

MICROSOFT

The Effect of Market Dispersion on the Performance of Hedge Funds

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Project submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Financial Risk Management

In the Financial Risk Management Program of the Faculty

of Business Administration

Approval

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Degree: Master of Financial Risk Management

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Abstract

We study the effect of market dispersion on the performance of hedge funds. Market dispersion is measured by the cross-sectional volatility of equity returns in a specific month.

We use hedge fund indices to measure performance of the hedge fund and stocks returns to calculate market dispersion. We found that there is a positive relationship between market dispersion and the performance of hedge funds.

Keywords: Hedge fund, Cross sectional volatility, Market Dispersion, Seven Factor Model

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1. Introduction

Hedge Funds have been in existence for more than 60 years. However, their growth has increased their prominence in the financial markets and the business press. Since the late 1980s, the number of hedge funds has risen by more than 25 percent per year. The rate of growth in hedge fund assets has been even more rapid. In 1997, there were more than 1200 hedge funds managing a total of more than \$200 billion. Though the number and size of hedge funds are small relative to mutual funds, their growth reflects the importance of this alternative investment vehicle for institutional investors and individual investors. The fund of hedge funds industry has been particularly affected by the economic downturn and the reputational damage following the revealing of the Madoff fraud in 2008. Total of assets of fund of funds was around \$500bn at the end of 2009, down 17% from the previous year, and over 40% below the peak seen two years earlier. The proportion of single manager hedge fund assets originating from fund of funds fell to 30% in 2009 from 40% a year earlier.

Moody's believes that, aside from the post-crisis track record, structural changes are taking place within the hedge fund market, mainly related to the banking and pension fund industries. These changes are generally caused by new regulations and the market environment, which are expected to have a positive impact on the hedge fund industry.

Volatility remains a key factor affecting the overall hedge fund industry, and continued high levels of volatility have forced hedge fund managers to reduce risk along with the financial community as a whole.

We examine the impact of market dispersion on the performance of hedge funds. Market dispersion is measured by the cross sectional volatility of equity returns in a given month. Using hedge fund indices, we are aiming to find the relationship between market dispersion and the performance of the hedge fund index. We want to test the hypothesis that cross-sectional volatility affects the profitability of hedge funds using hedge fund indices from Hedge Fund Research, Inc. (HFR). Our sample period starts from 1996 to 2011.

2. Literature Review

In following we are providing the summary of the background of the research which has been done in two categories: Studies which concentrated more on the performance of the hedge fund, its risks and returns and the researches which conducted on cross sectional volatility of the returns.

2.1. Hedge Fund Performance

Many studies have been done so far with the aim of explaining hedge fund performance that we will refer to some of the main ones as follow:

The distribution of hedge fund returns and their distinctly non-normal characteristics have been widely described in the literature. Regarding hedge fund risk exposures and returns, Edwards and Caglayan (2001), Liang (2001), and Fung and Hsieh (1997, 2002) they used variety of hedge fund databases and conduct the studies of historical hedge fund performance. Another literature studied of risk and return for specific hedge fund strategies, Mitchell and Pulvino (2001) study the risk-arbitrage strategy; Fung and Hsieh (2001) studied the trend-following strategy and found that equity-oriented hedge funds had nonlinear, option-like payoffs with respect to the market return.

Eichengreen et al., (1998) and Fung and Hsieh, (2000) studied the issue that if hedge funds have growing market volatilities and growing not stability of financial markets however they do not study if hedge funds show exposure to market volatility risk.

Bondarenko (2004) estimated the total value of options contract on variance of the market from prices of options which are traded and finds that the return to this contract gains a main determinant of hedge fund performance.

Ackermann and Ravenscroft (1999) show several interesting characteristics that could influence performance, such as flexible investment strategies, substantial managerial investment, sophisticated investors, strong managerial incentives and limited government oversight. Using a pretty large sample of hedge fund data during 1988–1995, they figured out that hedge funds

continuously outperform mutual funds, however, not standard market indices. Hedge funds are more volatile than either mutual funds or market indices. Incentive fees would explain some of the higher performance, but not high total risk. The effect of six data-conditioning biases is explored. They concluded that positive and negative survival-related biases can balance each other.

In 2006 Narayan and Ramadorai studied hedge fund Performance, Risk, and Capital Formation. They used a comprehensive amount of data base of funds-of-funds for their study from 1995 to 2004. They concluded that meanwhile the average fund-of-funds creates alpha, just during the period 1998 to 2000, a subset of funds-of-funds delivered alpha consistently. The alpha-producing funds are not as liquidate as those that do not deliver alpha, and experience higher capital inflows than the less fortunate counterparts.

Measuring Risk in the Hedge Fund Sector by Adrian (2007), also showed that high correlations among hedge fund returns could offer concentrations of risk compared to those before the hedge fund crisis of 1998. By comparison of the recent growth in correlations with the elevation before the 1998 event, shows a key difference. The current increase stems from a reduction in the volatility of returns, while the earlier growth was driven by high covariance, an alternative measure of co-movement in dollar. Because volatility and covariance are less today, the recent hedge fund environment differs from the environment in 1998.

Sundberg and Sandqvish (2009) studied the factors and risks that can influence the stock returns of the hedge fund during the financial crisis in year 2008. They analyzed what factors contribute in changing the Swedish hedge fund returns and how the fund's performance during was very volatile times. They applied Fung & Hsieh Asset Based variables and estimated seven different models for Swedish hedge funds return during period 2005-2007. In addition, they estimated seven other models to examine for parameter stability over the beginning levels of the sub-prime crisis during the year 2008. The result concluded that the estimated models forecast the returns have lower volatility compared the actual returns in 2008. The explanatory factors give a very good picture of what happened and they showed that four of the seven models approved to be the same model in both period.

2.2. Cross Sectional Volatility

The return dispersion or cross-sectional volatility in returns involves taking a universe of stock returns at a point in time, treating each return as a data point, and computing the usual formula for sample variance. In contrast, time series volatility is fluctuations in volatility over time. One of the measures of time series volatility is a VIX index which is closely watched by hedge fund managers. VIX index is the volatility index reflects a market estimate of the future volatility, based on the weighted average of the implied volatilities for the wide range of strikes. In contrast to the times series volatility studies, not many studies have been done on cross-sectional volatility.

Hwang (2001) applied GARCH Model in Cross-sectional Volatility. His study introduced GARCHX models with cross-sectional market volatility. The cross-sectional market volatility is equivalent to heteroscedasticity in returns, which was first suggested by Connor and Linton (2001) as part in individual asset volatility. They Used UK and US data, and they figure out that daily return volatility can be better described with GARCHX models, but GARCHX models do not necessarily in a better substitution than GARCH models in forecasting.

Campbell, Lettau, Malkiel and Xu (2001) disaggregated they approach to study the volatility of stocks at three levels (the market, industry, and firm). From 1962 to 1997 there has been an increase in the firm-level volatility compared to market volatility. Also, correlations among individual stocks and the power of the market model for a typical stock have reduced, whereas the number of stocks which is needed to gain a given level of diversification has increased. All the volatility measures help to forecast GDP growth.

Bartolomeo, (2006) showed that the cross-sectional dispersion of returns in the set of permissible securities predominantly will influence on the range of potential outcomes for active management, and hence the risk of underperformance the benchmark. He reviewed variety of investment applications such as estimation of the correlations of assets, risk management and performance analysis.

In addition to what mentioned above, Yi (2006), tested cross-sectional and multivariate tests of mean variance CAPM and Fama-French three factor models and the result do not clearly show that one model could fit better than other and sub-period results are not consistent with each other and the results from the whole period.

Ang (2004) examined the pricing of total volatility risk in the cross-section of returns. He found that stocks with very high sensitivities to innovations in total volatility have low mean returns. Furthermore, they concluded that that stocks with high idiosyncratic volatility compare to the Fama and French (1993) model has low average returns. This issue cannot be explained by exposure to total volatility risk. Size, book to-Market, momentum, and liquidity effects cannot responsible for the low mean returns gained by stocks with high exposing to systematic volatility risk or for the lower average returns of stocks in the market with high idiosyncratic volatility

Jiang (2009) suggested the two-factor asset-pricing model which incorporates market return and return dispersion. Accordingly, he found that stocks with more sensitivity to return dispersion have more mean returns, and that return dispersion has high positive price of risk. Specifically, the return dispersion factor will be a dominated factor than the book-to-market in explaining cross-sectional expected returns. The return dispersion model outperforms the CAPM, MVM, IVM, and FF-3M by applying 5×5 test portfolios constructed from NYSE and AMEX stock returns during August 1963 to December 2005. Return dispersion has a crucial part in describing the cross-sectional variation of returns, even when the other factors market volatility, size, book-to-market, idiosyncratic volatility and a momentum factor are considered. This study put some light on the ability of return dispersion to how it explains returns far beyond the standard asset-pricing factors. These conclusions can suggest that, return dispersion will capture systematic risk in the business cycle and fundamental economic restructuring dimensions.

Ankrim and ZhuanxinDing (2001) analyzed in which way different levels of cross-sectional volatility can be corresponded to active manager dispersion in the U.S countries and the other equity markets. They explained that changes in the level of cross-sectional volatility have a high correlation with the distribution of active manager returns.

Cross-sectional volatility has also been studied from other the perspectives. Huang (1995) used cross-sectional volatility to get herd behavior in stock markets. Also, Binder, Chan, and Seguin (1996) used cross-sectional dispersion of market stock returns as a proxy for company-specific information flows.

2.3. Cross Sectional Volatility and the Performance of the Hedge Fund

In our research we expand the result of the paper “Market Dispersion and the Profitability of Hedge Funds” by Connor and Li (2009).

In this paper, they studied the impact of market dispersion on the performance of hedge funds. They measured market dispersion by the cross-sectional volatility of equity returns in a given month by using used CRSP data from January of 1994 to December of 2004.

