Do Hedge Funds still Offer Diversification Benefit? Evidence from the Indian Capital Market

Himanshu Gupta
School of Business Management, IFTM University, Moradabad, Uttar Pradesh, India

This paper examines the diversification benefits from familiarizing hedge funds into a conventional set of two most popular asset classes vizbonds and stocks. The conventional portfolio model of Markowitz and mean-Conditional Value at Risk portfolio model are used on an investment opportunity set consisting of bonds, stocks and hedge funds with respect to Indian capital market.The findings reveals that the presence of hedge funds might ominously increase a portfolio's mean-variance features; in addition the study observes the autocorrelation partialities in portfolio construction where the investment opportunity set entails of traditional assets class and hedge funds. The consequences show that mean-conditional variance investors have an inferior demand for hedge fund investments as compared to mean-variance investors. This study also highlights the fact that hedge fund index returns are exhibiting normally low and negative correlation with the bond index returns and in contrary relatively high and positive correlation with equity index. These conclusions are steady with the concept that the intrinsic risk in hedge funds returns is found in the tail of the portfolio distribution. The outcomes of this study is extremely useful to the institutional asset allocation fund managers or portfolio managers and also to the individual investors as it helps them in understanding the Indian capital market behavior better.

Keywords: *autocorrelation, investment, mean-conditional value at risk, mean-variance analysis, value at risk, variance*

"Hedge funds are looking to the emerging markets for new profit opportunities."

Steve Hays

INTRODUCTION

A criterion for an efficacious distribution for investment is an exhaustive consideration of the diverse risk-return drivers in every stratagem. Hedge funds risk originates principally through acquaintance to the diverse core financial instruments which the funds employ to engender returns. The optimum portfolio distribution will continually be a covenant between the risks an investor is eager to suffer for an estimated level of return. A diversified portfolio which includes hedge funds delivers steady and considerably higher returns and low volatility than that of portfolio of bonds and stocks. The reasonable belief of portfolio diversification is also vital when capitalizing in hedge funds. Most investors are scratchy with the idea of being uncovered to a single hedge fund once they know the impermanence rate in this industry is estimated at 30% a year. Although backing a single horse may sporadically pay off with big returns, it is nearly always tremendously risky.

Markowitz (1952) seminal paper on MPT (Modern Portfolio Theory) comprises the substance of what appears to be the only "free lunch" in finance: risk can be diversifying through combination of different assets to form portfolio. "An investor who spreads

capital between many imperfectly correlated assets will witness a decrease in the volatility of their portfolio", says Markowitz. When appropriately accomplished, there is no reduction in the expected mean return and so, speciously, no bill for the lunch.

Whereas Markowitz (1952, 1959) provided the basis of constructing portfolio with mean-variance analysis, the concept has been applied progressively to a different set of asset classes. Nevertheless, it is in stock that most of the allied research has bourgeoned, failing to recognize the impact of diversification when other asset classes can be combined to form portfolio such as hedge funds.

The repercussion for portfolio choice is that erratic financial events (eg. the October 2008 Global financial meltdown) may persuade investors to have a sensitive dislike towards tail risk, i.e., investors may choose a portfolio model which restrains the left tail of the portfolio distribution rather than minimizing portfolio the second moment of the distribution i.e., the standard deviation or variance. This delivers the economic motivation to observe the shifts in portfolio choice when an investor re-estimates risk from the conventional variance measure to a tail risk metric.

Due to impervious investment methods, hedge fund investing needs dedicated skills, such as a thought ful understanding of complex financial instruments, widespread knowledge of economics finance, and most important logical ability to choose the right asset at right time. Hence, this paper examines the diversification benefits from familiarizing hedge funds into a conventional set of two most popular asset classes viz bonds and stocks. The presence of hedge funds might ominously increase a portfolio's mean-variance features; also the study observes the autocorrelation partialities in portfolio construction where the investment opportunity set entails of traditional assets class and hedge funds. The consequences show that mean-conditional variance investors have an inferior demand for hedge fund investments than mean-variance investors.

