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Evaluation of Hedge Funds Performance

Jing Qian

EVALUATION OF HEDGE FUNDS PERFORMANCE

by

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Under the Direction of Yu-Sheng Hsu

ABSTRACT

Hedge funds are private investment funds characterized by unconventional strategies. This thesis employed multi-factor CAPM to evaluate the performance, or manager skill of hedge funds investment segments by using CSFB/Tremont Hedge Fund Indices from January 1994 to September 2005. The performance evaluation is based on the concept of "Jansen's alpha", which is estimated by applying Generalized Method of Moment. The finding is that hedge funds industry in general displayed the ability to outperform market proxy. Global Macro shows the strongest manager skill, followed by Event Driven, Equity Market Neutral and Long/Short Equity. This thesis also investigates the consistency of hedge funds performance over market environment. It was discovered that the hedge funds industry in general and all the sub-category investment segments except Convertibly Arbitrage, Emerging Market and Fix income Arbitrage displayed the ability to cushion the impact of financial shocks.

INDEX WORDS: HEDGE FUNDS, MANAGER SKILL, CAPM, GMM

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I. Introduction

In literature, hedge funds are defined as “private investment partnerships/vehicles in which the managing partner/entity is given a broad investment mandate”.[1] Recent years hedge funds have attracted more and more attention. In the last ten years, the number of hedge funds increases from 1,000 to 8,000 approximately.[2] Assets under management of the hedge fund industry totaled $1.13 trillion at year end 2005. This was up 13% on the previous year and nearly twice the total three years earlier.[3]

It is widely believed that hedge funds are able to generate returns better than conventional investment instruments. Compare with the mutual funds, which is an open-ended fund operated by an investment company raising money from shareholders and invests in a group of assets, hedge funds are often recognized as private partnerships and resident offshore for tax and regulation purpose. Their legal status exempts them from many of the rules and regulations governing other mutual funds. This exemption enable hedge funds to use more aggressive strategies, including short selling, leverage, program trading, swaps, arbitrage, and derivatives.

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[1] Fung. W. “Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds” Review of Financial Studies Summer 1997 Vol.10 page 281

[2] Hedge Fund Index: Construction, Comparison and Application, produced by Credit Suisse First Boston LLC. 2004.

[3] www.wikipedia.org

As aggressive investment tools, hedge funds are restricted by law to no more than 100 investors per fund, and as a result most hedge funds set extremely high minimum investment amounts, ranging anywhere from $250,000 to over $1 million.

Investors in hedge funds pay a management fee; besides, hedge funds also collect a percentage of the profits (usually 20%), called incentive fees, which are paid only when these managers make a positive return. Therefore, hedge fund managers have mandates to make an absolute return regardless of the market environments. Consequently, hedge funds won the fame as skill-intensive investment tools. The performance evaluation for hedge funds focuses on assessing the hedge funds' ability to out-perform the market average or out-perform other funds. In hedge funds literature, such ability to generate excess return over market average or outperform other funds is believed to originate from hedge funds manager's skill.

As shown in Fung, Xu, and Yau [2004], the evidence on significant excess return to hedge funds is mixed, and results on manager skill and performance persistence are inconclusive due to different data and models in use.

This thesis will use CSFB/Tremont Hedge Fund Indices to evaluate the performance of hedge funds across nine investment styles/strategies. The CSFB/Tremont Hedge Fund Indices tracks over 2600 US and offshore hedge funds and represent the overall performance of hedge funds industry. The nine sub-indices are clearly defined and

mutually exclusive. Performance evaluation will be based on these data, and multi-factor CAPM will be used to identify the performance factor across nine investment styles, so that the performance of hedge funds from different investment segments could be evaluated and compared.

Another aspect the thesis is going to address is that the performance consistency of hedge funds over market environments. Consistency is especially meaningful for hedge funds, since hedge funds are usually deemed to be able to generate positive returns disregard the market environments. The Asian Crisis provides a good platform and will be considered as a financial shock to test the consistency of hedge funds performance over market trends.

In Part II we discussed the data source in this study. Part III discusses the models and methodology, Part IV presents the empirical results from data analysis, Part V explains the future studies.

II. Data Handling

In this thesis, we will use the CSFB/Tremont Hedge Fund Index[4] to investigate the performance of hedge funds and evaluate the manager skill accordingly. The research period in this thesis is from January 1994 to September 2005, in total 141 months.

The CSFB/Tremont Hedge Fund Index is an asset-weighted hedge fund index. Credit Suisse First Boston Tremont Index LLC uses the TASS+ database which tracks over 2600 funds. Only funds with a minimum of US $50 million under management and a current audited financial statement will be counted into the universe of the index.

CSFB/Tremont Hedge Fund Index is computed on a monthly basis and funds are reselected quarterly to be included in the index. In order to minimize the survivorship bias, the funds will not be excluded until they liquidate or fail to meet the financial reporting requirements. These features enable CSFB/Tremont Hedge Fund Index to be benchmark of the various hedge funds investment styles and thus provide reliable data source to track and compare hedge funds performance against other major asset classes.

Within the CSFB/Tremont Hedge Fund Index, there are nine sub-indices classified according to different investment styles or strategies:

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[4] Data were obtained from the CSFB/Tremont Hedge Fund Index website at http://www.hedgeindex.com

1) Convertible Arbitrage Sub-index

This strategy is identified by hedge investing in the convertible securities of a company. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.

2) Dedicated Short Bias Sub-index

The strategy is to maintain net short as opposed to pure short exposure. Short biased managers take short positions in mostly equities and derivatives.

3) Emerging Markets Sub-index

This strategy involves equity or fixed income investing in emerging markets around the world.

4) Equity Market Neutral Sub-index

This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country.

5) Event-driven Sub-index

This strategy is defined as equity-oriented investing designed to capture price movements generated by an anticipated corporate event. There are four popular sub-categories in event-driven strategies: risk arbitrage, distressed securities, Regulation D and high yield investing.

6) Fixed Income Arbitrage Sub-index

The fixed income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility.

7) Global Macro Sub-index

Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and/or events.

8) Long/Short Equity Sub-index

This directional strategy involves equity-oriented investing on both the long and short sides of the market.

9) Managed Futures Sub-index

This strategy invests in listed financial and commodity futures markets and currency markets around the world.

CSFB/Tremont Hedge Fund Index and nine Sub-indices provide a comprehensive scope for the hedge funds industry. The indices are transparent both in calculation and composition. The detailed index construction methodology can be found in CSFB/Tremont Hedge Fund Index website.

III. Methodology

III.1 Review of performance measurement

In the 1980s, performance measures based on the CAPM (Capital Asset Pricing Model), like Jensen's alpha (Dimson [1979]) and their extensions were commonly used in mutual fund performance evaluation. The recent interest in multi-factor models primarily comes from the literature on the cross-sectional variations in stock return. Multi-factor models include the eight-factor model developed by Grinblatt and Titman (1994), the asset class factor model from Sharpe (1992), the three-factor model from Fama and French (1993), the four-factor model from Carhart (1997), and the international model of Fama and French (1998).