Similar to previous studies (Campbell, Lettau, Malkiel and Xu (2001), Jones (2001), and Connor, Korajczyk and Linton (2006)) they concluded that the cross-sectional volatility of equity returns varies significantly over the sample period and is serially correlated. They tested the hypothesis that cross-sectional volatility affects the profitability of hedge funds using hedge fund indices from Hedge Fund Research, Inc. (HFR). By using hedge fund indices and a panel of monthly returns on individual hedge funds, they find that, market dispersion and the performance of hedge funds are positively related. They also found that the cross-sectional dispersion of hedge fund returns is positively related to the level of market dispersion.

To examine the incremental explanatory value of cross-sectional volatility to hedge fund returns, they conduct an analysis on risk adjustments for hedge fund returns to obtain hedge fund abnormal performance. Many studies have shown that due to the dynamic trading strategies and derivatives used by hedge funds, traditional linear asset pricing models give misleading results on hedge fund performance. They use the seven-factor model of Fung and Hsieh (2004). These factors have been shown to have considerable explanatory power for hedge fund returns.

In general, here we would like to classify the research which has been done in the field of our research topic to two categories: studies which concentrate more on the performance of the

hedge fund, its risks and returns and the researches which on cross sectional volatility of the returns.

In our research, we expand the paper of Connor and Li by conducting following steps. We

1. Expand the end period of survey from December 2004 to June 2011.
2. Use two measurements of calculating cross sectional volatility.
3. Apply Fama-French Three Factor Model addition to the Seven Factor Model to calculate risk adjusted return.
4. Use two sets of data which are S&P500 and Dow Jones 30 to calculate the cross sectional and time series volatility measures.
5. Use VIX index which is a measure for the implied volatility of S&P 500 as an alternative measurement of time series volatility.

3. Data

3.1. Hedge Funds Index Level Data

We analyze hedge funds at index level. We use the hedge fund indices from HFR database which has constructed an accurate and relevant strategy classification system. The classifications reflect the evolution of strategic trends in the hedge fund industry. HFR Database includes fund-level detail on historical performance and assets, as well as firm characteristics on both the broadest and most influential hedge fund managers. We have constructed our analysis through 7 indices in HFR database. There are more than 30 hedge indices that categorize according to the focus and investment strategy of the hedge fund index. The tickers and full names of those hedge fund indices are detailed in the table below.

We consider eight main fund indices for which data is available from the database inception. The sample period is from January 1994 to June 2011. Those include five equity related categories: Convertible Arbitrage, Distressed Securities, Equity Hedge, Equity Market Neutral, Event-Driven; and two aggregate categories: Fund of Funds and Weighted Composite.

The details of those 7 indices are listed below.

Distressed Securities – Fund managers focus on securities of companies in reorganization and bankruptcy, ranging from senior secured debt to the common stock of the company.

Convertible Arbitrage – Fund managers go long convertible securities and goes short the underlying equities.

Fund of Funds- Capital is allocated among a number of hedge funds, providing investors with access to managers they might not be able to discover or evaluate on their own.

Weighted Composite Index is one of the industry's most widely used standard benchmarks of hedge fund performance globally.

Equity Hedge: Fund Managers maintain positions both long and short in primarily equity and equity derivative securities.

Equity Market Neutral Fund Managers employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale.

Event-Driven: Fund Managers maintain positions in securities of companies that are involved in corporate transactions of a wide variety, including but not limited to: mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments.

Fixed Income: Fund Managers employ strategies in which the investment strategy is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a corporate fixed income instrument.

3.2. Equity Index Level

In order to calculate the market volatility and cross sectional volatility, we have used the returns of Dow Jones Index and S&P 500. For calculating cross sectional volatility, we have picked all listed stocks in Dow Jones; on the other hand, we have picked 50 stocks listed in S&P 500 using simple random sample method in which we chose is a subset of stocks from a set of population which was S&P 500. Each stock is chosen randomly and entirely by chance, such that each one of the selections has the same probability of being chosen at any stage during the sampling process. Also we use the companies' stocks 'returns which have valid monthly data during the entire sample period of survey from 1994 till June 2011. We use Bloomberg database to get the

monthly prices of each stock. Also for equally weighted portfolio we use Invesco Equally-Weighted S&P500 Fund data.

To calculate the time series volatility measurement we use the S&P500 index data from January 1994 to June 2011. Furthermore, we apply VIX index data as an alternative to measurement of time series volatility.

3.3. Fama-French Three Factor Model Data

We start with the Fama-French three-factor model, which has been well known for its explanatory power of mutual fund returns. The data needed to perform the Fama- French three factor model tests may be found in two datasets in Kenneth French's data library, which can be accessed at:

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

From the website, we can easily get the monthly data which details Risk Free Rate, return on the market minus the risk-free rate, the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (*SMB*); and the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (*HML*). The website uses the 2011-06 Center for Research in Security Prices (CRSP) database which collects data from various numbers of financial institutions, organizations and corporations.

3.4 Seven Factor Model Data

To obtain risk adjusted hedge fund returns, we also use 7 factor Model developed by Fung and Hsieh (2004). Fung and Hsieh (2004) show that their factor model substantially explains the variation in individual hedge fund returns.

The 7 factors comprise: the excess return on the S&P 500 index (SNPMRF); a small minus big factor (SCMLC) constructed as the difference between the Russell 2000 and S&P 500 stock indices; the excess returns on portfolios of look-back straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets;⁸ the yield spread of the U.S. 10-year Treasury bond over the three-month T-bill, adjusted for the

duration of the 10-year bond (*BDI0RET*); and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration (*BAAMTSY*).

The data needed to perform the 7- factor model tests may be found in David A. Hsieh's Data Library: Hedge Fund Risk Factors, which can be accessed at:

<http://faculty.fuqua.duke.edu/~dah7/HFRFDData.htm>

We estimate all equations using all index data with the OLS method. Since the 7 factor database is updated quarterly, with a 6 month lag, the sample period is from 1994 to 2010.

4. Analysis and Results

4.1 Measures of Time Series and Cross Sectional Volatility

One of the measures for the market dispersion is the cross-sectional volatility which takes into account the entire collection of individual security returns. There are several other measures, such as range, inter-quartile range, mean absolute deviation and the equally weighted volatility. In this project we have used both equally-weighted cross-sectional volatility and the mean absolute deviation and compare their results.

We define equally-weighted cross-sectional volatility as:

$$CSV = \sqrt{\frac{1}{n} \sum (r_{it} - r_{ew})^2}$$

r_{it} is the observed stock return on firm at time t and r_{ew} is the return to the equally-weighted portfolio at time t . This cross-sectional statistic quantifies the average dispersion of individual returns around the realized equally-weighted market average at time t . We compute this cross-sectional volatility measure using monthly data of 50 companies of S&P 500 composite from January of 1994 to June 2011.

We randomly select the data of stocks which had valid monthly return in during the period of survey. Also in calculating equally-weighted portfolio return of the Invesco equally weighted S&P 500 fund as the benchmark return.

Also we use 30 companies listed in Dow Jones Stock Exchange as the stock returns and its average indices as the benchmark during the sample period to check and compare the results of the S&P 500.

Also we use mean absolute deviation measure of the cross sectional volatility to compare the results with the results calculated using the previous measure.

We define, mean absolute deviation as:

$$MAD = 1/n \sum_{i=1}^n |r_i - \text{mean}r|$$

r_i is the stock return on a firm at time t and $\text{mean}r$ is the average of returns at month t . We calculate the MAD measure by using the same monthly data that is mentioned above from January 1994 to June 2011 time span.

Descriptive Statistics of volatility measures are; (CSV: Cross Sectional Volatility, MAD: Mean Absolute Deviation).

Table 1: Statistic Summary of Volatility Measures

	Mean	Variance	Skewness	Kurtosis
CSV	0.063885	0.0006529	1.39569259	4.843612
MAD	0.049492	0.0003623	1.35766983	4.79575

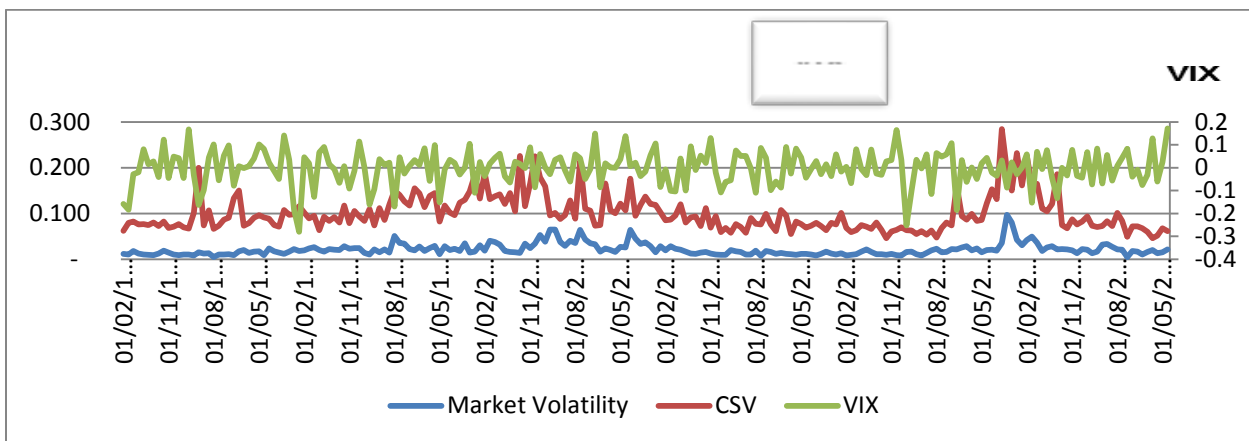
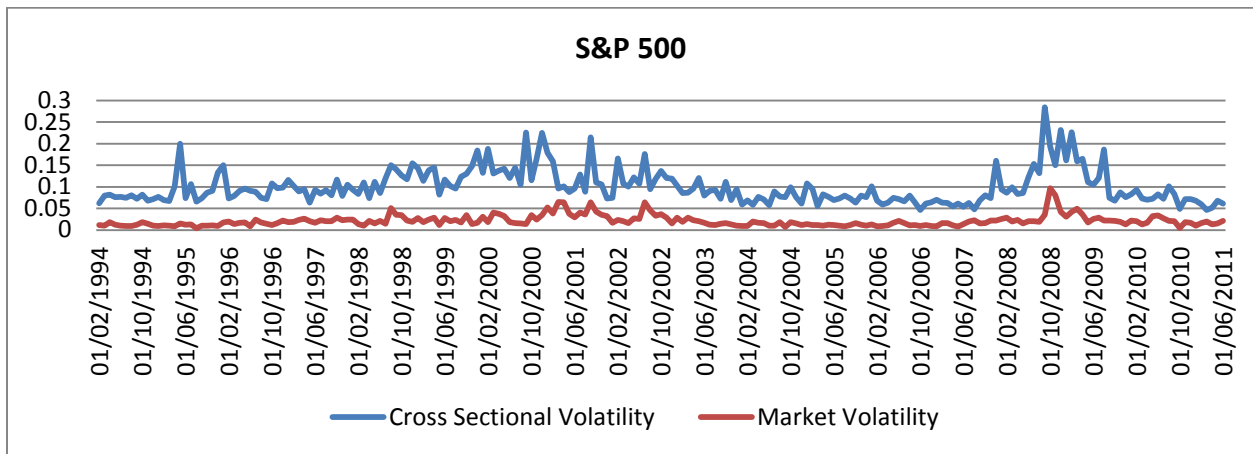
Skewness characterizes the degree of asymmetry of a distribution around its mean. For both of the volatility measures, skewness is positive and greater than 1. On the other hand, Kurtosis characterizes the relative peakness or flatness of a distribution compared with the normal distribution which is also positive for each of the measures.

