

RISK DECOMPOSITION OF HEDGE FUND INDEX

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ABSTRACT

As the booming of hedge fund industry from 1990, more and more investors put their money into hedge fund. However, with the collapse of Long Term Capital Management and the debacle of Portus Alternative Asset Management, many investors realize that hedge fund does not seem so attractive since it has abnormal return distribution and extreme potential downside risk. What is the key driver of the risk of hedge fund? Based on economic viewpoint of hedge fund returns, we argue that the total risk of hedge fund can be decomposed into systematic risk component and unsystematic risk component using our regression model. We use Lower Partial Moment as a measurement of risk to implement our model and reveal the real structure of hedge fund risk components with respect to different target returns.

Keywords: Hedge funds; Systematic risk components; Unsystematic risk Component; Lower partial moment; Risk measurement

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1 INTRODUCTION

From 1990, hedge fund industry experiences a dramatically growth and more and more investors put their money into vary hedge fund companies since the lower variance and higher absolute rate of return of hedge fund compared to that of the traditional market, such as stock market, bond market and commodity market. However, since the collapse of Long Term Capital Management which is one of the largest hedge funds in US and the debacle of Portus Alternative Asset Management, which is going to be the largest hedge fund in Canada, many scholars began to suspect the risk to reward of hedge fund industry and did a lot of research on the statistical analysis, risk analysis, risk to reward analysis on hedge fund return to reveal the risk embedded in hedge fund return.

Since Sharpe (1992) first put forward the fundamental factor regression model of mutual fund return in his paper, some papers extend his model into hedge fund industry using the regression method to perform risk analysis of hedge fund. For instance, Fung and Hsieh (1997) extend this model into hedge fund industry to find empirical characteristics of dynamic trading strategy in hedge fund industry. In additional, Lhabitant (2001) extend Sharpe's model by using style factors of hedge fund to build his style analysis model to analyze the Value At Risk of hedge fund index return. In our paper, based on the economic viewpoint of hedge fund investment, we suggest that the risk of hedge fund return could be decomposed into two components: systematic risk component and unsystematic risk component. We suggest that systematic risk component is the risk part that can be explained by the movements of traditional market, such as stock market, bond market and commodity market, while the rest part of risk is unsystematic risk component of hedge fund return. Then we build our risk analysis model illumined by the general form of Sharpe's model but use the systematic factors we figure out in our paper and one intercept that

represents the unsystematic risk part to implement our theory. According to our risk decomposition model, we decompose the total risk of hedge fund return into systematic component and unsystematic component. At the same time, we analyze the relationship between these three main traditional markets, stock market, bond market and commodity market, and hedge fund market from the economics viewpoint. After that, we perform the risk analysis with respect to different target return levels of different investors who have different risk tastes in order to disclose the main driver of risk factors for total hedge fund index. The infrastructure of this paper would be following: part 2 is the literature review of precedent papers and their contribution, part 3 illustrates the details of our risk decompose theory and the infrastructure of our model, part 4 explains how to implement our model to do risk decomposition and take HFRI return as an example to reveal some common results of hedge fund return, and finally in part 5, we analyze the results got in part 4 using HFRI return from economics viewpoint.

2 LITERATURE REVIEW

Based on the characteristics of hedge fund industry, Scholars usually use two main types of methods to analyze hedge funds performance: risk measurement methods and linear factor models. Risk Measurement methods are used to quantify the risks of different assets and portfolios and compare the risks and returns of different assets or portfolios, while the factor models give us a way to construct models using different factors related to the performance of assets and then regress the models in order to analysis the performance of the assets. We will discuss the precedent's successes of these two types of models respectively.

2.1 Risk Measurement Methods

Traditionally, when faced with the choice of two or multiple portfolios, we often analyze the trade off between return and risk of each portfolio according to efficient market assumption. The basic and most widely used measurement is Markowitz's Mean-Variance model in asset allocation problems. The simple logic of using Mean-Variance model to figure out efficient portfolio is that variation of the return of an asset or a portfolio, or uncertainty of the return of an asset or portfolio, is fully covered by the variance, which is the dispersion of normally distributed returns. Hence, the variance is regarded as the proxy of risk, while the return is the award of the investment. Therefore, we prefer the asset with the highest mean and lowest variance. Here, the most important assumption is: The variance or volatility of the return is a good proxy of the risk and accordingly, investors only care about the means and the variances of the returns.

However, in the empirical test, there are some problems of Mean Variance assumptions. First, investors care only about the means and variances of returns. Statisticians show that the variance fully summarizes the dispersion of any normally distributed returns. Hence the

efficiency of variance as a measure of dispersion to analyze investment risk depends on the close relation between the observed distribution of many portfolio returns and the normal distribution. But it is probably that returns of individual stocks or assets are not normally distributed (Fama 1976). And for hedge fund, the normality assumption cannot be established. Hence, using the mean variance method to analyze hedge fund performance is not efficient due to the fact that hedge fund returns are seldom normally distributed. The second problem is that variance does not completely capture the way in which investors perceive risk. Investors also pay attention to the higher moments of the asset returns rather than variance according to Taylor series extension. In other words, the variance does not capture precisely all the risk investors worrying about. Here, the revisions to Mean Variance Analysis are discovered.

For hedge fund, based on the problems of Mean Variance assumptions we should not use mean variance model to get an efficient analysis when the assets returns are non-normal. This non-normal characteristic is described widely by empirical test, such as Brooks and Kat (2002), who discovered that published hedge fund indices exhibit lower skewness and higher kurtosis than normally distributed assets. Besides, the assumption that the investors just care about the mean and variance of an asset cannot work with hedge fund according to Taylor series extension of expected utility function. The algebra expression of Taylor series extension is following:

$$f(x) = f(0) + f'(0)(x-0) + \frac{1}{2}f''(0)(x-0)^2 + \frac{1}{3}f'''(0)(x-0)^3 + \frac{1}{4}f^{(4)}(0)(x-0)^4 + \dots$$

Here, f is equivalent to the utility function, x is the return realization, 0 can be regarded as mean of return, Klein (2006) discover that it is unreliable to use the standard risk measures and ignore the higher moments such as third and fourth moments of the returns of hedge funds based on the equation above. In additional, according to Taylor series extension, we should use un-scaled measure rather than scaled measure¹.

The translations between scaled and un-scaled measures are:

¹ skewness and kurtosis are believed to be the scaled measures and third and fourth moments are un-scaled measures.

$$\text{Third.moment} = \text{skewness} * S^3; \text{Forth.moment} = \text{kurtosis} * S^4$$

Here, S stands for the standard deviation of the asset returns.

Another revision of mean variance performance measure is downside risk measures. Using downside risk measures are more reasonable than using variance to analyse the risks of asset returns for several reasons. According to the investor's utility function, investors prefer less probability of extreme loss when they do the same investments, so they just care about downside risk or downside volatility, in other word, they just care about the probability of the part of portfolio return falling below the mean level or below a target level of return that investors can bear. The other reason is that asset distributions might not be normal. Based on the research before, the hedge fund return distribution is non-normal. Hence, traditional volatility risk measure that assumes normal distribution of asset is not applicable for hedge fund returns. Instead, the downside risk measures do not assume normal distribution of the returns but just consider the subset of returns below the mean return or the target level that investors can bear. Hence, it is more reliable to use downside risk measures to analysis hedge fund risks and returns. We will elaborate the details of the general case of downside risk measures and semi-variance risk measure, which is one special case of downside risk measures.

