Selection and Performance Analysis of Asia-Pacific Hedge Funds

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Abstract

This paper studies portfolio selection and performance analysis of hedge funds located or invested in Asia-Pacific. It investigates the characteristics of the funds' returns and recommends optimization methods to create a 'Fund-of-Funds'. The returns of the hedge funds are then decomposed into asset class factors. Finally, portfolio optimizations and performance analyses are integrated to show how these methods are utilized in practice.

Introduction

Hedge funds that invest in Asia-Pacific markets have grown rapidly during the past decade. Eurekahedge estimates that the management capital of these funds reached the US$ 132 billion as of the end of 2006, increasing at a rate of 35% per year. Asia-Pacific focused hedge funds are poised to play a bigger role as important investment vehicles.

Many researchers and practitioners have investigated hedge fund performances in response to the explosive growth of hedge funds within the US and Europe during the 1990's. For example, Fung and Hsieh [1999], Ackermann, McEnally and Ravenscraft [1999], Agarwal and Naik [2000a, 2000b, 2004], Brown, Goetzmann and Ibbotson [1999], Liang[1999, 2000, 2001], Edwards and Caglayan [2001], Kao [2002], Amin and Kat [2003a, 2003b], Brooks and Kat [2002], Schneeweis [1998], and Brunnermeier and Nagel [2004] studied historical hedge fund performance using various hedge fund databases such as TASS, HFR and CISDM (formerly MARHedge). This paper makes use of Eurekahedge's Asia-Pacific hedge fund database for its analysis.

Hedge funds' returns having different characteristics from those of traditional asset classes. Amin and Kat [2002], Brooks and Kat [2002] and Markiel and Saha [2005] reported that hedge funds' returns exhibited negative skew and relatively high kurtosis. Agarwal and Naik [2004] emphasized the negative tail risks. This paper investigates the skew and kurtosis of Asia-Pacific hedge fund returns, and tests the hypothesis that they are normally distributed. The result indicates that they do not necessarily follow Gaussian distributions but, instead, follow so-called fat tail distributions. In this case, standard deviation is insufficient to capture the full risks inherent within these hedge funds.

Many researchers have tried to measure the risk involved in hedge funds. Davies, Kat and Lu [2003, 2004] examined the skew and kurtosis of fund of hedge funds' returns which was then used to recommend portfolio optimization methods. Other researchers proposed several kinds of risk measures that capture negative tail risk. Artzner, Delbaen, Eber and Heath [1999] present and justify a set of four desirable properties for measures, call the measures satisfying these properties "coherent". Value-at-Risk (VaR) is a popular risk measure, but it is not coherent. Moreover, Lo [2001] shows that VaR cannot fully capture the spectrum of risks that hedge funds exhibit. Conditional value-at-risk (CVaR) is an example of coherent measures of risk. CVaR with the confidence level 90% reflects the average of loss which occurs with the probability of 10%. Another popular risk measure is maximum drawdown. Chekhlov, Uryasev and Zabarankin [2000] proposed conditional drawdown (CDD). CDD with the confidence level 90% reflects the average of the worst 10% drawdown. In particular, maximum drawdown can be obtained by setting the confidence level at a sufficiently high level. Aside from risk measures, several risk-to-return ratios have also been introduced, such as Sortino ratio, Omega, and Kappa. They are explained in detail by Sortino and Price [1994], Kazemi, Schneeweis and Gupta [2003], and Kaplan and Knowles [2004].

The first part of this study aims to use CVaR and CDD to reveal the importance of negative tail risks of hedge funds, and then looks to construct an optimal portfolio of hedge funds, or a 'Fund-of-Funds'. Optimal allocation to hedge funds is argued in Amenc and Martellini [2002], Davies, Kat and Lu [2004], Lamm [2003], Krokhmal, Uryasev and Zrazhevszky [2002], and Cvitanic, Lazrak, Martellini and Zapatero [2003]. It is well-known that mean-variance optimization method is not appropriate when tail risk is crucial. This paper maximizes expected returns with constraints on CVaR or CDD, using the algorithms developed by Rockafellar and Uryasev [2000,2002], Chekhlov et al. [2000] and Krokhmal, Uryasev and Zrazhevszky [2002]. These algorithms optimize portfolios in myopic ways by using a sample-path approach that does not estimate distributions of the returns in parametric ways, but instead, regards the historical returns themselves as distributions of returns. Using linear programming techniques, these algorithms solve the optimization problem easily. This study also compares the allocation and performance differences between portfolios optimized through these algorithms and portfolios constructed using mean-variance optimization program. In practice, investors also tend to avoid having high concentrations on a single fund even if the fund performs very well. Hence, this study also looks at instances where the percentage of investment in a single fund is limited to at most 15%.

Factor analyses for hedge funds are necessary for a investment decision and risk management. Decisions to invest or withdraw investments from hedge funds are made by monitoring risks and estimating the funds' *alphas* through identifying their exposures to asset clsss factors. Given the funds' exposures and our own view on markets, we can adjust our total exposures to factors by decreasing or increasing their positions. Ideally, we expect to integrate the funds' *alphas* efficiently into our proprietary books. Fung and Hsieh [1997-2006], Schneeweis and Spurgin [1998], Brown and Goetzmann [2003], and Agarwal and Naik [2004] implemented style analysis for hedge funds. They found that hedge fund returns can be characterized by three key determinants: returns from assets in their portfolios, their dynamic trading strategies, and their use of leverage. Dynamic trading strategies result in returns of hedge funds to sometimes be non-linearly related to the returns of the underlying assets. Those articles introduce new proxies that explain the returns of dynamic trading strategies, event arbitrage, and illiquid securities. The derivatives of stock index are good examples representing those returns successfully.

This paper adopts the following variables as factors. In order to monitor the risk inherent in hedge funds, the fsctors are desirable to be observed on a daily basis like market indices. Stock index factors are represented by stock indices of Asian countries, S&P500, and the Dow-Jones European stock index. Bond index factors are representative of MSCI bond indices of Asian countries and the US. Foreign exchange factors are reflected in exchange rates of Asian currencies against the US dollar. Option factors are represented by options on stock indices. Fund returns are first decomposed into stock indexes, bond indexes, and foreign exchange factors based on time-series regressions. Then, it is checked how the fund returns and the factors are related. If non-linearity is observed, option factors are then added to the list of explanatory variables and time-series regression is implemented again. Hedge funds that follow fixed income and distressed debt strategies are expected to be explained by credit-related factors such as credit spreads. However, for the purposes of this study, stock indices are used as substitutes for credit spread data due to the difficulty in obtaining such data in Asia-Pacific financial markets. Through this, it becomes possible to estimate the performance of hedge funds and Fund-of-Funds as most factors are obtained on a daily basis. Tradable factors also allow for hedge funds' risks to be partially or completely hedged.

Finally, portfolio optimizations and factor analyses, which have been studied separately so far, are integrated to explain how such methods are utilized in practice. In closing, this study evaluates the exposure of hedge funds selected through optimization, and examines how hedge funds' portfolios and returns can be mimicked by factors and *alphas*. The optimization methods and risk analysis proposed in this study are useful for managing a Fund-of-Funds.

Characteristics of returns of Asia-Pacific hedge funds and portfolio optimization

Hedge funds that utilize dynamic trading strategies that frequently involve short sales, leverage, and derivatives, display returns that differ in characteristics from those of traditional asset classes. This section will discuss the distributions of Asia-Pacific hedge fund returns and recommend portfolio optimization methods.

Data

This study uses Eurekahedge's Asia-Pacific hedge fund database for its analysis. Eurekahedge provides information on the global hedge funds and alternative funds industry. It maintains a list of 13,200 funds across all strategies and asset classes, which is classified into hedge fund, private equity and specialist fund databases. The hedge fund databases include North American, European, Asia-Pacific and Latin American hedge fund database. Aside from these, Eurekahedge also provides long-only absolute return fund, global fund of funds and emerging markets fund databases. Each database has monthly returns and fund characteristics, including investment strategy, investment geography, managers, and so on. Eurekahedge's Asia-Pacific hedge fund database contains information on over 1,150 funds (including 158 obsolete funds) as of March 2007. The investment strategies within this database are broken down into ten categories: Arbitrage, CTA / Managed Futures, Distressed Debt, Event Driven, Fixed Income, Long / Short Equities, Macro, Multi-Strategy, Relative Value and Others. It also classifies by investment geography into ten areas: Asia excluding Japan, Asia including Japan, Australia / New Zealand, Emerging Markets, Global, Japan Only, Korea, Taiwan, Greater China and India. Managers are required to reveal their corresponding investment strategy and geography when they list their funds in the database. EXHIBIT 1-A illustrates the breakdown of hedge funds by investment strategy.

Insert EXHIBIT 1.

The percentage of Long / Short Equities in the Asia-Pacific region at 57% is much higher than that of North-America at 41%. On the other hand, the proportion of Arbitrage, CTA / Managed Futures and Event Driven in North-America exceed those of the Asia-Pacific region.

EXHIBIT 1-B illustrates the breakdown of hedge funds by investment geography, where a "global" hedge fund either locates its headquarters in the Asia-Pacific region or invests more than one-third of its asset in the Asia-Pacific region.

Most hedge fund studies use HFR, TASS or CISDM (formerly MARHedge) databases. According to Koh, Koh and Teo [2003], these databases cover mainly US-centric hedge funds, and the degree of overlap between Eurekahedge's Asia-Pacific and these other databases is very small.

EXHIBIT 1-C compares Eurekahedge's Asia-Pacific hedge fund database and a union of four large databases such as CISDM, HFR, MSCI, and TASS which Agarwal, Daniel and Naik [2007] constructed in their study. They classify funds into four broad strategies: directional, relative value, security selection, and multiprocess traders. This classification method is influenced by a study done by Fung and Hsieh [1997] and Brown and Goetzmann [2003] that shows there are few distinct style factors in hedge fund returns. The percentage of security selection in the Asia-Pacific region is much higher with Eurekahedge than with the consolidated database. However, the consolidated database holds a higher percentage of directional traders than Eurakahedge's Asia-Pacific database.

The procedure of classifying Eurekahedge's Asia-Pacific hedge fund database into the four broad strategies is as follows. Fixed income and distressed debt funds whose investments are within Asia excluding Japan, and Macro funds are categorized as directional traders. Fixed income funds whose investments are within Japan or Australia / New Zealand, arbitrage funds and relative value funds are categorized as relative value. Long / Short Equities funds are categorized as security selection. Distressed debt funds whose investment geographies are Japan or Australia / New Zealand, event driven funds and multi-strategy funds are categorized as multi-process traders. CTA / Managed Futures and ”other” hedge funds are excluded.

Characteristics of returns of Asia-Pacific hedge funds

In this subsection, the distributions of the hedge fund returns are studied. Eurekahedge’s Asia-Pacific hedge fund database provides monthly historical data from January 2001 to December 2005 for a total of 108 funds. EXHIBIT 2 shows the breakdown of funds by investment strategy and geography and the calculated average return, standard deviation, skew and kurtosis for each category. Statistical summaries for stock and bond indices in the Asia-Pacific region are also listed for comparative purposes. Here, the indices listed in EXHIBIT 13, other than indices in the US and Europe, are used. The values in the exhibit represent the average values of the assets within each category or asset class. EXHIBIT 2 also lists D’Agostino-Pearson (D-P) p-values. The D-P test examines the normality of a sample using the sample’s skewness and kurtosis. For instance, 5% p-value means that the probability to realize the returns is 5%, assuming that the return follows normal distribution.

Insert EXHIBIT 2.