Moreover we apply the realized time-series volatility of a market index as an alternative, volatility measure. We use French, Schwert and Stambaugh (1987) method, and compute each month the realized monthly volatility based on daily returns of the S&P 500 market index, with a first lagged term to adjust for autocorrelation in the index due to stale prices. That is:

$$MV_t = \sqrt{\sum_{d=1}^{D_t} r_{dt}^2 + 2 \sum_{d=1}^{D_t-1} r_{dt} r_{d+1,t}}$$

r_{dt} is the reported return to the S&P 500 market index on trading day d in month t and there are D_t trading days in month t . We calculated this measure from January 1994 to June 2011 as well.

Figure 1-2: Plot of cross sectional volatility and time series market volatility for S&P from Jan, 1994 to June, 2011



Volatility is fairly stable in a range except for the 1999-2000 equity bubble bursting and the 2008 credit crisis. The chart is distorted by overall high volatility across the industry.

4.2 Market Dispersion and Hedge Fund Performance

4.2.1 Statistics Summary

Our objective is to analyze the linkage between cross-sectional volatility and performance of hedge funds. We have selected 8 HFR indices which are HFRICAI (Convertible Arbitrage) Index, HFRIDSI (Distress Security) Index, HFRIEHI (Equity Hedged Total) Index, HFRIEMNI (Equity Market Neutral) Index, HFRIEDI (Event Driven) Index, HFRIFOF (fund of funds) Index, HFRIFWI (Weighted Composite) Index and HFRI RV (Fixed Income-Corporate) Index. The sample period is from January, 1994 to June, 2011 which makes 210 months.

Table shows monthly returns, variance, skewness, and kurtosis for the various hedge fund categories compared with these summary statistics for other asset classes.

Table 2: Statistics Summary of Hedge Fund Indices

	Monthly Mean	Monthly Variance	Skewness	Kurtosis
HFRICAI (Convertible Arbitrage) Index	0.67%	0.05%	-3.5801	33.4551
HFRIDSI (Distress Security) Index	0.79%	0.03%	-1.7869	10.3386
HFRIEHI (Equity Hedged Total) Index	0.87%	0.07%	-0.35	5.38886
HFRIEMNI(Equity Market Neutral) Index	0.49%	0.01%	-0.1414	4.62876
HFRIEDI(Event Driven) Index	0.86%	0.04%	-1.4969	8.45086
HFRIFOF(Fund of Fund) Index	0.46%	0.03%	-0.8364	7.26742
HFRI RV (Fixed Income-Corporate) Index	0.51%	0.03%	-2.5579	16.4427
S&P 500	0.85%	16.60%	-0.64	0.28
CSFB*	1.05%	5.40%	0.07	2.4
U.S. T Bill	0.29%	1.96%	-0.89	-0.8

- CSFB= Credit Suisse Hedge Fund Index

All of the hedge indices have a negative skewness which indicates a distribution with an asymmetric tail extending toward more negative values. The results for the hedge indices show positive kurtosis, showing a relatively peaked distribution. Table confirms that hedge fund returns are characterized by undesirably high kurtosis and that many hedge fund categories have considerable negative skewness.

All the equations are regressed using the “ordinary least square (ols)” function.

4.2.2. Fama-French Model

Before exploring that linkage, first, we need to calculate risk adjusted hedge fund returns but there is no universally accepted method that can be used due the complex and wide use of derivatives and dynamic trading strategies. We use the generally accepted method, Fama- French Three Factor Model. A large number of hedge fund indexes also show significant correlation with Fama-French’s Size factor.

Fama and French’s (1993) three-factor model postulates that

$$r_{jt} - r_{ft} = \alpha_j + b_{mj}(r_{mt} - r_t) + b_{SMBj}r_{SMBt} + b_{HMLj}r_{HMLt} + e_{jt}$$

r_{jt} , r_{mt} and r_t are the return on hedge index j, the market portfolio, and the riskless asset at time t.

b_{mj} , b_{SMBj} and b_{HMLj} are the factor sensitivities of index j to the returns on the market portfolio; the returns on an SMB portfolio, a long/short portfolio of small minus big stocks; and the returns on an HML portfolio, a long/short portfolio of book-to-market stocks (e.g., value stocks) minus low book-to-market stocks (e.g., growth stocks).

r_{SMBt} and r_{HMLt} are the returns on SMB and HML at time t.

According to Fama and French (2006), the size (SMBt) and value/growth (HMLt) returns in the three-factor model can be viewed as hedge fund returns. Thus, SMBt can be viewed as the return on a hedge fund that is long small stocks and finances this position by shorting big stocks. Similarly, HMLt can be viewed as the return on a hedge fund that is long value stocks, financing this position by shorting growth stocks. Therefore, the model is also easily applicable while calculating hedge fund excess returns.

Initially, we estimated the traditional Fama and French three-factor model for the group of 8 HFR indices. Generally, the adjusted R2 which is a measure of how good the model is are rather low.

The risk adjusted return of fund j at month t is calculated as:

$$\alpha'_{jt} = (r_{jt} - r_{ft}) - b_{mj}(r_{mt} - r_{ft}) - b_{SMBj}r_{SMBt} - b_{HMLj}r_{HMLt}$$

For a given hedge fund index, we take the time series of monthly risk adjusted returns and use it as dependent variable in the following regression:

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t$$

Cross sectional volatility in month t (CSV) and realized time series volatility during the month (MV) are the independent variables which are calculated based on the monthly stock returns.

The results at the hedge fund index level support a positive relationship between cross-sectional volatility and the performance of hedge funds when we use the stocks returns of Dow Jones Index.

For Dow Jones Index, the results of the regression models are in Table 3 and Table 4. The values in Table 3 are calculated using equally weighted cross sectional volatility, whereas the values in Table 4 are calculated using mean absolute deviation. For all 8 HFR indices, constant term shows a negative value. Also, the *t* statistic for β_0 demonstrates that it is statistically significant. Conversely, the coefficient β_1 shows positive values for each hedge indices. On the other hand, the coefficient β_2 shows negative values for each hedge indices except Equity Market Neutral Index. However, both coefficients, β_1 and β_2 , is economically insignificant.

For S&P Index, the results of the regression models are in Table 5 and Table 6. The values in Table 5 are calculated using equally weighted cross sectional volatility, whereas the values in Table 6 are calculated using mean absolute deviation. For all 8 HFR indices, constant term shows a negative value. Also, the *t* statistic for β_0 demonstrates that it is statistically significant. Conversely, the coefficient β_1 shows positive values for each hedge indices. On the other hand,

the coefficient β_2 shows positive values for each hedge indices. β_1 and β_2 are economically significant.

4.2.2.1 The Effect of Equally weighted Cross Sectional and Time Series Volatility Measurement (Dow Jones)

This table presents the results of the regression where CSV is the cross sectional volatility of 30 stocks from Dow Jones Index which is measured by using equally weighted cross sectional volatility and MV is the time series measurement of the market volatility. α'_{jt} is risk adjusted hedge fund return calculated for all the 8 indices listed below. The numbers in parentheses show the regression t-statistics of each variable and each index. R2 is the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t$$

Table 3: The Regression Result of the Effect of Equally weighted Cross Sectional and Time Series Volatility Measurement (Dow Jones)

	β_0	β_1	β_2	R2
HFRI RV (Fixed Income-Corporate) Index	-0.234 (-22.1478)	0.0071335 (2.089977)	-0.0202 (-1.444)	0.044696
HFRI CAI (Convertible Arbitrage) Index	-0.26653 (-23.1478)	0.007074 (2.089977)	0.0003 (0.08305)	0.024696

HFRIDI (Event Driven) Index	HFRMEMNI (Equity Market Neutral) Index	HFRIEHI (Equity Hedged Total) Index	HFRIDSI (Distress Security) Index
-0.2653 (-23.2773)	-0.26711 (-23.6681)	-0.26525 (-23.5038)	0.26571 (-23.0828)
0.008171 (2.43883)	0.006905 (2.08134)	0.00865 (2.607393)	0.00796 (2.3547)
-0.001 (-0.2829)	0.000269 (0.07702)	0.0027 (0.77295)	0.00032 (0.089)
0.03546	0.023175	0.047588	0.031093

As we can see from the table in all of the categories equally weighted measure of cross sectional volatility have the positive effect on the hedge fund returns and from the t-stat we can see that they are statistically significant. However since all the t stat are in the rejection part of the 95% interval in all of the categories we can see that there no statically significant relationship among time-series volatility of a market index and the hedge fund performance by applying Dow Jones data.