The general case of downside risk measures is called Lower Partial Moments. It was first developed by Bawa (1975) and Fishburn (1977), who worked on the below-target semi-variance. Bawa (1975) published his seminal work on relationship between the lower Partial Moment and stochastic dominance; besides, Bawa first defines the lower partial moment (LPM) as a general family of below-target risk in terms of risk tolerance.

The formula for Lower Partial Moments is:

$$LPM_n(\tau) = \frac{1}{T} * \sum_{i=1}^T \text{Max}[0, (\tau - R_i)]^n \quad (\text{Discrete expression}) \text{ Kaplan and James (2004)}$$

$$LPM_n(\tau) = \int_{-\infty}^{\tau} (\tau - R)^n dF(R) \quad (\text{Continuous expression}) \text{ Harlow (1991)}$$

Here, T is the number of observations, R_t is the t^{th} return observation, τ is the target rate of return, $F(\cdot)$ is the cumulative density function of total returns on investment. Fishburn argues that

n is supposed to reflect the decision maker's feeling about the relative consequences of falling short of target return by various amount. If his main concern is failure to meet the target without particular regard to the amount, then a small value of n is appropriate. On the other hand, if small deviations below target are relatively harmless when compare to large deviations, then a larger value of n is indicated. In additional, $n = 1$ is the point that separates risk seeking from risk-averse behaviour with regard to returns below target. (Fishburn, 1977, p 5.)

We should choose n values according to the degree of the risk tolerance of the investor.

When n is chosen to be 2, a special case of Lower Partial Moments is semi-variance risk measure, which is one of the special cases of downside risk measures and is most often used measurement. It is called semi-variance because that the algebra expression is the same as Lower Partial Moments but the value of n is 2. In additional, semi-variance only considers the second power of the lower part of assets returns. According to Markowitz (1959), there are two forms semi-variance with respect to the target level of return and the mean return. The expressions are:

$$\text{Below-mean semi-variance: } SVm = \frac{1}{K} \sum_{T=1}^K \text{Max}[0, (E - R_T)]^2$$

$$\text{Below-target semi-variance: } SVm = \frac{1}{K} \sum_{T=1}^K \text{Max}[0, (t - R_T)]^2$$

Where, as above, K is the number of observations, E is the expected return of the asset's return, R_t is the asset return during time period T , and t is the target rate of return. The maximum

function indicates that the formula just cares about the value dispersion below the mean or target level.

2.2 Linear Factor Models

The alternative way to perform risk and return analysis is by using factor models. Linear Factor Models use the factors related closely to the performance of underlying assets or portfolios, at the same time break down the returns of securities into different parts. In multifactor model, the return of each risky asset is determined by general two terms, one is common factors term and the other is specific risk component of the risky asset term. These common factors are proxies for events in the economy that affect the performance of a large number of different investments and the specific risk component is usually considered as the risk unique to the particular risky asset or investment. The same theory applies to one-factor Models. However, one-factor models are less realistic than multifactor models because an asset or a portfolio faces different types of risks caused by the movements of different factors rather than only one type of risk factor. There are many factors directly or indirectly linked to the performance of an asset or a portfolio. So, multifactor Models are very practical to interpret the returns of an asset or an investment portfolio.

Although factor models are very useful in determining the total returns and risks, which is crucial to analysis and diverse or hedge the risks, it is not easy to capture the most important and useful factors in reality. Generally, there are three ways to generate the common factors:

1) Factor Analysis method: This is a statistic estimation method based on the theory that the covariance between assets' return provides information that can be used to determine the common factors that generate the returns. The application of this procedure to stock returns was pioneered by Roll and Ross (1980).

2) Macroeconomic Variables to Generate Factors: This method takes the macroeconomic variables such as changes in GDP, interest rates, expected inflation, unexpected changes in the

price level, changes in the yield spread, and so on, as proxies for the common factors. Chen, Roll, & Ross (1986) and Chan, Chen, & Hsieh (1985) used this method in their paper.

3) Firm Characteristics: This method use firm's characteristic, such as firm size, leverage ratio, market index, book-to-market, etc, as proxies for the common factors. The characteristics should be selected on the basis of what common characteristics make the asset prices move up and down together.

Based on the research of these precedents, Sharpe (1992) believes that most mutual funds managers have the same motivation as the traditional asset managers to meet or exceed the returns on their asset classes. So, the returns of mutual funds tend to have highly correlation to the returns of standard asset classes. According to this logic, he generates a twelve-asset class factor model to analyses returns of mutual funds. The general algebra expression is:

$$\tilde{R}_i = [b_{i1}F_1 + b_{i2}F_2 + \dots + b_{in}F_n] + e_i$$

\tilde{R}_i : Represents the actual return on asset i

F_n : Value of factor n , each factor represents the return on an asset class

e_i : "non-factor" component of the return on i ,

b_{ij} : Sensitivities of each factor with respect to the return of mutual fund

According to Sharpe's theory, b_{ij} values are required to sum to 1, in addition, the non-factor return for one asset is assumed to be uncorrelated with that of every other (e_i). Sharpe also suggests that the usefulness of this model depend on the properties of the asset classes 1) mutually exclusive, 2) exhaustive, and 3) have returns that "differ". Specifically, no security should be included in more than one asset class; as many securities as possible should be included in the chosen asset classes; and the asset class returns should either have low correlations with one another or, in cases where correlations are high, different standard deviations. Sharpe concludes that the asset factor model is truly useful to help investors make economize on information flows and exploit comparative advantages.

The factors of twelve-asset class model Sharpe uses are: Bills, Intermediate-Term Government Bonds, Long-Term Government Bonds, Corporate Bonds, Mortgage-Related Securities, Large-Capitalization Value Stocks, Large-Capitalization Growth Stocks, Medium-Capitalization Stocks, Small-Capitalization Stocks, Non-U.S. Bonds, European Stocks and Japanese Stocks. We can find that the general two big commonly used categories of the factors are bonds and stocks.

Based on Sharpe (1992) twelve-asset factor model, Fung and Hsieh (1997) modify the common factors in linear factor model for hedge funds and mutual fund. He also defines five styles factors to stand for the hedge fund investment styles: Global/Macro style, Distressed style, Value style, Systems/Trend Following style and Systems/Opportunistic style. The regression function they use is:

$$R_t = \alpha + \sum_k b_{kt} F_{kt} + u_t$$

F_{kt} represents the asset class factor. Here, they use eight-asset class factors plus high yield bonds. The three equity classes are MSCI U.S. equities, MSCI non-U.S. equities, and IFC emerging market equities, while the two bond classes are JP Morgan US government bonds and JP Morgan non-US government bonds. For commodities they use the price of gold. For cash they use 1-month Eurodollar deposit. For currencies they use the Federal Reserve's Trade Weighted Dollar Index.

The paper result shows that the R^2 of value style is 70% against the eight asset classes plus the high yield corporate bonds and is highly correlated to U.S. equities (T-statistic is 7.73 and coefficient is 0.95), distressed style has R^2 of 56% and is highly correlated to high yield corporate bonds (T-statistic is 6.06 and coefficient is 0.89). Two styles out of five styles in total have low R^2 and don't correlate to any of the asset classes. The Global/Macro style has R^2 55% and correlates with U.S. bonds, U.S. dollar and IFC emerging market equities. So, for different investment styles, the factors explanation powers are different.

Kooli (2005) also uses meaningful factors in linear factor model especially for hedge funds based on many dimensions of financial risk inherent in hedge funds. To assess the hedge fund indexes performance, he uses Fama and French (1993) size and value factors, Carhart (1997) momentum factors, two bond indexes factors (Lehman US Aggregate Bond Index and JP Morgan Emerging Market Bond Index), and one commodity factor (Goldman Sachs Commodity Index).

