP.

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In relation to the four moments of a portfolio, a few observations can be made. As indicated in *Table 1*, investment objectives of the five types of investors are different. Referring the moment with the highest preference chosen by each investor, Investor#1 can be called as the skewness optimizer, Investor#2 as the mean optimizer, and Investor#3 as the kurtosis optimizer. Although the top preferences made by Investor #4 and Investors#5 are different, they both can be called as mean and skewness optimizer. It is interesting to see if the above preferences are reflected in the performance of optimal portfolio constructed for each type of investor.

Table 4: Portfolio Allocations Made for the Five Groups of Investors at Standard Deviation levels of 3 and 4

Panel A: Standard Deviation =3

Groups of Investors	1	2	3	4	5
Mean	1.70	1.80	1.58	1.76	1.64
Standard Deviation	3.00	3.00	3.00	3.00	3.00
Skewness	0.91	0.76	0.47	0.46	0.86
Kurtosis	2.04	2.05	0.50	0.71	1.37
Omega Ratio	3.25	3.08	2.78	2.64	2.92
Portfolio Allocation (Weight)					
AHF # 1	0.33	0.30	0.00	0.14	0.26
AHF # 2	0.00	0.00	0.00	0.00	0.00
AHF # 3	0.00	0.00	0.00	0.00	0.00
AHF # 4	0.04	0.00	0.00	0.00	0.00
AHF # 5	0.00	0.00	0.00	0.00	0.00
AHF # 6	0.00	0.00	0.49	0.00	0.00
AHF # 7	0.00	0.04	0.00	0.00	0.00
AHF # 8	0.13	0.00	0.00	0.00	0.36
AHF # 9	0.02	0.00	0.00	0.00	0.00
AHF # 10	0.00	0.04	0.00	0.07	0.00
AHF # 11	0.00	0.00	0.00	0.00	0.00
AHF # 12	0.34	0.29	0.31	0.12	0.34
AHF # 13	0.00	0.00	0.00	0.00	0.00
AHF # 14	0.14	0.27	0.00	0.48	0.02
AHF # 15	0.01	0.05	0.20	0.19	0.02
Total Allocation	1.00	1.00	1.00	1.00	1.00

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Panel B: Standard Deviation = 4

Groups of Investors	1	2	3	4	5
Mean	1.90	2.10	1.80	2.10	1.90
Standard Deviation	4.00	4.00	4.00	4.00	4.00
Skewness	1.10	0.80	0.70	0.50	1.00
Kurtosis	2.20	2.00	0.90	1.10	1.90
Omega Ratio	2.30	2.40	2.60	2.20	2.20
Portfolio Allocation (Weight)					
AHF # 1	0.14	0.04	0.00	0.04	0.06
AHF # 2	0.00	0.00	0.00	0.00	0.00
AHF # 3	0.00	0.00	0.00	0.00	0.00
AHF # 4	0.00	0.00	0.00	0.00	0.00
AHF # 5	0.00	0.00	0.00	0.00	0.00
AHF # 6	0.00	0.00	0.55	0.00	0.00
AHF # 7	0.00	0.01	0.00	0.00	0.00
AHF # 8	0.20	0.00	0.00	0.00	0.40
AHF # 9	0.00	0.00	0.00	0.00	0.00
AHF # 10	0.00	0.14	0.00	0.22	0.00
AHF # 11	0.00	0.00	0.00	0.00	0.00
AHF # 12	0.47	0.39	0.45	0.27	0.47
AHF # 13	0.00	0.00	0.00	0.00	0.00
AHF # 14	0.16	0.34	0.00	0.47	0.07
AHF # 15	0.02	0.07	0.00	0.00	0.00
Total Allocation	1.00	1.00	1.00	1.00	1.00

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Table 5: Portfolio Allocations Made for the Five Groups of Investors at Standard Deviation Levels of 5 and 6