4.2.2.2 The Effect of Mean Absolute Deviation and Time Series Measurement (Dow Jones)

This table presents the results of the regression where MAD is the monthly mean absolute deviation of 30 stocks from Dow Jones Index which is also a method to calculate market dispersion and MV is the market volatility. α'_{jt} is risk adjusted hedge fund return calculated for all the 8 indices listed below. The numbers in parentheses show the t-statistics of each variable and each index. R2 is the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 MAD_t + \beta_2 MV_t + \epsilon_t$$

Table 4: The Regression Result of the Effect of Mean Absolute Deviation and Time Series Measurement (Dow Jones)

	β_0	β_1	β_2	R2
HFRIEMNI (Equity Market Neutral) Index	-0.26672 (-23.6482)	0.007019 (2.215251)	-0.0007 (-0.28345)	0.023528
HFRIEHI (Equity Hedged Total) Index	-0.26728 (-23.724)	0.008821 (2.787114)	0.002616 (1.057792)	0.049986
HFRI DSI (Distress security) Index	-0.2662 (-23.1422)	0.007818 (2.419284)	0.00088 (0.348465)	0.031627
HFRI CAI (Convertible Arbitrage) Index	-0.26704 (-23.2098)	0.0069 (2.134671)	0.000937 (0.371096)	0.025315
HFRI RV (Fixed Income-Corporate) Index	-0.22954 (-21.887)	0.01155 (3.8475)	0.0003565 (0.21773)	0.0353677

HFRIFWI (Weighted Composite) Index	HFRIFO (Fund of Fund) Index	HFRIEDI (Event Driven) Index
-0.2673 (-23.529)	-0.26909 (-23.756)	-0.26632 (-23.395)
0.008311 (2.60418)	0.008013 (2.51816)	0.008052 (2.51793)
0.001791 (0.71818)	0.000839 (0.33767)	0.00158 (0.63257)
0.04021	0.033951	0.036956

If we use mean absolute deviation measure instead of the cross sectional volatility measure, we can still get the same results as our previous analysis (Cross sectional volatility has direct influence on the hedge fund performance and on the other hand, time series volatility has no significant effect).

4.2.2.3 The Effect of Cross Sectional and Time Series Measurement (S&P 500)

The table below presents the results of the regression where CSV is the market dispersion of 50 stocks from S&P Index which is measured by using equally weighted cross sectional volatility and MV is the market volatility. α'_{jt} is risk adjusted hedge fund return calculated for all the 8 indices listed below. The numbers in parentheses show the regression t-statistics of each variable and each index. R2 is the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t$$

Table 5: The Regression Result of the Effect of Cross Sectional and Time Series Measurement (S&P 500)

		β_0	β_1	β_2	R²
HFRIEMNI(Equity Market Neutral) Index	HFRIEHI (Equity Hedged Total) Index	HFRIEHI (Distress Security) Index	HFRICAI (Convertible Arbitrage) Index	HFRI RV (Fixed Income-Corporate) Index	
-0.22798 (-7.60507)	-0.22871 (7.54334)	-0.2194 (-7.17165)	-0.22874 (7.499)	-0.226 (-7.151)	
0.6094 (2.13154)	0.59209 (2.0476)	0.69235 (2.37299)	0.61816 (2.12517)	0.778 (3.6059)	
0.734463 (3.65237)	0.751422 (3.69451)	0.770661 (3.755356)	0.796737 (3.89424)	0.742 (3.875)	
0.068464	0.068723	0.074383	0.07541	0.08595	

HFRIIFI (Weighted Composite) Index	HFRIFOF (Fund of Fund) Index	HFRIEDI (Event Driven) Index
-0.22792 (-7.4966)	-0.22854 (-7.5696)	-0.224 (-7.3568)
0.60848 (2.098)	0.62747 (2.1791)	0.63298 (2.1797)
0.759671 (3.72477)	0.764607 (3.7752)	0.740333 (3.62460)
0.070149	0.072525	0.068258

By using the S&P 500 from the results of above table can conclude that there is positive and statically significant relationship between cross sectional volatility (using equally weighted measurement) of the stock return and time series market volatility.

4.2.2.4 The Effect of Mean Absolute Deviation and Time Series Measurement (S&P 500)

This table presents the results of the regression where MAD is the monthly mean absolute deviation of 50 stocks from S&P Index which is also a method to calculate market dispersion and MV is the market volatility. α'_{jt} is risk adjusted hedge fund return calculated for all the 8 indices listed below. The numbers in parentheses show the t-statistics of each variable and each index. R2 is the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 MAD_t + \beta_2 MV_t + \epsilon_t$$

Table 6: The Regression Result of the Effect of Mean Absolute Deviation and Time Series Measurement (S&P 500)

	β_0	β_1	β_2	R2
HFRIEDI (Event Driven) Index	-0.20879 (-6.60339)	1.08793 (2.60825)	0.7607 (3.74049)	0.077241
HFRIEMNI (Equity Market Neutral) Index	-0.21108 (-6.7860)	1.08005 (2.6321)	0.757697 (3.7872)	0.078897
HFRIEHI (Equity Hedged Total) Index	-0.21725 (-6.8885)	0.97752 (2.3495)	0.766014 (3.77620)	0.074567
HFRI DSI (Distress Security) Index	-0.2026 (-6.3838)	1.19219 (2.84755)	0.793184 (3.885683)	0.085094
HFRI CAI (Convertible Arbitrage) Index	-0.21383 (-6.75027)	1.06307 (2.54384)	0.816694 (4.008233)	0.083916
HFRI RV (Fixed Income- Corporate) Index	-0.22582 (-6.75027)	1.11307 (2.6684)	0.856694 (4.206223)	0.082215

By using mean absolute deviation as the alternative measure of cross sectional volatility recent set of data as it is shown in the table above the positive relation of volatilities and hedge fund risk adjusted returns is confirmed in all the categories.

4.2.2.5 The Effect of Cross Sectional volatility and VIX time series data (Dow Jones)

The table below presents the results of the regression where CSV cross sectional volatility of 30 stocks from Dow Jones Index which is also a method to calculate market dispersion and VIX is the market volatility. α'_{jt} is risk adjusted hedge fund return calculated for all the 8 indices listed below. The numbers in parentheses show the t-statistics of each variable and each index. R2 is the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 VIX_t + \epsilon_t$$

Table 7: The Regression Results of the Effect of Cross Sectional and VIX (Dow Jones)

	β_0	β_1	β_2	R2
HFRIRV (Fixed Income-Corporate) Index	-0.22046 (-6.527)	-0.71336 (-1.44)	-0.02023 (-0.206)	0.00133
HFRICAI (Convertible Arbitrage) Index	-0.23215 (-6.925)	-0.50602 (-1.029)	-0.03915 (-0.401)	0.00088
HFRIDSI (Distress Security) Index	-0.21739 (-6.481)	-0.72021 (-1.464)	-0.01372 (-0.141)	0.00131

HFRIEHI (Equity Hedged Total) Index	HFRIEMNI (Equity Market Neutral) Index	HFRIEDI (Event Driven) Index	HFRIFOF (Fund of Fund) Index	HFRIFWI (Weighted Composite) Index
-0.2289 (-6.892)	-0.22411 (-6.831)	-0.22282 (-6.692)	-0.2254 (-6.807)	-0.22567 (-6.774)
-0.53976 (-1.108)	-0.63844 (-1.327)	-0.63107 (-1.292)	-0.63957 (-1.317)	-0.59893 (-1.226)
-0.03459 (-0.358)	-0.00269 (-0.028)	-0.03229 (-0.333)	-0.01299 (-0.135)	-0.02519 (-0.26)
0.0095	0.00102	0.00120	0.00107	0.0103

If we use Dow Jones data as we can get from the above table there is no statistically significant relationship between the performance of the hedge fund and the volatilities.

4.2.2.6 The Effect of Cross Sectional measurement and VIX time series (S&P 500)

This table presents the results of the regression where CSV is cross sectional volatility of 50 stocks from S&P Index which is also a method to calculate market dispersion and VIX is the market volatility. α'_j is risk adjusted hedge fund return calculated for all the 8 indices listed below. The numbers in parentheses show the t-statistics of each variable and each index. R2 is

the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 VIX_t + \epsilon_t$$

Table 8: The Regression Results of Effect of Cross Sectional measurement and VIX time series data (S&P 500)

	β_0	β_1	β_2	R2
HFRIMNI (Equity Market Neutral) Index	-0.2022 (-6.329)	0.6393 (2.067)	-0.021 (-0.195)	0.002612
HFRIEHI (Equity Hedged Total) Index	-0.2056 (-6.357)	0.5878 (1.877)	-0.0452 (-0.416)	0.00244
HFRIDSI (Distress Security) Index	-0.1938 (-5.943)	0.711 (2.252)	-0.0341 (-0.311)	0.00321
HFRICAI (Convertible Arbitrage) Index	-0.2053 (-6.291)	0.6033 (1.911)	-0.0559 (-0.51)	0.0032112
HFRIRV (Fixed Income- Corporate) Index	-0.1982 (-6.028)	0.6931 (1.911)	-0.0339 (-0.307)	0.0026431

HFRIWI (Weighted Composite) Index	HFRIFOF (Fund of Fund) Index	HFRIEDI (Event Driven) Index
-0.2038 (-6.282)	-0.2024 (-6.28)	-0.2017 (-6.22)
0.612 (2.178)	0.651 (1.951)	0.6268 (2.087)
-0.0414 (-0.379)	-0.0269 (-0.248)	-0.0507 (-0.465)
0.002563	0.00272	0.002785

In the recent set of data (S&P) there is no significant relationship between VIX and the risk adjusted return of the hedge fund and there is the positive relationship between cross sectional volatility and the hedge fund performance. Therefore, from applying two sets of data, we can conclude that there is no significant relationship between VIX and the performance of the hedge fund.

4.2.3. Seven Factor Model

In order to test the validity of Fama- French Model and compare our results, we also use as performance benchmarks the seven-factor model developed by Fung and Hsieh (2004). Fung and Hsieh (2004) show that their factor model substantially explains the variation in individual hedge fund returns.

Asset-based style factors (ABS) are rule-based replications of hedge fund strategies using conventional assets and their derivatives. For diversified hedge fund portfolios, according to Fung and Hsieh (2004) analysis, the seven ABS factors can explain up to 80 percent of monthly return variations. Because ABS factors are directly observable from market prices, this model provides a standardized framework for identifying differences among major hedge fund indexes that is free of the biases inherent in hedge fund databases.