EXHIBIT 2 indicates that hedge fund returns are higher than other asset classes and their standard deviations are lower than stock indices. Amin and Kat [2002], Brooks and Kat [2002] and Markiel and Saha [2005] reported that hedge fund returns exhibit negative skew and relatively high kurtosis. However, our sample of hedge fund returns showed positive skew while returns of stock and bond indices showed negative skew. The kurtosis of hedge fund returns is also higher than those of stock and bond index returns. D-P p-values indicate that hedge fund returns follow normal distributions far less than other asset classes. D-P tests revealed that hedge funds returns were not normally distributed for 49 out of 108 hedge funds at 5% significance. A similar test for stock indices revealed only 5 out of 37 indices to be rejected.

These results indicate that hedge fund returns do not necessarily follow normal distributions. When the returns of hedge funds do not follow normal distributions, the risks of hedge funds cannot be captured only by standard deviations, and it becomes necessary to take higher moments of the returns or negative tail risks into account. This study considers negative tail risks and introduces two risk measures, namely CVaR and CDD, as discussed earlier. Mathematical definitions of these risk measures are described in the Appendix.

Average monthly returns, standard deviation, CVaR and CDD are calculated for each hedge fund. CVaR and CDD are calculated for confidence levels of 90%. This information is translated into graphs as illustrated by EXHIBIT 3, where the horizontal axis and the vertical axis denote risk measures and mean return respectively.

Insert EXHIBIT 3.

EXHIBIT 3 shows that even in cases where two funds exhibit similar performance in terms of mean-variance analysis, their CVaR and CDD differ. For instance, the average returns of FUND 60 and FUND 107 are 2.36% and 2.40%, and the standard deviations are 4.38% and 4.34% respectively. On the other hand, both FUND 60's and FUND 107's CVaR are 5.12% and 2.87%, and their CDD are 11.65% and 3.71% respectively. This shows that the negative tail risk of FUND 60 is much larger than FUND 107, even though they have similar average returns and standard deviations. This example shows that negative tail risks of hedge funds cannot be identified by standard deviation alone.

Portfolio optimization of hedge funds

In this subsection, the optimization methods for constructing portfolio of hedge funds. In the mean-variance approach, risk is identified as the standard deviation of asset returns. This approach is justified only when investor's utility is quadratic or when an asset's returns follow elliptical distributions including normal distributions. The previous subsection concluded that Asia-Pacific hedge funds do not necessarily follow normal distributions and stressed the importance of negative tail risk measures. Since the mean-variance approach is not an appropriate optimization method, this study uses optimization methods with constraints on CVaR or CDD; expected returns are maximized by investing in n hedge funds for a certain period of time with constraints on a risk measure. The $\mathbf{R}^n$-valued random variable $\mathbf{r} = (r_1, \cdots, r_n)'$ represents fund returns for that period, and $\Phi(\mathbf{x})$ represents a risk measure of the portfolio $\mathbf{x}$. In this setting, the optimization problem can be described as follows.

$$\max_{\mathbf{x}} E[\mathbf{r}'\mathbf{x}], \tag{1}$$

subject to

$$0 \le x_i \le 1, \quad i = 1, \cdots, n, \tag{2}$$

$$\sum_{i=1}^{n} x_i \le 1, \tag{3}$$

$$\Phi(\mathbf{x}) \le \omega, \tag{4}$$

where ω is a risk tolerance level. $\Phi(\mathbf{x})$ is then substituted with CVaR or CDD. In such cases, optimization problems can be solved using the algorithms developed by Rockafellar and Uryasev [2000, 2002], and Chekhlov et al. [2000]. Their algorithms optimize the portfolios by a sample-path approach which does not estimate the distributions of returns in a parametric way, but instead regards the historical returns themselves as distributions of returns. Their algorithms solve the optimization problem easily by linear programming. These algorithms are described in the Appendix.

The portfolio of 108 hedge funds is then optimized with constraints on CVaR or CDD. These results are then used to compare against portfolios optimized using the mean-variance approach. Historical monthly returns from January 2001 to December 2005 are used for this purpose and the one month US LIBOR is used as the risk-free asset.

A CVaR optimal portfolio is then constructed. The CVaR confidence level is set at 90%, and the optimal portfolios for risk tolerance levels of 0.1%, 0.5%, 1%, 3%, and 5%. EXHIBIT 4 reports the optimal portfolios and basic statistics.

Insert EXHIBIT 4.

The optimization method based on CVaR first allocates wealth to hedge funds with high expected returns and the remainder to funds which do not suffer losses when these initially selected funds do. FUND 23 is initially selected as it has the highest expected returns at 3.27%. Then, the rest of wealth is allocated to FUNDs 18, 72 and 98 based on their respective expected returns. As the risk tolerance level decreases, the wealth allocations to FUNDs 18, 23 and 72 decreases, while that to FUND 98 increases. The reason for this is due to FUND 98's low CVaR at 0.01% and high expected returns at 2.79%. When CVaR is regarded as a risk constraint, FUND 98 is almost a risk-free fund. In other words, CVaR optimization first allocates wealth to FUNDs 23, 18 and 72 as much as permitted by risk constraints and the remainder is then allocated to FUND 98.

A CDD optimal portfolio is then constructed. The CDD confidence level is set at 90%, and the optimal portfolios for risk tolerance levels of 0.1%, 0.5%, 1%, 3%, and 5%. EXHIBIT 5 reports the optimal portfolios and basic statistics.

Insert EXHIBIT 5.

The optimization method based on CDD is similar to that of CVaR except for the case when the risk tolerance level is at 0.1%. In that case, wealth cannot be fully(100%) allocated to FUND 98 as its CDD is greater than 0.1%. Therefore, wealth is allocated to the funds with the lower expected returns such as FUND 79.

Portfolios obtained through CVaR and CDD are different from portfolios obtained through the mean-variance method. Portfolios constructed using CVaR and CDD with a risk tolerance level of 0.1% has expected returns of 2.81% and 2.43%. To facilitate comparisons, optimal portfolios obtained through the mean-variance method are constructed for expected returns of 2.81% and 2.43%. EXHIBIT 6 shows the weights on hedge funds selected by the CVaR and mean-variance optimizations and EXHIBIT 7 shows the weights on funds selected by the CDD and mean-variance optimizations. The first figure in parentheses at the side of the fund name shows the weights by either CVaR or CDD optimization methods and the second figure shows the weights on hedge funds selected by the mean-variance optimization program. EXHIBIT 8 shows standard deviations, CVaR, and CDD of the mean-variance optimal portfolios.

Insert EXHIBITs 6-8.

EXHIBIT 6 shows the differences between the CVaR optimal portfolio and the mean-variance optimal portfolio. The CVaR optimal portfolio allocates 93% of wealth to FUND 98, while the mean-variance optimal portfolio allocates less at 87%. When CVaR is used as a risk measure to identify negative tails risks, FUND 98 is almost risk free. After allocating 93% of the wealth to FUND 98, the CVaR optimal portfolio allocates the rest to hedge funds that do not suffer losses when FUND 98 suffers losses. Consistent to this, wealth is not allocated to FUND 88 as it incurs losses at the same time FUND 98 does. On the other hand, the mean-variance optimal portfolio allocates 87% of wealth to FUND 98 and allocates the remainder to other hedge funds that have small standard deviations and low correlations with FUND 98. This is done to create a portfolio that has the smallest standard deviation. Wealth is also allocated to FUND 88 as it has low correlations with FUND 98 and has a smaller standard deviation than FUNDs 18 and 23.

EXHIBIT 7 shows differences between the CDD optimal portfolio and the mean-variance optimal portfolio. Unlike the CVaR optimal portfolio, the CDD optimal portfolio allocates less wealth to FUND 98 than the mean-variance optimal portfolio. In addition, FUND 56 is included within the mean-variance optimal portfolio. FUND 56's expected return is not high and its standard deviation is very small. FUND 56's inclusion can be explained by the difference of target returns. The used target return is between the expected returns of FUND 98 and FUND 56. As a result, the mean-variance optimal portfolio allocates 14% of the wealth to FUND 56. On the other hand, when the target return is equal to the expected return of the CVaR optimal portfolio, the mean-variance optimal portfolio allocates none of the wealth to FUND 56 as the target return is now higher than the expected return of FUND 98.

The mean-variance optimal portfolios have not only small standard deviations but also low CVaR and CDD as illustrated by EXHIBIT 8. This is attributed to the higher percentage of wealth allocated to FUNDs 98 and 56 within the mean-variance optimal portfolio. FUNDs 98 and 56 have not only very small standard deviations but also have a very small CVaR and CDD.

Out-of-sample Results

This subsection discusses the difference in the performances of the portfolios constructed by three methods introduced in the previous section. All three portfolios were constructed at the start of January 2002 using monthly returns from January 2001 to December 2001 as in-sample data. The portfolio was then invested in for the month of January 2002. Following this, the optimal portfolio for February 2002 was constructed using monthly returns from January 2001 to January 2002 as in-sample data. In the same way, the portfolio was constructed for each month, taking all previous monthly returns as in-sample data. EXHIBIT 9 shows the growth in wealth managed by each portfolio optimization method from January 2002 to December 2005.

Insert EXHIBIT 9.

EXHIBIT 9 shows that the CVaR and CDD optimal portfolios suffered drawdowns for the first one year. EXHIBIT 10 shows the transfers of weights allocated to each fund within the CDD optimal portfolio with a risk tolerance level at 0.1% and this helps to explain the drawdowns.

Insert EXHIBIT 10.

The CDD optimal portfolio allocated a high percentage of wealth to FUND 13 from January 2002 to March 2002. This is due to the very high returns and no large losses recorded by FUND 13 in 2001. However FUND 13 incurred large losses in March and April 2002 causing the portfolio to re-allocate a large percentage of wealth to FUND 88 in May 2002. In June, the CDD optimal portfolio allocated wealth to FUND 13 again since FUND 13 earned a high return in May. The portfolio once again incurred a large loss in June 2003 as FUND 13 incurred a large loss in June. As just explained, the CVaR optimization algorithm allocates wealth to the fund that earned a high return in the previous month and withdraws wealth from the fund that suffered a large loss in the previous month. The reliability of CVaR and CDD optimizations is low when there is only small set of sample data. For example, twenty months of in-sample data with a confidence level set at 90% means that only two months are referenced as having negative tail risk. As a result, shifts of allocations occur frequently in the first year. Drawdowns incurred during the first year by the CVaR optimal portfolio can be attributed to the above reasons. EXHIBIT 11 presents the basic statistics relating to the performance of the portfolios created by each of the three optimization methods in 2004-2005.

Insert EXHIBIT 11.

The CDD optimal portfolio with risk tolerance 0.1% has the highest Sharpe ratio. Its annualized return is also the highest at 24.04%. The CVaR and CDD of this portfolio are also very small at 1.14% and 1.19% respectively. That is to say, the CDD optimal portfolio with risk tolerance 0.1% achieves high returns with low risk. The CVaR optimal portfolio with risk tolerance 0.1% also performs well. The greater the risk tolerance levels of CVaR and CDD optimal portfolios, the riskier the portfolios are. Both optimization methods allocate a very large portion of wealth to FUND 98 as it earns high returns with low risk. Therefore, the lower the risk tolerance levels, the higher the percentage of wealth allocated to FUND 98. Due to this, the returns of CVaR and CDD optimal portfolios at lower risk tolerance levels are high and stable.

The portfolio with the higher risk tolerance level is expected to generate higher returns. However, the opposite came true in this analysis. This stems from the fact that performances were evaluated in 2004-2005, while the portfolios were optimized using data from January 2001. As risk tolerance levels are enlarged, the CVaR and CDD optimizations increase allocations to the hedge funds that have higher expected returns and higher risks than FUND 98. However, these funds that earned very high returns before 2003 could not achieve high returns after 2004.