In hedge funds literature, performance evaluation also employs different models. In an early study, Fung and Hsieh (1997) extend Sharpe's (1992) asset class factor model and find five dominant investment styles in hedge funds. Schneeweis and Spurgin (1998) also use style analysis based on a multi-factor approach. Brown et al. (1999) and Ackermann et al. (1999) use a single-factor model and focus only on total risk. Agarwal and Naik (2000) use regression-based (parametric) and contingency-table-based (nonparametric) methods. Their parametric method regresses alphas on their lags. For the nonparametric method, they construct a contingency table of winners and losers depending on the alpha. Liang (1999) uses the extension of Fung and Hsieh (1997) model,

regressions based on fund characteristics, and classical measure like the Sharpe ratio. Agarwal and Naik (2002) propose a general asset class factor model comprising of excess returns on passive option-based strategies and on buy-and-hold strategies to benchmark the performance of hedge funds. Agarwal (2001) uses a model consisting of trading strategy factors and location factors to explain the variation in hedge funds returns over time. These results suggest that it is necessary to evaluate performance based on multifactor models, rather than simple CAPM, but there exists no unanimously accepted model. Therefore, it is preferable to use several specifications in order to compare the results obtained.

III.2 Performance measurement models

As revealed from the hedge fund literature, CAPM is widely used in measuring the performance of hedge funds. The simple CAPM model can be expressed as the following:

$$R_{j,t}\text{-}R_{f,t} = \alpha_j + \beta_m (R_{m,t} - R_{f,t}) + \varepsilon_{j,\tau}$$

Where $R_{j,t}$ *= return of fund j in month t;*

$R_{f,t}$ *= risk-free return in month t;*

$R_{m,t}$ *= return of the benchmark market portfolio in month t;*

$\varepsilon_{j,\tau}$ *= error term.*

The intercept of this model, α_j is called Jensen's alpha, interpreted as the measurement of the fund's ability to out-perform or under-perform over the market proxy. The slope coefficient β_m is a risk metric to its corresponding benchmark market. It measures the sensitivity of an instrument or portfolio to benchmark market movements. [5]

The CAPM decomposes the fund's return into two sources: the return generated from the investment style and the excess return generated from the performance factor, which is generally recognized as "manager skill".

In this thesis, manager skill of hedge funds is measured by the intercept coefficient, Jensen's alpha. A positive and significant Jensen's alpha indicates a positive manager skill. Accordingly, comparison and statistical test of the hedge funds performance between different investment segments will be implemented based on Jensen's alpha.

In order to take into account the different investment characteristics of the hedge fund industry, a multi-factor CAPM is employed in this thesis to evaluate the funds performance in generating excess return over benchmark markets. The benchmark market factors include a default factor, Moody AAA Corporate Bond Index; two factors for both US and non-US equities investing funds, S&P 500 and MSCI World excluding US; three factors for bond market, JP Morgan US and Non-US Government Bond Index, and

[5] The stock market (represented by an index such as S&P 500) is assigned a beta of 1.0. By comparison, a portfolio (or instrument) which has a beta of 0.5 will tend to participate in broad market moves, but only half as much as the market overall. A portfolio (or instrument) with a beta of 2.0 will tend to benefit or suffer from broad market moves twice as much as the market overall.

Merrill Lynch High Yield Corporate Bond Index; a commodity factor, Goldman Sachs Commodity Index; a currency factor, Federal Reserve's Trade Weighted Dollar Index; and finally a factor that reflect the investment in emerging market, JP Morgan Emerging Market Index. In this thesis, 90-day T-bill interest rate is considered as risk-free return.

The multi-factor CAPM is as the following

$$Model\ \ (I):\quad R_{j,t}\text{-}R_{f,t} = \alpha_j + \sum_{m=1}^{p} \beta_m (R_{m,t} - R_{f,t}) + \varepsilon_{j,\tau}$$

Where p is the number of market benchmark returns included in the model for fund j.

As Fung, Xu, and Yau (2004) mentioned, several bias should be taken into consideration when evaluating excess return of hedge funds. Their research suggested the choice of benchmark market index could be one of the sources brought in bias in hedge funds return performance.

To minimize such bias, the benchmark market indices were carefully selected so that all the hedge fund investment segments will be evaluated based on their specific investment target markets. The target market indices for every investment segment are identified according to its investment style defined by CSFB/Tremont. Meanwhile, stepwise linear regression is applied in identifying the proper target market indices in the selection process.

For example, as stated in the investment style classification defined by CSFB/Tremont, Fix Income Arbitrage category mainly aims at interest rate swap

arbitrage, US and non-US government bond arbitrage, forward yield curve arbitrage and mortgage-backed security arbitrage. Base on such investing characteristic, JP Morgan US and Non-US Government Bond Index, and Merrill Lynch High Yield Corporate Bond Index were chosen as the target market benchmark indices for Fix Income Arbitrage. Stepwise linear regression was employed after the above qualitative selection and JP Morgan US Government Bond Index is not significant for this model and was removed from the model. So after the above selection process, the return performance of Fix Income Arbitrage segment is evaluated based on JP Morgan Non-US Government Bond Index and Merrill Lynch High Yield Corporate Bond Index.

Such election process has been applied to all the hedge fund investment segments to minimize the bias from the choice of benchmark market indices.

Another task of this thesis is to evaluate the consistency of performance over market trend. Asian Crisis is considered as a financial shock, or severe market environment, to measure the performance consistency. A dummy variable is introduced into the multi-factor CAPM to perform the consistency test. The crisis period is defined as from July 1997 to July 2000.

After introduce the dummy variable, the model is as the following:

$$Model\ \ (II):\ \ R_{j,t}\text{-}R_{f,t} = \alpha_j + \sum_{m=1}^{p} \beta_m (R_{m,t} - R_{f,t}) + \gamma_j D + \sum_{m=1}^{p} \tau_m (R_{m,t} - R_{f,t}) D + \varepsilon_{j,\tau}$$

$$D = \begin{cases} = 1 & if \quad July\,1997 < period\ date < July\,2000 \\ = 0 & \qquad\qquad Otherwise \end{cases}$$

By examining the coefficient of the dummy variable, we will be able to make judgment on whether hedge funds perform consistently across crisis/non-crisis period. If the coefficient of the dummy variable of the model for fund j is not statistically significant, then it implies that there is no difference between the performance factor, Jensen's alpha, through the crisis and non-crisis period. So that we can consider the investment segment j has consistent performance in different market environments.

IV. Empirical Results

IV.1 Basic performance

The following graphs display descriptive statistics of the returns of hedge funds indices. The entire research period is from January1994 to September 2005; the crisis period is from July 1997 to July 2000; the rest is the non-crisis period. Figure 1 shows the annualized mean excess returns of hedge fund index and the nine sub-category indices. The highest annualized mean excess return over the entire research period is achieved by Global Macro (9.7%), followed by Long/Short Equity (8%) and Event Driven (7.4%). The lowest return comes from the Dedicated Short Bias with negative annual mean excess return (-4.35%). Figure 1 also clearly displays the consistency of performance of hedge funds segments over market trends. It can be seen that the Global Macro earns very stable return disregard the market environments so does Event Driven. While the returns of some other investment segments, such as Emerging Market, Managed Futures and Fixed Income Arbitrage, reduced during the Asian Crisis period. While Long/Short Equity, Equity Market Neutral and Convertible Arbitrage were even able to generate better return during the crisis period.