The set of factors comprises: the excess return on the S&P 500 index (SNPMRF); a small minus big factor (SCMLC) constructed as the difference between the Russell 2000 and S&P 500 stock indices; the excess returns on portfolios of look-back straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets; the yield spread of the U.S. 10-year Treasury bond over the three-month T-bill, adjusted for the duration of the 10-year bond (*BD10RET*); and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration (*BAAMTSY*). The change in 10-year Treasury yields and the change in the yield spread between 10-year T-bonds and Moody's Baa bonds are the fixed-income ABS factors, and they are the major risk factors for a small portion of hedge funds. Market risk and the spread between small-cap stock returns and large-cap stock returns are found in equity long-short hedge funds. These two equity ABS factors are the major risk factors for a sizable portion of the industry. The portfolios of look-back straddles on bonds, on currencies, and on commodities are the trend following (ABS) factors. These seven factors have been shown to have considerable explanatory power for fund-of-fund and hedge fund returns. α_j in equation, therefore, measures hedge fund performance after systematic risk factors are controlled for.

We estimate all equations using all index data with OLS method. Since the 7 factor database is updated quarterly, with a 6 month lag, the sample period is from 1994 to 2010.

$$r_{jt} - r_{ft} = \alpha_j + b_{mj} + b_j X_j + e_{jt}$$

Where X is the vector of all mentioned factors (PTFSBD,PTFSFX, PTFSCOM, SNPMRF, SCMLC , BD10RET, BAAMTSY)

In order to calculate the monthly risk adjusted return is

$$\text{Alphas} = \text{ExcessReturn} - \text{PTFSBD} * \text{Beta1} - \text{PTFSFX} * \text{Beta2} - \text{PTFSCOM} * \text{Beta3} - \text{SNPMRF} * \text{Beta4} - \text{SCMLC} * \text{Beta5} - \text{BD10RET} * \text{Beta6} - \text{BAAMTSY} * \text{Beta7}$$

For a given hedge fund index, we take the time series of monthly risk adjusted returns and use it as dependent variable in the following regression:

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t$$

5.2.3.1 The Effect of Cross Sectional and Time Series Measurement (Dow Jones)

This table reports the results of the regression where CSV is the cross sectional volatility of 30 stocks from Dow Jones Index which is also a method to calculate market dispersion and MV is the market volatility. α'_{jt} is risk adjusted hedge fund return calculated for all the 8 indices listed below. The numbers in parentheses show the t-statistics of each variable and each index. R2 is the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t$$

Table 9: The Regression Result of Effect of Cross Sectional and Time Series Measurement (Dow Jones)

	β_0	β_1	β_2	R2
HFRICAI (Convertible arbitrage) Index	0.0498 (0.5715)	0.0221 (1.7456)	-2.318 (-4.996)	0.0115
HFRDSI (Distress security) Index	0.0983 (0.999)	0.0193 (1.3521)	-2.3535 (-4.50)	0.095
HFRIEHI (Equity hedged total) Index	0.0709 (0.787)	0.01979 (1.5131)	-2.454 (-5.127)	0.120

HFRI RV (Fixed Income-Corporate) Index	HFRI FWI (Weighted Composite) Index	HFRI FOF (Fund of fund) Index	HFRI EDI (Event driven) Index	HFRI EMNI (Equity market neutral) Index
0.064 (0.703)	0.0428 (0.479)	0.0726 (0.779)	0.03606 (0.4019)	0.0705 (0.724)
0.0202 (1.522)	0.0196 (1.5117)	0.02077 (1.533)	0.0215 (1.6507)	0.0194 (1.3756)
-2.352 (-4.828)	-2.314 (-4.870)	-2.427 (-4.897)	-2.306 (-4.834)	-2.327 (-4.498)
0.0108	0.0110	0.0111	0.0108	0.095

If we use Seven Factor Model for calculating the risk adjusted return using Dow Jones data, the result shows that, there is a direct significant relationship between cross sectional volatility and the performance however there is negative relationship between time series volatility and the hedge fund return.

5.2.3.2 The Effect of Cross Sectional and Time Series Measurement (S&P)

This table reports the results of the regression where CSV is the monthly mean absolute deviation of 50 stocks from S&P Index which is also a method to calculate market dispersion and MV is the market volatility. α'_{jt} is risk adjusted hedge fund return calculated for all the 8

indices listed below. The numbers in parentheses show the t-statistics of each variable and each index. R2 is the coefficient of determination whose main purpose is the prediction of future outcomes on the basis of other related information.

$$\alpha'_{jt} = \beta_0 + \beta_1 CSV_t + \beta_2 MV_t + \epsilon_t$$

Table 30: The Effect of Cross Sectional and Time Series Measurement (S&P 500)

	β_0	β_1	β_2	R2
HFRIEMNI (Equity Market Neutral) Index	-0.2017 (-6.22)	0.6268 (1.997)	-0.05076 (-0.465)	0.00279
HFRIEHI (Equity Hedged Total) Index	-0.20227 (-6.329)	0.63939 (2.067)	-0.021 (-0.195)	0.00261
HFRI DSI (Distress Security) Index	-0.20569 (-6.357)	0.58786 (1.877)	-0.04527 (-0.416)	0.00244
HFRI CAI (Convertible Arbitrage) Index	-0.19385 (-5.943)	0.71102 (2.252)	-0.03416 (-0.311)	0.00321
HFRI RV (Fixed Income- Corporate) Index	-0.2053 (-6.291)	0.60334 (1.911)	-0.05597 (-0.51)	0.00264

HFRIFWI (Weighted Composite) Index	HFRIFO (Fund of Fund) Index	HFRIEDI (Event Driven) Index
-0.1982 (-6.028)	-0.20385 (-6.282)	-0.20248 (-6.28)
0.69311 (2.178)	0.61281 (1.951)	0.6511 (2.087)
-0.03395 (-0.307)	-0.04145 (-0.379)	-0.02695 (-0.248)
0.00302	0.00256	0.00272

Applying S&P 500 data, we can see that there is a negative relationship between the cross sectional volatility and hedge fund performance and there is no significant relationship between the time series volatility and the hedge fund risk adjusted returns.

4.2.4. Comparison of Fama- French and Seven Factor Model Results

Using Dow Jones data and applying Fama- French and seven factor model, we conclude that there is a positive relationship among cross sectional volatility and the hedge fund return. However there is no relationship with time series volatility and returns in Fama- French and In seven factor model, there is negative relationship between time series volatility and the hedge fund return.

By using the S&P 500, in Fama-French and seven factors model there is a positive and statically significant relationship between cross sectional volatility of the stock return. About the time series market volatility there is a positive relationship existed in Fama-French model. However, there is no significant relationship between the time series volatility and the hedge fund risk adjusted returns.

One of the important conclusions we get from the results of either Fama-French or Seven Factors Model, is that, market dispersion has impact on all hedge fund strategies, including those that do not involve in trading equities. This might be due to the correlation which exists between equity markets and the indices such as fixed income or fund of fund.

4.2.5. Correlation between Time Series Volatility and Cross Sectional Volatility

In order to check the validity of the results, we also check the coefficient of correlation between two series Time Series Volatility and Cross Sectional Volatility. Correlation is a statistical measure for the level of interdependence between two variables.

A well-known property of correlation is that it is a number comprised between -1 and 1. The three perfect cases are:

Correlation Interpretation

- +1 The two variables are related with 100% certainty by a linear formula:

$$X = a + bY, \text{ where } b > 0.$$

- 0 The two variables are independent from each other.

- -1 The two variables are related with 100% certainty by a linear formula:

$$X = a - bY, \text{ where } b > 0.$$

Correlation coefficient for two series, Time Series Volatility and Cross Sectional Volatility is 0.226 which is a sign for low and positive correlation. This number supports the results of the tests which find a positive relationship between cross sectional volatility and the risk adjusted hedge fund returns and no definite relationship between time series volatility and risk adjusted hedge fund returns.

5. Conclusion

In this paper, we analyze the relationship between market dispersion and the performance of hedge funds. Firstly, we calculate the cross sectional volatility of stock return and time-series volatility of a market index. We use two-indices, S&P and Dow Jones to see if our model holds for both indices. For calculating cross sectional volatility we use equally weighted cross sectional volatility and mean absolute deviation measurement. And for the market volatility we used volatility of S&P index and VIX data which is a popular measure of implied volatility of S&P

500 index options. Moreover, we apply both Fama-French three factor model and Fung and Hsieh (2004)'s 7 factor model to calculate the performance (risk adjusted return) of the hedge funds.

All of the different methods show that there is a positive relationship between cross sectional volatility as a measure of market dispersion and hedge fund performance. Moreover, we demonstrate that using equally weighted cross sectional volatility and mean absolute deviation in calculation of market dispersion do not change the result of the regression tests.

However with regard to the time series volatility we found different results for the different analysis that we have done. Also by using VIX we concluded that there is no significant relationship between VIX and the performance of the hedge fund. So generally we can say that there is no meaningful relationship between performance of the hedge fund and time series volatility.

Our results have important implications for hedge fund portfolio management and performance evaluation. We have postulated that hedge funds are an integral part of the financial system and therefore suffered when stresses became systemic.

6. Appendices

Appendix 1: Theoretic Model of Market Dispersion and Hedge Fund Performance Analysis¹

Corner and Li (2009) introduced the model to show the links between hedge fund performance and market dispersion. That model describes the hedge fund portfolio selection in the existence of security selection and gives us the specification of the econometric models that we use in our paper. Here we give a summary of their model.

In that model they consider a one period investment on the one hedge fund. Assume r is the n -vector of security returns in the market and r_m is the market benchmark return. Consider $\tilde{r} = r - 1^n r_m$ asset return minus market return which if we consider market as a benchmark, the recent equation will be the vector of active returns.

Let assume that the hedge fund total value is \$1 which it invests in the risk free rate with r_0 return: Furthermore, the fund will buy and sell the individual stocks, the weights of hedge fund portfolio can be considered as n -vector w : as we know, total position in the equity market should sums to zero, therefore hedge fund should takes an position in the market benchmark of $-w'1^n$.