A mean-variance optimal portfolio constructed to obtain expected returns as high as the CVaR optimal portfolio at risk tolerance levels of 0.1% performs very well by allocating almost all wealth to FUND 98. However, when a mean-variance portfolio's target return is set at 3% and is constructed to obtain expected returns as high as the CDD optimal portfolio at risk tolerance levels of 0.1%, its Sharpe ratios are small. The mean-variance approach proves very unstable for high expected returns. In addition, among the three cases, the risk measures of mean-variance optimal portfolios are worse than those of the CVaR and CDD optimal portfolios with risk tolerance levels at 0.1%. These results suggest that for high returns, the CVaR and CDD optimizations are more appropriate methods than the mean-variance optimization. On the other hand, the mean-variance optimal portfolio with target return 1.5% achieves stable return at 12.55% per annum, has a Sharpe ratio of 4.20 and has a very small CVaR and CDD.

In reality, investors sometimes avoid allocating a large share of their wealth to a single fund as they are cautious of hidden risk in the fund. This study looks at instances where the percentage of investment in a single fund is limited to, at most, 15%. EXHIBIT 12 represents basic statistics relating to the performance of the portfolio obtained by each optimization method, keeping in mind an investment restriction of 15%.

Insert EXHIBIT 12.

Portfolios without 15% limitations perform better than those with 15% limitations in all three cases. Fifteen percent limitations reduce returns and increase risks.

The investment data used for this study is restricted to hedge funds that continued to operate for at least 5 years from 2001 to 2005. Therefore, it is not exposed to the risk of investing in funds that went bankrupt during the same period. If this study included those funds, they might be selected by the mean-variance optimization method, which does not take negative tail risks into account. In such a case, the 15% limitations could work well.

Performance analysis of hedge funds

As discussed in earlier sections, studies done by Fung and Hsieh [1997-2006], Schneeweis and Spurgin [1998], Brown and Goetzmann [2003], and Agarwal and Naik [2004] introduced new proxies for hedge fund returns and these proxies explain the returns of dynamic trading strategies, event arbitrage, and illiquid securities. In this section, the performance of Asia-Pacific hedge funds is analyzed in accordance with those practices. In theory, hedge fund returns can be decomposed into returns of the asset class factors and *alphas*:

$$R_i = \alpha_i + \sum_{j=1}^{m} \beta_{ij} f_j + \epsilon_i, \tag{5}$$

where R_i and f_j denote the returns of FUND i and factor j respectively. In this decomposition, Fung and Hsieh [1997] referred $\sum_{j=1}^{m} \beta_{ij} f_j$ as " style, " and $\alpha_i + \epsilon_i$ as " skill. "39 hedge funds are decomposed into asset class factors by time-series regressions. This study adopts following market indices as factors. Stock index factors are representative of stock indices of Asian countries, S&P500, and the Dow-Jones European stock index. Bond index factors are representated by MSCI bond indices of Asian countries and the US. Foreign exchange factors are reflected in exchange rates of Asian currencies against the US dollar. Option factors are representative of options on stock indices. Data on these indices is obtained from Bloomberg. EXHIBIT 13 lists the indices used in this analysis.

Insert EXHIBIT 13.

In addition to the above indices, size factors (small minus big, SMB) and book-to-market factors (high minus low, HML) are also used as factors. Stock indices themselves are used as stock factors in emerging countries where no style index such as large cap index, small cap index, value index and growth index exists. MSCI bond index return of each country and the yield spread between US treasury and a bond index of each country are used as bond factors. Hedge funds that follow fixed income and distressed debt strategies are expected to be explained by credit-related factors such as credit spreads. However, for the purposes of this study, stock indices are used as substitutes for credit spread data due to the difficulty in obtaining such data in Asia-Pacific financial markets. The results of calculations on the values of call and put options on the stock indices using the Black-Scholes formula are used as non-linear factors explaining dynamic trading strategies. Here, the historical volatilities are used and strike prices are set to ATM and OTM (101% and 99% of the spot prices for call and put options respectively). The returns of the options are obtained by the following trading method. For instance, the return in April is the return obtained by buying the option which expires in May at the end of March, and selling the option at the end of April. Agarwal and Naik [2004] showed that hedge funds which take distressed debt and event driven strategies tend to have non-linear relations with stock prices like options.

Fund returns are first decomposed into stock indices, bond indices and currency factors by time-series regressions. When fund returns and factors show non-linear relation, option factors are added to the list of explanatory variables and time-series regression is implemented again. Time-series regressions are executed for the monthly returns of 60 months from January 2001 to December 2005, 28 months from January 2001 to April 2003 and 32 months from May 2003 to December 2005. The returns are then categorized into one of two periods with April 2003 taken as the midpoint. April 2003 is the month when stock prices in Japan recorded the lowest price since the bubble boom. Funds' strategies and their main factors are listed as follows.

- Strategy: Distressed Debt

  Main Factors: stock index, SMB, option, and bond index

  Although option factors are significant in the first half, they affect few funds in the second half. The funds tend to suffer larger losses when the market falls substantially.

- Strategy: Relative Value

  Main Factors: stock index, SMB, HML, option, and bond index

  Option factors are significant especially in the first half. The factors related to stocks are generally important, while bond factors are not so significant.

- Strategy: Long / Short Equities

  Main Factors: stock index, SMB, HML, and option

  These factors explain the returns of hedge funds that invest in Korea, Greater China, AS/NZ, emerging markets, and Asia-ex Japan to a high degree. The explanation powers for hedge funds that invest only within Japan are lower in the first half than in the second half. These funds seem to use some special strategies that cannot be captured by typical factors in a bear market.

- Strategy: Fixed Income

  Main Factors: stock index, SMB, option, bond index, and US treasury-spread

  Stock-related factors are significant. Thus, it is conjectured that these returns have exposures to credit-related markets.

- Strategy: Multi Strategy

  Main Factors: stock index, SMB, option, bond index, US treasury-spread, and currency

  Significant factors are different among funds. Many funds change the exposures to factors very much from the first half to the second half.

- Strategy: Macro

  Main Factors: stock index, SMB, bond index, US treasury-spread, and currency

  Their P/Ls fluctuate very much when the market moves substantially, mainly because of the large use of leverage. Currency factors are significant while option factors are not.

- Strategy: CTA / Managed Futures

  Main Factors: stock index, SMB, option, bond index, and US treasury-spread

  Their P/Ls have similar characteristics to macro funds with lower volatilities. However, currency factors are not significant and option factors are important for some funds in the second half.

- Strategy: Event Driven

  Main Factors: stock index, SMB, and currency

  Stock-related factors are significant. Currency factors are important in the second half.

Option factors are very effective in explaining the returns from hedge funds that adopt the distressed debt strategy and those that are exposed to the stock-related factors in Japan.

Insert EXHIBIT 14.

EXHIBIT 14-A represents the regression results for investment strategies. Fund returns were more explained when the entire period is divided into first and second halves. This raises the adjusted R^2 for Macro and CTA / Managed Futures funds substantially, more than for Long / Short equity funds. EXHIBIT 14-B represents the regression results for investment geographies. The explanatory powers for hedge funds that have broad investment geographies such as "global" and "Asia including Japan" improve when the entire period is devided into first and second halves. The adjusted R^2 for funds investing in only Japan are relatively low in the first half. On the other hand, the returns of hedge funds investing in emerging markets or "Asia excluding Japan" can be well explained by linear factor models which do not have non-linear factors. Further, more detailed analysis reveales that most hedge funds have different exposures to factors in each period.[1]

Finally, portfolio optimizations and factor analyses are integrated to show how these methods are utilized in practice. The performance of hedge funds and Fund-of-Funds can be estimated before they are reported as most of the factors are obtained on a daily basis. Tradable factors also allow for hedge funds' risks to be partially or completely hedged. This study also examines the possibility of monitoring and controlling the risks of the optimal portfolio. In particular, this study tries to replicate the returns in 2005 of the CDD optimal portfolio with risk tolerance level 0.1% that achieves the highest Sharpe ratio. First, regressions are implemented in each quarter of 2005 by using the data of the past two years to identify the *alphas* and exposures to factors of the funds selected by the optimization.

Next, returns of the optimal portfolio are replicated by using *alphas* and factors. The first graph of EXHIBIT 15-A shows the increases in wealth of the CDD optimal portfolio and its mimicking portfolio.

Insert EXHIBIT 15.

Fund-of-Funds returns are estimated with high accuracy except for the months of May and October. From EXHIBIT 10, we can arrange funds in descending

[1]The results will be offered upon request.

order according to their weights as follows: FUNDs 98, 13, 73, 105 and so on. In particular, 90% of the wealth is allocated to FUND 98. EXHIBIT 15-B show the returns of the four hedge funds within the portfolio and their mimicking portfolios. FUND 98's returns could not be replicated in May and October and this explains the incorrect estimation of returns for the two months when mimicking the Fund-of-Funds portfolio.

On the other hand, the returns for the remaining three funds can be estimated and FUND 98's returns can also be estimated for the other 10 months. Overall, the portfolio returns in ten out of twelve months is estimated with high accuracy. This approach to portfolio optimization and performance analysis is useful in forming Fund-of-Funds and monitoring and controlling their risks.

Conclusion

This study investigated the returns of hedge funds whose locations or investment targets within the Asia-Pacific region. The analysis of the returns of hedge fund revealed the importance of the negative tail risk. This calls for optimization methods that take negative tail risks into account for creating a portfolio of hedge funds. Optimal portfolio of hedge funds subject to constraints on risk measures such as conditional value-at-risk (CVaR) or conditional drawdown (CDD) using the algorithms proposed by Rockafellar and Uryasev [2000,2002] and Chekhlov et al. [2000] were constructed. Their algorithms allowed for high returns with low negative tail risk. Out-of-sample results showed that those optimization methods are powerful in forming a hedge funds' portfolio upon having enough in-sample data.

The returns of 39 hedge funds were then decomposed into asset class factors by time-series regressions and their characteristics examined for investment strategies and geographical exposures. Finally, this study looked at the possibility of capturing the exposures of the hedge funds selected by the optimization process and replicating the returns of the optimal portfolio by factors and *alphas*. The returns in ten out of twelve months were able to be estimated with high accuracy. In order to estimate returns with higher accuracy, we will try in the future to find more appropriate factors and improve in the techniques of decomposing returns into factors.

Appendix

In appendix, we describe the mathematical definitions of CVaR and CDD, and the optimization algorithms. First, we define CVaR and CDD. R^i is a random variable that denotes return of FUND i in a certain period. Hence, the loss are represented by $-R^i$. We represent its cumulative distribution function by $\Psi_{R^i}(\zeta)$, i.e. $\Psi_{R^i}(\zeta) = P[-R^i \leq \zeta]$. Before defining CVaR, we describe the definition of VaR.

Definition 1 *The value-at-risk (VaR) V^i_α of FUND i with confidence level* $100\alpha\%$ *are defined by*

$$V^i_\alpha = \min\{\zeta | \Psi_{R^i}(\zeta) \geq \alpha\}. \tag{6}$$

CVaR is defined as follows.

Definition 2 *The conditional value-at-risk (CVaR) ϕ^i_α of FUND i with confidence level* $100\alpha\%$ *are defined by*

$$\phi^i_\alpha = E[-R^i | -R^i \geq V^i_\alpha], \tag{7}$$

where, the cumulative distribution function of the conditional expectation is

$$\Psi^\alpha_{R^i}(\zeta) = \begin{cases} 0 & \text{for } \zeta < V^i_\alpha, \\ \dfrac{\Psi_{R^i}(\zeta) - \alpha}{1-\alpha} & \text{for } \zeta \geq V^i_\alpha. \end{cases} \tag{8}$$

Next, we define CDD following Chekhlov et al. [2000]. R^i_t denotes the return of FUND i at time t, and let $v^i_\tau = 1 + \sum_{s=1}^{\tau} R^i_s$. In other words, v^i_τ represents the wealth at time τ maneged by FUND i without compounding.

