Hedge Funds' Performance Measurement and Optimization Portfolios Construction

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ABSTRACT

Nowadays, the hedge fund market is consistently growing and attracting more and more assets and institutional investors. As a general indicator of scale, the industry has managed around $2.5 trillion at its peak in the summer of 2008 (wilipedia.org). The alternative investment industry is growing and it is evidenced that CSFB-Tremont hedge fund index gained more than the MSCI World Index over the period January 2005 to May 2010. Due to the fact that the hedge fund market is huge and the fund returns are generally more favorable than the traditional investment instruments, such as equity and bonds, it becomes more and more important to develop a portfolio optimization method within the universe of hedge funds. In our paper, we develop four models and run the OLS regression of the fund returns with respect to different factors as specified in each model. We found that all of the four models are agree on the sign and ranking of alphas. By indicating alphas as measurement of the managers' skill, we are able to rank hedge funds' performance by ranking alphas. Choosing the portfolio with the highest alpha and also with the minimal variance by imposed some constrains on the weights of individual funds gives us the optimal portfolio.

Keywords: Hedge Fund Returns, Risk Factors, Alpha, Variance, and OLS

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1. Introduction

1.1 Hedge fund characteristics

The first hedge fund was created by Alfred Winslow Jones in 1949 and originally used as a means of reducing the risk of an investment. Hedge funds utilize a wide variety of strategies, which may or may not utilize hedging techniques to reduce or eliminate risk. However, the term "hedge fund" doesn't begin to describe this broad asset class that has evolved over the past two decades. More and more people are using it as a speculation instrument, which can be very risky because of the unique characteristics of hedge fund, such as leverage effect, lack of regulation and lack of transparency. It becomes a widely held belief that hedge fund has excessive market risk while at the same time producing superior return performance (Fung and Hsieh 1997, 2001 or Liang 1999, 2001), so the hedge fund market is attracting more and more institutional and individual investors.

However, there is no formal measurement of the hedge fund market return and it is hard to measure exactly how much better the hedge fund is and also difficult to form an optimal portfolio. Professor Carol Alexander and Anca Dimitriu have investigated the hedge fund performance and optimal portfolio construction in 2005. We want to prove whether their results and portfolio construction method is still valid or not, since the hedge fund market is changing dramatically and continuously. We improved their study by updating the data to May 2010. We also improved the precedent paper by comparing the hedge fund performance not only to traditional investment but also to mutual fund.

The majority of hedge fund managers utilize some form of leverage in order to enhance returns. While some arbitrage opportunities may have such a small return that leverage is necessary to make the strategy meaningful, leveraged positions can sometimes backfire and cause losses to be magnified. Leverage also plays a central role in hedge funds' investment strategies. It can be active in a wide array of financial markets, combining long and short positions. This investment profile makes leverage, on the one hand, key supplier of risk and arbitrage capital and, hence, positive contributor to market efficiency. On the other hand, the use of leverage can become a source of systemic risk if it reaches excessive levels. Crisis episodes, such as the one that followed the Russian default and the subsequent implosion of LTCM in the autumn of 1998, highlight the possible role of hedge fund leverage in the propagation of stresses across the financial system (CGFS (1999)).

1.2 Hedge fund data bias

There are numerous hedge fund indices designed to measure historical performance; however, they may not provide much meaningful information on hedge funds as an asset class because each hedge fund's structure is so unique. Hedge funds are not legally required to publicly disclose performance, so only those hedge funds that elect to disclose performance information are included in the indices. This may cause some biases that specific to hedge funds. All of the above characteristics increase the difficulty of evaluating the hedge fund performance and make the hedge fund market more speculated than expected.

First, survivorship bias exists when a database does not include the performance of funds that ceased operating during the sample period. Therefore, the historical return performance of the sample is biased upward and the historical risk is biased downward relative to the universe of all funds. Fung and Hsieh (2000b) estimated the survivorship bias of hedge funds in the TASS database and roughly got an average of 3 percentage points a year. This figure is consistent with Brown, Goetzmann and Ibboston (1999), who studied offshore hedge funds. According to Alexander and Dimitriu (2005), including "dead" funds that have sufficiently long reporting history and presenting all performance results on a relative basis can be interpreted as bias-free since both the portfolios and their benchmark are affected by the same biases.

Second, selection or self-reporting bias exists when the hedge funds in the database are not representative of the population of hedge funds. In addition to the biases arising from the voluntary nature of fund participation in a database, the database vendors themselves may introduce sampling biases through their inclusion criteria. For example, of the three major hedge-fund database vendors, HFR excludes managed futures programs but TASS and MAR include them.

Third, instant history bias exists when the funds entering the database are allowed to back-fill their results. To estimate the magnitude of the instant history bias, Fung and Hsieh (2000b) studied and measured the hedge funds in the TASS database. The adjusted return was found to be lower, on average, by 1.4 percentage points a year.

Fourth, multi-period sampling bias exists when the analysis is restricted to funds having a minimum amount of history available. As indicated in Alexander and Dimitriu (2005), the estimated multi-period bias is at -0.33 percentage points a year, which is small enough to be negligible.

Measurement errors and index differences are also important biases in measuring hedge funds' performance. Vendors have created two broadly based hedge-fund indexes to benchmark the performance of the hedge fund industry. They are the Hedge Fund Research Performance Index (HFRI) and the CSFB/Tremont Hedge Fund Index (CTI). The HFRI is an equally weighted index of more than 1,000 hedge funds tracked by HFR, and the CTI is a value-weighted index based on a sample of approximately 300 funds extracted from the TASS database. According to Ackerman, McNally, and Ravenscraft (1999) and Liang (2000), both databases have limited records of funds that became defunct before 1994. Hence, both HFR and TASS suffer from survivorship bias for pre-1994 data. For these reasons, in our study, we ignored the data prior to 1994 in both database.

2. Hedge Fund Performance Measurement

2.1 Compared to traditional investments

Compared to traditional investment, such as equity and bond, hedge fund market is more leveraged and risky. Kat/Lu (2002) and Getmansky/Lo/Makarov (2004) examine the statistic characteristics of hedge fund returns and show a possibility of integrating the autocorrelation of returns in the performance measurement.

Christansen/Madsen/Christensen (2003) and Cappochi/Huebner (2004) both investigate hedge fund performance using a multifactor model and give a very detailed bias analysis. Favre/Galéano (2002) use a modified value at risk for hedge fund evaluation with consideration of the higher moments of return distribution, whereas Agarwal/Naik (2004) incorporate the fat-tail problem by choosing a mean-conditional value at risk framework. The basic question is considering these problems; do hedge funds actually represent attractive investments?

To answer this question, we examine monthly returns of the Credit Suisse First Boston/Tremont (CSFB) hedge fund indices over the period from February 1995 to May 2010. Various hedge fund strategies are reflected in the hedge fund indices. CSFB places all the hedge funds in three strategy groups depending on their risk characteristics, which is market neutral, event driven and opportunistic. A total of ten individual strategies can be differentiated within the strategy groups. In addition, an aggregated index (CSFB Hedge Fund Index) comprising the performance of all the strategies is considered as the eleventh strategy. The hedge fund indices are compared with four market indices; two of them measure equity performance, the other two measure bond performance. Standard & Poor's (S&P) 500 and Morgan Stanley Capital International (MSCI) World are used as equity indices and J.P. Morgan (JPM) Global Government Bond and Merrill Lynch US Government Bond index (GVQA) are the bond indices. All indices were calculated on USD basis. The data was collected from Bloomberg Morning Star.