Panel A: Standard Deviation = 5

Groups of Investors	1	2	3	4	5
Mean	2.14	2.28	1.98	2.30	2.08
Standard Deviation	5.00	5.00	5.00	5.00	5.00
Skewness	1.14	1.00	0.91	0.87	1.15
Kurtosis	2.43	2.38	1.50	2.03	2.29
Omega Ratio	2.29	2.19	2.40	2.64	2.09
Portfolio Allocation (Weight)					
AHF # 1	0.00	0.00	0.00	0.00	0.00
AHF # 2	0.00	0.00	0.00	0.00	0.00
AHF # 3	0.00	0.00	0.00	0.00	0.00
AHF # 4	0.00	0.00	0.00	0.00	0.00
AHF # 5	0.00	0.00	0.00	0.00	0.00
AHF # 6	0.00	0.00	0.39	0.00	0.00
AHF # 7	0.00	0.00	0.00	0.00	0.00
AHF # 8	0.20	0.00	0.00	0.00	0.28
AHF # 9	0.00	0.00	0.00	0.00	0.00
AHF # 10	0.00	0.12	0.00	0.28	0.00
AHF # 11	0.00	0.00	0.00	0.00	0.00
AHF # 12	0.60	0.56	0.61	0.57	0.62
AHF # 13	0.00	0.00	0.00	0.00	0.00
AHF # 14	0.20	0.31	0.00	0.15	0.10
AHF # 15	0.00	0.00	0.00	0.00	0.00
Total Allocation	1.00	1.00	1.00	1.00	1.00

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Panel B: Standard Deviation = 6

Groups of Investors	1	2	3	4	5
Mean	2.35	2.37	2.18	2.39	2.31
Standard Deviation	6.00	6.00	6.00	6.00	6.00
Skewness	1.15	1.13	1.04	0.99	1.15
Kurtosis	2.55	2.51	1.92	2.18	2.43
Omega Ratio	2.52	2.40	2.29	2.40	2.40
Portfolio Allocation (Weight)					
AHF # 1	0.00	0.00	0.00	0.00	0.00
AHF # 2	0.00	0.00	0.00	0.00	0.00
AHF # 3	0.00	0.00	0.00	0.00	0.00
AHF # 4	0.00	0.00	0.00	0.00	0.00
AHF # 5	0.00	0.00	0.00	0.00	0.00
AHF # 6	0.00	0.00	0.24	0.00	0.00
AHF # 7	0.00	0.00	0.00	0.00	0.00
AHF # 8	0.02	0.00	0.00	0.00	0.08
AHF # 9	0.00	0.00	0.00	0.00	0.00
AHF # 10	0.00	0.04	0.00	0.26	0.03
AHF # 11	0.00	0.00	0.00	0.00	0.00
AHF # 12	0.75	0.75	0.76	0.74	0.76
AHF # 13	0.00	0.00	0.00	0.00	0.00
AHF # 14	0.24	0.21	0.00	0.00	0.13
AHF # 15	0.00	0.00	0.00	0.00	0.00
Total Allocation	1.00	1.00	1.00	1.00	1.00

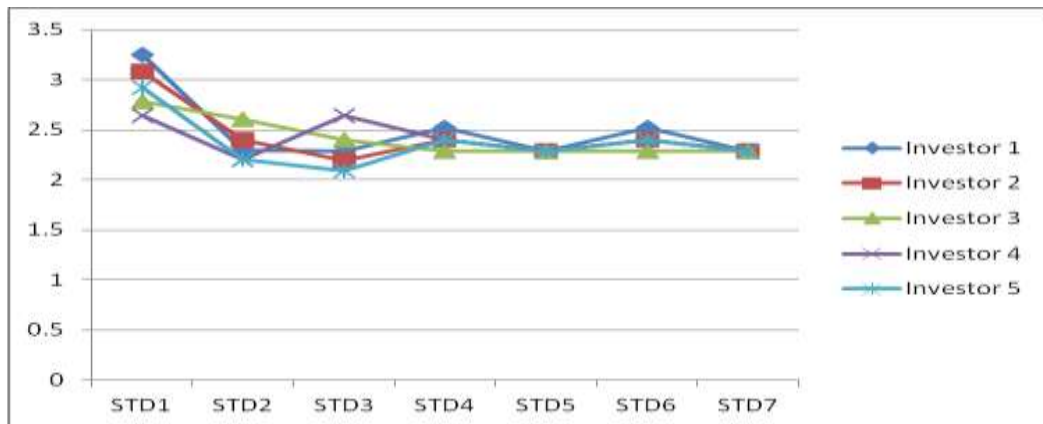
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Table 6: Portfolio Allocations Made for the Five Groups of Investors at Standard Deviation Levels of 7