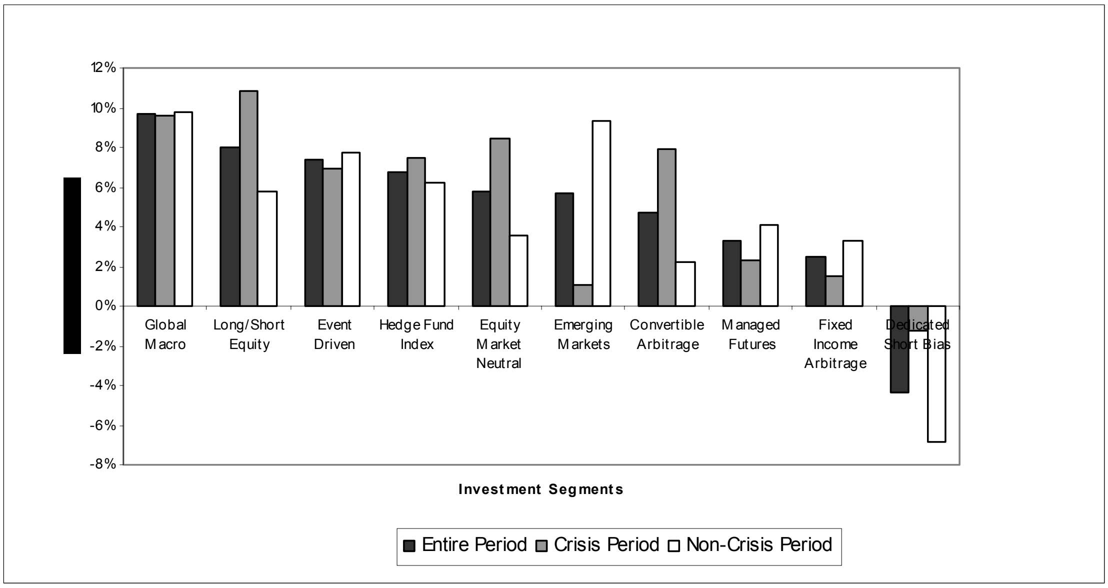

Figure 1: Annualized Mean Excess Returns

When standard deviation is taken into account through the Sharpe Ratio (the ratio of mean excess return and standard deviation), the rank ordering is quite different as shown in Figure 2.The Sharpe Ratio is a measure of the risk-adjusted return of an investment, or r*eward-to-variability ratio* as defined *by* William F. Sharpe in 1966. Funds offering the best trade-off between risk and return over entire research period are Equity Market Neutral, followed by Event Driven and Convertible Arbitrage. The worst Sharpe Ratio is from Dedicated Short Bias, which is consistent with the rank ordering without risk adjustment. An interesting observation is that the Equity Market Neutral and Convertible Arbitrage earned much higher risk adjusted returns during the crisis period relative to other investment categories.

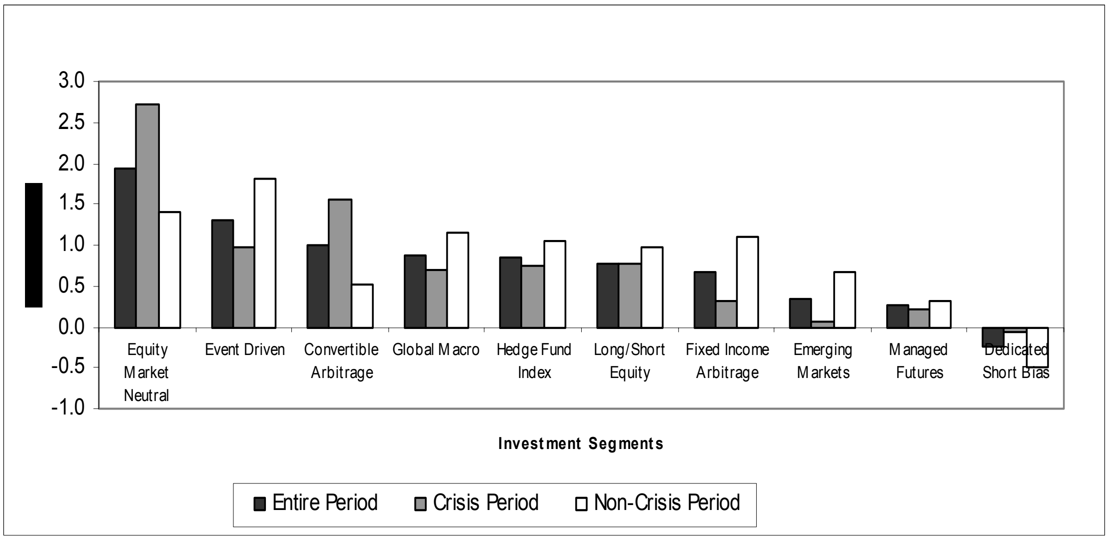

Figure 2: Sharpe Ratio of Investment Segments

Even though the Sharpe Ratio enables us rank the performance of the hedge funds investment segment on the risk adjusted basis, it can not distinguish the return generated from the investment style and the return generated from skill. If we would like to decide the asset allocation based on the funds performance relative to market average, CAPM model that incorporates the factors of benchmark market returns is necessary.

The aim of using CAPM is to determine whether or not hedge funds in different investment segments display “manager skill”, or out-perform their target markets after investment style is considered.

IV.2 Performance measured by CAPM

IV.2.1 Heteroscedasticity and Autocorrelation Tests

Before starting estimating the parameters in the model, it is necessary to check whether the model satisfies the OLS assumptions including homoscedasticity and uncorrelated the error term. If such assumptions are violated, it will not be proper to use OLS to estimate the model. In this thesis Breusch-Pagan test is used to test the Heteroscedasticity; Durbin Watson test is used to test the autocorrelation.

Test results from Breusch-Pagan statistics for model (I) and (II) are shown in the Table 1. It can be seen that Heteroscedasticity appears in models (I) for Convertible Arbitrage, Dedicate Short Bias and Global Macro models. In model (II), only Dedicate Short Bias violated the homoskedasticity assumption.

Table 1: Breusch-Pagan Statistics

BP Test statistics/p-Value	Model (I)			Model (II)		
	d.f.	Chi-Square	Pr>Chi-sq	d.f.	Chi-Square	Pr>Chi-sq
Hedge Fund Index	9	10.70	0.297	19	22.87	0.243
Convertible Arbitrage	9	19.27	**0.023**	18	24.52	0.139
Dedicated Short Bias	5	10.37	**0.065**	10	15.76	**0.107**
Emerging Markets	9	8.21	0.514	18	23.92	0.158
Equity Market Neutral	2	2.40	0.300	5	1.52	0.911
Event Driven	9	7.36	0.600	18	19.21	0.379
Fixed Income Arbitrage	5	3.90	0.563	11	11.16	0.430
Global Macro	9	18.89	**0.026**	18	21.75	0.243
Long/Short Equity	9	11.32	0.254	13	14.88	0.315
Managed Futures	9	3.94	0.915	16	13.66	0.624

Test results from Durbin Watson statistics for model (I) and (II) are displayed in Table 2 and Table 3. From the DW test statistics, we can see that autocorrelation, more or less appears both in models (I) and model (II) for all the hedge funds categories.