This paper provides important contributions to the literature in the line that it observes the autocorrelation biasesin selection of portfolio where the investment opportunity set consists of bonds, stocks and hedge funds. Also, in the study it reveals that investors have a trend to over-weight their portfolio mix to wards assets such as bonds and hed gefunds in the presence of autocorrelation biases in the actual returns.

Furthermore, the study also examines the shifts in portfolio structure amongst mean-variance investors and M-CVaR(mean-conditional value at risk) investors. The conclusions show that mean-conditional value at risk investors has a lesser demand for hedge fund investments thanmean-variance investors. This study uses the Rockafellar and Uryasev (2002) mean-conditional value at risk asset allocation, whereby risk can be considered as size of the left tail of portfolio return distribution.

Although extensive research has been conducted on the subject in various international markets but Indian market has been still in the nascent stage relative to the mammoth growth of the bourses have witnessed. This lack of initiative of formally understanding the importance of hedge funds as regards to Indian context has created a knowledge gap in effective use of hedge funds as diversified investment. To date, this is the first study, which examines the differences in portfolio structure between MVA (mean-variance analysis) investors and M-CVaR (mean-conditional value at risk) investors in an investment opportunity set consist of bond, stocks and hedge funds especially in Indian context. This study would also offer motivating insights to institutional fund managers, portfolio managers and individual investors who ignore the performance of hedge funds just because of a myth that hedge funds are more risky assets to invest as compare to stocks and bonds.

LITERATURE REVIEW

Whilst the Markowitz (1952,1959) mean-variance model has become a basis of economic finance, it depends on the conventions of the investor utility function i.e., the quadraticutility. However, capacious research recommends that the normality assumption is not simply perceived in finance. The autocorrelation in the actual returns is the first empirical characteristic which disrupts the normality postulation. Famaand French (1989) and further Ilmanen (1995) in their study observed the signal of autocorrelation in bondreturns. Also, Asnesset al.,(2001);Lo(2002); Getmansky et al., (2004) illustrate due to illiquidity and certain smoothed return factors such as beta coefficient, hedge funds returns are autocorrelated. In addition, Lo (2001); Geman and Kharoubi (2003); Agarwal and Naik (2004);Malkiel and Saha (2005); Brown and Spitzer (2006); Morton et al., (2006); Giomouridis and Vrontos (2007); in their studies reported that the in most of the cases hedge fund returns are not normally distributed. They exhibit asymmetric distribution in the terms of higher moments. Also, the study of portfolio selection argues that the presence of autocorrelation in asset returns have serious consequences for investors operating within the normality postulation of Markowitz (1952, 1959).

The hedge fund studies by Asness et al., (2001); Getmansky et al., (2004) clearly recognizes the autocorrelation impact on beta coefficients and variance estimates in Sharperatios, therefore, it is expected that these impacts must also influence on portfolio selection models which rely on estimated variance. To account for autocorrelation, bias this study employs the technique used in his literature by Geltner (1991,1993) which suggests an adjustment method for calculating returns which eliminates the autocorrelation effect from every data observation. A number of scholarly studies on hedge fund employs Geltner (1991, 1993) to remove severe autocorrelation in asset returns (Kat and Lu, 2002; Bacmann and Gowran, 2005; Loudon et. al., 2006; Binachi et. al., 2009).