Under the concept of risk-adjusted performance measurement, the return is related to a suitable risk measurement. In hedge fund performance analysis, the Sharpe ratio is generally chosen as the performance measure. The Sharpe ratio uses the mean excess return over the risk-free interest rate as a measure of the return and the standard deviation of the returns as a measure of risk. Using historical monthly returns $r_{i1} \dots r_{iT}$ for security i, the Sharpe ratio (SR) can be calculated as follows:

$$SR_i = \frac{r_i^d - r_f}{\sigma_i}$$

$r_i^d = \frac{(r_{i1} + \ldots + r_{iT})}{T}$ represents the average monthly return for security i, r_f the risk-free monthly interest rate, and $\sigma_i = \frac{((r_{i1} - r_i^d)^2 + \ldots + (r_{iT} - r_i^d)^2)}{\sqrt{T-1}}$ the estimated standard deviation of the monthly return generated by security i. We use the arithmetic mean of discrete returns and the returns are calculated at the end of each month. We use ten-year U.S. treasury bonds as risk-free interest rates corresponding to the period above.

On the Sharpe ratio basis, hedge funds yield a better performance than traditional investments; the performance of the aggregated CSFB Hedge Fund Index (0.23) is higher than the maximum performance of the traditional investments (-0.01, regarding the ML Government Bond Index from the Table 1. Market-neutral and event-driven hedge funds obtain a higher performance than stocks and bonds. The Distressed strategy offers by far the best performance. Apart from Global Macro and Long/Short Equity, opportunistic hedge funds show a smaller performance than the other strategy groups—Dedicated Short Bias even has a negative Sharpe ratio. Thus, on basis of the Sharpe ratio, it can be concluded that many hedge fund indices exhibit a better performance than traditional investment indices.

Table 1 Mean, SD and SR comparison between Hedge Fund and Market Indices

	Strategy Group	Index	Mean (r_i^d)	SD (σ_i)	Sharpe Ratio (SR_i)
CSFB Indices	Aggregated	Hedge Fund	0.85%	2.24%	0.23
	Market Neutral	Fixed Income Arbitrage	0.45%	1.78%	0.06
		Convertible Arbitrage	0.73%	2.10%	0.19
		Equity Market Neutral	0.52%	3.20%	0.06
	Event Driven	Distressed	0.96%	1.93%	0.32
		Risk Arbitrage	0.59%	1.23%	0.20
		Multi Strategy	0.84%	1.90%	0.27
	Opportunistic	Global Macro	1.13%	2.93%	0.27
		Dedicated Short Bias	-0.23%	4.97%	-0.11
		Emerging Markets	0.75%	10.92%	0.04
		Long/Short Equity	0.94%	2.93%	0.21
Market Indices	Stocks	S&P 500	0.19%	2.02%	-0.08
		MSCI World	0.14%	1.92%	-0.11
	Bonds	JPM Global Government Bond	0.24%	0.50%	-0.21
		ML Government Bond	0.33%	1.14%	-0.01

In Table 2, we can see that the returns of ten out of the eleven hedge fund indices display unattractive combination of negative skewness and positive excess kurtosis. This combination also occurs for one of the four market indices (Table 3), but their values for skewness and excess kurtosis are less extreme than those shown for hedge funds. On the basis of the JB statistic, the assumption of normally distributed hedge fund returns is valid only for the Global Macro and Long/Short Equity strategies. The monthly returns of the S&P 500 and MSCI-World fail to display a normal distribution as the hedge fund indices do. The Equity Market Neutral strategy exhibits extreme excess kurtosis because the negative return of 40.45% on November 2008 due to economic downturn.

Table 2 and 3 Skewness, Excess Kurtosis and JB comparison between CSFB Hedge Fund Indices and Market Indices (S&P 50, MSCI World, JPM Global Government Bond and ML Government Bond)

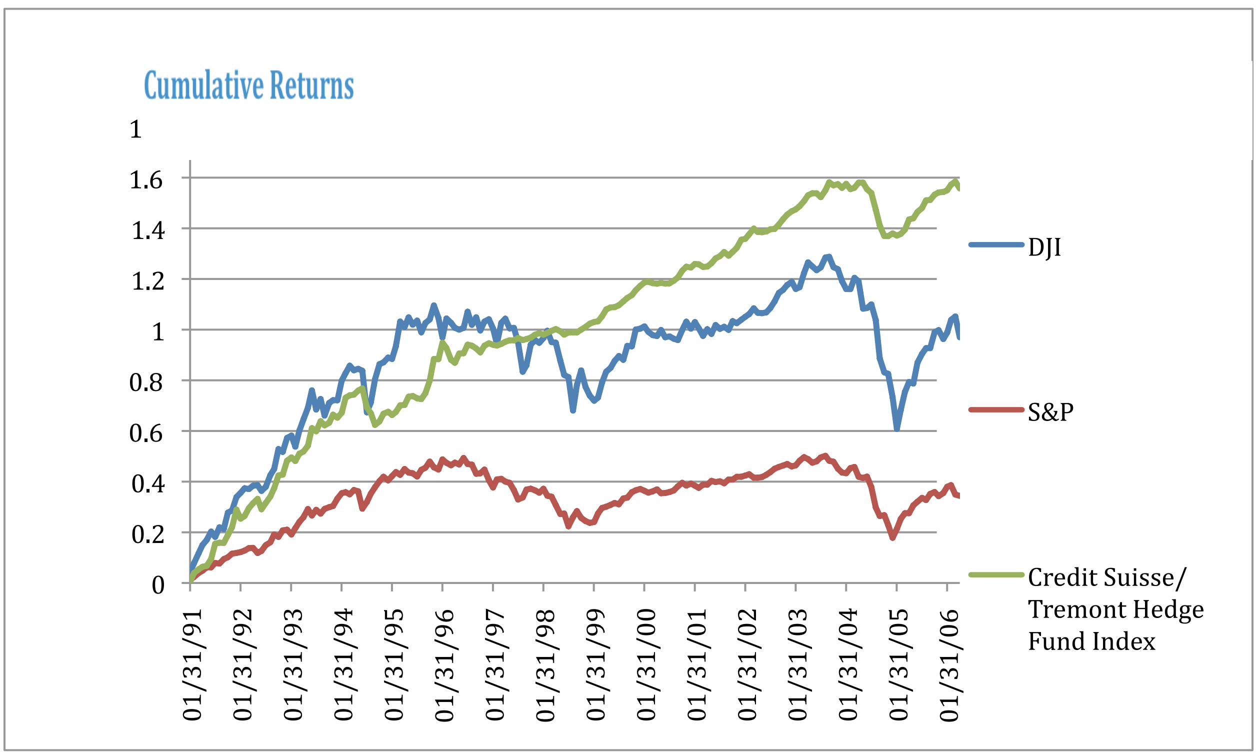
Index	Hedge Fund	FI Arbitrage	Convertible Arbitrage	Equity Market Neutral	Distressed	Risk Arbitrage	Multi Strategy	Global Macro	Dedicated Short Bias	Emerging Markets	Long/Short Equity
Skewness	-0.23	-4.27	-2.89	-11.6	-2.51	-1.13	-2.11	-0.03	0.80	-1.19	-0.06
Excess Kurto	-0.27	24.65	13.47	145.5	10.11	2.21	7.44	0.72	-1.37	3.06	0.59
JB	2.18	5217	1648	166458	976	76.7	560	3.96	33.8	115.6	2.79