Table 2: Durbin-Watson Statistics for Model (I)

	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6
Hedge Fund Index	1.88	1.96	1.95	2.14	1.79*	1.98
Convertible Arbitrage	0.82**	1.02**	1.40**	1.56**	1.82	1.66**
Dedicated Short Bias	1.73**	1.92	2.12	2.09	2	1.79
Emerging Markets	1.54**	1.76*	1.75*	2.01	1.88	1.73
Equity Market Neutral	1.39**	1.62**	1.85	2.04	1.94	1.87
Event Driven	1.37**	1.64**	1.62**	1.69*	1.9	1.85
Fixed Income Arbitrage	1.32**	1.85	1.97	1.82	1.9	1.9
Global Macro	1.9	1.98	1.8	2.08	1.5**	2.17
Long/Short Equity	1.78*	1.9	2.18*	2.28**	2.36**	1.72
Managed Futures	1.98	2.27**	2.02	2.09	2.96	2.17*

** significant at 5% level

* significant at 10% level

Table 3: Durbin-Watson Statistics for Model (II)

	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6
Hedge Fund Index	1.97	2.04	1.98	1.99	1.72	2.02
Convertible Arbitrage	0.93**	1.23**	1.40**	1.72*	1.83	1.68*
Dedicated Short Bias	1.78*	1.94	2.12	2.13	2.05	1.90
Emerging Markets	1.68**	1.95	1.90	2.10	1.93	1.79
Equity Market Neutral	1.42**	1.66**	1.81	2.06	2.00	1.95
Event Driven	1.43**	1.65**	1.5**	1.57**	1.77	1.97
Fixed Income Arbitrage	1.66**	1.90	1.87	1.68**	1.71*	1.78
Global Macro	2.00	1.96	1.81	2.04	1.46**	2.22
Long/Short Equity	1.83	1.95	2.25*	2.36**	2.46**	1.77
Managed Futures	2.01	2.32**	2.06	2.17	1.96	2.18*

** significant at 5% level

* significant at 10% level

The Breusch-Pagan test and Durbin Watson test indicate that Heteroscedasticity and Autocorrelation (HAC) exist for both model (I) and model (II), therefore the OLS assumptions are violated. Even though the parameter estimates are still unbiased had we use OLS estimation but the standard error of the estimated coefficients will not be efficient. Such inefficiency will lead to misleading inference results, e.g. inflate the chance to reject the null hypothesis. So that it is safer for us to use GMM (Generalized Method of Moment) to estimate the models' parameters and implement significance test.

Another benefit is that the GMM estimation doesn't require complete knowledge of the data distribution. Only specified moments derived from an underlying model are needed for GMM estimation. Usually the return distribution of hedge funds hardly follows normal distribution. In this sense, GMM is superior to OLS. Specifically this thesis uses Heteroscedasticity and Autocorrelation Consistent (HAC) Covariance Matrix proposed by Newey and West (1987) to correct the standard error of the estimates.

IV.3 Performance Measurement

The Jensen's alpha estimations for model (I) by using GMM and OLS are displayed in Table 4. From this table, it is quite clear that the coefficient estimations for Jensen's alpha are the same for both OLS and GMM in every investment segment. However, the standard errors for the estimates are quite different, and such difference

does change the significant/non-significant status of estimated coefficient in some models. Convertible Arbitrage investment segment obtains a strong positive Jensen's alpha when estimated by OLS; however this performance factor is not statistically significant under GMM. The Fix Income Arbitrage segment also experiences the same situation and results in a non-significant Jensen's alpha.

As shown in Table 4, the Jensen's alpha estimates classify the nine investment styles into two categories: the funds display positive and statistically significant "skill" and the funds fail to demonstrate "skill". Global Macro shows the strongest manager skill, followed by Event Driven, Equity Market Neutral and Long/Short Equity. The Hedge Fund Index, which represents the average performance of the Hedge Funds Industry in study, also demonstrates the ability to outperform the market average.

For the rest of five investment segments, Convertible Arbitrage, Managed Futures, Fix Income Arbitrage, Emerging Market and Dedicate Short Bias, the estimates for Jensen's alpha are all positive but not statistically different from zero. So that the hedge funds in these investment segments can be considered, on the average, lack of skill.

Table 4: CAPM Parameters Estimation for Model (I)

Estimated Coefficient / s.e.	Jensen's Alpha		Adjusted R-square
	OLS	GMM	
Hedge Fund Index	**0.00411** **	**0.00411** **	**0.31**
Convertible Arbitrage	**0.00682** **	**0.00682**	
	0.00275	*0.00476*	**0.24**
Dedicated Short Bias	**0.00037**	**0.00037**	
	0.00272	*0.00317*	**0.60**
Emerging Markets	**0.00150**	**0.00150**	
	0.00338	*0.00413*	**0.34**
Equity Market Neutral	**0.00444** **	**0.00444** **	
	0.00065	*0.00084*	**0.14**
Event Driven	**0.00456** **	**0.00456** **	
	0.00096	*0.00151*	**0.54**
Fixed Income Arbitrage	**0.00171** *	**0.00171**	
	0.00089	*0.00119*	**0.08**
Global Macro	**0.00733** **	**0.00733** **	
	0.00271	*0.00297*	**0.06**
Long/Short Equity	**0.00430** **	**0.00430** **	
	0.00196	*0.00194*	**0.41**
Managed Futures	**0.00225**	**0.00225**	
	0.00277	*0.00233*	**0.16**

** significant at 5% level
* significant at 10% level

Jensen's alpha enables us to distinguish the hedge funds investment segments with "skill" and without "skill". The funds with positive Jensen's alpha have the ability to outperform the market average. But if we want to investigate whether or not one fund statistically outperforms the other, further inference is a necessity to draw the conclusion.

IV.4 Inference about the performance

The purpose of the inference is to find statistical evidence to determine whether or not one hedge funds investment style is superior to other styles in terms of performance. Pair-wise comparisons are implemented for four hedge fund sub-indices that display positive ability to outperform the market average. The null hypothesis is that there is no performance difference between two funds in comparison. The Alternative hypothesis is that the Fund j outperforms Fund i.

$$H_0:\ \alpha_i = \alpha_j$$

$$H_1:\ \alpha_i > \alpha_j$$

α_i is the intercept of CAPM mode for hedge fund index sub-category i, measure the average performance or manager skill of sub-category investment style i.

α_j is the intercept of CAPM mode for hedge fund index sub-category j, measure the average performance or manager skill of sub-category investment style j.

$$\alpha_i \sim N(\alpha_i,\ V\mathrm{ar}(\alpha_i))$$

$$\alpha_j \sim N(\alpha_j,\ V\mathrm{ar}(\alpha_j))$$

$$\alpha_i - \alpha_j \sim N(\alpha_i - \alpha_j,\ Var(\alpha_i - \alpha_j))$$

$$Var(\alpha_i - \alpha_j) = Var(\alpha_i) + Var(\alpha_j) - 2Cov(\alpha_i, \alpha_j)$$

In order to calculate the covariance of the two intercepts, we express CAPM in a matrix form.

$$\mathbf{R_j} = \mathbf{R_{m,j}}\boldsymbol{\beta}_\mathbf{j} + \boldsymbol{\varepsilon}_\mathbf{j}$$

$$\hat{\boldsymbol{\beta}}_\mathbf{j} = (\mathbf{R'_{m,j}}\,\mathbf{R_{m,j}})^{-1}\mathbf{R'_{m,j}}\,\mathbf{R_j} = \mathbf{P_{m,j}}\mathbf{R_j}$$

Where $\mathbf{R_j}$ is the excess return of hedge fund segment j, and $\mathbf{R_{m,j}}$ is the matrix includes the benchmark market excess returns of hedge fund segment j with the first column is all ones, and $\mathbf{P_{m,j}} = (\mathbf{R'_{m,j}}\,\mathbf{R_{m,j}})^{-1}\mathbf{R'_{m,j}}$.