Definition 3 *We define the drawdown of FUND i at time t by*

$$d^i_t = \max_{0 \leq \tau \leq t}\{v^i_\tau\} - v^i_t. \tag{9}$$

Next, we define the conditional drawdown (CDD) with confidence level $100\alpha\%$. $\{\hat{d}^i_1, \cdots, \hat{d}^i_T\}$ represent the sorted $\{d^i_1, \cdots, d^i_T\}$ in decreasing order, and let $\frac{k-1}{T} < 1 - \alpha \leq \frac{k}{T}$.

Definition 4 *The conditional drawdown (CDD)* D^i_α *with confidence level* $100\alpha\%$ *is defined by*

$$D^i_\alpha = \frac{\sum_{t=1}^{k-1} \hat{d}^i_t}{(1-\alpha)T} + \left\{1 - \frac{k-1}{(1-\alpha)T}\right\}\hat{d}^i_k. \tag{10}$$

Finally, we describe the optimization algorithms with constraints on CVaR and CDD. We maximize the expected return by investing in n funds for a certain period with constraint on a risk measure. The $\mathbf{R}^n$-valued random variable $\mathbf{r} = (r_1, \cdots, r_n)'$ represents fund returns for that period, and let $\Phi(\mathbf{x})$ be a risk measure of the portfolio $\mathbf{x}$. In this setting, the optimization problem is stated as follows.

$$\max_{\mathbf{x}} E[\mathbf{r}'\mathbf{x}], \tag{11}$$

subject to

$$0 \leq x_i \leq 1, \quad i = 1, \cdots, n, \tag{12}$$

$$\sum_{i=1}^{n} x_i \leq 1, \tag{13}$$

$$\Phi(\mathbf{x}) \leq \omega, \tag{14}$$

where ω denotes a risk tolerance level. We substitute CVaR and CDD for $\Phi(\mathbf{x})$. We state the theorem that reduces the optimization problem to a linear programming problem.

Theorem 1 *As a function of* ζ*,*

$$\zeta + \frac{1}{1-\alpha} E[(-\mathbf{r}'\mathbf{x} - \zeta)_+] , \tag{15}$$

$$\zeta + \frac{1}{1-\alpha}\frac{1}{T}\sum_{t=1}^{T}(d^{\mathbf{x}}_t - \zeta)_+ \tag{16}$$

are finite and convex. Moreover,

$$\phi^{\mathbf{x}}_\alpha = \min_\zeta \left\{\zeta + \frac{1}{1-\alpha} E[(-\mathbf{r}'\mathbf{x} - \zeta)_+]\right\} , \tag{17}$$

$$D^{\mathbf{x}}_\alpha = \min_\zeta \left\{\zeta + \frac{1}{1-\alpha}\frac{1}{T}\sum_{t=1}^{T}(d^{\mathbf{x}}_t - \zeta)_+\right\} . \tag{18}$$

(The proof is described in Uryasev[2001].)

By theorem 1, when we have T historical data, for the case of the CVaR optimization, the equations (11) and (14) can be expressed as follows.

$$\max_{\mathbf{x}} \frac{1}{T}\sum_{t=1}^{T} \mathbf{r}_t'\mathbf{x}, \tag{19}$$

$$\zeta + \frac{1}{1-\alpha}\frac{1}{T}\sum_{t=1}^{T}(-\mathbf{r}_t'\mathbf{x} - \zeta)_+ \leq \omega,\ \zeta \in \mathbf{R}. \tag{20}$$

Here $\mathbf{r}_t$ denotes the returns of funds at time t. Because we can rewrite the equation (20) as follows, the CVaR optimization problem can be reduced to a linear programming problem.

$$\zeta + \frac{1}{1-\alpha}\frac{1}{T}\sum_{t=1}^{T} w_t \leq \omega, \tag{21}$$

$$-\mathbf{r}_t'\mathbf{x} - \zeta \leq w_t,\quad t = 1, \cdots, T, \tag{22}$$

$$\zeta \in \mathbf{R},\ w_t \geq 0,\quad t = 1, \cdots, T. \tag{23}$$

For the case of the CDD optimization, the equations (11) and (14) can be expressed as follows.

$$\max_{\mathbf{x}} \frac{1}{T}\sum_{t=1}^{T} \mathbf{r}_t'\mathbf{x}, \tag{24}$$

$$\zeta + \frac{1}{1-\alpha}\frac{1}{T}\sum_{t=1}^{T}(\max_{1\leq s\leq T}\sum_{\tau=1}^{s}\mathbf{r}_\tau'\mathbf{x} - \sum_{\tau=1}^{t}\mathbf{r}_\tau'\mathbf{x} - \zeta)_+ \leq \omega,\ \zeta \in \mathbf{R}. \tag{25}$$

Because we can rewrite the equation (25) as follows, the CDD optimization problem can be reduced to a linear programming problem.

$$\zeta + \frac{1}{1-\alpha}\frac{1}{T}\sum_{t=1}^{T} z_t \leq \omega, \tag{26}$$

$$z_t \geq u_t - \sum_{\tau=1}^{t}\mathbf{r}_\tau'\mathbf{x} - \zeta,\quad 1 \leq t \leq T, \tag{27}$$

$$z_t \geq 0,\quad 1 \leq t \leq T, \tag{28}$$

$$u_t \geq \sum_{\tau=1}^{t}\mathbf{r}_\tau'\mathbf{x},\quad 1 \leq t \leq T, \tag{29}$$

$$u_t \geq u_{t-1},\quad 1 \leq t \leq T, \tag{30}$$

$$u_0 = 0. \tag{31}$$

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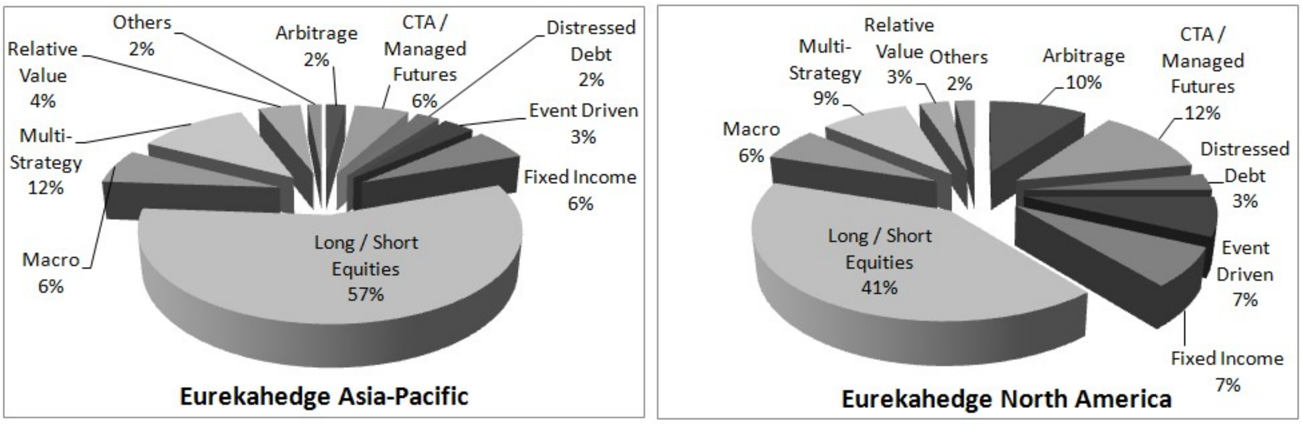
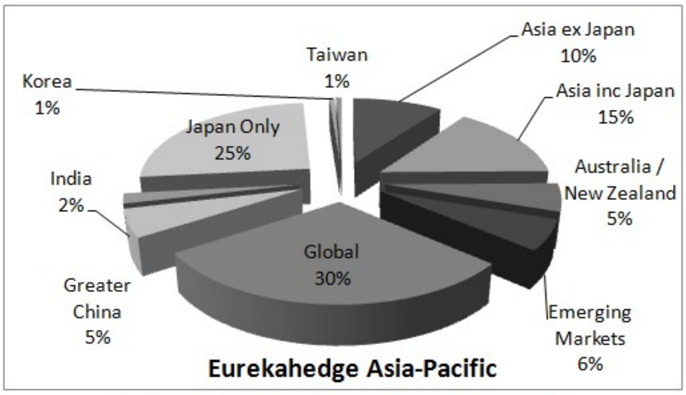
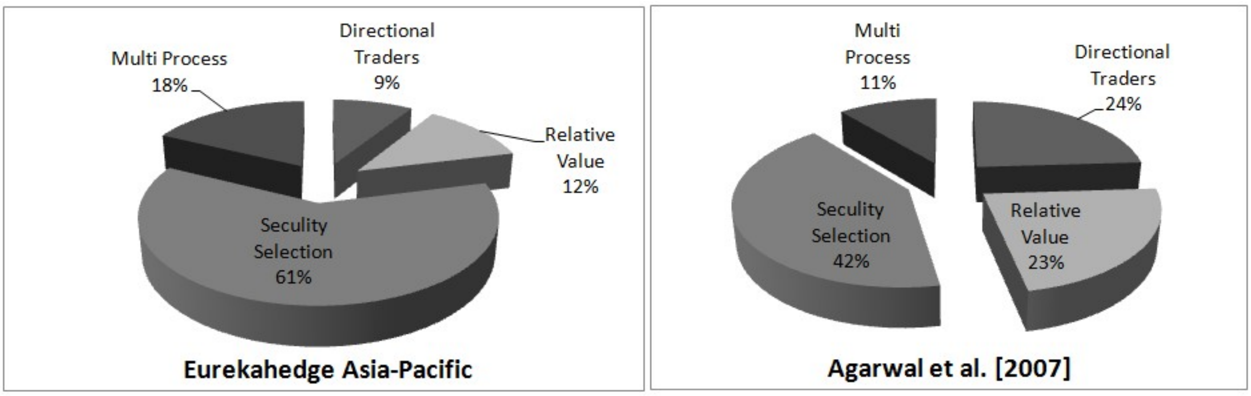


A: Breakdown by Investment Strategy



B: Breakdown by Investment Geography



C: Comparison with Other Databases

EXHIBIT 1: Breakdown of Hedge Funds by Investment Strategy and Geography

	Number of Funds in our sample	Average Return	Standard Deviation	Skew	Kurtosis	D-P p-value
Investment Strategy						
Long / Short Equities	58	1.30%	3.85%	0.46	5.21	0.96%
Multi-Strategy	17	1.01%	3.25%	0.10	4.75	1.37%
CTA / Managed Futures	6	0.63%	4.42%	0.33	4.12	7.95%
Relative Value	6	1.30%	4.63%	0.39	4.68	0.45%
Distressed Debt	5	1.15%	1.44%	−0.14	4.86	0.47%
Macro	5	1.80%	9.24%	0.28	5.79	35.14%
Fixed Income	4	1.38%	2.00%	1.22	8.22	0.00%
Arbitrage	3	0.49%	1.32%	−0.36	3.64	19.93%
Event Driven	2	1.77%	1.56%	0.80	6.15	0.03%
Others	2	1.66%	12.11%	0.20	3.19	61.43%
Investment Geography						
Japan Only	26	1.08%	3.59%	0.70	5.35	0.19%
Asia incl Japan	21	1.26%	3.76%	0.54	4.75	1.37%
Global	20	1.01%	3.90%	0.07	4.63	7.95%
Asia ex-Japan	15	1.37%	4.58%	0.27	6.23	0.45%
Emerging Markets	13	1.60%	3.81%	0.44	5.75	0.47%
Australia / New Zealand	8	0.96%	2.85%	−0.12	3.70	35.14%
Korea	2	1.96%	6.03%	0.32	3.56	25.87%
Greater China	1	2.17%	7.32%	0.14	2.98	83.87%
India	1	2.13%	9.54%	−0.98	4.86	0.07%
Taiwan	1	0.78%	5.75%	−0.17	6.98	0.22%
Asset Class						
Hedge Fund Universe	108	1.23%	3.94%	0.36	5.10	1.76%
Asia-Pacific Stock Indices	37	0.83%	5.22%	−0.13	3.03	81.2%
Asia-Pacific Bond Indices	9	0.52%	1.22%	−0.32	4.75	3.71%