The regression function is:

$$R_{jt} - R_{Ft} = \alpha_j + \beta_{j1}(R_{Mt} - R_{Ft}) + \beta_{j2}SMB_t + \beta_{j3}HML_t + \beta_{j4}PRIYR_t + \beta_{j5}(LBUSBI_t - R_{Ft}) + \beta_{j6}(JPMEMBI_t - R_{Ft}) + \beta_{j7}(GSCI_t - R_{Ft}) + jt$$

R_{Ft} : Risk-free return on month t

R_{Mt} : Return of Market Proxy on month t

SMB_t : Factor-mimicking portfolio for size (small minus big)

HML_t : Factor-mimicking portfolio for book-to-market equity (high minus low)

$PRIYR_t$: Factor-mimicking portfolio for the momentum effect

$LBUSBI_t$: Return of the Lehman Aggregate U.S. Bond Index

$JPMEMBI_t$: Return of the JP Morgan Emerging Market Bond Index

$GSCI_t$: Return of the Goldman Sachs Commodity Index.

The paper results show that in the Dedicated Short Bias index, the HML factor seems to add less explanatory power as only 1 out of 10 indexes of the factors is significantly at the 5% level. The Momentum factor does not prove to be a strong indicator of hedge fund behaviour because it is significant for only 2 out of 10 indexes. On the other hand, the premium on the SMB factor is significantly positive in 6 out of 10 hedge fund indexes. The U.S. bond factor adds explanatory power in 7 of the indexes considered, and the emergent bond and commodity factors add explanatory power in 30% and 20% of the cases, respectively. Hence, the SMB factor, U.S bond factor, the emergent bond and commodity factors are powerful explanatory factors in regressing hedge fund returns.

Lhabitant (2001) applied Sharpe (1992) twelve-factor model to analyze market risk of hedge funds and hedge funds portfolios by using his composed Value at Risk method. He uses returns-based style analysis method first introduced by Sharpe (1988) to category the hedge funds to the corresponding night investment styles: Convertible Arbitrage, Dedicated Short Bias, Event Driven, Global Macro, Long Short Equity, Emerging Markets, Fixed Income Arbitrage, Market Neutral and Managed Futures. Then he constructs an empirical model assuming the factors are the asset classes of the nine styles. The model is:

$$R_t = \alpha + \sum_{i=1}^9 \beta_i \cdot I_{i,t} + \varepsilon_t$$

$I_{1,t}$ is the return on the CSFB Tremont Convertible Arbitrage index at time t;

$I_{2,t}$ is the return on the CSFB Tremont Short Bias index at time t

$I_{3,t}$ is the return on the CSFB Tremont Event Driven index at time t

$I_{4,t}$ is the return on the CSFB Tremont Global Macro index at time t

$I_{5,t}$ is the return on the CSFB Tremont Long Short Equity index at time t

$I_{6,t}$ is the return on the CSFB Tremont Emerging Markets index at time t

$I_{7,t}$ is the return on the CSFB Tremont Fixed Income Arbitrage index at time t

$I_{8,t}$ is the return on the CSFB Tremont Market Neutral index at time t

$I_{9,t}$ is the return on the CSFB Tremont Managed Futures index at time t

He divides the risk into two parts. One is the systematic risk, which is the market risk that can be explained by the nine systematic factors and the other is the specific risk, which is the unexplained part. When they know the Value at Risk of every risk factor of the nine factors, they can use the following model to find the Value at Market Risk that represents the total market risk of the hedge fund portfolio.

$$VaR = \sqrt{\sum_{i=1}^9 \sum_{j=1}^9 \rho_{i,j} \cdot \beta_i \cdot F_i^* \cdot \beta_j \cdot F_j^*}$$

$\rho_{i,j}$ is the correlation between the returns of hedge fund indices i and j.

F_i^* is the VaR of index i returns at 99% confidence level.

The specific risk is the difference between total risk, the variance of the portfolio and systematic risk estimated before.

3 OUR RISK DECOMPOSE MODEL

Based on the economics view of hedge fund investment, we argue that the risk of hedge fund might have high correlation with the fluctuation of traditional markets. Such as stock market, bond market and commodity market. Therefore, we try to build a regression model based on the Sharpe's fundamental model (1992) to decompose the risk of hedge fund return into two components: systematic risk component and unsystematic risk component.

3.1 Systematic Risk and Unsystematic Risk

First of all, we should clarify the definitions of systematic risk component and unsystematic risk components discussed in this paper. We define the systematic risk as the risk of hedge fund returns caused by the fluctuation of the traditional financial markets, including stock market, bond market and commodity market. Although some papers point out that the returns of hedge fund have very low correlation with these traditional markets, we have to figure out that these comments only look at their relationships from the statistic viewpoint, which would make no sense from the viewpoint of economic. Generally speaking, hedge funds are divided into nine or eleven types with respect to the specific strategy each hedge fund uses, such as convertible arbitrage, dedicated, Emerging Market, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity, Managed Futures, Multi-strategy and so on. Even though some strategies are trying to take the arbitrage among different markets or using vary kinds of derivative instruments to mitigate the risk they are exposed to and increase the return at the same time, they superficially look the fluctuation of the traditional markets independently. However, either derivative instruments or arbitrages are based on these three main traditional markets: stock market, fixed income market and commodity market. The difference is that these

strategies are not directly putting money into the three traditional markets, rather they have indirect or chain effects with the traditional markets. For example, if a hedge fund manager pursues the fixed income arbitrage or long short equity, it is obviously that they have to pay most attention to the fluctuations of the bond market or stock market in order to make decision whether to terminate the transactions or not. Somebody would argue that he can forecast the trends of these markets and adjust his strategy immediately to avoid falling with the traditional markets and these rational adjustments would lead to low correlation with the fluctuation of traditional market. However, this case would happen sometimes but most of the time it would not happen if the market is efficient. According to the efficient market hypothesis (Fama, 1960), it says that at any given time, security price fully reflects all available information. This means that nobody can predict the future trend of a market return before it really happens. There are three forms of efficient market: weak form, semi-strong form and strong form². Many empirical tests argue that the real markets are neither perfectly efficient nor completely inefficient. But most of the time, the semi-efficient market hypothesis can hold. Therefore, the return of the hedge fund investment still mainly depends on the trend of the traditional market and the risk of hedge fund arising from the fluctuation of traditional markets is always the major part of the risk of hedge fund.