The intercept of the above model can be expressed as a linear combination as $\hat{\alpha}_j = \sum_{\ell=1}^{T} p_{j\ell} R_{j\ell}$ where $p_{j\ell}$ is an element in the first row of $\mathbf{P_{m,j}}$

Accordingly, the covariance of the intercepts for hedge funds segments i and j, α_i *a*nd α_j, is as the following

$$\begin{aligned} C\hat{o}v(\alpha_i,\alpha_j) &= Cov(\sum_{\ell=0}^{T-1} p_{i,T-\ell}R_{i,T-\ell}\ ,\ \sum_{\tau=0}^{T-1} p_{j,T-\tau}R_{j,T-\tau}) \\ &= \sum_{\ell=0}^{T-1} p_{i,T-\ell}\cdot\left(\sum_{\tau=0}^{T-1} p_{j,T-\tau}Cov\left(R_{i,T-\ell},R_{j,T-\tau}\right)\right) \end{aligned}$$

In order to be able to calculate the above covariance, it is important that the returns of the hedge funds indices are weakly stationary over time, which implies that, the mean of R_t and the covariance between R_t and $R_{t-\ell}$ are time invariant, where ℓ is an arbitrary integer.

Weakly stationary is a very common assumption when dealing with asset return time series. Dickey-Fuller unit root test is implemented to test whether the returns of hedge funds indices are weakly stationary.

$$H_0: \text{"The time series has a unit root"}$$

$$H_1: \text{"The time series is stationary"}$$

Table 5: Dickey-Fuller t test for Stationary

Segments	p-Value
Global Macro	0.0012
Event Driven	0.0001
Equity Market Neutral	0.0012
Long/Short Equity	0.0001

The Dickey-Fuller t test results indicate that it is reasonable to assume that the returns of hedge funds segments in comparison are weakly stationary.

For a multivariate process, the weakly stationary assumption will give us a cross-covariance, specifically the autocovariance $Cov(R_{i,t}, R_{j,t-\ell}) = \gamma_{ij,\ell}$ only depends on the length of the time period. This assumption simplifies the calculation of the covariance between estimated intercepts from model i and model j.

The sum of all the elements in the following matrix will be an estimate of the covariance of two intercepts.

$$\begin{bmatrix} p_{iT}p_{jT}Cov(R_{i,T},R_{j,T}) & p_{iT}p_{jT-1}Cov(R_{i,T},R_{j,T-1}) & \cdots & p_{iT}p_{j1}Cov(R_{i,T},R_{j,1}) \\ p_{iT-1}p_{jT}Cov(R_{i,T-1},R_{j,T}) & p_{iT-1}p_{jT-1}Cov(R_{i,T-1},R_{j,T-1}) & \cdots & p_{iT-1}p_{j1}Cov(R_{i,T-1},R_{j,1}) \\ \vdots & \vdots & \vdots & \vdots \\ p_{i1}p_{jT}Cov(R_{i,1},R_{j,T}) & p_{i1}p_{jT-1}Cov(R_{i,1},R_{j,T-1}) & \cdots & p_{i1}p_{j1}Cov(R_{i,1},R_{j,1}) \end{bmatrix}$$

$$= \begin{bmatrix} p_{iT}p_{jT}\gamma_{ij} & p_{iT}p_{jT-1}\gamma_{ij,1} & \cdots & p_{iT}p_{j1}\gamma_{ij,T-1} \\ p_{iT-1}p_{jT}\gamma_{ji,1} & p_{iT-1}p_{jT-1}\gamma_{ij} & \cdots & p_{iT-1}p_{j1}\gamma_{ij,T-2} \\ \vdots & \vdots & \vdots & \vdots \\ p_{i1}p_{jT}\gamma_{ji,T-1} & p_{i1}p_{jT-1}\gamma_{ji,2} & \cdots & p_{i1}p_{j1}\gamma_{ij} \end{bmatrix}$$

In order to simplify the calculation, we investigated the cross correlation between the two return series. We will assume $Cov\left(R_{i,t}, R_{j,t-\ell}\right) = \gamma_{ij,\ell} = 0$ for the lag ℓ whose cross correlation is not significantly different from zero. SAS provides the procedure VARMAX to calculate the cross correlations for the two time series. Detailed cross correlations between hedge funds return series are displayed in Appendix C.

Based on the variance calculation formula, we can get the variance of the difference between two intercepts of model i and model j. The distribution of their intercepts difference follows normal distribution as the following:

$$\alpha_i - \alpha_j \sim N(\alpha_i - \alpha_j,\ Var(\alpha_i - \alpha_j))$$

The pair-wise comparisons of intercepts from the four winning investment segments, or manager skill, are implemented based on the above distribution. T-test

statistic will provide the evidence to support or against the null hypothesis that there is no difference in performance between the two hedge funds investment categories in study.

The test results are presented in the Table 6. From the results we notice that there is no statistically significant performance difference between Global Macro, Event Driven, Equity Market Neutral and Long/Short Equity at 10% significant level. However, with closely to be significant we may state that in the period studied, Global Macro marginally outperforms Event Driven and Long/ Short Equity.

Table 6: t Test for the Difference between Jensen's alphas

Segments	$(\alpha_i - \alpha_j)$	$s.e(\alpha_i - \alpha_j)$	t	p-Value
Global Macro	-	-	-	-
Event Driven	0.00277	0.00225	1.232	0.110
Equity Market Neutral	0.00289	0.00482	0.599	0.275
Long/Short Equity	0.00303	0.00316	0.960	0.169

Segments	$(\alpha_i - \alpha_j)$	$s.e(\alpha_i - \alpha_j)$	t	p-Value
Event Driven	-	-	-	-
Equity Market Neutral	0.00012	0.00422	0.028	0.489
Long/Short Equity	0.00026	0.00067	0.386	0.350

Segments	$(\alpha_i - \alpha_j)$	$s.e(\alpha_i - \alpha_j)$	t	p-Value
Equity Market Neutral	-	-	-	-
Long/Short Equity	0.00014	0.00419	0.033	0.487

IV.5 Performance Consistency Test

An impression about the hedge funds is that they are able to generate absolute returns disregard the market environments. The study period in this thesis includes the Asian Crisis; a financial shock started in July 1997 in East Asian. Its effects rippled throughout the globe and caused a global financial crisis, with major effects felt as widely as Russia, Brazil, and the United States. Asian Crisis provides a platform for this thesis to study the consistency of hedge funds performance under severe market environment.

As proposed in Part III, CAPM with dummy variable is employed to evaluate the performance consistency.

$$Model\ \ (II):\ \ R_{j,t}\text{-}R_{f,t} = \alpha_j + \sum_{m=1}^{p} \beta_m (R_{m,t} - R_{f,t}) + \gamma_j D + \sum_{m=1}^{p} \tau_m (R_{m,t} - R_{f,t}) D + \varepsilon_{j,\tau}$$

$$D = \begin{cases} = 1 \ \ if \quad July\,1997 < period\ date < July\,2000 \\ = 0 \qquad\qquad\qquad Otherwise \end{cases}$$

The estimated results are present in Table 7 Model II are estimated both by OLS and GMM. Similar to Model (I), the GMM does not differ from OLS in parameter estimation but does give quite different estimated standard errors for estimates and accordingly changes the significant/non-significant status of some parameter estimates. GMM results will be used to draw conclusions.