Table 3

Index	S&P 500	MSCI World	JPM Global Government Bond	ML Government Bond
Skewness	-0.94	-1.07	-0.19	-1.58
Excess Kurtosis	-1.40	-1.14	-1.60	2.23
JB	42.11	45.65	20.78	114.84

Furthermore, hedge fund indices are outperform the traditional investment indices can also be seen by comparing the cumulative returns of hedge fund indices with the S&P indices return and DJS indices return. From the following graph we can see that the Credit Suisse/Tremont Hedge Fund Index is consistently growing with lower volatility over the past fifteen years. The graph also shows that both S&P indices and DJI indices are positively related with the Credit Suisse/Tremont Hedge Fund Index. Fortunately, the Hedge Fund Indices movement is less volatile and the Return is more stable.

Figure 1



2.2 Compared to mutual fund

Hedge fund managers are target at absolute returns, while most mutual fund managers have investments mandates similar to traditional asset managers with relative return target. They are typically constrained to hold assets in a well-defined numbers of asset classes and are frequently limited to little or no leverage. Since their mandates are to meet or exceed the returns on their asset classes, they are likely to generate returns that tend to be highly correlated to the returns of standard asset classes, as indicated in Sharpe's (1992). As in "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds" by William Fung and David A. Hsieh, hedge funds are dramatically different from mutual funds. Mutual fund returns have high and positive correlation with asset class returns, which suggests that they behave as if deploying a buy-and –hold strategy. Hedge fund returns have low and sometimes negative correlation with asset class returns, which makes hedge fund being more attractive when combining with traditional investments.

3. Factor Models for Hedge Funds

Assuming only managers with superior performance are rewarded. Therefore the management skills can't be replicated easily. The fund returns contribute not only to the standard asset baskets, but also to the common trading strategies that applied to individual fund. In our factor models, we measure alpha to be the indicator of the manager's skill. So far, there are lots of fundamental and statistical multi-factor models for hedge funds: Fung and Hsieh (1997, 2001), Liang (2001) and Mitchell and Pulvino (2001). However, no such a single model that could be replaced and better explained all other factor models since hedge funds employ various diversified strategies and their dynamic nature. The general factor model representation is:

$$r_{it} = \alpha_i + \sum_{j=1}^{j} \beta_{ij} F_{jt} + \varepsilon_{it}$$

Where r_{it} is the excess return on fund i during month t; α_i is the risk-adjusted performance, that is the alpha of fund i over the sample period; F_{jt} is the excess return on the j^{th} risk factor over the month t; β_{ij} is the coefficient of the fund i on the j^{th} risk factor, that is the sensitivity of the fund i to the factor j over the sample period; and ε_{it} is the error term.

In order to better measure the management performance, we employ four factor models:

- The base case model only includes two risk factors, U.S equities (S&P 500 index) and bonds (JP Morgan index). According to Alexander and Dimitriu (2005), the risk factors they use in base case model is Wilshire 5000 index and Lehman Government/Credit Intermediate index. Due to the illiquidity of the hedge funds, we expect that the hedge fund strategies have more market exposure than traditional investment method.

- The broad fundamental model includes more factors: equity indices (S&P 500 index, NASDAQ, S&P mid-cap, and small-cap to capture differences in equity investment styles, MSCI world index and MSCI emerging market index to capture the emerging markets investment opportunities); bond indices (JP

Morgan, Merrill Lynch Bond Index, Morgan global aggregate bond index and Citi bank); the Fed trade-weighted foreign exchange rate index as a proxy for the foreign exchange risk; the CPI to capture the commodity-related investment risk. To capture the market timing ability, as suggested by Treynor and Mazuy (1996), squared market returns can be used to analyze the dynamic performance nature of hedge funds. In addition, we use two other factors to measure the non-linear trading strategies: the price dispersion to account for the equilibrium trading strategies and the change in the 36 south global implied volatility equity indexes to capture the volatility trades. While Alexander and Dimitriu (2005) use Lehman indices as most of the bond representatives.

- The HFR model includes HFR indices as risk factors. We expect these indices represent portfolios with non-linear exposures to the traditional asset classes. So this model should explain the returns on individual funds better than the first two models, which only include traditional asset classes. The 17 HFR indices we employ are: convertible, regulation D, relative value, fix-income convertible, equity neutral, emerging, event-driven, fix-income arbitrage, macro, distressed, merger arbitrage, funds of fund, equity hedge and four sector strategies including finance, health care, technology and energy.

- The PCA factor model uses portfolios from principal component analysis of all funds' return. Since lots of funds use similar strategies in the same markets, there must be some correlation among those funds. We use four principal component factors, which are denoted by PC1 to PC4. The PC1 portfolio is equal weighted emphasis on funds of fund and equity funds, which capture the common trend in the return of funds. The PC2 portfolio is major dominated by managed futures, which is normally uncorrelated to the common trend but still standing out a significant part of hedge fund return. The PC3 portfolio includes equity market neutral and funds of fund. The last but not the least portfolio is dominated by technology funds and again equity market neutral funds, which can be used to capture the fund return of technology sector. According to Alexander and Dimitriu (2005), the first principal component has strong relationship with the broad fundamental factors, i.e., the traditional asset classes, while the other three principal components have no obvious significant linear relationship with fundamental factors. In our case, the PC1 portfolio doesn't work well on the database. The R^2 equals to 2% with the broad fundamental factors and only 1.5% with the hedge fund indices, respectively. However, the PC2 portfolio is significantly linear-related to our broad fundamental factors (R^2 = 24.56%) and hedge fund indices (R^2 = 18.3%). Our results provide little evidence that the portfolio replicating the higher principal components is capturing dynamic trading strategies. The reason here is that the hedge fund strategies we employed in our model are different from the most common and dynamic strategies used in hedge fund market.

4. Model Estimation

Each of the four models is estimated by least square regressions over the period January 1995 to December 2009 on each of the 300 fund returns in excess of the three-month U.S. T-bill rate. We use the entire database in each model. To measure the most accurate management skill, we use all the risk factors mentioned above in each model, i.e. we don't remove any factors, which are not significant. The cells in appendix Table 4 to 7 report two figures: the coefficient estimate over all funds in that strategy and the t-test of these funds for which the coefficient is statistically significant at 5% level. We also estimate the standard errors for each model using the information matrix computed from the Maximum Likelihood Estimation. We can see that the standard errors for the PCA model are the smallest while highest for the HFR model.