With the growth of the J.P. Morgan(1995)VaR (Value at Risk), studies have established the M-VaR (mean value at risk) portfolio frame work where the decisions to invest in portfolio are based on reducing or minimizing value-at-risk (Basak and Shapiro,2001; Alexander and Baptista, 2002). These studies indicate that mean value-at-risk is steady with expected utility maximization when the normality assumption is fulfilled; however, mean-VaR portfolios are less efficient than mean value-at-risk portfolios under less restricting assumptions. To discourse the deficit of M-VaR (mean value-at-risk), the literature has realized the growth of the Rockafellar and Uryasev (2000,2002); Pflug (2000); Acerbi and Tasche (2002); Xiong and Idzorek (2011) M-CVaR (mean-conditional value at risk) portfolio framework which estimates the probable loss when the specified value at risk for a specified confidence level is exceeded. Mean-Conditional Value at Risk portfolio studies by Pflug (2000); Rockafellar and Uryasev (2000,2002); Krokhmal etal., (2002) focused on the left tail of the distribution whilst the study by Xiong and Idzorek (2011) have shown that the “fat tailed” distributions often do an improved job of fitting realized returns. Also, all the above mentioned studies have found that CVaR is a better risk management tool in comparison to other measures including VaR and mean absolute deviation. The literature seems to suggest that the Rockafellar and Uryasev (2000, 2002); Pflug (2000) M-CVaR (mean-conditional value at risk) model are the best framework and has more attractive properties to examine tail risk which also adheres to the von Neumaan and Morgenstern (1944) sayings of expected utility maximization and to the Artzner, Delbsen, Eber, and Heath (1997,1999) principles of “coherent measure of risk”.

In an exceptional framework, Johri (2004) in the study propose to use risk measures like C-VaR and

Conditional Draw-Down at Risk especially in the case of alternative investments like hedge funds because their returns deviate from the normal distribution. In addition, Morton et. al., (2006) introduce a more general and flexible framework known as NORTA (normal-to-anything) for asset allocation to construct portfolios of hedge funds. In addition, Popova, et al., (2007) develop a stochastic programming model which integrates Monte Carlo simulation and optimization to observe the effects on the optimal allocation to hedge funds. Finally, Giamouridis and Vrontos (2007) introduce GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity) based methods to model time-varying volatility and correlation methods in hedge fund portfolio construction.

Optimal portfolio choice not only entails an appropriate model, it also needs to integrate the important concept of estimation risk. The studies of Brown (1976,1979); Jobson et. al., (1979) reveal that actual mean return estimates are not acceptable in portfolio selection frameworks. The sensitivities of portfolio selection to variations in mean returns were familiar in Best and Grauer (1991); Chopra and Ziemba (1993). To discourse the deficiencies of historical mean returns, Eun and Resnick (1988); Jorion (1985,1991); Topaloglou et. al., (2002) postulate the virtues of Bayes-Stein estimation of future expected return which has been shown to progress the in put parameters in optimal portfolio selection. The literature on Bayes-Stein estimation evidently shows that a comprehensive portfolio selection study must address the matter of estimation risk. Finally, in the search for more efficient portfolio model, Ortobelli et. al., (2005) admit that it is practically impossible to govern a portfolio model which is superior over another because there is no single risk measure subsists which can complete measure the portfolio risk as every risk measure has its distinctive features and limitations.

NEED AND RESEARCH OBJECTIVES OF THE STUDY

The assessment of the hedge fund works points a number of important matters which have not been enlightened. First, very few studies have diagnosed the amount of diversification benefits that hedge funds offer during adverse market situation in a portfolio combination with conventional asset classes especially in the context of Indian capital market. Given the progress of mutual funds as well as pension funds and the high demand for investments in hedge funds, it seems suitable that this study contemplates portfolio choice with conventional assets class and hedge funds in the investment opportunity set. Second, rare research attention has considered the sensitivities of autocorrelation bias on mean-variance and mean-conditional value at risk portfolio models. This research paper objects to address the above research questions in order to expand the current body of knowledge in the hedge fund literature. In addition, this paper offers investor with a model to discover the risks of hedge funds while constructing portfolio by accounting for autocorrelation bias and by determining the tail dependency of hedge fund returns with stock and bond returns in a mean-conditional value at risk model.