After fitting the data into Model (II), the statistical significance of the dummy variable will indicate whether or not hedge funds have the ability to stabilize the returns

under different market environments. As shown in Table 7 there are three hedge funds investment segments, Convertibly Arbitrage, Emerging Market and Fix income Arbitrage, obtained statistically significant dummy variable coefficients and their dummy variable coefficients are all negative. This indicated hedge funds in these three segments on the average failed to display the ability to stabilize the returns during the Asian Crisis period. The rest of the Sub-indices hedge funds and the overall Hedge Fund Industry, on the average, demonstrate the ability to cushion the impact from financial shocks.

Table 7: CAPM Parameters Estimation for Model (II)

	Jensen's Alpha		Dummy		Test: Alpha+D=0		Adjusted
Estimated Coefficient / s.e.	**OLS**	**GMM**	**OLS**	**GMM**	**OLS: F-test**	**GMM: Wald Test**	**R-square**
Hedge Fund Index	**0.00450** **	**0.00450** **	**-0.00377**	**-0.00377**			
	0.00184	*0.00152*	*0.00362*	*0.00418*	0.06	0.04	**0.36**
Convertible Arbitrage	**0.00731** **	**0.00731** **	**-0.02213** **	**-0.02213** **			
	0.00332	*0.00370*	*0.01132*	*0.00905*	1.98	3*	**0.35**
Dedicated Short Bias	**0.00084**	**0.00084**	**0.00098**	**0.00098**			
	0.00311	*0.00331*	*0.00621*	*0.00684*	0.12	0.09	**0.61**
Emerging Markets	**0.00367**	**0.00367**	**-0.01671** **	**-0.01671** *			
	0.00405	*0.00417*	*0.00745*	*0.00992*	4.35**	2.11	**0.39**
Equity Market Neutral	**0.00376** **	**0.00376** **	**0.00240** *	**0.00240**			
	0.00075	*0.00100*	*0.00148*	*0.00173*	23.4**	19.31**	**0.16**
Event Driven	**0.00542** **	**0.00543** **	**-0.00509** **	**-0.00509**			
	0.00103	*0.00084*	*0.00200*	*0.00504*	0.04	0.00	**0.63**
Fixed Income Arbitrage	**0.00289** **	**0.00289** **	**-0.00460** **	**-0.00460** **			
	0.00092	*0.00011*	*0.00180*	*0.00238*	1.29	0.65	**0.31**
Global Macro	**0.01008** **	**0.01008** **	**-0.00668**	**-0.00668**			
	0.00299	*0.00272*	*0.00574*	*0.00708*	0.48	0.27	**0.18**
Long/Short Equity	**0.00192**	**0.00192**	**0.00892** **	**0.00892**			
	0.00226	*0.00165*	*0.00437*	*0.00592*	5.05**	3.54*	**0.43**
Managed Futures	**0.00248**	**0.00182**	**-0.00191**	**-0.00007**			
	0.00325	*0.00292*	*0.00629*	*0.00462*	0.35	0.26	**0.17**

** significant at 5% level
* significant at 10% level

V. Future Study

Hedge fund is a fast growing industry and attracts a lot if research interest. But hedge funds do not have obligation to disclose their performance data, therefore there are many limitations in research due to the lack of reliable hedge funds data. CSFB/Tremont Hedge Fund Index provides a transparent and comprehensive data source for hedge funds study, however these indices only present the performance trend of the hedge funds as an industry or for a particular investment strategy. The low R square (relative to mutual fund) of the CAPM model revealed the limitation of using market benchmarks returns in explaining the variation in hedge funds returns. Different from the mutual funds, the hedge funds feature in dynamic trading strategies, which can not be captured by stationary benchmark returns. When individual hedge funds data are available, we may use principal component analysis to discover the patterns of dynamic strategies as new factors to improve the CAPM performance in capturing the variation in hedge funds returns.

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Appendices

A.1 The descriptive statistics of the Returns of Hedge Funds Indices

Smaple Period: Jan. 1994~Sept. 2005

Hedge Fund Index series	Mean of Monthly Return	s.d of Monthly Return	T (mean=0)	Monthly Mean Excess Return	Annual Mean Excess Return	Annual s.d. of Return	Sharpe Ratio
Hedge Fund Index	0.883%	2.289%	4.57**	0.57%	6.797%	7.929%	0.86
Global Macro	1.125%	3.243%	4.11**	0.81%	9.708%	11.236%	0.86
Long/Short Equity	0.987%	2.984%	3.92**	0.67%	8.043%	10.338%	0.78
Event Driven	0.934%	1.643%	6.74**	0.62%	7.409%	5.693%	1.30
Equity Market Neutral	0.794%	0.856%	11.01**	0.48%	5.735%	2.966%	1.93
Emerging Markets	0.788%	4.781%	1.95**	0.47%	5.654%	16.563%	0.34
Convertible Arbitrage	0.712%	1.384%	6.11**	0.40%	4.746%	4.794%	0.99
Managed Futures	0.590%	3.488%	2.01**	0.27%	3.288%	12.081%	0.27
Fixed Income Arbitrage	0.524%	1.092%	5.70**	0.21%	2.498%	3.782%	0.66
Dedicated Short Bias	-0.046%	5.047%	-0.11	-0.36%	-4.348%	17.483%	-0.25

Crisis Period:Jul.1997~Jul. 2000

Hedge Fund Index series	Mean of Monthly Return	s.d of Monthly Return	T (mean=0)	Monthly Mean Excess Return	Annual Mean Excess Return	Annual s.d. of Return	Sharpe Ratio
Managed Futures	0.606%	3.166%	1.51	0.19%	2.334%	10.967%	0.21
Long/Short Equity	1.317%	4.031%	2.59**	0.91%	10.867%	13.964%	0.78
Hedge Fund Index	1.035%	2.849%	2.88**	0.62%	7.483%	9.871%	0.76
Global Macro	1.214%	4.021%	2.39**	0.80%	9.625%	13.928%	0.69
Fixed Income Arbitrage	0.536%	1.323%	3.21**	0.12%	1.494%	4.582%	0.33
Event Driven	0.991%	2.042%	3.85**	0.58%	6.959%	7.074%	0.98
Equity Market Neutral	1.116%	0.900%	9.83**	0.70%	8.454%	3.119%	2.71
Emerging Markets	0.503%	5.666%	0.7	0.09%	1.096%	19.626%	0.06
Dedicated Short Bias	0.305%	6.100%	0.39	-0.11%	-1.274%	21.131%	-0.06
Convertible Arbitrage	1.068%	1.454%	5.83	0.66%	7.877%	5.036%	1.56

Non-Crisis Period: Jan 1994~Jun.1997 and Aug.2000~Sept.2005

Hedge Fund Index series	Mean of Monthly Return	s.d of Monthly Return	T (mean=0)	Monthly Mean Excess Return	Annual Mean Excess Return	Annual s.d. of Return	Sharpe Ratio
Managed Futures	0.578%	3.747%	1.36	0.34%	4.058%	12.982%	0.31
Long/Short Equity	0.719%	1.717%	3.7**	0.48%	5.761%	5.949%	0.97
Hedge Fund Index	0.760%	1.718%	3.90**	0.52%	6.244%	5.952%	1.05
Global Macro	1.054%	2.470%	3.76**	0.81%	9.775%	8.555%	1.14
Fixed Income Arbitrage	0.515%	0.871%	5.22**	0.28%	3.309%	3.016%	1.10
Event Driven	0.887%	1.244%	6.29**	0.65%	7.773%	4.310%	1.80
Equity Market Neutral	0.534%	0.726%	6.49**	0.29%	3.539%	2.516%	1.41
Emerging Markets	1.017%	3.950%	2.27**	0.78%	9.336%	13.682%	0.68
Dedicated Short Bias	-0.330%	4.021%	-0.72	-0.57%	-6.831%	13.929%	-0.49
Convertible Arbitrage	0.424%	1.262%	2.96**	0.18%	2.216%	4.372%	0.51