Groups of Investors	1	2	3	4	5
Mean	2.44	2.44	2.37	2.45	2.44
Standard Deviation	7.00	7.00	7.00	7.00	7.00
Skewness	1.16	1.16	1.11	1.11	1.16
Kurtosis	2.40	2.40	2.19	2.31	2.40
Omega Ratio	2.29	2.29	2.29	2.29	2.29
Portfolio Allocation (Weight)					
AHF # 1	0.00	0.00	0.00	0.00	0.00
AHF # 2	0.00	0.00	0.00	0.00	0.00
AHF # 3	0.00	0.00	0.00	0.00	0.00
AHF # 4	0.00	0.00	0.00	0.00	0.00
AHF # 5	0.00	0.00	0.00	0.00	0.00
AHF # 6	0.00	0.00	0.09	0.00	0.00
AHF # 7	0.00	0.00	0.00	0.00	0.00
AHF # 8	0.00	0.00	0.00	0.00	0.00
AHF # 9	0.00	0.00	0.00	0.00	0.00
AHF # 10	0.00	0.00	0.00	0.09	0.00
AHF # 11	0.00	0.00	0.00	0.00	0.00
AHF # 12	0.91	0.91	0.91	0.91	0.91
AHF # 13	0.00	0.00	0.00	0.00	0.00
AHF # 14	0.09	0.09	0.00	0.00	0.09
AHF # 15	0.00	0.00	0.00	0.00	0.00
Total Allocation	1.00	1.00	1.00	1.00	1.00

4.3 Trade-Offs among the five Moments of a Portfolio's Return Distribution

Figure 1: Omega ratios of Optimal Portfolios Constructed for the Five Types of Investors



As the standard deviation increases from 1 to 2 (*Figure 1*), omega ratio of the constructed optimal portfolio declines to a certain level and then remain in a stabilizing range as the standard deviation increases beyond 2 for all investors. This implies that standard deviation is kept away from affecting greatly the performance of the constructed portfolios under the PGP framework. Due to the preferences made by Investor#3, its performance seems to be the lowest amongst others'. Portfolios constructed for Investor#1 perform best at most of the standard deviations. The highest mean and no kurtosis preferences made by Investor#1 may be the reason for its good performance. The performances of portfolios constructed for all investors seem to be closer at higher standard deviations, i.e. 4, 5, 6, and 7. This may imply that significant differences in performance of optimal portfolios are mostly found at lower levels of standard deviations, i.e. 1, 2, and 3. This supports the fact that PGP is able to tailor different portfolios according to individual investors' preferences over the four moments of a return distribution, especially at low standard deviation levels.