RESEARCH METHODOLOGY

The inspiration of this study is to observe the alterations in portfolio mix between bonds, stocks and hedge funds with respect to Indian capital market. To realize these swings in portfolio choice, this study presumes two set of assumptions viz, (i) Risk-freeborrowing and lending and (ii) short sales disallowed. In short, this conforms that the study allows assets allocations to risky class only while selecting optimal portfolio. The similar assumptions have been used by other scholars in their portfolio selection studies (Black,1972; Elton and Gruber, 1995; Amin and Kat, 2003; Binachi et. al., 2009). The practical motivation for this method is to observe the diversification effects on asset allocation when hedge funds are comprised in an investment universe comprising of the two most imperative asset classes in the world viz, bonds and stocks.

This study observes the effects of autocorrelation bias in actual returns and also studies the issue of risk in estimating mean return in portfolio selection under the aforementioned assumptions. To account for autocorrelation bias, this study uses the Geltner (1991, 1993) methods to correct the second sample moment (variance) for calculating returns to remove the biases of autocorrelation. This study employs the original returns and the autocorrelation adjusted returns in the Rockafellar and Uryasev (2000,2002)mean-Conditional Value at Risk portfolio and a traditional Markowitz (1952) mean-variance analysis to compare the effects of minimizing tail risk. To contemplate estimation risk in the analysis, this study uses the Bayes-Stein mean shrinkage estimation in a mean-variance analysis framework. The following part detailed the mathematical stipulations of the empirical models employed in this paper.

Mean Variance Analysis (MVA) Framework

Levy and Levy (2004) in their study states that the mean-variance investment decision rule developed by Markowitz (1952, 1959) and Tobin (1958) is best under uncertainty in economics finance, and it is broadly used by many scholars, academician and practitioners.

Now to define the Markowitz (1952) mean-variance analysis portfolio selection framework, this study employs the procedure proposed by Marling and Emanuelsson (2012). Let us consider a portfolio which comprises of m number of distinct assets and the return R_j is corresponding to asset j. Let μj and σj^2 denotes the respective mean and variance of the asset j and $\sigma_{j,k}$ denotes the covariance between two assets R_j and R_k. Let us consider that the relative amount of assets j that is to be invested in portfolio is u_i. Now if the portfolio return is denoted by R_p then:

$$\mu_p = E(R_p) = \sum_{j=1}^{m} \mu_j u_j$$

$$\sigma_p^2 = Var(R_p) = \sum_{j=1}^{m}\sum_{k=1}^{m} \sigma_{j,k} u_j u_k$$

$$\sum_{j=1}^{m} u_j = 1 \text{and} u_j \geq 0, j = 1,2,3, \ldots \ldots, m$$

Now on the basis of the assumption set in this study, the Markowitz (1952) mean-variance portfolio selection as optimization problem can be mathematically expressed as:

$$\min \text{u} \quad Var(R_p)$$

where $$Var(R_p) = U'\text{VU}$$

subject to, $$\sum_{j=1}^{m} u_j = 1, \text{and} u_j \geq 0, j = 1,2,3, \ldots \ldots, m$$

Where R_p and $Var(R_p)$ are the respective m-assets portfolio return and variance respectively, $U=(u_1,u_2,\ldots\ldots\ldots\ldots\ldots,u_m)'$ is the vector matrix comprising the proportion of investment made in different assets in the portfolio mix and V is the $mx\,m$ variance-covariance matrix.

Mean-CVaR (mean-Conditional Value at Risk) Framework

Rockafellar and Uryasev (2000, 2002) in their study formulate a convex linear programming model for portfolio optimization, which is widely accepted further in the several studies (Binachi et al.,2009; Xiong and Idzorek, 2011). The mean-Conditional Value at Risk portfolio optimization model used in this study follows the above literature and the model can be expressed as:

expressed as: $$\min u \quad CVar\left(F_{R_p}, \alpha\right)$$

subject to $$\sum_{j=1}^{m} u_j = 1 \text{ and } u_j \geq 0, j = 1,2,3, \ldots \ldots, m$$

where $$CVar\left(F_{R_p}, \alpha\right) = -E(R_p | R_p \leq -VaR)$$

$$Var\left(F_{R_p}, \alpha\right) = -F_{R_p}^{-1}(1-\alpha)$$

where F_{R_p} denotes the cumulative probability density function of R_p, and α the probability level.