As a result the return on the hedge fund would be $r_0 + w'\tilde{r}$. Let's consider that the manager in the hedge fund has information about the returns to securities in the form of a signals s : The conditional returns to securities would be: $\tilde{r} = s + \eta$ (1)

Where $E[\eta | s] = 0^n$

There can be an assumption that the vector of conditional returns η has a multivariate normal distribution. If hedge fund manager optimizes the weights of the portfolio to maximize the expected utility of return; $r_w = r_0 + w'\tilde{r}$ then the utility function has risk aversion with parameter λ that $E[u(r_w)] = E[-\exp(-\lambda r_w)]$

¹ Connor C. & Li S., (2009). Market Dispersion and Profitability of the Hedge Fund.

If we take the expectation of lognormal utility, the optimization problem will be simplified to maximizing the risk-aversion-weighted linear combination of expected return and variance as:

$$w^* = \arg \max E[r_0 + w'\tilde{r}] - 1/2\lambda w'E[\eta\eta']w \quad (2)$$

If we improve this model we will be able to conduct the analysis the impact of changing market dispersion on the performance of the hedge fund. In order to do this, we should consider adding of parameters a ; b ; c to the active returns equation (1) and all three parameters should set equal to 1: To analyze the effects on hedge fund performance we throw the parameters away from one. The three scalar parameters a ; b ; c show three changes 1- balanced change, 2-signal-only change, 3- noise-only change in dispersion respectively. The improved version of (1) will be:

$$\tilde{r} = a(bs + c\eta)$$

Here it should be noticed that by adding these positive parameters the nature of the portfolio optimization problem is unchanged: if we take first derivative of (2) and set that equal to zero we can find the optimal portfolio w^* and the expected return and variance as follow:

$$w^* = \left(\frac{b}{\lambda ac^2}\right)(E[\eta\eta']^{-1} s$$

$$E[r_{w^*}] - r_0 = \left(\frac{b}{\lambda c^2}\right)s'(E[\eta\eta']^{-1} s$$

$$\text{Var}[r_{w^*}] = \left(\frac{b}{\lambda c^2}\right)s'(E[\eta\eta']^{-1} s$$

By taking the first derivative from the portfolio return and variance with respect to a , we would have:

$$\frac{\partial E[r_{w^*}]}{\partial a} = \frac{\partial \text{var}[r_{w^*}]}{\partial b} = 0$$

That is, the effect of a balanced change in dispersion on hedge fund return and risk is zero.

The reason is, because the fund manager adjusts the active portfolio weights to keep his optimal risk-return trade off, a balanced shift in the hedge fund risk-Return opportunity set, has no effect on the optimal portfolio's characteristic.

Now the first derivative with respect to parameter b is taken, as comparative statics of a signal-only change in market dispersion:

$$\frac{\partial E[r_{w^*}]}{\partial b} = -\left(\frac{2}{\lambda}\right)s'(E[\eta\eta'])^{-1}s > 0$$

$$\frac{\partial \text{var}[r_{w^*}]}{\partial b} = -\left(\frac{2}{\lambda^2}\right)s'(E[\eta\eta'])^{-1}s > 0$$

The above results shows that , If market dispersion increases because of the increased signals to the hedge fund, then the excess return and variance of the fund will increase; the relative effect will depend to the fact that whether the risk aversion coefficient is greater or less than one. Lastly, if the first derivative with respect to c is taken, it gives:

$$\frac{\partial E[r_{w^*}]}{\partial c} = -\left(\frac{2}{\lambda}\right)s'(E[\eta\eta'])^{-1}s < 0$$

$$\frac{\partial \text{var}[r_{w^*}]}{\partial c} = -\left(\frac{2}{\lambda^2}\right)s'(E[\eta\eta'])^{-1}s > 0$$

Therefore they conclude from the above results that a noise purely increase in market dispersion causes a decrease in the fund's excess return and in its variance.

In the mentioned model, a balanced change in market dispersion has no effect, a signal has a positive effect on mean and variance, and a noise effect has a negative effect on them.

The conclusion is that, increased market dispersion will grow hedge fund expected returns, also the level of active risk.

Appendix 2: Code 1

OBJECTIVE: TO CALCULATE MONTHLY CROSS SECTIONAL VOLATILITY OF 50 STOCKS FROM S&P AND CALCULATE MONTHLY MEAN ABSOLUTE DEVIATION OF THOSE STOCKS

```
%this code is for calculating the csv with the help of sp and the for mul formula was
```

```
% csv= sqrt(1/n* sum( r-rew)^2)
```

```
clear all
```

```
close all
```

```
clc
```

```
format compact
```

```
%%
```

```
%Read the data from the excel file
```

```
[data, date] = xlsread('sp-inv.xlsx');
```

```
%Calculate the size of the data
```

```
[m,n] = size(data);
```

```
%Calculate the simple monthly return
```

```
R = log(data(2:end,:)./data(1:end-1,:));
```

```
%R(:,n) is equally weighted index in Investco.
```

```
for idx = 1:n-1;
```

```
    minus(:,idx)= R(:,idx)- R(:,n);
```

```
end
```

```
%Calculate the square root of excess returns
```

```
minus2= (minus.^2);
```

```
sm=sum(minus2)';
```

```
% csv result "csvs"
```

```
csvs= sqrt(1/50*sm);
```

```
%Calculate the statistics of each stock
```

```
m_csv=mean(csvs);  
var_csv = var(csvs);  
S_csv = skewness(csvs, 0);  
K_csv = kurtosis(csvs, 0);
```

```
% writing to excel
```

```
xlswrite('S&P','date','A1:A1')  
xlswrite('S&P','csv','B1:B1')  
xlswrite('S&P','Mean','C1:C1')  
xlswrite('S&P','Variance','D1:D1')  
xlswrite('S&P','Skewness','E1:E1')  
xlswrite('S&P','Kurtosis','F1:F1')  
xlswrite('S&P',date,'A2:A211')  
xlswrite('S&P',csvs,'B3:B211')  
xlswrite('S&P',m_csv,'C3:C3')  
xlswrite('S&P',var_csv,'D3:D3')  
xlswrite('S&P',S_csv,'E3:E3')  
xlswrite('S&P',K_csv,'F3:F3')
```

```
% caclulating mean absolute deviation "sabsm"
```

```
absms=abs(minus);  
sabsms=(1/50)*sum(absms)';
```

```
%Calculate the statistics of each stock
```

```
m_s=mean(sabsms);  
var_s = var(sabsms);  
S_s = skewness(sabsms, 0);  
K_s = kurtosis(sabsms, 0);
```

```
% writing to excel
```

```
xlswrite('S&P','date','Sheet2','A1:A1')  
xlswrite('S&P','mean absolute dev','Sheet2','B1:B1')  
xlswrite('S&P','Mean','Sheet2','C1:C1')  
xlswrite('S&P','Variance','Sheet2','D1:D1')  
xlswrite('S&P','Skewness','Sheet2','E1:E1')
```

```
xlswrite('S&P',Kurtosis,'Sheet2','F1:F1')  
xlswrite('S&P',date,'Sheet2','A2:A211')  
xlswrite('S&P',sabsms,'Sheet2','B3:B211')  
xlswrite('S&P',m_s,'Sheet2','C3:C3')  
xlswrite('S&P',var_s,'Sheet2','D3:D3')  
xlswrite('S&P',S_s,'Sheet2','E3:E3')  
xlswrite('S&P',K_s,'Sheet2','F3:F3')
```

Appendix 3: Code 2

OBJECTIVE: TO CALCULATE MONTHLY CROSS SECTIONAL VOLATILITY OF 30 STOCKS THAT MAKE THE WHOLE DOW JONES INDEX AND CALCULATE MONTHLY MEAN ABSOLUTE DEVIATION OF THOSE STOCKS

```
% this code is for calculating the cross sectional volatility using dow jones  
%daily prices, in Dow Jones Index there are 30 stocks and we analyze all of  
%those stocks.  
% instead of using the equally weighted data the mean the formula was used  
% which is:  
% csv= sqrt(1/n* sum( return-meanreturn)^2)
```

```
clear all
```

```
close all
```

```
clc
```

```
format compact
```

```
%%
```

```
%Read the data from the excel file
```

```
[data, date] = xlsread('aa.xlsx');
```

```
%Calculate the size of the data
```

```
[m,n] = size(data);
```

```
%Calculate the simple monthly return
```

```
R = log(data(2:end,:)./data(1:end-1,:));
```

```
%Calculate the mean of the monthly returns of
```

```
mr = mean(R)';
```

```
%Calculate the excess return for each stock
```

```
for idx = 1:n;
```

```
    minus(:,idx)= R(:,idx)- mr;
```

```
end
```

```
%Calculate the square root of excess returns
```

```
minus2=minus.^2;
```

```
%Total of excess returns
```

```
sm=sum(minus2)';
```

```
% Calculate the cross sectional volatility
```

```
csv= sqrt(1/30*sm);
```

```
%Calculate the statistics of each stock
```

```
m_csv=mean(csv);
```

```
var_csv = var(csv);
```

```
S_csv = skewness(csv, 0);
```

```
K_csv = kurtosis(csv, 0);
```

```
% writing to excel
```

```
xlswrite('DowJones','date','CSV','A1:A1')
```

```
xlswrite('DowJones','csv','CSV','B1:B1')
```

```
xlswrite('DowJones','Mean','CSV','C1:C1')
```

```
xlswrite('DowJones','Variance','CSV','D1:D1')
```

```
xlswrite('DowJones','Skewness','CSV','E1:E1')
```

```
xlswrite('DowJones','Kurtosis','CSV','F1:F1')
```

```
xlswrite('DowJones',date,'CSV','A2:A211')
```

```
xlswrite('DowJones',csv,'CSV','B3:B211')
```

```
xlswrite('DowJones',m_csv,'CSV','C3:C3')
```

```
xlswrite('DowJones',var_csv,'CSV','D3:D3')
```

```
xlswrite('DowJones',S_csv,'CSV','E3:E3')
```

```
xlswrite('DowJones',K_csv,'CSV','F3:F3')
```

```
% caculating mean absolute deviation "sabsm
```

```
absm=abs(minus);
```

```
sabsm=(1/30)*sum(absm)';
```

```
%Calculate the statistics of each stock
```

```
m_s=mean(sabsm);
```

```
var_s = var(sabsm);
```

```
S_s = skewness(sabsm, 0);
```

```
K_s = kurtosis(sabsm, 0);
```

```
% writing to excel
```

```
xlswrite('DowJones','date','SABSM','A1:A1')  
xlswrite('DowJones','mean absolute dev','SABSM','B1:B1')  
xlswrite('DowJones','Mean', 'SABSM','C1:C1')  
xlswrite('DowJones','Variance','SABSM','D1:D1')  
xlswrite('DowJones','Skewness','SABSM','E1:E1')  
xlswrite('DowJones','Kurtosis','SABSM','F1:F1')  
xlswrite('DowJones',date,'SABSM','A2:A211')  
xlswrite('DowJones',sabsm,'SABSM','B3:B211')  
xlswrite('DowJones',m_s,'SABSM','C3:C3')  
xlswrite('DowJones',var_s,'SABSM','D3:D3')  
xlswrite('DowJones',S_s, 'SABSM','E3:E3')  
xlswrite('DowJones',K_s,'SABSM','F3:F3')
```