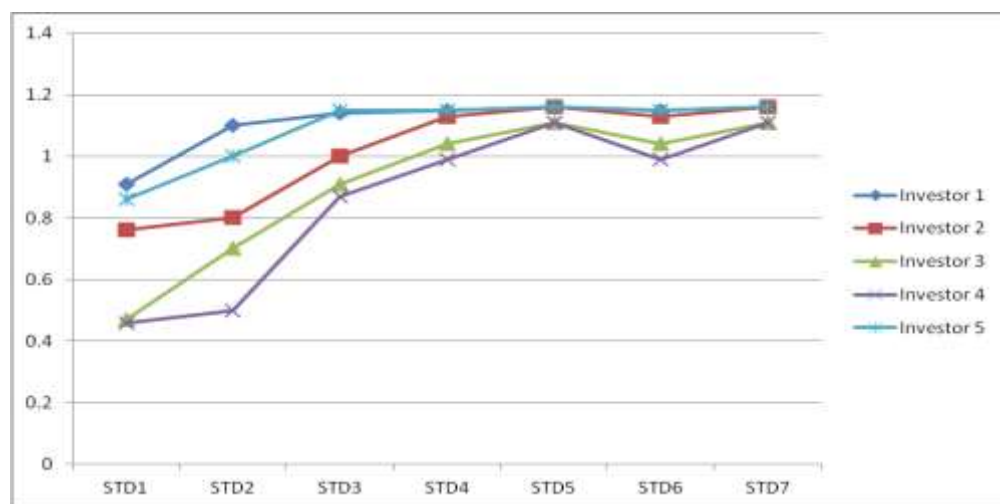
For example, when comparing the performances of portfolios constructed for Investor#1 and Investor#2, at 5 out of 7 standard deviations, portfolios constructed for Investor#1 (the skewness optimizer) have higher omega ratios than those constructed for Investor#2 (the mean optimizer) (*Figure 1*). This may imply that at a given level of standard deviation, maximizing the skewness of a portfolio will likely result in a better performing optimal portfolio as compared to that when maximizing the mean of a portfolio. This may imply the benefit of taking skewness into account when constructing an optimal portfolio of AHFs.

Figure 2: Average Returns of Optimal Portfolios Constructed for the Five Types of Investors



Figure 2 presents the average returns versus the standard deviations of optimal portfolios constructed for the five types of investors. As shown in Figure 2, although Investor#2 and Investor#4 prefer to achieve the highest mean, there seems to be a lower positive correlation between means and standard deviations of their constructed portfolios as compared to those constructed for other types of investors. This might suggest that under the PGP method, maximizing the average returns of a portfolio does not necessarily mean that there would be a significant increase in its standard deviation. On the other hand, with Investor#1, Investor#2, and Investor#3, there seems to be a larger trade-off between the mean and the standard deviation for their constructed portfolios.

Figure 3: Skewnesses of Optimal Portfolios Constructed for the Five Investors



In terms of skewness, Investor#1 and Investor#5 prefer to achieve the highest level of skewness for their portfolios, skewnesses of their portfolios are among the highest. On the other hand, it is interesting to see that portfolios constructed for Investor#4 have the lowest skewnesses at all levels of standard deviation. This

may be due to the fact that, Investor#4 prefers to have the highest mean, medium skewness, and low kurtosis. In other words, skewnesses of Investor#4's portfolios may be scaled down because of the highest mean and low kurtosis preferences.

In overall (see *Figure 3*), as the standard deviation of a portfolio increases, its skewness increases at a decreasing rate to a certain level and then stays within a narrow range. Maximum skewness for a portfolio is achieved when its mean is low, as an increase in the mean of a portfolio will result in a decrease in its skewness.