EXHIBIT 2: Statistics for Hedge Fund Categories, 2001-2005

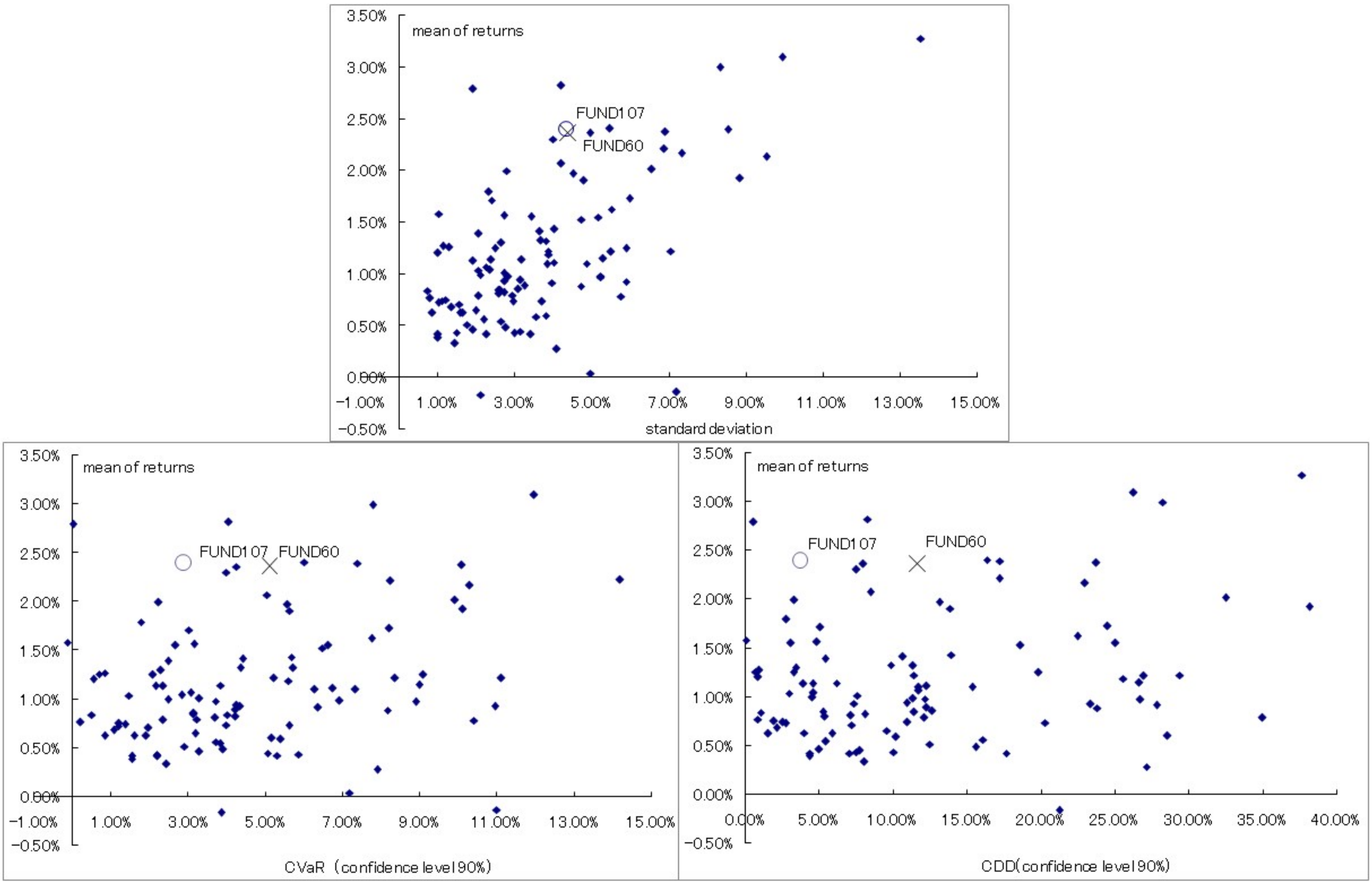


EXHIBIT 3: Risk to Return of the Hedge Funds

Risk Tolerance Levels	0.10%	0.50%	1.00%	3.00%	5.00%
FUND18	0.39%	2.13%	4.01%	7.05%	10.58%
FUND23	2.12%	4.76%	11.17%	20.12%	28.72%
FUND72	4.39%	12.36%	12.27%	28.30%	41.77%
FUND98	93.10%	80.76%	72.55%	44.53%	18.94%
Expected Returns	2.81%	2.85%	2.88%	2.97%	3.05%
Standard Deviations	1.89%	2.12%	2.58%	4.04%	5.60%
CVaR(confidence level 90%)	0.10%	0.50%	1.00%	3.00%	5.00%
CDD(confidence level 90%)	0.44%	0.65%	1.21%	3.69%	8.15%

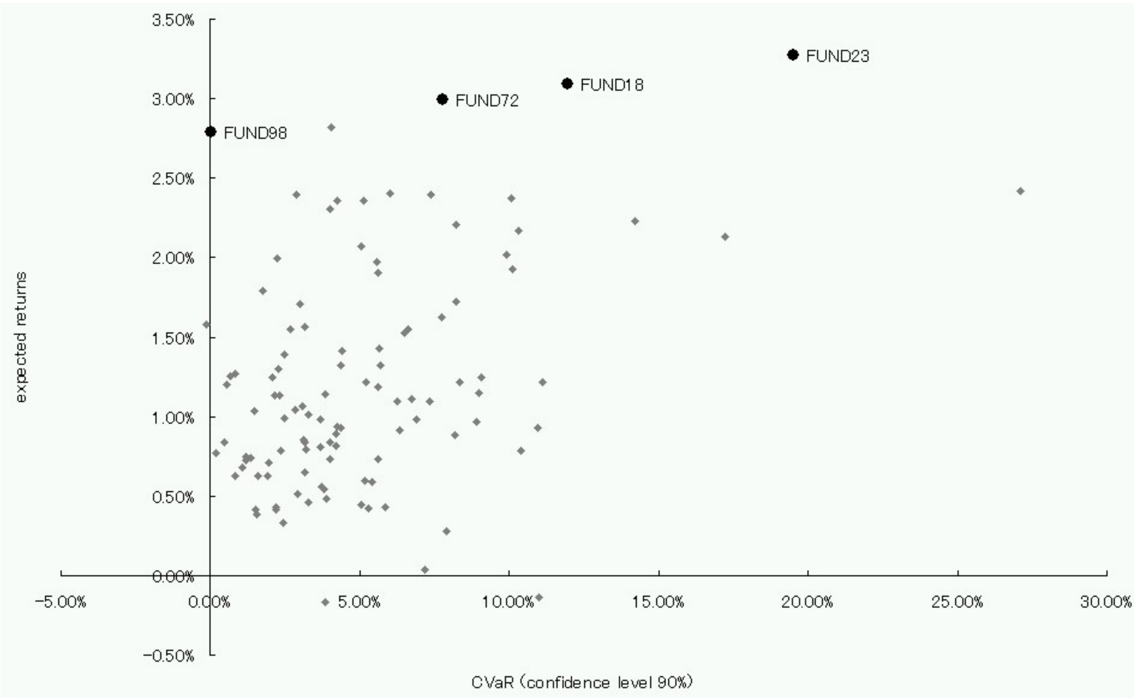


EXHIBIT 4: CVaR (confidence level of 90%) Optimal Portfolios

Risk Tolerance Levels	0.10%	0.50%	1.00%	5.00%	10.00%
FUND13	17.84%	0.00%	0.00%	0.00%	0.00%
FUND18	0.00%	0.00%	2.97%	3.31%	8.96%
FUND23	5.01%	3.28%	10.94%	27.22%	44.26%
FUND29	1.86%	0.00%	0.00%	0.00%	0.00%
FUND49	1.59%	0.00%	0.00%	0.00%	0.00%
FUND72	0.00%	9.16%	10.90%	32.08%	31.38%
FUND73	11.69%	0.00%	0.00%	0.00%	0.00%
FUND79	2.29%	0.00%	0.00%	0.00%	0.00%
FUND88	0.00%	0.00%	0.00%	0.00%	14.00%
FUND91	3.59%	0.00%	0.00%	0.00%	0.00%
FUND98	56.13%	87.56%	75.19%	37.38%	1.40%
Expected Returns	2.43%	2.83%	2.88%	3.00%	3.10%
Standard Deviations	1.75%	1.95%	2.51%	4.88%	7.01%
CVaR(confidence level 90%)	0.10%	0.33%	0.97%	4.26%	7.60%
CDD(confidence level 90%)	0.10%	0.50%	1.00%	5.00%	10.00%