The other part risk of hedge fund return would be the unsystematic risk that is caused by the other factors other than the fluctuation of the three main traditional markets. This type of risk is widely defined and it includes the specific risk which is caused by the specific investment strategies used by hedge fund managers, liquidity risk which is caused by the long term holding period of hedge fund investors, credit risk which is caused by the default of the hedge fund managers and some other risks. There are two main characteristics of unsystematic risk. First, this type of risk is diversifiable. This means that most part of unsystematic risk could be mitigated by

² Weak form: all past market price and data are fully reflected in securities prices. In other words, technical analysis is of no use. Semi-Strong form: all publicly available information is fully reflected in securities price, in other words, fundamental analysis is of no use. Strong form: all information is reflected in securities price. In other word, even insider information is of no use.

diversified investments. For example, if one investor puts all of his money into only one hedge fund, he will be exposed to a higher credit risk relative because if this hedge fund company becomes insolvency, this investor has to lose most of his money or perhaps all of the money. However, if he divides his money into several parts and puts them into different hedge fund categories, he would not be so worried about that one of these hedge funds fails or is insolvency. This diversifiable strategy costs nothing but mitigates the credit risk this investor bearing. Therefore, we argue that unsystematic risk can be mitigated by diversifiable strategy although might not be totally diversified. Secondly, unsystematic risk of each type of hedge fund strategy is specific and is different from others. This means, for example, the unsystematic risk of fixed income arbitrage is different from that of convertible arbitrage. Fixed income arbitrage strategy tries to look for some fixed income securities where the risk characteristics are same but prices are different. Then the hedge fund managers who pursue this strategy would take this arbitrage opportunity. So the main unsystematic risk of fixed income arbitrage would focus on the magnitude of arbitrage opportunity and the leverage they use to enlarge this arbitrage profits. However, when come to the convertible arbitrage strategy that tries to take arbitrage opportunity via convertible right of securities, the unsystematic risk would focus on the gap between the market price of the common stock and the market price of the convertible securities. So the fluctuation of market price of common stock would be the key driver of this strategy's unsystematic risk.

3.2 Lower Partial Moments and Variance

After defining systematic and unsystematic risk components, we should choose a method to measure these risks. Variance used to be a traditional measure of risk. From literature review, we know that the more close to normal distribution, the more efficient the variance method is. Markowitz (1952, 1970) and Tobin (1958, 1965) first put forward the mean-variance selection rule for risk-averse investors using variance as a risk measure. Their theory sounds good, but the

main point is that if the distribution of sample return is not normal, the variance would be not so efficient.

When we use the data set from January 1991 to February 2006, we find that HFRI index has higher mean and lower standard deviation relative to those of S&P 500 index returns (Table.1). What is more important, we should take more attention to the extremely higher excess kurtosis of the HFRI index returns compared to that of S&P 500 index returns (Table 1). Higher excess kurtosis means a fatter tail of the hedge fund's return distribution, which would lead to a serious potential loss to the hedge fund investors. In additional, the non-zero skewness of hedge fund returns figures out that the distribution of hedge fund return is asymmetric, and negative skewness of HFRI index shows that there would be a serious potential loss. Therefore, the traditional risk measure, such as volatility of the return, would not be so efficient for hedge funds.

However, since the investors mainly consider the downside risk more seriously than the upside risk, Bawa (1975) and Fishburn (1977) extend the downside risk measure to Lower Partial Moments. This is a real progress in risk measure field. From literature review part, we know that Lower Partial Moment is defined as following:

$$LPM(a,t) = \frac{1}{k} * \sum_{t=1}^K Max[0, (t - R_t)]^a$$

K : The number of observations.

t : The target return

R_t : The return of asset during time period t .

a : The degree of lower partial moment

One of the main merits of Lower Partial Moments is that it liberates the investors from a constraint of having only one utility function. In additional, Fishburn (1977) pointed out that a , which is the degree of lower partial moment, could be any rational positive number and different value of a supposed to reflect decision maker's feelings about the relative consequence of falling short of target return by various amount. The conclusion in Fishburn's paper is that

If the manager's main concern is failure to meet the target without particular regard to the amount, then a small value of n is appropriate. On the other hand, if small deviations below target are relatively harmless when compared to large deviations, then a larger value of n is indicated. In addition, $n = 1$ is the point that separates risk seeking from risk-averse behaviour with regard to returns below target. (Fishburn, 1977, p.5)

Therefore, we can use Lower Partial Moment to do research on investors with different risk taste while variance does not work here.

However, a drawback of Lower Partial moment is that it is not additive, but which is the important property of variance. For example, if we have a portfolio contains independent³ asset A and asset B, how can we measure the risk of the total portfolio consisting asset A and asset B? If we use variance as a risk measure, we can calculate the variance of asset A and B, respectively. Then use this formula to compute the variance of portfolio,

$$\sigma_{Total}^2 = \sigma_A^2 + \sigma_B^2$$

This means additive property works well on variance measurement. But when come to Lower Partial Moment, the situation would be totally different since Lower Partial Moment is not additive.

$$LPM_{Total} \neq LPM_A + LPM_B$$

³ Independent means the correlation of Asset A and Asset B is 0.

Table 1 The statistic characteristic of HFRI return, S&P500 index return, Weighted Total Return of T-bill index return, Dow Jones AIG commodity index return from January 1991 to February 2006 Annualized monthly data.

	Mean	variance	Excess Kurtosis	Skewness	Jarque-beta Test
HFRI	0.1410	0.0550	3.0989	-0.6113	84.1609
S&P 500	0.0994	0.2325	0.8745	-0.4866	12.9824
Total Return of T-bonds index	0.0467	0.0002	-0.8459	-0.4454	11.4426
DJ AIG commodity index	0.0773	0.1664	0.2155	0.0468	0.4186

Table 2 The correlation coefficient matrix of HFRI index return, S&P 500 index return, weighted Total Return of T-bill index return and Dow Jones AIG commodity index return from January 1991 to February 2006 Annualized monthly data

	HFRI index	S&P500	Total Return of T-bonds index	DJ commodity index
HFRI index	1.00			
S&P 500	0.6902	1.00		
Total Return of T-bonds index	0.0984	0.0834	1.00	
DJ commodity index	0.1250	0.0233	-0.0397	1.00

3.3 Our Risk Decompose Model

After classifying the systematic and unsystematic risk and the measurement of these risks, we argue that the total risk of hedge fund return composes systematic risk and unsystematic risk regardless of the distribution of the hedge fund return. The equation is following:

$$\text{Total risk of hedge fund return} = \text{systematic risk} + \text{unsystematic risk}$$

From literature review discussed above, we find that Sharpe (1992) first suggest to use multi-factor model to do return-based style analysis. Although Sharpe (1992) built this model to regress mutual fund rate of return, Fund and Hsieh(1997) extend this model into hedge fund field. Then Lhabitant (2001) uses nine styles of hedge fund strategy indexes to reconstruct this model and extend this model to evaluate the VaR of hedge fund rate of return. In additional, Kooli (2005) employs other factors to compare the performance of hedge fund based on factors in Sharpe's fundamental model. From the previous research, we can clearly conclude that Sharpe's basic model can be extended to do regression on hedge fund index return if we use the proper factors.

Our model is based on Sharpe's general model but we use the returns of the stock index, bond index and commodity index as the three main factors in our model. According to the discussion above, the fluctuation of these three indexes would be the systematic risk component of hedge fund return. The fluctuation of error term: ε_t would be unsystematic risk of hedge fund return. So our model is primarily following:

$$R_t = \underbrace{\beta_1 S_t + \beta_2 B_t + \beta_3 C_t}_{\text{systematic_risk}} + \underbrace{\alpha + \varepsilon_t}_{\text{Unsystematic_risk}}$$

R_t : Return of hedge fund at time t

α : Intercept

S_t : Return of stock proxy at time t

B_t : Return of bond proxy at time t

C_t : Return of commodity proxy at time t

ε_t : Error term

Using above formula, we decompose the total risk of hedge fund return into two main components: systematic risk which is explained by the fluctuation of traditional market and unsystematic risk which is explained by the other factors. Since the distribution of vary hedge fund strategies' returns has non-zero skewness and positive kurtosis, we choose Lower Partial Moments to measure each risk component of hedge fund return as the investors only care about the downside risk of the hedge fund return (the details of this argument would be discussed in the application of our model). Given a target return r_t and the power of Lower Partial Moment that represents the risk taste of investors, we can easily compute the Lower Partial Moment of hedge fund return, which represents the total risk of the hedge fund return. Then we can also calculate the Lower Partial Moments of the fitted hedge fund return explained by the three traditional markets, which represents LPM of systematic risk component. The Lower Partial Moment of sum of intercept and error term in this regression would be LPM of unsystematic risk component of hedge fund return.