- The results of estimating the base case model are shown in Table 4. First, among all the alphas, only the alpha of the "all funds" is negative, and all the other alphas are positive and between 0.58 and 1.6. At 95% confidence level, all of the t-statistical values are greater than the critical value, which means that all of the alphas are significant. However, the average alpha in Alexander and Dimitriu (2005) is insignificant for only 20% of funds and being negative and significant for only three out of 282 funds. Second, all of the coefficients of S&P 500 are negative, which is a little surprise since a large number of hedge fund strategies performing relatively in line with S&P 500. In our paper, we expect the reason to be the strategies we employ are negatively related to the S&P 500. However, 77%

of funds are still significantly correlated with S&P 500 Index. In the Alexander and Dimitriu (2005), 80% of funds are significantly correlated with the Wilshire 5000 excess returns. Finally, JP Morgan has all negative coefficients too and significantly correlated with RV Statistical Arbitrage and RV Market Neutral (EQ). Moreover, JP Morgan is a significant risk factor for all funds. For Alexander and Dimitriu (2005), bond index returns are significant for only 20% of funds. On average, the base case model explains only 2% of the total variance of fund excess returns, while it is 27% in the Alexander and Dimitriu (2005). This is mainly due to the diverse dynamic strategies employed in the alternative investment industry, which induce non-linear exposures to traditional asset classes. The average R^2 is 1% and even the highest R^2 is only 3%, which indicate that the explanation power of these two risk factors is small. We expect the reason of the weak explanation power to be the data biases and hedge fund strategies used in our database.

- The broad fundamental model (Table 5) includes a total of 15 factors but the average number of significant factors for an individual fund is only 3.2. It is 2.5 out of 17 factors in the Alexander and Dimitriu (2005). The average R^2 across all funds is 14%, a great increase compared to 2% of the base case model. In Alexander and Dimitriu (2005) the average R^2 is 36%, even a greater increase compared to the base case model. The alphas are all positive and significant at the 95% confidence level. Within all the fourteen strategies, the LS Long Only has the highest alpha and the RV Market Neutral has the lowest one. The broad fundamental model better explained the returns of the funds in the following classes: RV Statistical Arbitrage, LS Long Bias, Hedge Funds, LS Variable Bias and RV SSED Blend. However, the returns for Multi-Style, Macro, RV SSED Distressed, RV Market Neutral and LS Long Only are not well explained by this model. The most significant factor which gives 25.47 is the small-cap S&P index, which is the same as the Alexander and Dimitriu (2005). The index also influences the funds trading on the following strategies: RV Statistical Arbitrage, LS Variable Bias and RV SSED Blend. In addition, the S&P 500 Index is also significant for Hedge Funds and RV SSED Blend. However, the squared returns of the market are not significant, indicating less use of leverage and market timing abilities. While in the Alexander and Dimitriu (2005), the squared excess returns is highly significant and positive for funds in distressed securities and managed futures but negatively significant for funds of funds and technology funds. The other equity style indices are only significant at about 7% of the funds. For the bond style indices, the most significant factor is Merrill Lynch Bond Index, which influences funds trading on the strategies of Hedge Funds, LS Variable Bias and RV SSED Blend. The MSCI emerging market Index is a significant factor for Hedge Funds and the Morgan Global Aggregate Bond Index is a significant factor for LS Long Bias. While both the JP Morgan index and the 36 south Global Implied Volatility Equity Indices are generally less significant than other factors, the change in Price Dispersion Index is among the most significant factors, which is the same as in Alexander and Dimitriu (2005). Moreover, the Price Dispersion Index has negative coefficients and significant for about all of the funds.

- From the Multi-Factor HFRI Model (Table 6), we can see that all the alphas are positive, ranging from 0.54 to 1.70 and also significant at 95% confidence level. In Alexander and Dimitriu (2005), there are 17% of funds have negative and significant alphas, mainly from equity non-hedge and event-driven. The average R^2 is 7%, which is lower than the broad fundamental model but higher than the base case model and PCA model, since the Multi-Factor HFRI Model captures more systematic factors beyond the ones included in the base case model. Furthermore, the model explains an overall average of 12% of the variance in fund excess returns (ranging from 7% for RV Broad strategy to 15% CTA Trend –following strategy). While in Alexander and Dimitriu (2005), the model can explain an overall average of 46% of the variance in funds excess returns. On average, sixteen out of seventeen risk factors are non-significant at the 95% confidence level. Only the risk factor "energy" is significant with a coefficient of -5.58 and t-statistical value of -1.82. There are still up to 90% of all funds are significant correlated with the risk factors, such as Equity Neutral, Fix Income Arbitrage.

- For the PCA model (Table 7), all the strategies have positive and significant alphas, but they also have a low average R^2. In Alexander and Dimitriu (2005), the strategies with positive and significant alphas are convertible arbitrage and merger arbitrage. We expect that the abnormal returns could be contributed to the omitted risk factors, which are not included in the model. The average R^2 across all the strategies is 1%, less than for both the HFR and the broad fundamental models. This result is quite different from that in Alexander and Dimitriu (2005), which indicate that the average R^2 is 39%, greater than for the fundamental factor model but less than the HFR model. The strategies with the highest R^2 are Multi-Style, RV Statistical Arbitrage, LS Long Bias, CTA Trend-following, Macro and RV Market Neutral as expected since the database is dominated by these strategies. The PC1 portfolio is a significant factor for 26% funds, PC2 for 61% funds, PC3 for 4% funds and PC4 for 4% funds. While in Alexander and Dimitriu (2005), the results are much more significant for PC1portfolio and less significant for the PC2 portfolio. All strategies, except for the RV SSED Blend and LS Long Only have negative average betas on the PC1 portfolio. Moreover, most strategies have negative average betas on the PC2 portfolio and positive betas on the PC3 portfolio.

5. Rank Alpha

After running the linear regression for each model, we get the alphas and also the t-statistical values. Although the values of alphas are different between the factor models, we find significant agreement on the sign of alpha from different models, and on the rank of a funds' alpha, which is the same as indicated in Alexander and Dimitriu (2005). For example, the "LS Long Bias" factor has the highest alpha in 2 models and has the second highest alpha in the other 2 models, while the "RV Market Neutral (EQ)" factor has the smallest alpha in all models. In sum, the agreement can be achieved on the sign and ranking of alpha for individual factors.

6. Optimization portfolio construction

To test the benefit of diversification, we construct portfolios by randomly drawing funds from our database. First, we randomly draw 5 funds from our database to form a portfolio and compute the mean return and variance of the portfolio. We repeat it 1,000 times and take the average of the results. Then we randomly form 1000 portfolios of 10 funds, 25 funds, and up to 60 respectively. For each size portfolio, we compute the mean and variance and repeat it 1000 times.

From the distribution of the variances of different sized portfolios, we can see that as long as the portfolios include up to 30 funds, the variances of the portfolios are small. Although the larger the portfolio sizes, the smaller the variance, the variance dose not reduces much. So we are going to use the portfolio of size 30 for our further investigation. This is the same as our precedent paper, which used portfolios of at least 20 to 30 funds. We use the sample covariance matrix and the cleared covariance matrix to compute the mean and volatility respectively. We also impose some restriction on our model to better explain the dynamic strategies.