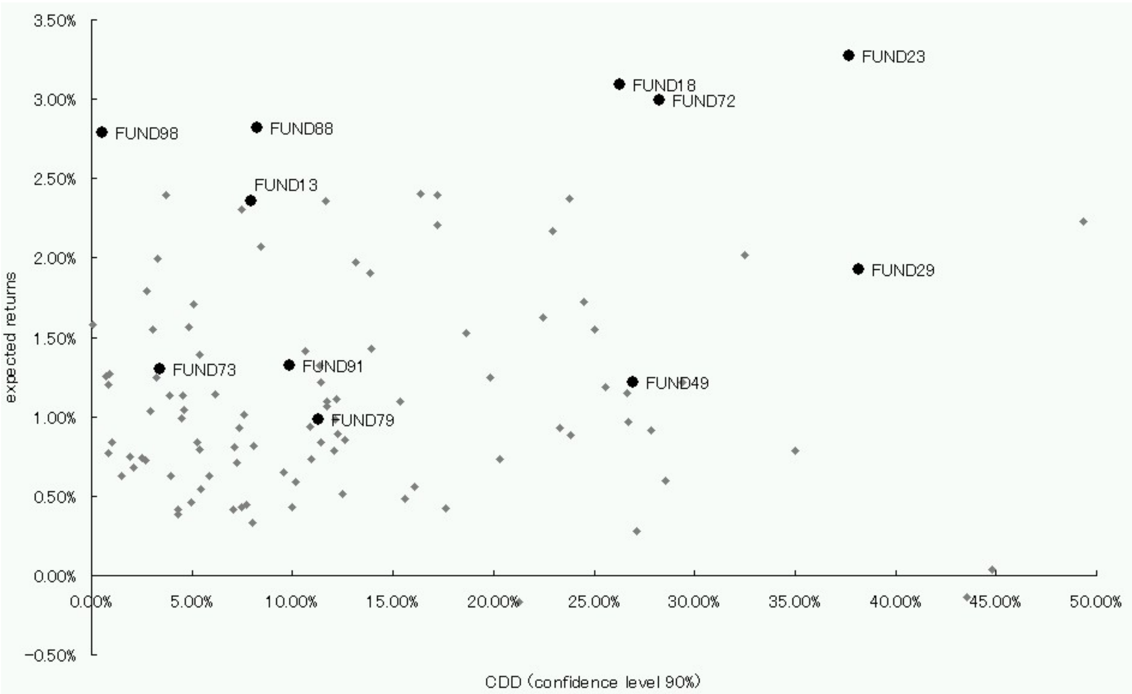
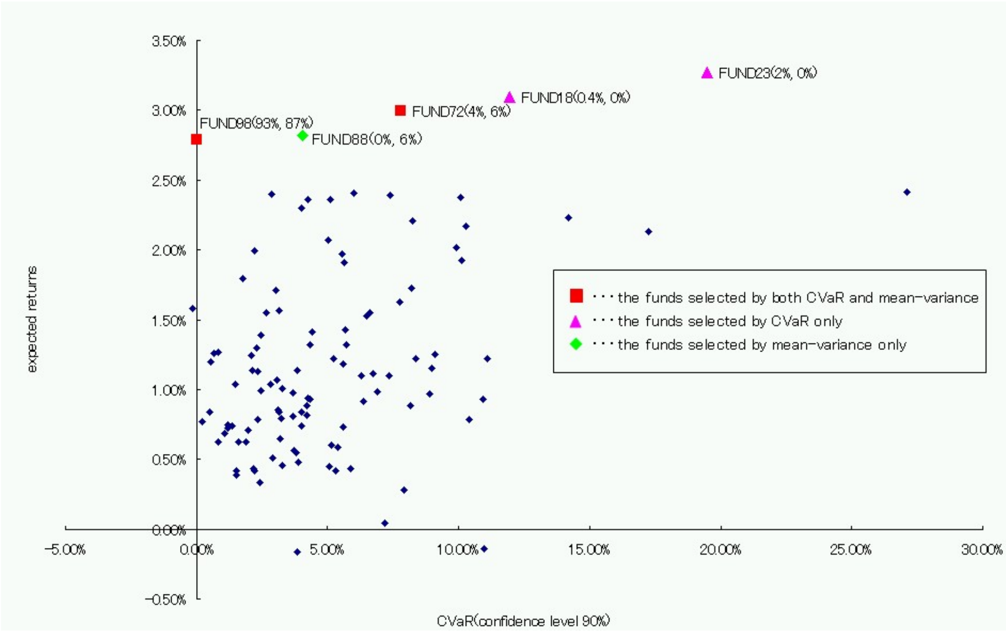
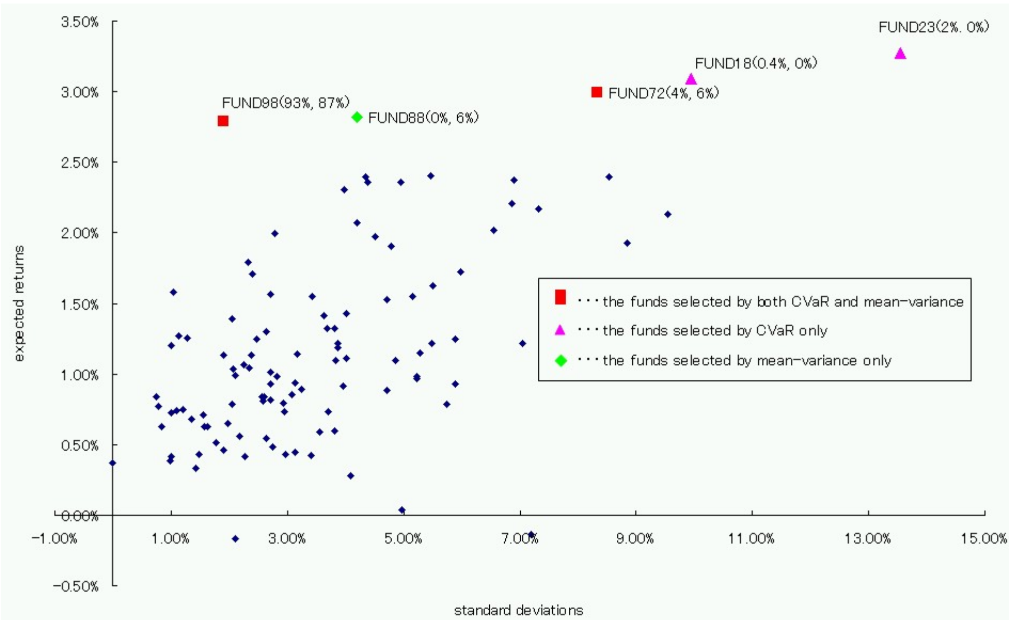


EXHIBIT 5: CDD (confidence level of 90%) Optimal Portfolios

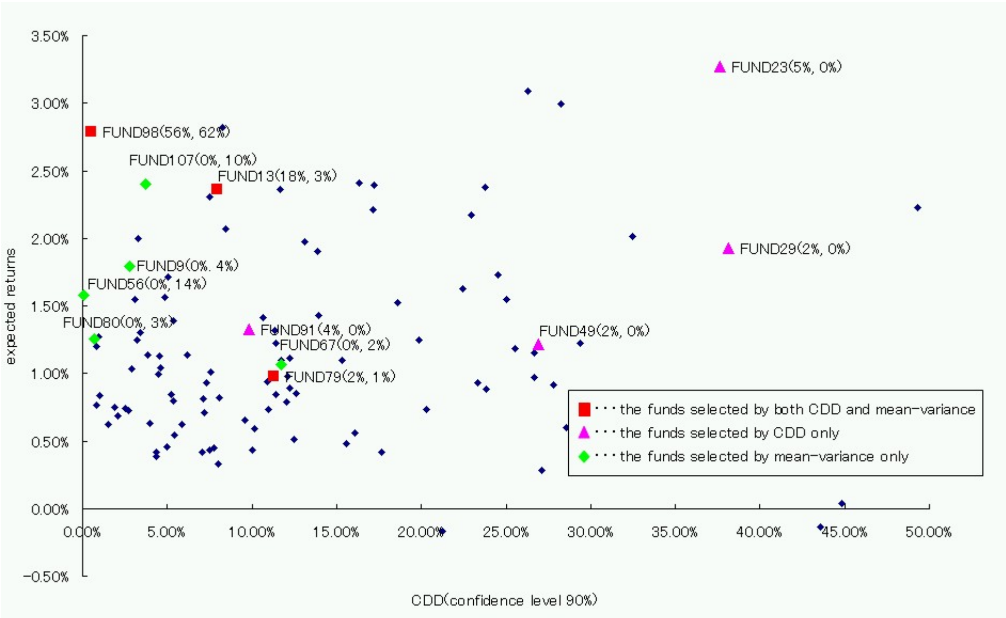


A: Mean-CVaR

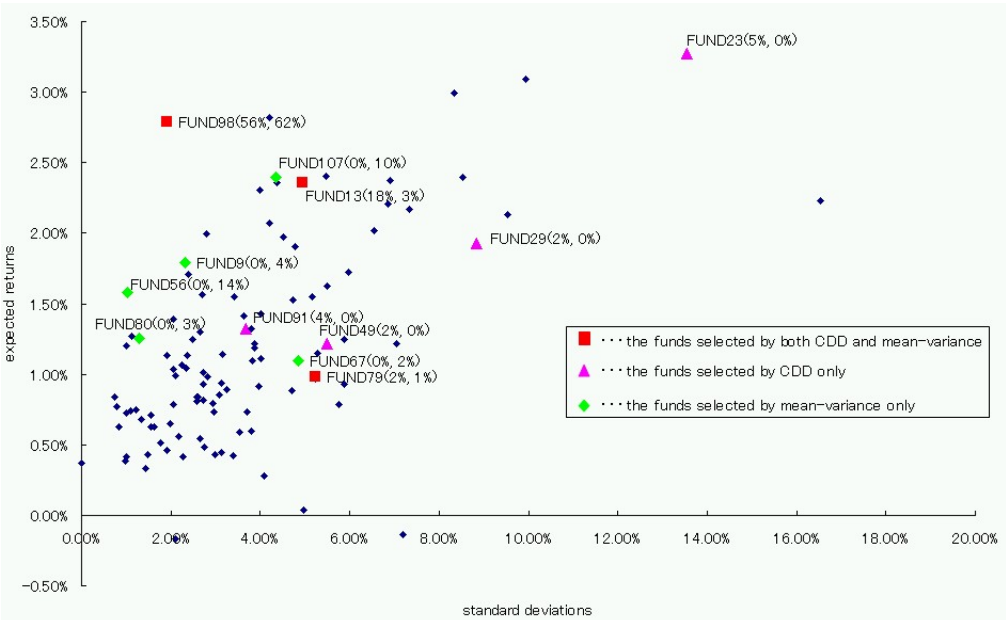


B: Mean-Standard Deviation

EXHIBIT 6: Hedge Funds Selected by CVaR or Mean-Variance Optimization Programs



・A: Mean-CDD



B: Mean-Standard Deviation

EXHIBIT 7: Hedge Funds Selected by CDD or Mean-Variance Optimization Programs

Expected Returns	1.50%	2.43%	2.81%
Standard Deviations	0.61%	1.38%	1.86%
CVaR(confidence level 90%)	-0.39%	-0.23%	0.21%
CDD(confidence level 90%)	0.05%	0.32%	0.49%