As Xiong and Idzorek (2011) states that CVaR (Conditional Value at Risk) measures the entire part of the tail distribution completely by taking average losses and for this reason is the better measure of downside risk while in contrary value at risk is a statement about only one particular point. Also, the study of Rockafellar and Uryasev (2000) showed that, if one presumes that the returns are normally distributed then both CVaR (conditional value at risk) and VaR (value at risk)can be estimated by using only the first two moments of the return distribution.

Geltner Adjustments: Transforming Auto-correlated Returns to IID (Independent and Identically Distributed) Returns

To account for autocorrelation, the Geltner (1991,1993) established a method in his literature that focus on removing estimated bias normally used in real estate returns. Soon after the development of the Geltner (1991, 1993) method, many scholars have applied this procedure with success to different return series that exhibits autocorrelation bias in returns (Brooks and Kat,2002; Loudon et al.,2006; Binachi et al., 2009). The above procedure is used to construct an IID (Independent and Identically Distributed) returns which transform the actual data to an unsmoothed returns in order to evaluate the effect of autocorrelation. The adjusted return which accounts for autocorrelation bias in actual return may be calculated via:

$$R_{u,t} = \frac{R_t - ACF(R_{t-1}) * R_{t-1}}{1 - ACF(R_{t-1})}$$

Where $R_{u,t}$ is the Geltner adjusted return, R_t is the original return at time t and R_{t-1} is one-period lagged return of series R respectively, and $ACF(R_{t-1})$ is the first order autocorrelation coefficient.

Bayes-Stein Mean Shrinkage Estimation

Kinkawa (2010) in his study presume that in a mean-variance model the objective function of an investor is to select portfolio weights w in such a manner so as to maximize the portfolio expected return. So coupled with this, to stem Bayes-Stein mean estimated returns for mean, this study follow Jorion (1985,1991); Topaloglou et. al.,(2002); Okhrin and Schmid (2007);Binachi et. al., (2009) and calculate the estimate as:

$$V(\tilde{r}) = (1-\omega)\bar{\text{¥}} + \omega z \text{¥}_0$$

where $\bar{\text{¥}}$ represents the vector of sample mean return, ¥_0 is the minimum variance portfolio mean return, z represents the vector of unity, and ω denotes the shrinkage parameter for shrinking mean return vector $\bar{\text{¥}}$ and ¥_0. The shrinkage parameter ω is expressed as:

$$\omega = \frac{\hat{\lambda}}{T + \hat{\lambda}}$$

where $\hat{\lambda}$ can be calculated as:

$$\hat{\lambda} = \frac{(N+2)(T-1)}{(\bar{\text{¥}} - \text{¥}_0 z)' T \Sigma^{-1} (T-N-2)(\bar{\text{¥}} - \text{¥}_0 z)}$$

Where T represents the total number of observations in the study, N is the total number of asset classes studied and Σ istheco-variancematrixcalculated fromthepastobservations.

SOURCES OF DATA

This research paper work is primarily focused on Indian context to discover the findings. To account for the data for stocks, bonds and hedge funds this paper considered the major indices which are designed to measure the performances of the Indian capital universe as the proxies for all the three asset classes, i.e., this study employs the S&P CNX 500 Equity Index as the proxy for India stocks, the NSE G-SEC India Bond Index as the proxy for India bonds and the Eureka Hedge Indian Hedge Fund Index as the proxy for India hedge fund returns. Data have been sampled from January 2000 to June 2012 consisting of 150 observations of all the indices mentioned above.