From Jan 2005 to Dec 2009, we group every six months as a sample period. Within each period, there are 1800 individual fund returns. In each period, we construct 10 portfolios by randomly drawn 30 funds. So we construct 100 portfolios in total.

We compute the average mean returns, volatility, skewness and excess kurtosis of the 100 portfolios using two different methods: the "sample matrix method" and the "cleaned matrix method".

6.1 Sample Matrix

For each individual portfolio, we compute its covariance matrix Σ using the matlab comment and then substitute it into the minimal variance portfolio weights formula $W_{mv} = \frac{\Sigma^{-1}1}{1^{'}\Sigma^{-1}1}$ where Σ is the covariance matrix of the fund returns and $\underline{1}$ is a vector of ones. With the known individual fund returns and the weights, we are able to compute the portfolio returns, variance, skewness and excess kurtosis. We repeat this process 100 times and get 100 sets of returns, variance, skewness and excess kurtosis. By taking the average of these results, we will get the results shown in Table 8.

6.2 Cleaned matrix

Same as above, we also compute the covariance matrix of a portfolio first, and then we compute the eigenvalues ($\lambda_1, \lambda_2, ..., \lambda_{25}$) and eigenvectors (matrix K) of the covariance matrix Σ. By substituting the eigenvalues and eigenvectors into the formula $C = K\Lambda_C K^{'}$ where Λ_C is the diagonal matrix of the ordered eigenvalues of the correlation matrix of fund returns with all but the first four eigenvalues replaced by zeros, we can get C which is the "cleaned" correlation matrix. We also need to compute D, which is the diagonal matrix of the Standard Deviation of each fund returns in the portfolio. Finally we can find the "cleaned" covariance matrix V using the formula V=DCD. The next step is the same as the sample matrix method; substitute the V into the minimal variance portfolio weights formula to replace Σ, to get the "cleaned" minimal variance portfolio weights. And then use these weights combined with the individual fund returns to compute the portfolio return, variance, skewness and excess kurtosis. Repeat it 100 times and take the average of the results, we will get the results shown in Table 8.

Next, we use the same algorithm as above, to calculate the mean returns, volatility, skewness and excess kurtosis using both the “Sample Matrix” and “Cleaned Matrix” one by one, but we improved it by setting two restrictions on the weights of individual funds in the minimal variance portfolio. One restriction is that all weights must be non-negative which means that no short sales allowed; the other one is that the maximum weight of any individual fund must be less or equal to 20%. The results are displayed in the last two columns of Table 8.

Table 8 Annual Volatility, Annual Returns, Skewness and Excess Kurtosis of Unbounded and Bounded portfolios based on Sample Matrix and Cleaned Matrix respectively

	Unbounded		Bounded	
	Sample Matrix	Cleaned Matrix	Sample Matrix	Cleaned Matrix
Annual Volatility	4.28	3.96	3.56	4.53
Annual Returns	6.31	6.09	6.94	6.77
Skewness	0.02	-0.19	-0.13	-0.37
Excess Kurtosis	3.14	1.07	3.91	2.96

In sum, the “noise cleaning” process is efficient, since the portfolio volatility is smaller using the “cleaned matrix method” compare to using the “sample matrix method” if there is no restriction on the weights of the individual funds within the minimal variance portfolio. However, this condition in unreal since there is a strict restriction on short sale in hedge fund market. After including the non-negative and upper boundary of fund weights, we found that the “Sample Matrix Method” is outperforming the “Cleaned Matrix Method”. These results are the same as our precedent paper. We want our model to be meaningful in the real world, so we decide to use the “sample matrix method” to build the covariance matrix in our model.

7. Performance Analysis of Rank Alpha Portfolios

The simulation results showed in Table 8 only gives a rough idea of the average performance measurement from the minimum variance portfolios of hedge funds. In order to get a more accurate measurement, we employ a fund selection criterion based on the ranking of funds’ alpha from each of the previous four models. We still investigate the fund returns from January 2005 to December 2009. Same as above, we group every six months as a sample period. Within each period, we form 4 portfolios, which contain the funds whose alphas are on the top 30 in each model. So we constructed 40 portfolios based on the ranking of alpha in total. Since all the alphas from the factor models are positive and significant at 5% significant level, except for the all funds in the PCA model, we impose a more restrictive criterion that each individual fund could not give more than 20% weight in all 40 portfolios.

In order to make our fund selection criterion more meaningful and for comparison purpose, we also formed equally weighted portfolios of the funds with top 30 alpha in each model, and computed the averaged mean, variance, skewness and excess kurtosis as well.

Compared to the randomly selected portfolios in the previous part, portfolios formed base on the ranking of alphas have a significant superior performance. We can see from Exhibit 14 that all portfolios have average annual return around 9%, except for the equally weighted portfolio, which is 11.01%. The average annual volatility of each of the four models is in the range of 1.5% to 2.2%. The annual volatility for the equally weighted portfolio is much higher than the portfolios using alpha select criterion. The HFR portfolio has the highest annual return while the base case portfolio has the lowest annual volatility. We also showed the skewness and kurtosis measurement in Table 9. The null hypothesis of normally distributed performance cannot be rejected for all the portfolios. Moreover, almost all portfolios are skewed to the right, which is a good sign, except for the equal-weighted one. All the kurtosis are small, the broad fundamental portfolios and the PCA portfolios even have negative excess kurtosis, indicating that these portfolios have thinner tails than the normal distribution. So these selected portfolios are less risky compared to others, especially to the equal-weighted portfolio. Thus, we proved that Carol Alexander and Anca Dimitriu's results in their paper "Rank Alpha Funds of Hedge Funds" are still valid up to now. In sum, we can conclude that the portfolios, formed base on the ranking of alpha, are optimal.

Table 9 Annual Volatility, Annual Returns, Skewness and Excess Kurtosis of four factor models, Overall and Equal Weighted portfolios using Sample Matrix Method

	Base Case	Broad Fundamental	HFR	PCA	Overall	Equal Weighted
Annual Volatility	9.02	8.96	9.73	8.91	9.14	11.01
Annual Returns	1.44	1.79	2.03	1.85	2.13	7.04
Skewness	0.41	0.07	0.26	0.53	0.82	-0.11
Excess Kurtosis	0.04	-0.01	0.59	-0.62	0.49	2.58

8. Conclusion

Nowadays, alternative investments stand for attractive opportunities despite the modeling complexity caused by the data biases and their dynamic nature. More and more institutional investors find that the hedge funds investment is increasingly attractive. So the requirement for academic studies of the portfolio optimization of hedge funds becomes essential and popular. That's why we choose this topic as our thesis. It is essential to understand the characteristics of many different hedge fund strategies. Unfortunately, up to now, there is still no formal system of classification for hedge fund strategies exist for at least two main reasons. The first reason is that the strategies are continuously changing; and the other reason is that the hedge fund disclosure is not mandatory. In our paper, we deal with the instant history bias and the multi-period biases by reporting performance on a relative basis, which is benchmarked against portfolios affected by the same biases. We also use out-of-sample database to neutralize the data mining bias.