EXHIBIT 8: Statistics for Mean-Variance Optimal Portfolios

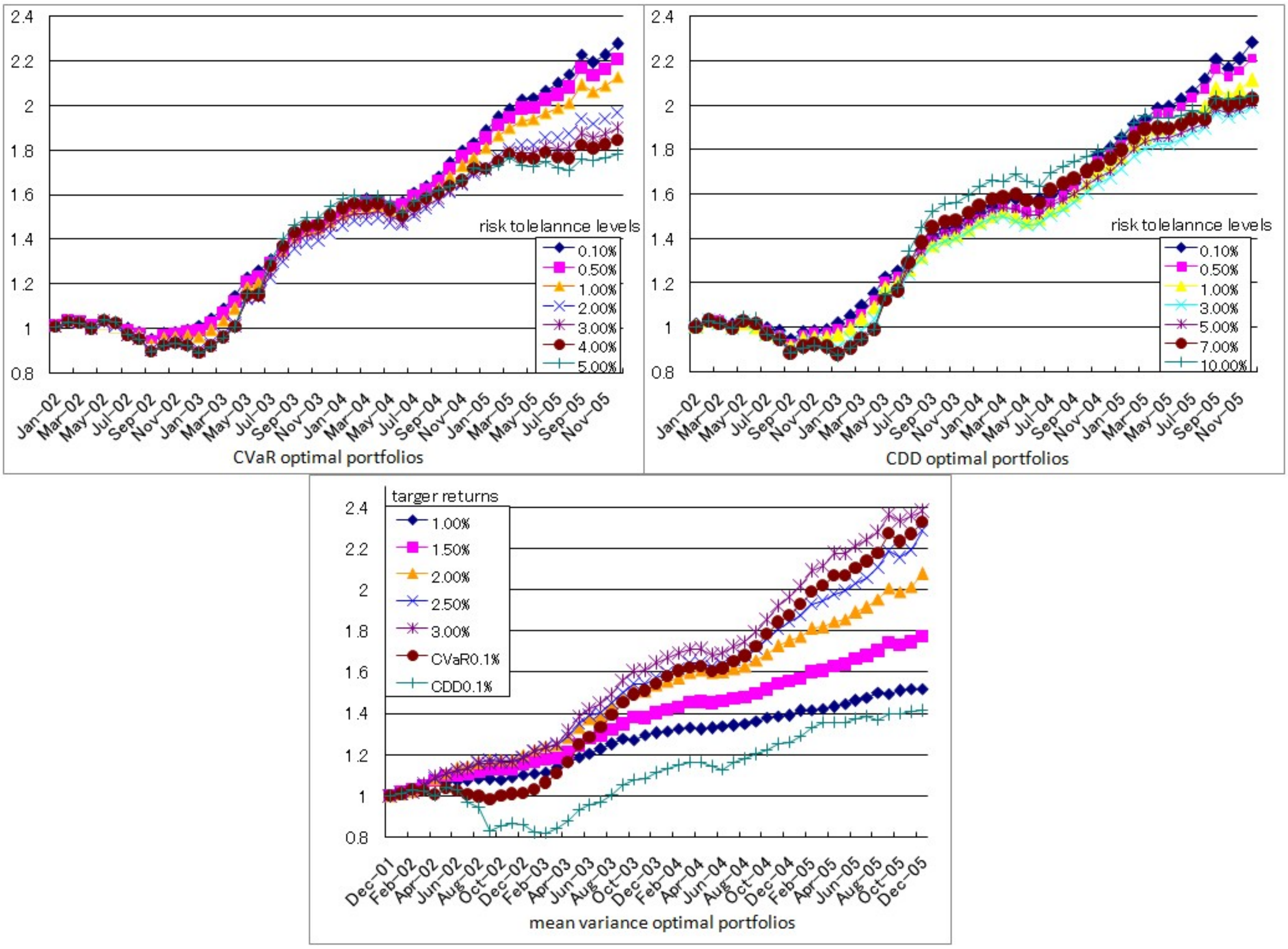


EXHIBIT 9: Growth in Wealth Managed by Optimal Portfolios

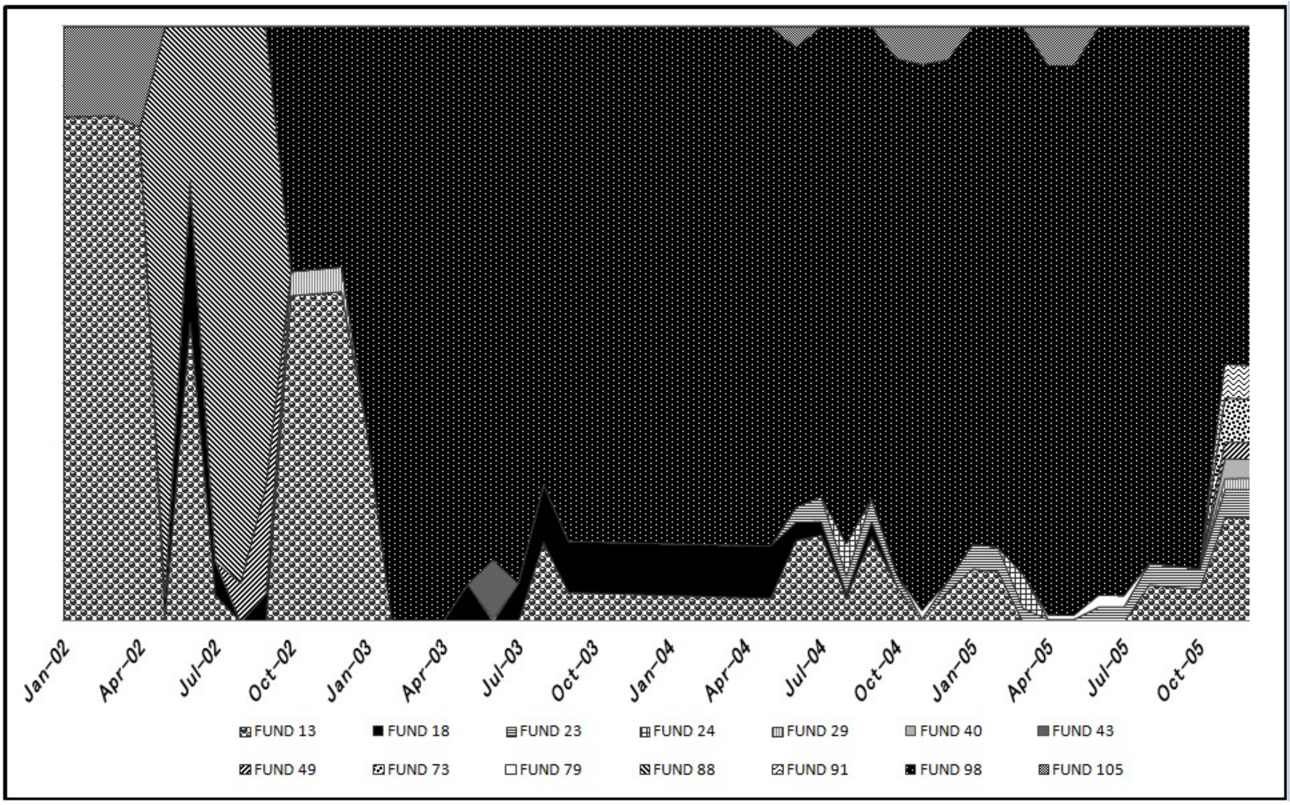


EXHIBIT 10: Transfers of Weights Allocated to each fund within the CDD (risk tolerance level at 0.1%) Optimal Portfolio

Risk Tolerance Levels	0.10%	0.50%	1.00%	2.00%	3.00%	4.00%	5.00%
Annualized Returns	23.40%	21.92%	20.43%	17.49%	13.93%	10.67%	7.36%
Standard Deviations	4.87%	4.72%	4.63%	4.59%	4.91%	5.34%	5.87%
Sharpe ratios	4.31	4.13	3.90	3.29	2.35	1.55	0.85
maximum drawdowns	1.68%	1.54%	1.42%	2.02%	2.98%	3.76%	4.63%
CVaR(Confidence Level 90%)	1.22%	1.18%	1.11%	1.19%	1.41%	1.79%	2.20%
CDD(Confidence Level 90%)	1.43%	1.41%	1.29%	1.63%	2.07%	2.55%	3.73%

A: CVaR Optimal Portfolio

risk tolerance levels	0.10%	0.50%	1.00%	3.00%	5.00%	7.00%	10.00%
annualized returns	24.04%	23.12%	20.98%	17.81%	16.49%	15.50%	13.10%
standard deviations	4.94%	4.89%	5.03%	4.64%	4.52%	4.46%	5.15%
Sharpe ratios	4.38	4.23	3.69	3.32	3.11	2.94	2.08
maximum drawdowns	1.80%	1.65%	2.87%	2.67%	2.50%	2.42%	3.29%
CVaR(confidence level 90%)	1.14%	1.23%	1.47%	1.30%	1.16%	1.11%	1.49%
CDD(confidence level 90%)	1.19%	1.47%	2.30%	2.39%	2.14%	1.83%	2.33%

B: CDD Optimal Portfolio

expected returns	1.00%	1.50%	2.00%	2.50%	3.00%	CVaR0.1%	CDD0.1%
annualized returns	7.90%	12.55%	16.30%	20.48%	20.42%	22.78%	12.82%
standard deviations	1.90%	2.42%	3.33%	4.50%	4.93%	4.83%	4.45%
Sharpe ratios	2.90	4.20	4.17	4.02	3.65	4.22	2.34
maximum drawdowns	0.62%	0.61%	0.88%	1.35%	2.05%	1.68%	3.04%
CVaR(confidence level 90%)	0.37%	0.41%	0.64%	1.04%	1.38%	1.20%	1.45%
CDD(confidence level 90%)	0.41%	0.46%	0.77%	1.12%	1.60%	1.30%	2.21%

C: Mean-Variance Optimal Portfolio

EXHIBIT 11: Performances of the Optimal Portfolios, 2004-2005

risk tolerance levels	0.10%	0.50%	1.00%	2.00%	3.00%	4.00%	5.00%
annualized returns	15.42%	16.30%	15.09%	13.97%	12.66%	8.76%	8.45%
standard deviations	6.39%	7.18%	7.11%	7.19%	6.73%	7.28%	7.95%
Sharpe ratios	2.04	1.94	1.79	1.61	1.52	0.87	0.76
maximum drawdowns	5.16%	6.33%	5.93%	5.74%	4.49%	5.00%	6.18%
CVaR(confidence level 90%)	2.16%	2.66%	2.56%	2.36%	2.45%	2.84%	2.89%
CDD(confidence level 90%)	5.06%	6.10%	5.64%	5.14%	4.14%	4.74%	5.55%

A: CVaR Optimal Portfolio

risk tolerance levels	0.10%	0.50%	1.00%	3.00%	5.00%	7.00%	10.00%
annualized returns	13.58%	14.83%	13.20%	14.52%	12.18%	10.27%	7.48%
standard deviations	5.88%	6.91%	7.74%	6.75%	6.91%	7.14%	8.29%
Sharpe ratios	1.90	1.80	1.40	1.80	1.42	1.10	0.61
maximum drawdowns	5.27%	6.50%	7.77%	4.73%	4.55%	4.07%	8.27%
CVaR(confidence level 90%)	2.16%	2.66%	3.25%	2.24%	2.75%	2.59%	3.10%
CDD(confidence level 90%)	5.20%	6.47%	7.75%	4.65%	4.21%	3.88%	7.61%

B: CDD Optimal Portfolio

expected returns	1.50%	2.00%	2.50%	3.00%
annualized returns	12.49%	14.29%	12.79%	11.95%
standard deviations	2.75%	4.07%	5.31%	5.43%
Sharpe ratios	3.68	2.92	1.96	1.76
maximum drawdowns	0.85%	1.89%	4.28%	4.01%
CVaR(confidence level 90%)	0.52%	0.93%	1.72%	2.07%
CDD(confidence level 90%)	0.72%	1.74%	3.91%	3.70%

C: Mean-Variance Optimal Portfolio

EXHIBIT 12: Performances of the Optimal Portfolios with 15% Limitations, 2004-2005