4 APPLICATION OF RISK DECOMPOSE MODEL

4.1 Data

There are tremendous indexes of hedge funds right now since the hedge fund industry is booming in the recent years. We choose the HFRI⁴ (hedge fund research index) because it is composed of equal weighted composite of the performance of hedge fund. HFRI is composed a widely range of hedge funds since there is no requirement of the minimum asset size for fund inclusion in this index and no requirement of length of time a fund must be actively trading before inclusion in this index. Both domestic and offshore hedge funds are all included in this hedge fund index. In addition, the most important merit of this index is that it includes the hedge fund which liquidates or closes as of fund's last reported performance update. This characteristic would mitigate the survival bias of this hedge fund index to some extent, which could lead us to an objective result.

We choose S&P 500⁵ index as the representative of the stock factor because this index is widely regarded as the best single gauge of US equity Market. It composes of 500 leading companies in the leading industry in the US market. Even though it only consists of large cap segment of market, it is also an ideal proxy for the total market because of its 80% coverage of US equity. Although HFRI composes of the hedge funds all over the world, most of these hedge funds are US companies and they all focus on the American market as well. Therefore, the fluctuation of US stock market would have a high correlation with the fluctuation of these hedge funds. Using the sample data from January 1991 to February 2006, we find the correlation between return of S&P 500 index and return of HFRI index is 0.69 (Table 2). We choose Dow

⁴ HFRI index is available on website www.hedgefundresearch.com

⁵ S&P 500 index is available on website <http://finance.yahoo.com/>

Jones AIG Commodity index⁶ as the representative of the commodity factor. Dow Jones-AIG commodity, which is composed of future market on 19 physical commodities, is a highly liquid and diversified benchmark for the commodity future market. Most of the commodities including in Dow Jones AIG index are traded on US exchange, with the exception of aluminium, nickel and zinc, which trade on the London Metal Exchange (LME). Therefore, the fluctuation of this commodity index would be a good indicator of the movement of commodity. In addition, we have to point out that Dow Jones AIG Commodity index is a “rolling index” since the commodity future contracts specify a delivery date for the underlying physical commodity. In order to avoid delivery and maintain a long futures position, nearby contracts must be sold and contracts that have not yet reached the delivery period must be purchased. This process is known as “rolling” a futures position. As this character of Dow Jones AIG commodity index, the index relies primarily on liquidity data, or the relative amount of trading activity of a particular commodity to determine its components weightings. What is more, this index is a real diversified index that no single commodity may constitute less than 2% or more than 15% of the index and nearly covers all kinds of main commodities in US commodity market. For the fixed income factor, we use the weighted average of total return of treasury bonds with different maturity dates since the investment period is very different with respect to different hedge fund corporations and different strategies used. But since the longest term of investment should be no longer than 10 years and the shortest term should be no less than 3 months, we give the same weight to each treasury bonds with different maturity terms between 3 months and 10 years to reflect the fluctuation of fixed income market.

⁶ Dow Jones AIG commodity index is available on website: <http://www.djindexes.com/mdsidx/?event=showAigHome>

4.2 Application of Risk Decompose Model

Based on our model, we try to divide the total risk of hedge fund return into two components: systematic risk component and unsystematic risk component and use lower partial moment as a measurement of risk. Our methodology is mainly consisted of five procedures.

Step1. Choose the representative of the three systematic factors. We use annualized monthly HFRI return as a representative of hedge fund return, annualized monthly S&P 500 index return as a representative of the stock market return, annualized monthly weighted average treasure bill index as a representative of fixed income market return and annualized monthly Dow Jones AIG Commodity index return as a representative of commodity market return.

Step2. Based on our model following:

$$R_t = \underbrace{\beta_1 S_t + \beta_2 B_t + \beta_3 C_t}_{\text{systematic_risk}} + \underbrace{\alpha + \varepsilon_t}_{\text{Unsystematic_risk}}$$

R_t : Return of hedge fund at time t

α : Intercept

S_t : Return of stock index at time t

B_t : Return of bond index at time t

C_t : Return of commodity index at time t

ε_t : Error term

We do the regression using OLS method to calculate the coefficient of each factor. These coefficients: $\beta_1, \beta_2, \beta_3$ are the weights for each part of the three systematic factors.

Step3. Based on $\beta_1, \beta_2, \beta_3$, we calculate the systematic return explained by three traditional markets: stock market, bond market and commodity market using following formula:

$$R_s = \beta_1 S_t + \beta_2 B_t + \beta_3 C_t$$

R_s : is the return of systematic component

Step4. Calculate the unsystematic part rate of return using following formula:

$$R_{us} = R_t - R_s.$$

R_{us} : Return of unsystematic component; R_t : Return of hedge fund index

Step5. Choose a threshold or target rate of return: r_t according to the investors' target and the power of Lower Partial Moments α according to the risk tolerance of investors. Use this threshold return and fixed power of Lower Partial Moment to calculate the LPM of R_s as the systematic risk component and LPM of R_{us} as the unsystematic risk of component.

4.3 Results

We use HFRI index return as the representative of hedge fund return, S&P 500 index as the representative of stock factor, weighted average of treasury bond yield to maturity as the representative of fixed income factor and Dow Jones AIG index as the representative of commodity factor. We run the regression using our risk decomposition model and get result in Table 3. From this table, we can clearly see that the t-statistic value for each systematic factor is significant at 95% confidence level except for the bond factor with t-statistic value: 0.851894. This means hedge fund return have very low correlation with return of treasury bonds. When we see the t-statistic value of stock factor: 12.7279, we can clearly see that hedge fund focus more on stock market fluctuation relative to bond market fluctuation, which makes the stock factor very significant. In additional, the coefficient of each factor is positive. This means that the return of HFRI index has positive correlation with the fluctuation of the traditional markets and the coefficient of S&P 500 has a large value: 0.331721, which means the fluctuation of S&P 500 have a greater effect on the return of HFRI index relative to other factors as well. We can find this

result from Table 2 as well since the return of S&P 500 have the highest positive correlation with the return of HFRI index while the other two systematic factors have lower correlation with HFRI index. We can also see that R-square is 0.4903, which means that these three systematic risk components account only half part of total risk of HFRI return while the other part is defined as the unsystematic risk of HFRI return.

Since we use LPM (lower partial moment) as a measure of risk, different investors who put money into hedge fund would have different target rate of return levels with respect to their own purpose and different investors would choose different powers of LPM to measure the downside risk they are exposing based on their risk appetites. Therefore, we change the target return levels and power of lower partial moment to implement risk decompose of HFRI return, respectively and got a series of figures. Figure 1 shows the curve of HFRI risk decomposition using 0.5 as the power of lower partial moment, which reflects the behaviour of a typical risk seeking. In this graph, the solid line, which represents the LPM of unsystematic risk part and the dotted line, which represents the LPM of systematic risk factors, are much above the pointed line, which represents the LPM of HFRI return. This means that the total downside risk of hedge fund index return is much lower than the sum of systematic risk and unsystematic risk or even much less than the individual part of each components of risk. In additional, we can clearly see that LPM of systematic factors and LPM of unsystematic factors are nearly same only with little difference. This proves the result of our regression that systematic risk and unsystematic risk take almost the same weight in the total downside risk of HFRI index. At the same time, Figure 2 using first moment of LPM shows the risk decomposition with respect to a typical behaviour of separator between risk seeking and risk averse. From this picture, we found that the LPM of HFRI return is above LPM of systematic factors and LPM of unsystematic factors with lower target return, but with the increasing of target return levels, the LPM of systematic factors and LPM of unsystematic factors go up quickly relative to that of HFRI index. When come to the risk aversion investors represented by the second moment of LPM, the situation would be totally different.