We use four models to measure alphas of 300 individual funds, spanning up to fourteen hedge fund strategies. Compared to the expected return estimation of individual security, like the estimation in the traditional investments, the sign and the ranking of the funds' alphas are the same in different models. To get better estimation of hedge funds' performance, we also compute the covariance matrix and construct 100 portfolios based on database from the sample period January 2005 to December 2009. In the meanwhile, we construct a cleaned covariance matrix to measure the same 100 portfolios mentioned above to make comparison. We conclude that the sample covariance matrix is simpler but better than the cleaned one since the sampling errors have already reduced through the weights constraining imposed on the hedge funds.

We then use the sample covariance matrix to select funds to construct the optimized portfolios. To make our results more significant, we only select funds whose alphas are ranked at the top 30 in our four factor models respectively. These optimized portfolios are superior to the equally weighted portfolio of all funds and to the randomly selected portfolios based only on minimum variance. By using the performance measurement tools for traditional investments, we can construct the optimized portfolios for hedge funds. We have showed that the alternative investments can achieve superior results by using various strategies with respect to the traditional investments, which is the same results as Carol Alexander and Anca Dimitriu generated in their paper “Rank Alpha Funds of Hedge Funds”.

Appendices

Appendix A: Source of Data

CSFB Hedge Fund Indices: the monthly continuously compounded returns are constructed from the monthly index level. The monthly indices level for February 1995-May 2010 comes from http://hedgeindex.com

Standard & Poors 500 Stock Index, MSCI World Index, JP Morgan Global Government Bond and ML Government Bond Indices: the monthly indices levels for February 1995-May 2010 come from Bloomberg.

US Risk Free Interest Rate, Fed Trade-Weighted Foreign Exchange Rate Index CPI: the ten-year bonds equivalent monthly continuous compounded rate is used as the risk free rate. The data for February 1995-May 2010 comes from http://research.stlouisfed.org

300 individual Hedge Funds and 15 Hedge Fund Indices: the monthly returns are continuously compounded from January 1995-December 2009, coming from http://hedgefund.net

NASDAQ Stock Index: the monthly index level for January 1995- December 2009 comes from CRSP. The monthly continuous compounded returns are constructed from the monthly index level.

S&P Mid-Cap, Small-Cap, MSCI Emerging, Citi bank, the Price Dispersion and the Change in the 36 South Global Implied Volatility Equity Indexes: the monthly index level from January 1995- December 2009 comes from Morning Star.

Appendix B: Tables

Table 4.1 OLS Regression results of Base Case Model for All Funds and the first six Hedge Fund Strategies

	ALL Funds	Multi-Style	RV Statistical Arbitrage	LS Long Bias	Hedge Funds	CTA Trend-following	LS Variable Bias
Alpha	-8.48	1.05	1.18	1.60	0.85	1.21	1.31
	7.23	6.25	6.91	4.48	6.50	3.85	6.23
S&P 500	-8.48	-9.65	-10.17	-15.99	-9.69	-12.33	-6.14
77%	-1.27	-1.27	-1.32	-0.99	-1.63	-0.87	-0.65
JP Morgan	-45.08	-41.18	-59.01	-88.15	-32.18	-22.76	-60.34
100%	-1.67	-1.34	-1.89	-1.35	-1.34	-0.40	-1.57
R^2	**0.02**	0.02	0.01	0.01	0.02	0.00	0.01

Table 4.2 OLS Regression results of Base Case Model for the last seven Hedge Fund Strategies

	Macro	RV SSED Distressed	RV SSED Blend	RV Broad	RV SSED Merger Arbitrage	RV Market Neutral (EQ)	LS Long Only
Alpha	1.28	0.92	1.25	0.77	0.58	0.58	1.34

	5.70	5.12	5.40	6.01	8.52	5.99	4.18
S&P 500	-9.52	-5.47	-9.05	-3.98	-1.65	-5.71	-10.94
	-0.93	-0.67	-0.86	-0.69	-0.54	-1.30	-0.76
JP Morgan	-42.28	-33.09	-47.57	-33.47	-13.12	-39.78	-73.13
	-1.03	-1.01	-1.12	-1.44	-1.06	-2.25	-1.25
R^2	0.01	0.01	0.01	0.01	0.01	0.03	0.01

Table 5.1 OLS Regression results of Broad Fundamental Model for All Funds and the first six Hedge Fund Strategies

	ALL FUNDS	Multi-Style	RV Statistical Arbitrage	LS Long Bias	Hedge Funds	CTA Trend-following	LS Variable Bias
Alpha	1.33	1.23	1.42	1.90	1.24	1.16	1.49
	5.91	**4.97**	**5.63**	**3.50**	**6.31**	**2.41**	**4.62**
S&P	-12.17	-12.18	-13.06	-21.35	-14.53	-16.59	-8.17
	-1.64	-1.49	-1.57	-1.19	-2.25	-1.04	-0.77
JP MORGAN	-1.13	3.40	2.74	86.56	11.64	-8.05	36.81
	-0.03	0.07	0.06	0.86	0.32	-0.09	0.62
NASDAQ	-3.22	-5.39	1.37	-6.30	-3.21	5.05	-5.85
	-0.41	-0.63	0.16	-0.33	-0.47	0.30	-0.52

	ALL FUNDS	Multi-Style	RV Statistical Arbitrage	LS Long Bias	Hedge Funds	CTA Trend-following	LS Variable Bias
MID	-21.98	-24.79	-37.76	-56.19	-9.69	23.80	-40.51
	-1.10	-1.13	**-1.68**	-1.16	-0.56	0.56	-1.41
SML	25.47	23.54	29.98	50.96	15.16	-4.86	43.37
	1.68	1.41	**1.76**	1.38	1.14	-0.15	**1.99**
MSCI	0.38	-9.30	-8.01	-12.39	-0.23	9.75	2.27
	0.02	-0.45	-0.38	-0.27	-0.01	0.24	0.09
MSCI E	6.58	13.24	3.79	37.18	6.20	-13.19	12.99
	0.71	1.30	0.37	**1.66**	0.77	-0.67	0.98
ML	-24.22	-23.96	-24.47	-52.15	-22.01	-22.57	-59.18
	-1.80	**-1.62**	**-1.62**	-1.60	**-1.88**	-0.78	**-3.06**
Morgan Global	-32.70	-31.43	-53.19	-132.10	-37.55	-29.22	-69.99
	-1.04	-0.91	-1.50	**-1.73**	-1.37	-0.43	-1.55
Citi Bank	9.84	2.32	-1.46	22.14	11.46	28.21	16.89
	0.98	0.21	-0.13	0.91	1.31	1.31	1.17
EX	-31.77	-47.44	-86.84	-55.59	-39.92	15.97	-47.56
	-0.93	-1.27	**-2.27**	-0.67	-1.35	0.22	-0.97
CPI	0.00	1.07	0.71	1.13	-0.68	-1.26	0.04
	0.00	1.39	0.90	0.66	-1.11	-0.83	0.04
36 SG I-V	0.66	-0.63	-2.63	0.95	-0.25	16.06	-3.79