Appendix 4: Code 3

OBJECTIVE: TO REGRESS THE RELATIONSHIP BETWEEN CROSS SECTIONAL VOLATILITY, MARKET VOLATILITY AND HEDGE FUND PERFORMANCE FROM 1994 TO 2011 USING THE RESULTS FROM CODE 1

```
clear all
close all
addpath(genpath('C:\Program Files\matlab\r2010a\toolbox\jplv7'))
%%

%read the excel file
[num,date]=xlsread('final2.xlsx');

indecex=date(1,2:8);

%calculates the one-period simple returns of the time series
%data which takes one input parameter, the raw data of values.
Returns = log(num(2:end,1:7)./num(1:end-1,1:7));

%number of months
nm=length>Returns);

%number of indices
ni=length(indecex);

%Risk free rate
Rf=num(1:end,8);
Rf=Rf*ones(1,ni);

%Difference between the return on a portfolio of small
%stocks and the return on a portfolio of large stocks
SMB=num(1:end,9);

%Difference between the return on a portfolio of high book
```

```

%to market stocks and the return on a portfolio of low book to market
%stocks
HML=num(1:end,10);
%HML=HML*ones(1,ni);

%Market Return- Risk Free Rate
RmRf=num(1:end,11);

ExcRet>Returns-Rf(2:end,1:7);

%Cross sectional volatility
CSV=num(2:end,12);

MV=num(2:end,13);

X=[ones(size(RmRf)),RmRf,SMB,HML];

X=X(2:end,:);
%ExcRet is the dependent variable vector
%Ordinary least square regression
for idx=1:7
    %for i=1:7
    Result=ols(ExcRet(:,idx),X);
    outcome(:,idx)=Result.beta;
    %end
end

%Assign the values for alpha, betam, betasmb and betahml for each portfolio
Alpha=outcome(1,1:7);
Betam=outcome(2,1:7);
Betasmb=outcome(3,1:7);
Betahml=outcome(4,1:7);

prt(Result)

%%

```



```

for k=1:7
    Alphas(:,1:k)= ExcRet(1:209,1:k)-RmRf(1:209,1)*Betam(1,1:k)-SMB(1:209,1)*Betasm(1,1:k)-
HML(1:209,1)*Betahml(1,1:k);
end

%%

A=[ones(size(MV)),CSV,MV];

%Ordinary least square regression
for idx=1:7
    Result2=ols(Alphas(:,idx),A);
    Outcome(:,idx)=Result2.beta;
    tstat(:,idx)=Result2.tstat;
    R2(:,idx)=Result2.rsqr;
end

Alph=outcome(1,1:7);
Beta0=outcome(2,1:7);
Beta1=outcome(3,1:7);
tstat=tstat(1:3,1:7);
R2=R2(1,1:7);

% % writing to excel
xlswrite('S&P','hedge index names','Results-csv','A1:A1')
xlswrite('S&P','Beta0','Results-csv','B1:B1')
xlswrite('S&P','Beta1','Results-csv','C1:C1')
xlswrite('S&P','Beta2','Results-csv','D1:D1')
xlswrite('S&P','tsat','Results-csv','E1:G1')
xlswrite('S&P','R2','Results-csv','H1:H1')
xlswrite('S&P','indeces','Results-csv','A2:A8')
xlswrite('S&P','Outcome','Results-csv','B2:D8')
xlswrite('S&P','tstat','Results-csv','E2:G8')
xlswrite('S&P','R2','Results-csv','H2:H8')

```

Appendix 5: Code 4

OBJECTIVE: TO REGRESS THE RELATIONSHIP BETWEEN CROSS SECTIONAL VOLATILITY, MARKET VOLATILITY AND HEDGE FUND PERFORMANCE FROM 1994 TO 2011 USING THE RESULTS FROM CODE 2

```
clear all
close all
addpath(genpath('C:\Program Files\matlab\r2010a\toolbox\jplv7'))
%%

%read the excel file
[num,date]=xlsread('finaldata.xlsx');

%There are 7 indices we use and regress.
indices=date(1,2:8);

%Calculate the one-period simple returns of the time series
%data which takes one input parameter, the raw data of values.
Returns = log(num(2:end,1:7)./num(1:end-1,1:7));

%Calculate the statistics of each index
m_R=mean>Returns(:,1:7));
var_R = var>Returns);
S_R = skewness>Returns, 0);
K_R = kurtosis>Returns, 0);

xlswrite('DowJones',indices,'Stats','A2:A8')
xlswrite('DowJones',m_R,'Stats','B2:B8')
xlswrite('DowJones',var_R,'Stats','C2:C8')
xlswrite('DowJones',S_R,'Stats','D2:D8')
xlswrite('DowJones',K_R,'Stats','E2:E8')

%number of months
nm=length>Returns);

%number of indices
ni=length(indices);
```

```

%Risk free rate
Rf=num(1:end,8);
Rf=Rf*ones(1,ni);

%Difference between the return on a portfolio of small
%stocks and the return on a portfolio of large stocks
SMB=num(1:end,9);

%Difference between the return on a portfolio of high book
%to market stocks and the return on a portfolio of low book to market
%stocks
HML=num(1:end,10);

%Market Return- Risk Free Rate (Excess Return)
RmRf=num(1:end,11);

ExcRet>Returns-Rf(2:end,1:7);

%Cross sectional volatility which is calculated in another matlab code
CSV=num(1:end,9);
%Mean variance
MV=num(1:end,10);

%Form the Fama- French Regression function
X=[ones(size(RmRf)),RmRf,SMB,HML];

X=X(2:end,:);

%ExcRet is the dependent variable vector
%Ordinary least square regression
for idx=1:7
Result=ols(ExcRet(:,idx),X);
outcome(:,idx)=Result.beta;

```

```
end
```

```
% Assign the values for alpha, betam, betasmb and betahml for each portfolio
```

```
Alpha=outcome(1,1:7);
```

```
Betam=outcome(2,1:7);
```

```
Betasmb=outcome(3,1:7);
```

```
Betahml=outcome(4,1:7);
```

```
prt(Result)
```

```
%%
```

```
% Calculate the monthly alpha for all indeces.
```

```
for k=1:7
```

```
Alphas(:,1:k)= ExcRet(1:209,1:k)-RmRf(1:209,1)*Betam(1,1:k)-SMB(1:209,1)*Betasmb(1,1:k)-  
HML(1:209,1)*Betahml(1,1:k);
```

```
end
```

```
%%
```

```
% Regress the equation MV,CSV and alpha
```

```
A=[ones(size(MV)),CSV,MV];
```

```
A=A(2:end,:);
```

```
% Ordinary least square regression
```

```
for idx=1:7
```

```
Result2=ols(Alphas(:,idx),A);
```

```
Outcome(:,idx)=Result2.beta;
```

```
tstat(:,idx)=Result2.tstat;
```

```
R2(:,idx)=Result2.rsqr;
```

```
end
```

```
Alph=outcome(1,1:7);
```

```
Beta0=outcome(2,1:7);
```

```
Beta1=outcome(3,1:7);
```

```

%% % writing to excel
xlswrite('DowJones','hedge index names','Result-csv','A1:A1')
xlswrite('DowJones','Beta0','Result-csv','B1:B1')
xlswrite('DowJones','Beta1','Result-csv','C1:C1')
xlswrite('DowJones','Beta2','Result-csv','D1:D1')
xlswrite('DowJones','tsat','Result-csv','E1:G1')
xlswrite('DowJones','R2','Result-csv','H1:H1')
xlswrite('DowJones','indecas','Result-csv','A2:A8')
xlswrite('DowJones','Outcome','Result-csv','B2:D8')
xlswrite('DowJones','tstat','Result-csv','E2:G8')
xlswrite('DowJones','R2','Result-csv','H2:H8')

```

Appendix 6: Code 5

OBJECTIVE: TO REGRESS THE RELATIONSHIP BETWEEN WEIGTED AVERAGE CROSS SECTIONAL VOLATILTY, MARKET VOLATILITY AND HEDGE FUND PERFORMANCE FROM 1994 TO 2011 USING THE RESULTS FROM CODE 2

```

clear all
close all
addpath(genpath('C:\Program Files\matlab\r2010a\toolbox\jplv7'))
%%

%read the excel file
[num,date]=xlsread('final2.xlsx');

indecas=date(1,2:8);

%calculates the one-period simple returns of the time series
%data which takes one input parameter, the raw data of values.
Returns = log(num(2:end,1:7)./num(1:end-1,1:7));

%number of months
nm=length>Returns);

%number of indices
ni=length(indecas);