** significant at 5% level

* significant at 10% level

A.2 Selection of benchmark market indices for hedge fund indices

Benchmark Markets Indices		Hedge Fund Index	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity	Managed Futures
Default Factor	Moody AAA Corporate Bond		√								
Equity Market Factors	S&P 500	√		√		√	√		√	√	√
	MSCI World ex. US	√	√	√	√		√			√	
Bond Market Factors	JP Morgan US Gov. Bond	√									
	JP Morgan Non-US Gov.Bond				√			√			√
	Merrill Lynch High Yield Bond		√				√	√	√		
Commodity Factor	Goldman Sachs Commodity									√	√
Currency Factor	Fed Trade Weighted Dollar								√		√
Emerging Market Factor	JP Morgan Emerging Market				√						

A.3 Cross Correlations between Hedge Funds Return Series

Schematic Representation of Cross Correlation

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12
Global Macro	..	.+	..	..	++	..	..	..	..	..	..	..
Equity Market Neutral	.+	..	..	..	..	..	..	++	..	..	..	..

+ is >2*std error, - is < -2*std error,. is between

Schematic Representation of Cross Correlation

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12
Global Macro	.+	.+	..	..	+.	..	..	..	..	..	..	..
Event Driven	.+	..	..	..	..	..	..	..	..	..	..	..

+ is >2*std error, - is < -2*std error,. is between

Schematic Representation of Cross Correlation

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12
Global Macro	..	..	..	..	+.	..	..	..	..	..	..	..
Lgshortf	..	..	..	..	- -	..	..	..	..	..	-.	..

+ is >2*std error, - is < -2*std error,. is between

Schematic Representation of Cross Correlation

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12
Event Driven	++	..	..	..	..	..	..	..	..	..	..	..
Equity Market Neutral	.+	..	..	..	..	..	..	.+	..	..	..	..

+ is >2*std error, - is < -2*std error,. is between

Schematic Representation of Cross Correlation

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12
Event Driven	++	..	..	..	..	..	..	..	..	..	..	..
Long/short Equity	..	..	..	..	.-	..	..	..	..	..	..	..

+ is >2*std error, - is < -2*std error,. is between

Schematic Representation of Cross Correlation

Variable/Lag	1	2	3	4	5	6	7	8	9	10	11	12
Long/short Equity	..	..	..	..	-.	..	..	..	..	..	..	..
Equity Market Neutral	.+	..	..	..	..	..	..	++	..	..	..	..

+ is >2*std error, - is < -2*std error,. is between

A.4 SAS Code Examples

1. Selection of Benchmark Market Indices

```
PROC REG data=thesis.hedgef;
Model fixincmF=GVBNUSf GVBUSf HGYLBDf /SELECTION=STEPWISE;
RUN;
```

2. OLS Regression Estimation

```
PROC REG data=thesis.period;
ModelI:model FixincmF=GVBNUSF  HGYLBDF;
ModelII:Model FixincmF=GVBNUSF HGYLBDF D1 GVBNUSFp1 HGYLBDFp1;
Test intercept+D1=0;
RUN;
```

3. GMM Estimation

```
PROC MODEL data=thesis.hedgef;
Var FixincmF GVBNUSF  HGYLBDF;
Parms a b2 b3;
FixincmF=a + b2*HGYLBDF + b3*GVBNUSf;
Fit FixincmF  /GMM  kernel=(bart,5,0);
Instruments GVBNUSF  HGYLBDF;
Run;

PROC MODEL data=thesis.period;
Var FixincmF GVBNUSF  HGYLBDF D1 GVBNUSFp1 HGYLBDFp1;
Parms a  b2 b3 c c1 c2;
FixincmF=a +  b2*HGYLBDF + b3*GVBNUSf +c*D1 +c1*GVBNUSFp1+c2* HGYLBDFp1;
Fit FixincmF  /GMM  kernel=(bart,5,0);
Instruments GVBNUSF  HGYLBDF D1 GVBNUSFp1 HGYLBDFp1;test a+c=0;
Run;
```

4. Breusch-Pagan test for Heteroscedasticity.

```
PROC REG data=thesis.period;
ModelI:model FixincmF=GVBNUSF  HGYLBDF/spec;
ModelII:Model FixincmF=GVBNUSF HGYLBDF D1 GVBNUSFp1 HGYLBDFp1/spec;RUN;
```

5. Durbin-Watson test for Autocorrelation

```
PROC AUTOREG data=thesis.period;
ModelI:model FixincmF=GVBNUSF  HGYLBDF/ nlags=6 dw=6 dwprob;
ModelII:Model FixincmF=GVBNUSF HGYLBDF D1 GVBNUSFp1 HGYLBDFp1/ nlags=6 dw=6
dwprob;
Run;
```

6. Dickey-Fuller t test for stationary

```
%dftest( thesis.hedgef, GlbMacroF, ar=4 );
%put p=&dftest;
%dftest( thesis.hedgef, EvntdrvF, ar=4 );
%put p=&dftest;
%dftest( thesis.hedgef, MktNutlF, ar=4 );
%put p=&dftest;
%dftest( thesis.hedgef, LgshortF, ar=4 );
%put p=&dftest;
```

7. Calculation of Cross Correlations between return series

```
PROC VARMAX data=thesis.period;
Model GlbMacrof MktNutlF/ p=0 print=(corry)printform=both lagmax=12 ;
Run;
PROC VARMAX data=thesis.period;
Model GlbMacrof Evntdrvf/ p=0 print=(corry)printform=both lagmax=12 ;
Run;
PROC VARMAX data=thesis.period;
Model GlbMacrof Lgshortf/ p=1 print=(corry)printform=both lagmax=12 ;
Run;
PROC VARMAX data=thesis.period;
Model Evntdrvf MktNutlF/ p=0 print=(corry)printform=both lagmax=12 ;
Run;
PROC VARMAX data=thesis.period;
Model Lgshortf MktNutlF/ p=0 print=(corry)printform=both lagmax=12 ;
Run;
PROC VARMAX data=thesis.period;
Model Evntdrvf Lgshortf/ p=0 print=(corry)printform=both lagmax=12 ;
Run;
```