Figure 3 exhibits risk decomposition using second moment of LPM. Obviously, the LPM of HFRI return is dominantly larger than each component risk regardless of systematic risk or unsystematic risk. When we combine these three figures together, we can see that the total lower partial moment for risk lover would be the smallest relative to that of risk neutral and risk aversion investors. This means that hedge fund is more suitable for investors who love risk or can bear a big risk.

What's more, since most of the investors are risk aversion, we focus on Lower Partial Moment of systematic risk, unsystematic risk and total risk with power larger than 2. In order to consistent with traditional statistic angle, such as variance, skewness and kurtosis, we draw Figure 4 using third moment of LPM and Figure 5 using fourth moment of LPM. Obviously, we can see that LPM of total risk is extremely more than that of systematic component and unsystematic component in these two figures. In additional, when we observe the scale of y-axis, we find that the third and fourth moments of LPM would be pretty small and almost the same to each other. In order to see this proper clearly, we choose sample investors with fixed target return: 0.03. Then we change the power of LPM to get Figure 6. This figure reveals that the LPM of total, systematic and unsystematic risk decreases dramatically with the increasing Power. In additional, when the power of LPM is larger than 3, the LPM of systematic component and unsystematic component would be close to each other toward to zero. But at the same time, although the LPM of systematic component and unsystematic component are closing to zero, LPM of HFRI return would be stable around 0.01. This means that the total risk of hedge fund would be no difference for investors whose risk aversion level is larger than a specific level, which is the third moment of LPM in this case.

Table 3 Regression result of HFRI Return

The regression result of this equation:

$$R_t = \beta_1 S_t + \beta_2 B_t + \beta_3 C_t + \varepsilon_t$$

R_t : The return of HFRI S_t : the return of S&P 500 index

B_t : The total return of weighted average T-bonds index

C_t : The return of Dow Jones AIG commodity index

The critical value of t-statistic with 95% confidence level is 1.96.

Variable	Coefficient	t-statistic
alpha	0.067958	1.579078
S&P 500	0.332620	12.727914
Weighted Total return of T-Bonds	0.749917	0.851894
DJ AIG commodity index	0.063758	2.069690
R-squared	0.4903	

Figure 1 Risk decompose of HFRI return with power 0.5

We use monthly data from January 1991 to February 2006 to run regression and get the result following our model. Then we use 0.5 as the power of Lower Partial Moment to calculate the LPM of systematic factors as systematic risk, to calculate the LPM of unsystematic factors as unsystematic risk and to calculate the LPM of HFRI return as total risk.

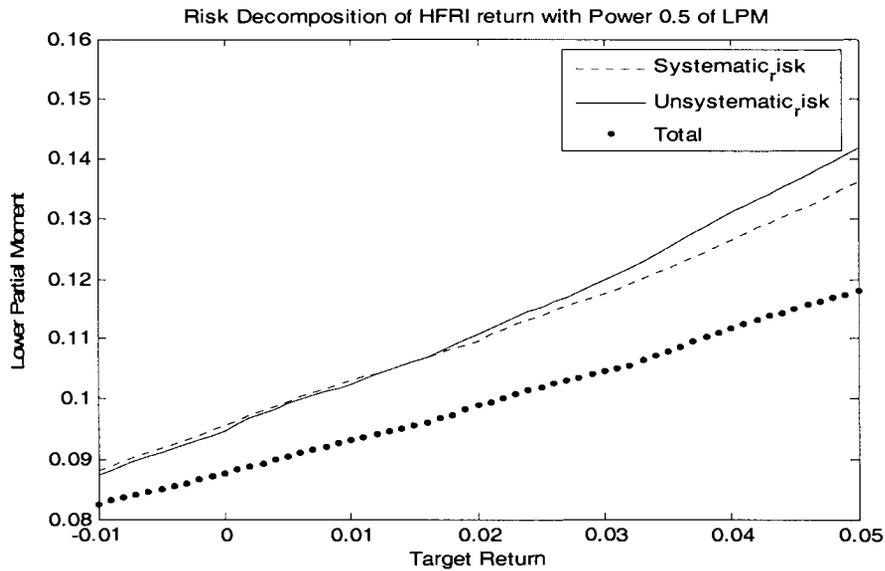


Figure 2 Risk decompose of HFRI return with first moment of LPM

We use monthly data from January 1991 to February 2006 to run regression and get the result following our model. Then we use 1 as the power of Lower Partial Moment to calculate the LPM of systematic factors as systematic risk, to calculate the LPM of unsystematic factors as unsystematic risk and to calculate the LPM of HFRI return as total risk.

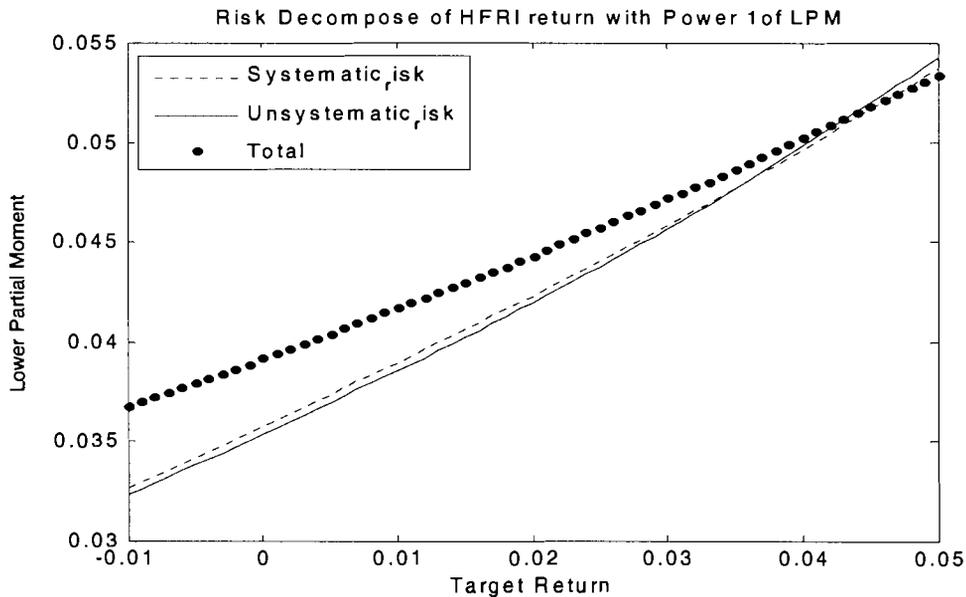


Figure 3 Risk decompose of HFRI return with second moment of LPM

We use monthly data from January 1991 to February 2006 to run regression and get the result following our model. Then we use 2 as the power of Lower Partial Moment to calculate the LPM of systematic factors as systematic risk, to calculate the LPM of unsystematic factors as unsystematic risk and to calculate the LPM of HFRI return as total risk