To minimise the impact of systematic risk, this study employ monthly index returns for each investment rather than employing the returns of individual bonds, stocks or hedge funds. Also, this study involves the estimation of multi-asset portfolios; this study employs periodic monthly excess (original return – risk free rate) returns when assessing mean-variance and mean-conditional value at risk port folio selection. The choice of taking risk-free rate is of utmost important. This study uses the average of worst three annualized yield of one year maturity T-bills from 2000 to 2012. The National Stock Exchange T-bill index is used for the proxy for risk-free rate of return and it was observed that the worst three yields arises in the year 2010, 2004 & 2003 respectively and the average is found to be 5.04% annually (.42% monthly).

The statistical summary(seeTable1 in appendix), which reflects the significant features of financial market returns like negative skewness (third moments), excess kurtosis (fourth moments) and auto correlation in the first and second moments. It has been observed that the Geltner (1991, 1993) procedure reports approximately 31% rise (from 5.740 to 7.475 percent) in the estimate of hedge fund volatility while bond rose only 4.87% (from 1.765 to 1.851 percent) and stocks rose only 10.43% (from 8.569 to 9.463). This clearly indicates that Geltner returns penalize the volatility of hedge fund return more than the conventional asset classes returns.

Empirical Results and Findings

Portfolio construction needs selection of the asset classes (stocks, bonds and hedge funds). This paper proposes that when there is non-normality in the market, the Markowitz (1952, 1959) mean-variance model would not be the effective model for constructing portfolios; hence provide the need to go for the alternative models such as mean-conditional value at risk model. This paper is an attempt to know how the mean-variance model and mean-conditional value at risk model works when asset classes (especially in the case of hedge funds) behaviour are not normal. The normality of the asset classes returns was tested by employing the Jarque-Bera (JB) test statistic and observes the probability i.e., the p-value associated with the JB test statistic. The probability below the definite level of 0.05 and .01 concludes the acceptance of normality condition of Markowitz (1952, 1959) with 95% and 99% confidence level respectively (see the statistical summary Table 1 in appendix). It can be observed that, the hedge fund have a lesser monthly mean return than stocks monthly mean returns over the sample period studied.

Mean-Variance Analysis and Mean-CVaR (Conditional Value at Risk) Analysis of Original Sample

The portfolio compositions of mean-variance analysis for the original sample is presented in Table 2(see appendix).It can observe that the maximum hedge fund allocation found in the Table 2 is 58.5%which clearly implies that hedge funds have its own importance in portfolio selection. For the minimum variance portfolio, as shown in Panel A of Table 2, highlights the importance of bonds when the portfolio is consists of only stocks and bonds, but when the portfolio includes hedge funds along with these two asset classes, the minimum variance portfolio indicates the small weightage to the hedge funds. The prominence of hedge fund can also be visualized in the portfolio choice through Table 2 which reveals that the hedge funds not only reflect its significance in the minimum variance portfolio

but almost in all portfolio combinations of the mean-variance efficient set calculation. Also, it can be observe that the involvement of hedge funds significantly reduces the volatility of the portfolio returns for example, in the Table 2 for a minimum variance portfolio the volatility is decreasing near about 4.18% from 1.747 to 1.674, which implies that the involvement of hedge funds in the portfolio mix offers the diversification benefit but at the same time provides the undesirable movement of skewness and excess kurtosis. The above finding is coupled with the study done by Amin and Kat (2003). Also the result can be understood in a financial logic as if portfolio includes hedge funds than one has to bear its holding price. A major finding which adds to the literature of the hedge funds shows that the hedge funds presence significantly drops the equivalent conditional value at risk both at 95%at 99% confidence level, thus reducing the probability of falling portfolio return below expected return.