Figure 4: Kurtosises of Optimal Portfolios Constructed for the Five Investors

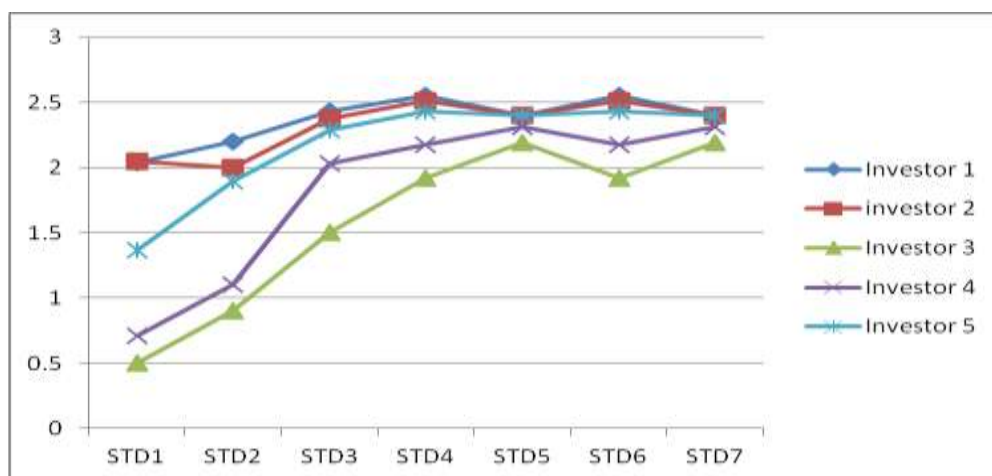


Figure 4 clearly shows that there is a significant positive relationship between kurtosis and standard deviation for Investor#3. This may suggest that maximizing the kurtosis of a portfolio surely comes at a cost of increasing its standard deviation. There seems to be also a positive relationship between the kurtosis and the standard deviation of portfolios constructed for Investor#4 and Investor#5. As investors#1 and 2 prefer none kurtosis, the kurtosis of their constructed portfolios seems to have low or zero correlation with their standard deviations; however, they are the two highest kurtosis among the five at all levels of standard deviation. This interesting finding suggests that maximizing the skewness or the mean of a portfolio will come at a cost of increasing its kurtosis. Investor#3 prefers the highest kurtosis for their portfolio; however, at all levels of standard deviation, the kurtosis of their portfolios is the lowest. This may be due to the low mean and zero skewness preferences made by Investor#3. This confirms the previous finding one more time that the kurtosis of a portfolio increases if, and only if the mean or the skewness of that portfolio increases. In overall, as the standard deviation increases, kurtosis of the optimal portfolio constructed for each type of investors increases to a certain level and then remains unchanged.

5. Key Conclusions and Implications

Using a new portfolio construction method - PGP - , a sample of 95 AHFs is selected from the Eurekahedge database to construct optimal portfolios consisting of maximum 15 best-performing funds in terms of their omega ratios, the following are our key findings.

Fund-selection and fund-allocation decisions for different types of investors seem to be significantly different at higher levels of standard deviation. Funds with high skewness seem to be selected and given higher weights in an optimal portfolio. Investors with preferences of higher skewness seem to have better performing portfolios as compared to those of others.

In terms of the relationship between omega ratio and standard deviation of a portfolio, as the standard deviation of a portfolio increases, its omega ratio will decrease at a decreasing rate to a certain level and then stays in a narrow range. This implies that the performance of a portfolio will not be affected much once its standard deviation reaches to a certain level such as 4 in this study.

In terms of the relationship between skewness and standard deviation of a portfolio, as the standard deviation of a portfolio increases, its skewness will increase at a decreasing rate to a certain level and then remains unchanged. A similar relationship between the kurtosis and the standard deviation of a portfolio is observed. This may suggest that an increase in a portfolio's standard deviation may result in less than a proportional increase in its skewness or its kurtosis.

Furthermore, there seems to be a positive relationship between the kurtosis and each of the other three moments (standard deviation, skewness, and mean) of a portfolio. In other words, when the kurtosis of a portfolio increases, its standard deviation, skewness, and mean also increase, and vice versa.

In short, there must be a trade-off among the four moments of a portfolio's return distribution. An optimal portfolio has the highest omega ratio if its skewness is maximized. Maximizing mean of a portfolio will not certainly come at the cost of lowering its skewness, increasing standard deviation; thus, lowering its performance in terms of omega ratio. This explains the weakness of the MV approach as indicated in Brooks and Kat (2002) and points out the importance of using the PGP method in constructing an optimal portfolio for AHFs. The study suggests that taking into account all higher moments of a return distribution allows different optimal portfolios to be constructed for individual AHF investors, whose risk preferences over the four moments may be different. In other words, using the MV approach, an identical optimal portfolio will be tailored to all types of investors disregard their individual risk-return preferences.

We acknowledge that this study faces three main limitations. Firstly, the study limits a maximum number of only 15 best-performing AHFs to be in a portfolio. Secondly, the study period is only from 1st January 2000 to 15th June 2008. Finally, the main database used for this study is provided by the Eurekahedge.

For comparison purposes, further study may also be conducted with a portfolio consisting of more than 15 best-performing funds, with a longer study period, and with another AHF data provider rather than the EurekaHedge, if available.

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