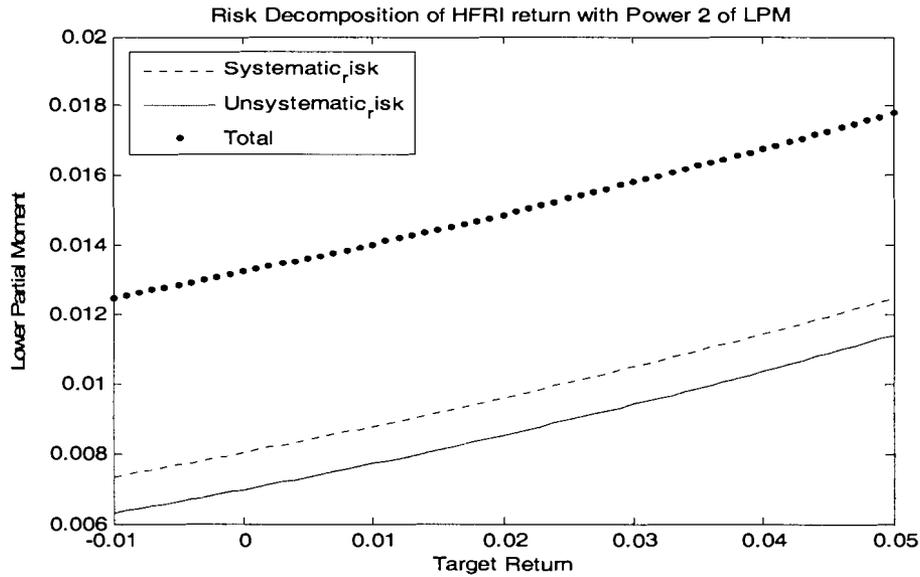


Figure 4 Risk decompose of HFRI return with third moment of LPM

We use monthly data from January 1991 to February 2006 to run regression and got the result following our model. Then we use 3 as the power of Lower Partial Moment to calculate the LPM of systematic factors as systematic risk, to calculate the LPM of unsystematic factors as unsystematic risk and to calculate the LPM of HFRI return as total risk.

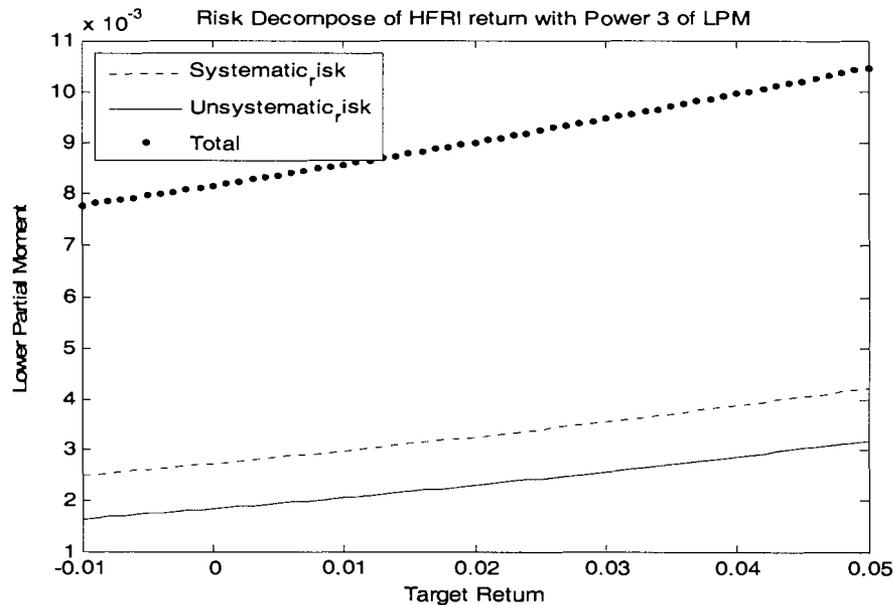


Figure 5 Risk decompose of HFRI return with fourth moment of LPM

We use monthly data from January 1991 to February 2006 to run regression and get the result following our model. Then we use 4 as the power of Lower Partial Moment to calculate the LPM of systematic factors as systematic risk, to calculate the LPM of unsystematic factors as unsystematic risk and to calculate the LPM of HFRI return as total risk.

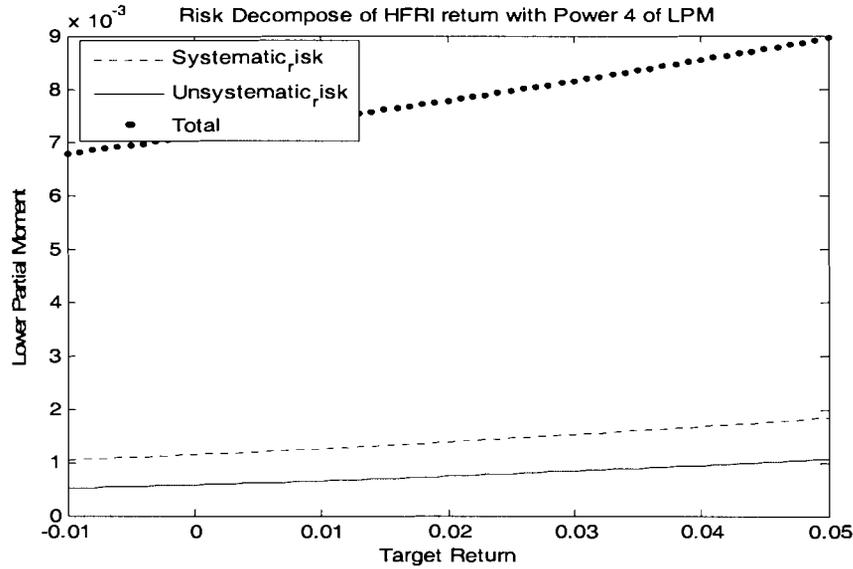
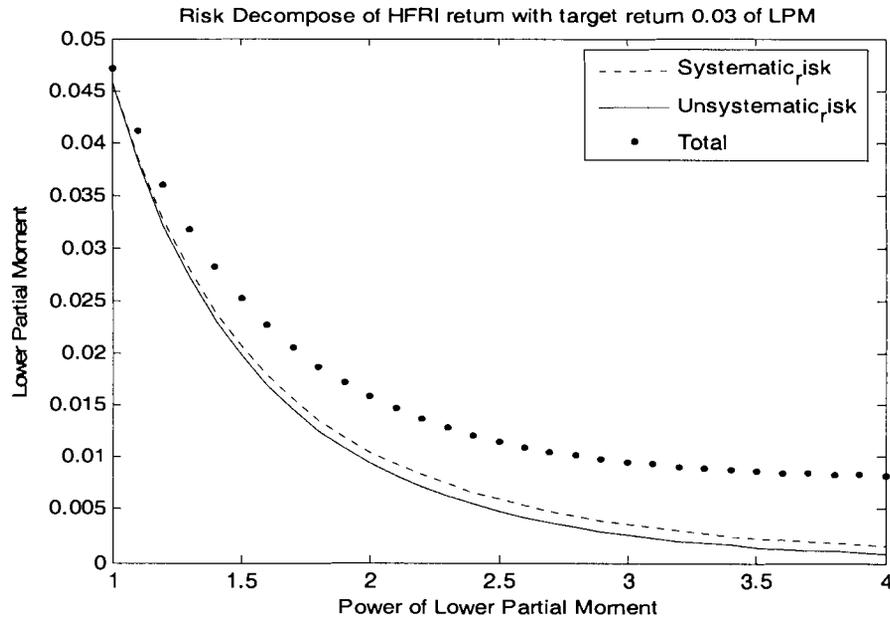


Figure 6 Risk decompose of HFRI return with respect to power of LPM

We use monthly data from January 1991 to February 2006 to run regression and get the result following our model. Then we only care about risk aversion investors whose target return is 0.03. We use the power of LPM as x axis and LPM of systematic risk, unsystematic risk and total risk as y axis.