	ALL FUNDS	Multi-Style	RV Statistical Arbitrage	LS Long Bias	Hedge Funds	CTA Trend-following	LS Variable Bias
	0.21	-0.18	-0.75	0.13	-0.09	**2.38**	-0.84
(MARKET RETURN)^2	78.34	91.76	173.74	117.62	58.90	-141.36	180.95
	0.63	0.67	1.23	0.39	0.54	-0.53	1.00
PRICE DISPERSION	-381.70	-535.31	-504.57	-816.61	-371.32	518.42	-277.28
	-4.09	**-5.22**	**-4.82**	**-3.61**	**-4.57**	**2.59**	**-2.07**
R^2	0.14	0.19	0.19	0.13	0.17	0.11	0.12

Table 5.2 OLS Regression results of Broad Fundamental Model for the last seven Hedge Fund Strategies

	Macro	RV SSED Distressed	RV SSED Blend	RV Broad	RV SSED Merger Arbitrage	RV Market Neutral (EQ)	LS Long Only
Alpha	1.46	1.31	1.67	1.00	0.72	0.70	1.94
	4.11	**4.87**	**4.83**	**5.14**	**6.93**	**4.55**	**4.06**
S&P	-10.29	-11.69	-20.38	-3.15	-3.38	-6.03	-17.47
	-0.88	-1.32	**-1.78**	-0.49	-0.99	-1.19	-1.11
JP MORGAN	-48.08	-12.99	72.57	-64.36	-1.23	-32.16	-61.53

	Macro	RV SSED Distressed	RV SSED Blend	RV Broad	RV SSED Merger Arbitrage	RV Market Neutral (EQ)	LS Long Only
	-0.73	-0.26	1.13	**-1.78**	-0.06	-1.14	-0.70
NASDAQ	0.49	-7.53	-18.51	-4.89	-0.53	6.84	-3.37
	0.04	-0.80	-1.53	-0.72	-0.15	1.28	-0.20
MID	-10.80	-10.29	-59.09	-17.77	-17.20	1.69	-27.17
	-0.34	-0.43	**-1.92**	-1.03	**-1.87**	0.12	-0.64
SML	29.83	17.63	60.66	13.13	8.41	-1.51	44.81
	1.24	0.97	**2.59**	1.00	1.20	-0.15	1.39
MSCI	9.08	5.66	29.62	1.85	11.52	-14.95	-19.95
	0.31	0.25	1.03	0.11	1.34	-1.18	-0.50
MSCI E	-10.31	2.53	12.33	5.50	1.35	3.63	10.33
	-0.70	0.23	0.87	0.69	0.32	0.58	0.53
ML	-22.20	-6.94	-33.57	-12.87	-6.20	-5.35	-23.36
	-1.04	-0.43	**-1.62**	-1.10	-1.00	-0.58	-0.82
Morgan Global	16.46	-15.13	-102.59	38.59	-8.67	-5.42	5.21
	0.33	-0.40	-2.11	1.41	-0.60	-0.25	0.08
Citi Bank	8.22	6.63	15.00	3.55	0.88	3.36	10.68
	0.52	0.55	0.97	0.41	0.19	0.49	0.50
EX	41.64	-39.86	-75.89	3.45	-20.27	-18.43	-42.17

	Macro	RV SSED Distressed	RV SSED Blend	RV Broad	RV SSED Merger Arbitrage	RV Market Neutral (EQ)	LS Long Only
	0.77	-0.98	-1.45	0.12	-1.30	-0.80	-0.58
CPI	-0.49	-0.25	-0.28	-0.05	-0.05	0.05	0.08
	-0.44	-0.29	-0.26	-0.08	-0.15	0.10	0.05
36 SG IMPLIED V	1.95	-1.44	1.38	-2.07	-0.12	0.12	-0.98
	0.39	-0.38	0.29	-0.76	-0.09	0.05	-0.15
(MARKET RETURN)^2	40.77	110.51	176.27	40.90	21.13	-40.78	187.79
	0.21	0.74	0.91	0.38	0.37	-0.48	0.70
PRICE DISPERSION	-182.04	-576.06	-583.09	-304.58	-157.12	-141.34	-1031.20
	-1.23	**-5.16**	**-4.06**	**-3.76**	**-3.66**	**-2.22**	**-5.20**
R^2	0.06	0.15	0.16	0.12	0.11	0.08	0.16

Table 6.1 OLS Regression results of HFR Indices Model for All Funds and the first six Hedge Fund Strategies

	ALL Funds	Multi-Style	RV Statistical Arbitrage	LS Long Bias	Hedge Funds	CTA Trend-following	LS Variable Bias
Alpha	1.09	1.24	1.28	1.68	0.93	1.70	1.18
	5.40	5.47	5.42	3.41	5.25	4.06	4.14
Convertible	-4.83	-0.64	5.49	2.97	7.97	-12.19	-3.91
-0.20	-0.33	-0.04	0.32	0.08	0.62	-0.40	-0.19
Regulation D	1.72	-22.52	-15.88	8.51	-18.31	-10.07	18.35
0.06	0.09	-1.06	-0.72	0.18	-1.10	-0.26	0.69
Relative Value	24.12	21.22	41.80	8.81	30.16	-108.43	79.99
0.22	0.36	0.29	0.54	0.05	0.52	-0.79	0.86
Fix-Income Convertible	-26.26	-21.08	-36.49	-14.34	-24.04	-37.56	-61.05
-0.48	-0.79	-0.56	-0.94	-0.18	-0.82	-0.55	-1.30
Emerging	0.71	-9.96	-6.71	-22.91	-9.59	61.21	21.03
0.01	0.02	-0.31	-0.20	-0.32	-0.38	1.02	0.51
Equity Neutral	8.11	10.73	7.80	18.60	7.86	8.03	15.59
0.95	1.56	1.85	1.29	1.47	1.73	0.75	2.13
Event-Driven	2.72	2.55	1.58	16.14	2.51	10.90	-0.53
0.35	0.58	0.49	0.29	1.41	0.61	1.12	-0.08
Fix-Income A	-29.55	-34.38	-21.06	-64.45	-20.84	-9.17	-43.15