8. Calculation of Covariance of the difference between intercepts

```
/*1.Global Macro vs. Event Driven*/
PROC VARMAX data=thesis.period;
Model GlbMacrof Evntdrvf/ print=(covy) lagmax=12 ;
Run;
PROC IML;
Eye=I (141);
U1=j(141,141,0);U2=j(141,141,0);U3=j(141,141,0);
L1=j(141,141,0);L2=j(141,141,0);L3=j(141,141,0);

Do i=1 to 140;
L1 [i+1, i] =1;
U1 [i, i+1] =1;
End;
Do i=1 to 139;
L2 [i+2, i] =1;
U2 [i, i+2] =1;
End;
Do i=1 to 136;
L3 [i+5, i] =1;
U3 [i, i+5] =1;
End;

V=.000032*L1+.000091*U1-.000056*L2+.00014*U2-.000075*L3+.000089*U3+0.00
0195*Eye;

Use thesis.period;
Read all var {ones CURCYF HGYLBDF SP5F} into macro;
macrob=inv(macro`*macro)*macro`;
macrob0=macrob[1,];

Use thesis.period;
Read all var{ones HGYLBDF MSCINUSF SP5F} into evnt;
evntb=inv(evnt`*evnt)*evnt`;
evntb0=evntb[1,];

macro_evnt=macrob0`*evntb0;
```

```
Test=V#macro_evnt;

One=j (141, 1, 1);
Covariance=one`*test*one;
Print covariance;
Quit;

/*2.Global Macro vs. Equity Market Neutral*/
PROC VARMAX data=thesis.period;
Model GlbMacrof MktNutlF/ print=(covy)printform=univariate lagmax=12 ;
Run;
PROC IML;
Eye=I(141);
U1=j(141,141,0);U2=j(141,141,0);U3=j(141,141,0);U4=j(141,141,0);
L1=j(141,141,0);L2=j(141,141,0);L3=j(141,141,0);L4=j(141,141,0);

Do i=1 to 140;
L1 [i+1, i] =1;
U1 [i, i+1] =1;
End;
Do i=1 to 139;
L2 [i+2, i] =1;
U2 [i, i+2] =1;
End;
Do i=1 to 136;
L3 [i+5, i] =1;
U3 [i, i+5] =1;
End;
Do i=1 to 133;
L3 [i+8, i] =1;
U3 [i, i+8] =1;
End;

V=-.000011*L1-.0000044*U1-.000036*L2+.000057*U2+.000019*L3+.000046*U3
+.000048*L4+.00003*U4+0.000053*Eye;


Use thesis.period;
Read all var {ones CURCYF HGYLBDF SP5F} into macro;
```

```
macrob=inv(macro`*macro)*macro`;
macrob0=macrob[1,];


Use thesis.period;
Read all var{ones SP5F} into eqtneu;
eqtneub=inv(eqtneu`*eqtneu)*eqtneu`;
eqtneub0=eqtneub[1,];

macro_eqtneu=macrob0`*eqtneub0;

Test=V#macro_eqtneu;

One=j (141, 1, 1);
Covariance=one`*test*one;
Print covariance;
Quit;

/*3.Global Macro vs. Long/short Equity*/
PROC VARMAX data=thesis.period;
Model GlbMacrof LgshortF/p=1 print=(covy) printform=univariate lagmax=12 ;
Run;
Proc IML;
Eye=I (141);
U1=j (141, 141, 0); U2=j (141, 141, 0);
L1=j (141, 141, 0);L2=j(141,141,0);

Do i=1 to 136;
L1 [i+5, i] =1;
U1 [i, i+5] =1;
End;
Do i=1 to 130;
L2 [i+11, i] =1;
U2 [i, i+11] =1;
End;


V=-.00019*L1+.000042*U1-.000184*L2+.000099*U2+0.0004*Eye;
```

```
Use thesis.period;
Read all var {ones CURCYF HGYLBDF SP5F} into macro;
macrob=inv(macro`*macro)*macro`;
macrob0=macrob[1,];


Use thesis.period;
Read all var{ones SP5F MSCINUSF COMDTYF} into lgshort;
lgshortb=inv(lgshort`*lgshort)*lgshort`;
lgshortb0=lgshortb[1,];

macro_lgshort=macrob0`*lgshortb0;

Test=V#macro_lgshort;

One=j (141, 1, 1);
Covariance=one`*test*one;
Print covariance;
Quit;

/*4.Event Driven vs. Equity Market Neutral */
PROC VARMAX data=thesis.period;
Model Evntdrvf MktNutlF/ print= (covy) printform=univariate lagmax=12;
Run;
Proc IML;
Eye=I (141);
U1=j (141, 141, 0); U2=j (141, 141, 0);
L1=j (141, 141, 0); L2=j (141, 141, 0);

Do i=1 to 140;
L1 [i+1, i] =1;
U1 [i, i+1] =1;
End;
Do i=1 to 133;
L2 [i+8, i] =1;
U2 [i, i+8] =1;
End;
V=.0000059*L1+.000031*U1+.000005*L2+.000015*U2+.00005*Eye;
```

```
Use thesis.period;
Read all var{ones HGYLBDF MSCINUSF SP5F} into evnt;
evntb=inv(evnt`*evnt)*evnt`;
evntb0=evntb[1,];

Use thesis.period;
Read all var{ones SP5F} into eqtneu;
eqtneub=inv(eqtneu`*eqtneu)*eqtneu`;
eqtneub0=eqtneub[1,];

evnt_eqtneu=evntb0`*eqtneub0;

Test=V#evnt_eqtneu;

One=j (141, 1, 1);
Covariance=one`*test*one;
Print covariance;
Quit;

/*5.Event Driven vs. Longshort Equity */
PROC VARMAX data=thesis.period;
Model Evntdrvf LgshortF/ print=(covy) printform=univariate lagmax=12 ;
Run;
Proc IML;
Eye=I (141);
U1=j (141, 141, 0); U2=j (141, 141,0);
L1=j (141, 141, 0); L2=j (141, 141, 0);

Do i=1 to 140;
L1 [i+1, i] =1;
U1 [i, i+1] =1;
End;

Do i=1 to 136;
L2 [i+5, i] =1;
U2 [i, i+5] =1;
End;

V=.000021*L1+.000114*U1-.000032*L2-.000035*U2+.00032*Eye;
```

```
Use thesis.period;
Read all var{ones HGYLBDF MSCINUSF SP5F} into evnt;
evntb=inv(evnt`*evnt)*evnt`;
evntb0=evntb[1,];

Use thesis.period;
Read all var{ones SP5F MSCINUSF COMDTYF} into lgshort;
lgshortb=inv(lgshort`*lgshort)*lgshort`;
lgshortb0=lgshortb[1,];

evnt_lgshort=evntb0`*lgshortb0;

Test=V#evnt_lgshort;

One=j (141, 1, 1);
Covariance=one`*test*one;
Print covariance;
Quit;

/*6.Equity Market Neutral vs. Longshort Equity */
PROC VARMAX data=thesis.period;
Model MktNutlF LgshortF/ print= (covy) printform=univariate lagmax=12;
Run;
Proc IML;
Eye=I (141);
U1=j (141, 141, 0); U2=j (141, 141, 0);
L1=j (141, 141, 0); L2=j (141, 141, 0);

Do i=1 to 140;
L1 [i+1, i] =1;
U1 [i, i+1] =1;
End;
Do i=1 to 133;
L2 [i+8, i] =1;
U2 [i, i+8] =1;
End;

V=.000035*L1+.000025*U1+.000039*L2+.000054*U2+.000083*Eye;
```

```
Use thesis.period;
Read all var{ones SP5F} into eqtneu;
eqtneub=inv(eqtneu`*eqtneu)*eqtneu`;
eqtneub0=eqtneub[1,];

Use thesis.period;
Read all var{ones SP5F MSCINUSF COMDTYF} into lgshort;
lgshortb=inv(lgshort`*lgshort)*lgshort`;
lgshortb0=lgshortb[1,];

eqtneu_lgshort=eqtneub0`*lgshortb0;

Test=V#eqtneu_lgshort;

One=j (141, 1, 1);
Covariance=one`*test*one;
Print covariance;
Quit;
```