Further, Table 3 (see Appendix) provide the results of the mean-variance analysis done on the basis of Bayes- Stein mean shrinkage estimator which lets the effects of estimated risk to be integrated in portfolio selection. Both results report a very small range in the returns of the efficient set calculation and show a negligible decrease to the hedge funds allocation of approximately 0.3 per cent. The results sustain the view that the historic mean returns of the all the three asset classes are not excessively extreme or conventional given the underlying co-variance structure of all asset class. Hence, the comparison of actual mean returns in Table 2 versus the Bayes-Stein mean estimates in Table 3 reveals a very small or insignificant difference in portfolio mix also same time ignoring the movement of higher moments. Henceforth, we continue to use actual returns rather than Bayes-Stein means estimate in the subsequent part of this paper.

The Mean-Conditional Value at Risk portfolio optimization results for original mean returns are presented in Table 4 (see appendix). One of the major outcomes of the study is reported in Panels A to D of Table 4 that the presence of hedge funds in the portfolio mix, there is a systematic drop in CVaR at 95 and 99 percent thus reducing the probability of falling portfolio return below expected return. Consistent with Table 2, the mean-conditional value at risk bound portfolios reveals significantly less variance but undesirable movement in the skewness and kurtosis (especially at CVaR 99%). However, a remarkable finding can be realized in Panel D of Table 4 which report the highest allocation to hedge funds is merely 35.6% that to be in the middle range of the efficient set portfolio and a very low or insignificant demand for hedge funds, thus revealed the tail behaviour feature of hedge funds. Also, it is evident from the findings that a mean conditional value at risk investor restraining 99 percent CVaR will give less weightage to hedge fund investments while constructing his portfolio but this is not true with mean conditional value at risk investor restraining at 95 percent CVaR, as the Table 4 reports the highest allocation in hedge funds is approximately 74%. The second noticeable feature of Panel D of Table 4 shows that investors who pursue high returns will distribute a less fraction of their portfolio mix to hedge funds. This replicates the desire of mean conditional value at risk investors to reduce the tail risk of their portfolio from a focus of bonds. Further, if mean conditional value at risk investors are risk averse; means they want to minimize their risk then they require more conventional rates of return, but at the same time they are exposed to tail risk in bond returns. Hence, to reduce the likelihood of tail risk from a focus of bonds, a mean conditional value at risk investor will distribute a proportion of their portfolio mix to hedge funds but same time they have to bear the cost resulting from the undesirable movements of higher moments.

Mean-Variance Analysis and Mean-CVaR (Conditional Value at Risk) Analysis with the Geltner Adjustment

The mean-variance results with the Geltner (1991, 1993) transformed returns are shown in Table 5 (see appendix). Analysis of these results and compare with the original mean-variance estimates presents in Table 2 reveals some remarkable findings. It has been evidently noticeable that across all the efficient set calculation while constructing portfolio, Table 5 report higher volatility for the same estimates that has been calculated while constructing portfolio through original returns. Also, Panels B of Table 5 show prominent decrease of approximately 43.33 percent (from 9% to 5.1%) in the allocation to hedge funds while comparing with the original mean-variance analysis with respect to minimum variance portfolio.

The overall assessment of Table 5 suggests that auto-correlation bias can cause mean-variance or the rational investors to over-estimate their optimum portfolio allocations to significantly auto-correlated asset returns like hedge funds. As per the literature available and the author's best knowledge there is no known literature that clearly observes the effects of auto-correlation of hedge funds portfolio returns. The study done by Asness et al.,(2001) and Lo (2002) report effects of auto-correlation of the actual returns in the variance analysis and this study is consistent with the result reported by them. Finally, the inference to be concluded from the Geltner (1991, 1993) method is that mean-variance analysis portfolios investors significantly over-weight their proportion to hedge funds due to the effect of auto-correlation biases of actual returns.