```

```

%Risk free rate
Rf=num(1:end,8);
Rf=Rf*ones(1,ni);

%Difference between the return on a portfolio of small
%stocks and the return on a portfolio of large stocks
SMB=num(1:end,9);

%Difference between the return on a portfolio of high book
%to market stocks and the return on a portfolio of low book to market
%stocks
HML=num(1:end,10);
%HML=HML*ones(1,ni);

%Market Return- Risk Free Rate
RmRf=num(1:end,11);

ExcRet>Returns-Rf(2:end,1:7);

%Cross sectional volatility
CSV=num(2:end,14);

MV=num(2:end,13);

X=[ones(size(RmRf)),RmRf,SMB,HML];

X=X(2:end,:);
%ExcRet is the dependent variable vector
%Ordinary least square regression
for idx=1:7
    %for i=1:7
    Result=ols(ExcRet(:,idx),X);
    outcome(:,idx)=Result.beta;
    %end
end

```

```

% Assign the values for alpha, betam, betasmb and betahml for each portfolio
Alpha=outcome(1,1:7);
Betam=outcome(2,1:7);
Betasmb=outcome(3,1:7);
Betahml=outcome(4,1:7);

prt(Result)

%%

for k=1:7
    Alphas(:,1:k)= ExcRet(1:209,1:k)-RmRf(1:209,1)*Betam(1,1:k)-SMB(1:209,1)*Betasmb(1,1:k)-
HML(1:209,1)*Betahml(1,1:k);
end

%%
A=[ones(size(MV)),CSV,MV];

% Ordinary least square regression
for idx=1:7
    Result2=ols(Alphas(:,idx),A);
    Outcome(:,idx)=Result2.beta;
    tstat(:,idx)=Result2.tstat;
    R2(:,idx)=Result2.rsqr;
end

Alph=outcome(1,1:7);
Beta0=outcome(2,1:7);
Beta1=outcome(3,1:7);
tstat=tstat(1:3,1:7);
R2=R2(1,1:7);

% % writing to excel
xlswrite('S&P','hedge index names','Results-sabsm','A1:A1')

```

```

xlswrite('S&P','Beta0','Results-sabsm','B1:B1')
xlswrite('S&P','Beta1','Results-sabsm','C1:C1')
xlswrite('S&P','Beta2','Results-sabsm','D1:D1')
xlswrite('S&P','tsat','Results-sabsm','E1:G1')
xlswrite('S&P','R2','Results-sabsm','H1:H1')
xlswrite('S&P','indecas','Results-sabsm','A2:A8')
xlswrite('S&P','Outcome','Results-sabsm','B2:D8')
xlswrite('S&P','tstat','Results-sabsm','E2:G8')
xlswrite('S&P','R2','Results-sabsm','H2:H8')

```

CODE 6:

OBJECTIVE: TO REGRESS THE RELATIONSHIP BETWEEN WEIGHTED AVERAGE CROSS SECTIONAL VOLATILITY, MARKET VOLATILITY AND HEDGE FUND PERFORMANCE FROM 1994 TO 2011 USING THE RESULTS FROM CODE 2

```

clear all
close all
addpath(genpath('C:\Program Files\matlab\r2010a\toolbox\jplv7'))
%%

%read the excel file
[num,date]=xlsread('final2.xlsx');

indecas=date(1,2:8);

%calculates the one-period simple returns of the time series
%data which takes one input parameter, the raw data of values.
Returns = log(num(2:end,1:7)./num(1:end-1,1:7));

%number of months
nm=length>Returns);

%number of indices
ni=length(indecas);

%Risk free rate
Rf=num(1:end,8);

```



```

Rf=Rf*ones(1,ni);

%Difference between the return on a portfolio of small
%stocks and the return on a portfolio of large stocks
SMB=num(1:end,9);

%Difference between the return on a portfolio of high book
%to market stocks and the return on a portfolio of low book to market
%stocks
HML=num(1:end,10);
%HML=HML*ones(1,ni);

%Market Return- Risk Free Rate
RmRf=num(1:end,11);

ExcRet>Returns-Rf(2:end,1:7);

%Cross sectional volatility
CSV=num(2:end,14);

MV=num(2:end,13);

X=[ones(size(RmRf)),RmRf,SMB,HML];

X=X(2:end,:);
%ExcRet is the dependent variable vector
%Ordinary least square regression
for idx=1:7
    %for i=1:7
    Result=ols(ExcRet(:,idx),X);
    outcome(:,idx)=Result.beta;
    %end
end

% Assign the values for alpha, betam, betasmb and betahml for each portfolio

```

```

Alpha=outcome(1,1:7);
Betam=outcome(2,1:7);
Betasm=outcome(3,1:7);
Betahml=outcome(4,1:7);

prt(Result)

%%

for k=1:7
    Alphas(:,1:k)= ExcRet(1:209,1:k)-RmRf(1:209,1)*Betam(1,1:k)-SMB(1:209,1)*Betasm(1,1:k)-
HML(1:209,1)*Betahml(1,1:k);
end

%%
A=[ones(size(MV)),CSV,MV];

%Ordinary least square regression
for idx=1:7
    Result2=ols(Alphas(:,idx),A);
    Outcome(:,idx)=Result2.beta;
    tstat(:,idx)=Result2.tstat;
    R2(:,idx)=Result2.rsqr;
end

Alph=outcome(1,1:7);
Beta0=outcome(2,1:7);
Beta1=outcome(3,1:7);
tstat=tstat(1:3,1:7);
R2=R2(1,1:7);

% % writing to excel
xlswrite('S&P','hedge index names','Results-sabsm','A1:A1')
xlswrite('S&P','Beta0','Results-sabsm','B1:B1')
xlswrite('S&P','Beta1','Results-sabsm','C1:C1')

```

```

xlswrite('S&P','Beta2','Results-sabsm','D1:D1')
xlswrite('S&P','tsat','Results-sabsm','E1:G1')
xlswrite('S&P','R2','Results-sabsm','H1:H1')
xlswrite('S&P','indecas','Results-sabsm','A2:A8')
xlswrite('S&P','Outcome','Results-sabsm','B2:D8')
xlswrite('S&P','tstat','Results-sabsm','E2:G8')
xlswrite('S&P','R2','Results-sabsm','H2:H8')

```

Appendix 7: Code 6

OBJECTIVE: TO REGRESS THE RELATIONSHIP BETWEEN CROSS SECTIONAL VOLATILITY, MARKET VOLATILITY AND HEDGE FUND PERFORMANCE FROM 1994 TO 2010 USING 7 FACTOR MODEL

```

clear all
close all
addpath(genpath('C:\Program Files\matlab\r2010a\toolbox\jplv7'))
%%

%read the excel file
[num,date]=xlsread('final3.xlsx');

%There are 7 indeces we use and regress.
indecas=date(1,2:9);

%Calculate the one-period simple returns of the time series
%data which takes one input parameter, the raw data of values.
Returns = log(num(2:end,1:8)./num(1:end-1,1:8));

%number of months
nm=length>Returns);

%number of indices
ni=length(indecas);

%Risk free rate
Rf=num(1:end,9);
Rf=Rf*ones(1,ni);

```

```

%Difference between the return on a portfolio of small
%stocks and the return on a portfolio of large stocks
SMB=num(1:end,10);

%Risk Free
Rf=num(1:end,20);
Rf=Rf*ones(1,ni);

%PTFSBD
PTFSBD=num(1:end,9);

%7 factors
PTFSFX=num(1:end,10);
PTFSCOM=num(1:end,11);
Rsp=num(1:end,12);
Rus=num(1:end,13);
Bond=num(1:end,14);
MoodyS=num(1:end,15);

ExcRet>Returns-Rf(2:end,1:8);

%Cross sectional volatility which is calculated in another matlab code
CSV=num(1:end,16);
%Mean variance
MV=num(1:end,17);

%Form the 7 factor Regression function
X=[ones(size(PTFSBD)),PTFSBD,PTFSFX,PTFSCOM,Rsp,Rus,Bond,MoodyS];

X=X(2:end,:);

%ExcRet is the dependent variable vector
%Ordinary least square regression
for idx=1:8

```

```

Result=ols(ExcRet(:,idx),X);
outcome(:,idx)=Result.beta;
end

```

```

% Assign the values for alpha, betas

```

```

Alpha=outcome(1,1:8);
Beta1=outcome(2,1:8);
Beta2=outcome(3,1:8);
Beta3=outcome(4,1:8);
Beta4=outcome(5,1:8);
Beta5=outcome(6,1:8);
Beta6=outcome(7,1:8);
Beta7=outcome(8,1:8);

```

```

%%

```

```

% Calculate the monthly alpha for all indeces.

```

```

for k=1:8
    Alphas(:,1:k)= ExcRet(1:209,1:k)-RmRf(1:209,1)*Betam(1,1:k)-SMB(1:209,1)*Betasm(1,1:k)-
HML(1:209,1)*Betahml(1,1:k);
end

```

```

%%

```

```

% Regress the equation MV,CSV and alpha

```

```

A=[ones(size(MV)),CSV,MV];

```

```

A=A(2:end,:);

```

```

% Ordinary least square regression

```

```

for idx=1:8
    Result2=ols(Alphas(:,idx),A);
    Outcome(:,idx)=Result2.beta;
    tstat(:,idx)=Result2.tstat;
    R2(:,idx)=Result2.rsqr;
end

```

```

Alph=outcome(1,1:8);
Betac=outcome(2,1:8);
Betam=outcome(3,1:8);

%% writing to excel
xlswrite('DowJones','hedge index names','Result-7','A1:A1')
xlswrite('DowJones','Alph','Result-7','B1:B1')
xlswrite('DowJones','Betac','Result-7','C1:C1')
xlswrite('DowJones','Betam','Result-7','D1:D1')
xlswrite('DowJones','tsat','Result-7','E1:G1')
xlswrite('DowJones','R2','Result-7','H1:H1')
xlswrite('DowJones','indecas','Result-7','A2:A9')
xlswrite('DowJones','Outcome','Result-7','B2:D9')
xlswrite('DowJones','tstat','Result-7','E2:G9')
xlswrite('DowJones','R2','Result-7','H2:H9')

```

Appendix 8: Code 7

OBJECTIVE: TO FIND THE CORRELATION COEFFICIENT BETWEEN TIMES SERIES VOLATILITY AND CROSS SECTIONAL VOLATILITY

```

clear all
close all
clc
format compact

%%
%Read the data from the excel file
[data] = xlsread('corr.xlsx');

MV= data(1:end,1)
CSV=data(1:end,2)

A=corrcoef(MV,CSV)

```

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