5 CONCLUSION

Based on the economics viewpoint of hedge fund investment, we use our risk decomposition model to break down the total risk of hedge fund index into systematic component and unsystematic component. Then we use Lower Partial Moment as a measure of risk considering the properties of distribution of hedge fund return. We get the following results for different investors with different risk consideration. (1). For risk seeking behaviour, the LPM of HFRI return is much lower than the LPM of systematic factors or LPM of unsystematic factors. (2). For separator of risk seeking behaviour and risk averse behaviour, the LPM of HFRI return is larger than that of systematic factors or unsystematic factors with lower target return, but LPM of HFRI increases very fast with respect to the increasing of target return and finally when the target rate of return is above 0.05, the total risk is larger than systematic risk or unsystematic risk. (3). For risk-averse behaviour, the LPM of HFRI is much larger than the LPM of systematic factors or the LPM of unsystematic factors. (4) For risk-averse behaviour, if the risk aversion level is greater than a specific level of aversion, the LPM of total risk of hedge fund would be stable no matter how greater the power of the lower partial moment is.

According to the results showing above, we can figure out that hedge fund is more suitable for investor who has risk seeking behaviour intuitively. What is the economic logic behind these figures? Because for risk seeking behaviour, it could accept more risk with a given level of return relative to that of risk averse behaviour, hence their risk taste would encourage hedge fund managers to use more unusual financial instruments to offset the downside risk caused by of traditional markets. So if the traditional markets go down, the other untraditional financial instruments would offset this downside risk and vice versa. But for risk-averse behaviour, it would ask for less risk with a given level of return compared to that of risk seeking behaviour. It

would prefer only expose to systematic risk caused by fluctuation of traditional markets. So the investors who have risk averse behaviour would choose hedge fund managers who use less unusual financial instruments because they cannot predict the risk of unusual financial instruments, such as the derivatives and the leverage, accurately enough to meet the clients' requirement. Therefore, if the markets go down at one time, there are limited financial instruments that move to the other direction to offset the downside risk of traditional markets or maybe make the downside risk worse. However, when come to the behaviour of separator between risk seeking and risk averse, it would take the middle position. This means that when choose the hedge fund manager and consequently strategy the manager will use, it will prefer the strategy between the strategies for risk lover and risk aversion. So their LPM of HFRI return, LPM of systematic factors and LPM of unsystematic factors are looks the same to each other. Such behaviours would lead to above results for different investors with different risk appetites. In additional, if the risk averse level of investors is above a specific level, the LPM of hedge fund index return would be nearly constant because of the intrinsic of hedge fund industry. Hedge fund is a fund using different investment strategies and finance derivatives to take the profits. Usually the risk of hedge fund would be much larger than the traditional investment or the mutual fund investment and there should be a minimum risk level of hedge fund investments. So if investors are too risk averse to bear the minimum risk level of hedge fund investment, they'd better to put their money in mutual fund. That's why no matter how risk averse the investor is, the LPM of HFRI return would be no less than a specific level. All in all, when we consider the logic behind these figures, we could firm our conclusion discussed above.

APPENDICES

Appendix A: Definition of Specific Hedge fund Strategies

Hedge Fund Strategy	Definition
Short Selling	Short Selling involves the sale of a security not owned by the seller; a technique used to take advantage of an anticipated price decline.
Fixed income arbitrage	Fixed Income: Arbitrage is a market neutral hedging strategy that seeks to profit by exploiting pricing inefficiencies between related fixed income securities while neutralizing exposure to interest rate risk.
Convertible arbitrage	Convertible Arbitrage involves purchasing a portfolio of convertible securities, generally convertible bonds, and hedging a portion of the equity risk by selling short the underlying common stock.
Equity Market Neutral	Equity Market Neutral investing seeks to profit by exploiting pricing inefficiencies between related equity securities, neutralizing exposure to market risk by combining long and short positions.
Distressed Security	Distressed Securities strategies invest in, and may sell short, the securities of companies where the security's price has been, or is expected to be, affected by a distressed situation.
Event Driven	Event-Driven is also known as "corporate life cycle" investing. This involves investing in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks.
Fund of Fund	Fund of Funds invest with multiple managers through funds or managed accounts. The strategy designs a diversified portfolio of managers with the objective of significantly lowering the risk (volatility) of investing with an individual manager.
Macro Index	Macro involves investing by making leveraged bets on anticipated price movements of stock markets, interest rates, foreign exchange and physical commodities.
Merger Arbitrage	Merger Arbitrage, sometimes called Risk Arbitrage, involves investment in event-driven situations such as leveraged buy-outs, mergers and hostile takeovers.

**Hedge Fund
Strategy**

Definition

Sector Total

Investments can be long and short in various instruments with funds either diversified across the entire sector or specializing within a sub-sector,

**Relative
Arbitrage**

Relative Value Arbitrage attempts to take advantage of relative pricing discrepancies between instruments including equities, debt, options and futures.

Appendix B: Matlab Code for Regression

%this code used to implement our model

```
N = length(HFRI_index);
```

```
X = [ones(N,1) SP_index Tbill_index DJ_commodity];
```

```
Y = HFRI_index;
```

```
results = ols(Y,X);
```

```
prt(results);
```

%this is used to count number

```
i=1;
```

%this is Power of LPM

```
P=2;
```

%T is the target rate of return

```
for T=-.01:.001:.05;
```

```
    Total(i) = LPM(HFRI_index,T,P);
```

```
    Systematic_risk(i)=LPM(results.beta(4)*X(:,4)+  
        results.beta(2)*X(:,2)+results.beta(3)*X(:,3),T,P);
```

```
    Unsystematic_risk(i)=LPM(HFRI_index-(results.beta(4)*X(:,4)+  
        results.beta(2)*X(:,2)+results.beta(3)*X(:,3)),T,P);
```

```
    i=i+1;
```

```
end
```

```
figure
```

```
plot(-.01:.001:.05,[Systematic_risk' Unsystematic_risk' Total]);
```

```
legend('Systematic_risk','Unsystematic_risk','Total');
```

%this is the function used to calculate Lower Partial Moment

```
function v = LPM(X,T,P);
```

%this code used to calculate array X semi-variance

%X: the data array

%T: the threshold return

%P: the power of Lower Partial Moments

```
N=length(X);
```

```
down =0;
```

```
for i=1:N;
```

```
    down = (max(0,T-X(i)))^P+down;
```

```
end
```

```
v = down/N;
```

```
% disp(v);
```

%This code used to draw Figure 6

```
N = length(HFRI_index);
```

```
X = [ones(N,1) SP_index Tbill_index DJ_commodity];
```

```
Y = HFRI_index;
```

```
results = ols(Y,X);
```

```
prt(results);
```

```
i=1;
```

%T is target return

```

T=.03;

%P is power of Lower Partial Moment

for P=1:.1:4;

    Total(i) = LPM(HFRI_index,T,P);

    Systematic_risk(i) =LPM(results.beta(4)*X(:,4)+
        results.beta(2)*X(:,2)+results.beta(3)*X(:,3),T,P);

    Unsystematic_risk(i) = LPM(HFRI_index-(results.beta(4)*X(:,4)+
        results.beta(2)*X(:,2)+results.beta(3)*X(:,3)),T,P);

    i=i+1;

end

figure

plot(1:.1:4,[Systematic_risk' Unsystematic_risk' Total']);

legend('Systematic_risk','Unsystematic_risk','Total');

```

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