Stock Indices			
Japan	Russell/Nomura Large Cap Growth Index With Dividend	New Zealand	NZSE NZX ALL INDEX
	Russell/Nomura Large Cap Index With Dividend		NZSEG NZX ALL GROSS INDEX
	Russell/Nomura Large Cap Value Index With Dividend		NZSE10 NZX TOP 10 INDEX
	Russell/Nomura Mid Cap Growth Index With Dividend		NZSEMC NZX MID CAP INDEX
	Russell/Nomura Mid Cap Index With Dividend		NZSESC NZX SMALLCAP INDEX
	Russell/Nomura Mid Cap Value Index With Dividend	Philippines	PASHR PHILIPPINES ALL SHARE IX
	Russell/Nomura Mid-Small Cap Growth Index With Dividend		PCOMP PHILIPPINES COMPOSITE IX
	Russell/Nomura Mid-Small Cap Index With Dividend		SME PHILIPPINES SM-MED ENTER
	Russell/Nomura Mid-Small Cap Value Index With Dividend	Singapore	BTSRI SING: BUSINESS TIME REGN
	Russell/Nomura Small Cap Growth Index With Dividend		SESALL SINGAPORE ALL INDEX
	Russell/Nomura Small Cap Index With Dividend		STI STRAITS TIMES INDEX
	Russell/Nomura Small Cap Value Index With Dividend		UOBDAQ SING: UOB SESDAQ INDEX
	Russell/Nomura Top Cap Growth Index With Dividend	South Korea	KRX100 KOREA EXCHANGE 100 INDEX
	Russell/Nomura Top Cap Index With Dividend		KOSPI KOREA COMPOSITE INDEX
	Russell/Nomura Top Cap Value Index With Dividend		KOSPI2 KOREA KOSPI 200 INDEX
	Russell/Nomura Total Market Growth Index With Dividend		KOSDAQ KOSDAQ COMPOSITE INDEX
	Russell/Nomura Total Market Index With Dividend		KOSPI100 KOREA KOSPI 100 INDEX
	Russell/Nomura Total Market Value Index With Dividend		KOSPI50 KOREA KOSPI 50 INDEX
Australia	AS25 S&P/ASX 100 INDEX		KOSPLMKC KOSPI LARGE CAP INDEX
	AS26 S&P/ASX 20 INDEX		KOSPMMKC KOSPI MID CAP INDEX
	AS31 S&P/ASX 50 INDEX		KOSPSMKC KOSPI SMALL CAP INDEX
	AS34 S&P/ASX MIDCAP 50 INDEX		KOSTAR KOSDAQ STAR INDEX
	AS38 S&P/ASX SMALL ORDS INDEX		KOSDAQ50 KOSDAQ50 INDEX
	AS39 ASX SMALLCAP RESOURCES		KOSD100 KOSDAQ 100 INDEX
	AS40 ASX SMALLCAP INDUSTRIALS		KOSDM300 KOSDAQ MID300 INDEX
	AS51 S&P/ASX 200 INDEX		KOSDSMAL KOSDAQ SMALL INDEX
	AS52 S&P/ASX 300 INDEX	Taiwan	TWSE TAIWAN TAIEX INDEX
Shenzen	SZASHR CHINA SE SHENZHEN A		TW50 TSEC TAIWAN 50 INDEX
	SZBSHR CHINA SE SHENZHEN B		TWMC TSEC MID-CAP 100 INDEX
	SZCOMP CHINA SE SHENZ COMPOSITE		TWIT TSEC TECHNOLOGY INDEX
	SIASA SSE A-SHARE INDEX		TWOTCI TAIWAN GRE TAI EXCHANGE
	SIBSB SSE B-SHARE INDEX	Thailand	SET STOCK EXCH OF THAI INDEX
	SICOM SSE CONSTITUENT STOCK IX		SET50 THAI SET 50 INDEX
	SHSZ300 SHSE-SZSE300 INDEX		MAI THAI STOCK EXCHG MAI IX
	FXTID FTSE/XINHUA CHINA 25		SET100 THAI SET 100 INDEX
	XIN3I FTSE XINHUA CH A200 INDX	Bangladesh	DHAKA DHAKA STK EXG DHAKA EXCH
	XIN5I FTSE XINHUA CH A400 INDX	India	BSE100 BOMBAY STOCK EX 100 IDX
Shanghai	SHASHR CHINA SE SHANGHAI A		BSE200 BOMBAY STOCK EX 200 IDX
	SHBSHR CHINA SE SHANGHAI B		SENSEX BSE SENSEX 30 INDEX
	SHCOMP CHINA SE SHANG COMPOSITE		DOLLEX DOLLEX INDEX DOLLEX IDX
	SSE180 CHINA SE SHANG 180 A SHR		NIFTY NSE S&P CNX NIFTY INDEX
	SSE50 SHANGHAI SE 50 A-SHR IDX		DOLL30 DOLLEX INDEX DOLL BSE30
	SHSZ300 SHSE-SZSE300 INDEX		BSE500 BOMBAY STOCK EX 500 IDX
Hong Kong	HKX AMEX HONG KONG 30 INDEX		DEFTY NSE S&P CNX DEFTY INDEX
	HSI HANG SENG INDEX		BSEMDCAP BSE MID-CAP INDEX
	HSHKLI HANG SENG HK LARGE CAP		BSESMCAP BSE SMALL-CAP INDEX
	HSHKMI HANG SENG HK MID CAP IDX		NIFTYJR NSE S&P CNX MIDCAP INDEX
	HSHKSI HANG SENG HK SMALL CAP		CNXBANK BANK NIFTY INDEX
	HKSPLC25 S&P/HKEx LargeCap Index		CNXMCAP NSE CNX MIDCAP INDEX
	HKSPGEM S&P/HKEx GEM Index		FTY1ID FTSE World India
Jakarta	JCI JAKARTA COMPOSITE INDEX	Pakistan	KSE Pakistan All Share
	MBX JAKARTA SE MAIN BOARD IX		KSE100 PAKISTAN 100 INDEX
	DBX JAKARTA SE DEVEL BRD IDX	Sri Lanka	CSEALL Sri Lanka All Share
	LQ45 JAKARTA LQ-45 INDEX	the US	S&P 500
	D300IN HSBC Dragon INDONESIA	Europe	Dow-Jones European stock index
	JAKISL JAKARTA ISLAMIC INDEX		
Surabaya	SSXCSPI SSX CSPI		
Malaysia	KLSI KUALA LUMPUR SYARIAH IX		
	KL2ND KUALA LUMPUR 2ND BOARD		
	KLCI KUALA LUMPUR COMP INDEX		
	MCI MESDAQ COMPOSITE INDEX		

Bond Indices
MSCI Australia TR
MSCI Japan TR
MSCI New Zealand TR
MSCI US Treasury TR
MSCI Hong Kong Dollar Swap TR
MACI Indonesia Rupiah Swap TR
MSCI Phlippines Peso Swap TR
MSCI Singapore Dollar Swap TR
MSCI South Korea Won Swap TR
MSCI Thailand Baht Swap TR
MSCI Taiwan Dollar Swap TR

Currencies
Japanese Yen
Euro
Singapore Dollar
South Korea Won
Taiwanese Dollar
Hong Kong Dollar
Thai Buht
Malaysia Ringgit
Indonesian Rupiah
Australian Dollar
New Zealand Dollar
Indian Rupee
Philippenes Peso
China Yuan

EXHIBIT 13: Market Indices

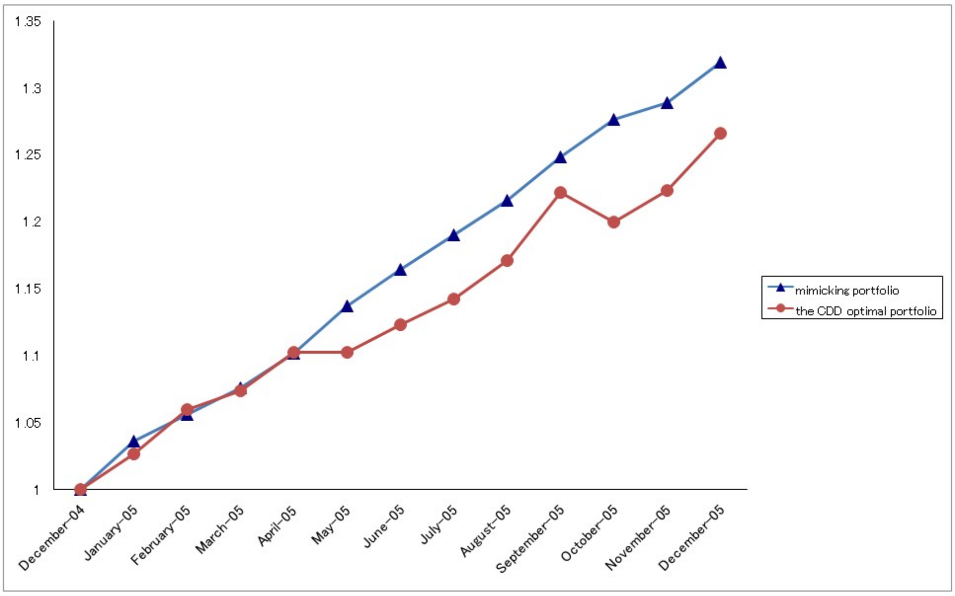
investment strategies	Distressed Debt	Relative Value	Long / Short Equities	Fixed Income	Multi-Strategy	Macro	CTA / Managed Futures	Event Driven
number of funds (total 39)	4	3	18	3	4	3	3	1
average adjusted R^2(entire)	0.45	0.37	0.58	0.50	0.39	0.32	0.35	0.38
average adjusted R^2(first half)	0.64	0.57	0.65	0.74	0.60	0.64	0.59	0.51
average adjusted R^2(latter half)	0.65	0.52	0.69	0.73	0.66	0.62	0.62	0.57

A: Results for Investment Strategies

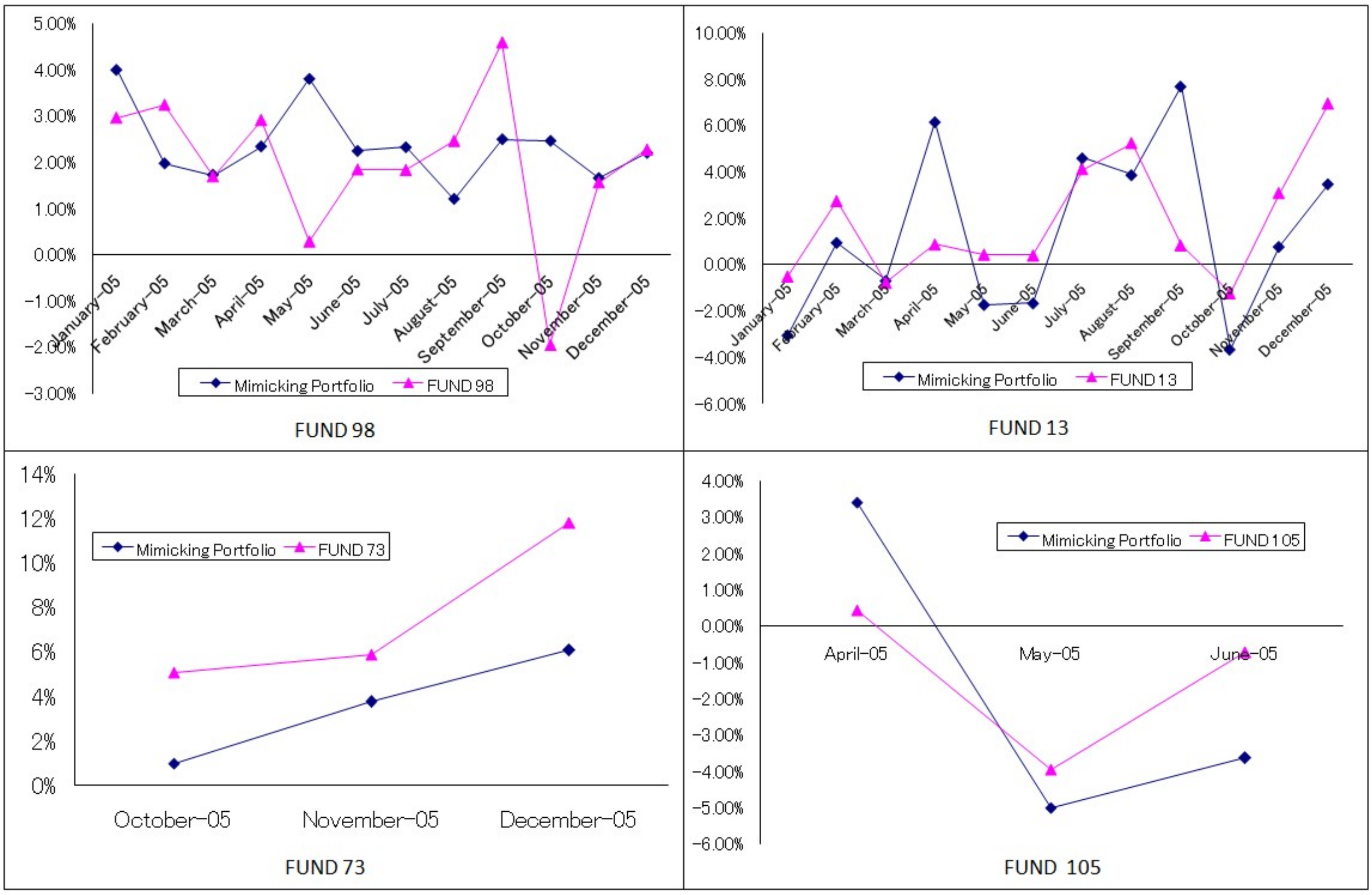
investment geographies	Asia ex-Japan	Asia incl Japan	Korea	Global	Emerging Markets	Greater China	Australia / New Zealand	Japan Only
number of funds (total 39)	7	7	2	8	5	1	2	7
average adjusted R^2(entire)	0.59	0.39	0.64	0.34	0.52	0.56	0.75	0.46
average adjusted R^2(first half)	0.73	0.62	0.78	0.56	0.75	0.69	0.83	0.35
average adjusted R^2(latter half)	0.73	0.67	0.57	0.64	0.70	0.66	0.76	0.58

B: Results for Investment Geography

EXHIBIT 14: Regression Results for Investment Strategies and Investment Geography



A: Increases in Wealths of the CDD Optimal Portfolio (risk tolerance level 0.1%) and its Mimicking Portfolio



B: Returns of the Single Hedge Funds and Their Mimicking Portfolios

EXHIBIT 15: Results of Return Replications