	ALL Funds	Multi-Style	RV Statistical Arbitrage	LS Long Bias	Hedge Funds	CTA Trend-following	LS Variable Bias
-0.93	-1.54	-1.60	-0.94	-1.38	-1.24	-0.23	-1.60
Macro	7.97	14.56	6.48	1.81	-4.02	41.26	-6.29
0.32	0.53	0.87	0.37	0.05	-0.31	1.34	-0.30
Distressed	0.89	-0.72	-2.31	0.92	2.65	-7.90	0.29
0.10	0.16	-0.12	-0.36	0.07	0.54	-0.69	0.04
Merger A	8.70	3.87	7.72	7.02	3.57	-8.25	12.80
0.46	0.76	0.30	0.57	0.25	0.35	-0.35	0.79
Funds of Fund	11.27	15.82	-7.61	16.45	11.80	-47.80	26.51
0.33	0.54	0.68	-0.31	0.33	0.65	-1.12	0.91
Equity Hedge	-0.81	-12.86	-19.52	12.25	4.08	12.16	4.81
-0.02	-0.03	-0.40	-0.59	0.18	0.16	0.21	0.12
Finance	-3.31	-5.29	-4.62	-4.49	-8.30	7.15	-5.84
-0.34	-0.55	-0.79	-0.66	-0.31	-1.59	0.58	-0.69
Health Care	-2.06	-5.06	-2.03	-2.42	-1.85	0.48	-0.82
-0.30	-0.49	-1.08	-0.42	-0.24	-0.51	0.06	-0.14
Technology	1.63	5.76	3.85	4.40	2.61	6.36	-2.04
0.24	0.39	1.25	0.80	0.44	0.72	0.75	-0.35
Energy	-5.85	-6.13	-3.64	-9.91	-6.62	-6.33	-8.15
1.00	-1.82	-1.70	-0.97	-1.26	-2.34	-0.95	-1.79
R^2	0.07	0.09	0.05	0.05	0.09	0.11	0.08

Table 6.2 OLS Regression results of HFR Indices Model for the last seven Strategies

	Macro	RV SSED Distressed	RV SSED Blend	RV Broad	SSED Merger Arbitrage	RV Market Neutral (EQ)	LS Long Only
Alpha	1.08	0.77	1.40	0.63	0.59	0.54	1.18
	3.56	3.13	4.43	3.56	6.41	4.07	2.70
Convertible	-14.98	-2.98	-21.54	-8.66	-1.07	3.91	-17.15
	-0.68	-0.17	-0.94	-0.68	-0.16	0.41	-0.54
Regulation D	55.36	-32.52	-12.93	3.38	7.56	-1.17	42.63
	1.94	-1.41	-0.44	0.20	0.88	-0.09	1.04
Relative Value	116.46	42.26	25.27	51.24	9.90	-9.27	4.13
	1.17	0.52	0.24	0.89	0.33	-0.21	0.03
Fix-Income Convertible	-51.56	-25.69	-12.28	-15.44	-8.84	-16.71	-16.36
	-1.03	-0.63	-0.24	-0.53	-0.58	-0.77	-0.23
Emerging	-7.13	15.31	-10.83	4.90	-13.00	-12.98	-0.08
	-0.16	0.43	-0.24	0.19	-0.98	-0.68	0.00
Equity Neutral	8.11	-2.50	11.18	0.56	1.93	2.84	14.71
	1.04	-0.39	1.38	0.12	0.81	0.84	1.31
Event-Driven	-3.63	0.32	6.76	-1.60	-1.04	0.96	0.47
	-0.51	0.06	0.92	-0.39	-0.49	0.31	0.05
	Macro	RV SSED Distressed	RV SSED	RV Broad	SSED Merger	RV Market Neutral	LS Long

			Blend		Arbitrage	(EQ)	Only
Fix-Income A	-27.68	-20.34	-35.52	-9.17	-2.21	-18.38	-77.80
	-0.96	-0.87	-1.18	-0.55	-0.25	-1.47	-1.87
Macro	8.57	-8.21	15.93	7.11	-1.92	1.16	27.13
	0.38	-0.45	0.68	0.55	-0.28	0.12	0.84
Distressed	1.41	7.81	0.20	2.79	-0.81	2.02	5.27
	0.17	1.15	0.02	0.58	-0.32	0.56	0.44
Merger A	8.63	19.56	11.67	9.02	5.47	9.58	22.51
	0.50	1.39	0.65	0.90	1.04	1.28	0.90
Funds of Fund	3.80	25.46	5.66	12.54	6.10	27.72	50.05
	0.12	1.01	0.17	0.69	0.65	2.05	1.11
Equity Hedge	-18.01	0.83	11.73	-23.61	5.17	14.78	-2.38
	-0.42	0.02	0.26	-0.95	0.40	0.80	-0.04
Finance	6.65	-8.60	-4.32	-1.44	-4.64	-7.53	-1.74
	0.74	-1.18	-0.46	-0.28	-1.71	-1.93	-0.13
Health Care	0.29	-0.42	-0.19	-3.94	-3.26	-4.48	-3.11
	0.05	-0.08	-0.03	-1.08	-1.71	-1.64	-0.34
Technology	-3.70	2.17	0.80	1.69	0.71	0.76	-2.23
	-0.60	0.43	0.12	0.47	0.38	0.28	-0.25
Energy	-11.04	-2.73	-6.62	-4.52	-0.66	-2.09	-7.55
	-2.28	-0.70	-1.31	-1.61	-0.45	-0.99	-1.08
R^2	0.08	0.05	0.06	0.04	0.06	0.08	0.05

Table 7.1 OLS Regression results of PCA Model for All Funds and the first six Hedge Fund Strategies

	ALL FUNDS	Multi-Style	RV Statistical Arbitrage	LS Long Bias	Hedge Funds	CTA Trend-following	LS Variable Bias
Alpha	0.96	0.96	1.03	1.39	0.77	1.15	1.17
	7.11	**6.26**	**6.54**	**4.24**	**6.41**	**4.03**	**6.10**
PC1	-0.01	0.00	0.00	-0.03	0.00	-0.04	-0.02
-25.57%	-0.42	0.10	0.15	-0.50	-0.02	-0.73	-0.49
PC2	-3.85	-5.35	-4.21	-4.13	-3.01	-6.55	-1.90
-60.72%	-1.00	-1.23	-0.95	-0.45	-0.88	-0.81	-0.35
PC3	0.28	0.40	-1.15	-1.68	0.53	-3.71	2.11
4.20%	0.07	0.09	-0.25	-0.17	0.15	-0.44	0.37
PC4	-0.27	-0.40	1.14	1.70	-0.53	3.73	-2.10
-4.12%	-0.07	-0.09	0.25	0.18	-0.15	0.44	-0.37
R^2	0.01	0.01	0.01	0.01	0.00	0.01	0.00

Table 7.2 OLS Regression results of PCA Model for the last seven Hedge Fund Strategies

	Macro	RV SSED Distressed	RV SSED Blend	RV Broad	RV SSED Merger Arbitrage	RV Market Neutral (EQ)	LS Long Only
Alpha	1.18	0.85	1.17	0.69	0.56	0.47	1.15
	5.75	**5.19**	**5.55**	**5.93**	**9.07**	**5.34**	**3.94**
PC1	-0.03	0.01	-0.03	0.00	-0.01	-0.02	0.03
	-0.82	0.24	-0.77	0.06	-1.02	-1.30	0.50
PC2	-2.64	-4.99	-7.09	-2.95	-1.38	-0.08	-5.77
	-0.45	-1.08	-1.19	-0.89	-0.79	-0.03	-0.70
PC3	1.46	-0.22	2.18	0.18	0.91	1.89	0.73
	0.24	-0.05	0.35	0.05	0.50	0.72	0.08
PC4	-1.45	0.22	-2.16	-0.18	-0.91	-1.88	-0.75
	-0.24	0.05	-0.35	-0.05	-0.50	-0.72	-0.09
R^2	0.01	0.01	0.01	0.00	0.01	0.03	0.01

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