The mean conditional value at risk portfolio optimizations with the Geltner (1991, 1993) transformed returns are shown in Table 6 (see appendix) and can be compared with the original returns presented in Table 4. The inconsistency in results between Tables 4 and 6 shows a noticeable increase in the proportion of bonds in both two asset and three asset universe. The remarkable feature is observed when the comparison of Table 4 and 6 reveals that for mean conditional value at risk investor restraining both at 95 percent and 99 percent CVaR, the hedge funds demands significantly falls for almost all the efficient set calculation. Hence, from the above findings, the conclusion has drawn that the significant decrease in the proportion of hedge funds in the portfolio mix at 95 and 99 percent CVaR caused due to auto-correlation biases presence in the actual returns. Also, mean-CVaR(Conditional Value at Risk) portfolio optimization results with the Geltner (1991, 1993) method suggest that investors, who overlook the presence of auto-correlation biases in the actual returns, may allocate more to hedge funds while constructing their portfolio, but on the contrary as mean-CVaR(Conditional Value at Risk) investors become more tail risk averse, the hedge fund demand vanishes.

Comparison of MVA (Mean-Variance Analysis) Portfolio and Mean-CVaR (Conditional Value at risk) Portfolio Selection model

The extreme dependence effect in mean-conditional value at risk portfolio choice model provides the root for comparative analysis between these two portfolio selection choices. This comparison result study reveals two perplexing findings; first, the results display that the hedge funds offer some diversification benefits when the investors construct their portfolio restrained at the 95% CVaR, contrariwise, hedge funds are not cup of tea for investors restrained the CVaRat 99% region. The second mystifying finding is relate to those investors who desire to include hedge funds in their portfolio and wishes to generate conventional portfolio returns. This segment provides a modest and logical basis to explain these findings.

The 95% mean-conditional value at risk portfolio choice effectively defines optimum portfolio mix by selecting assets at the specified rate of returns that is expected by the portfolio and by limiting losses corresponding to the lower quantile of the portfolio return distribution when the probability level is set to 95 per cent. Also, this study contains the data set which involves 150 monthly observations, so this implies that the data used to restrain portfolio risk is effectually determined by the two (eventually one) worst observation of the three assets class. As we know that stock markets, particularly in developing economies like India, are repeatedly found to be highly unpredictable. The one reason may be the second moment of the return distribution but it can also due to extreme profits or losses, which are mentioned as fat tails. Also, it is noticeable that the many times market moves in either direction only, i.e., it shows either a bearish or a bullish pattern. This movement in either direction specifies the existence of skewness in the return series, and extreme events specify the existence of kurtosis. Due to this fact, the Markowitz (1952, 1959), mean-variance analysis model itself may not be satisfactory to elucidate the risky performance of the combination of portfolio which comprises of hedge funds and stocks. The result confirms that hedge funds and stocks returns jointly own extremal dependence in the extreme left tail of the return distribution. This extreme dependence between hedge funds and stocks is apprehended in the stocks and at 99 per cent portfolio structure which results in a noticeable reduction in the hedge funds allocation.

The scatterplots of the 150 monthly returns between the three assets classes are presented in Figures 1 to 3 (see appendix). As the stocks and portfolio choice procedure selects the allocation of asset classes based on desired rates of portfolio returns and same time minimizes the extreme left tail of return distribution, so it is worthwhile that the reader should sensibly observe the position of negative outlier returns (also highlighted separately in Figures 1 to 3).

The scatterplot in Figure 1 shows that the dependency of stocks and hedge fund is persistent in terms of returns and is viewed for both negative and positive extreme returns. The bottommost left quadrant of Figure 1displays that when stocks tormented their worst monthly return of -27%, hedge funds also produced their worst monthly return of -16%. This mystifying data point occurs in the month of October 2008, the time when global financial crisis hits the Indian capital market. Soon after in year 2009, the Indian stock market has recover its position by reporting the best monthly return of 34% also at the same time hedge funds reported its best monthly return of 24%.The extreme observation reported in this study suggests that the stocks and hedge fund returns hold asymptotic dependence in rare events (Poon et. al.,2004).

In contrast, the scatter plot between the monthly returns of stocks and bonds is presented in Figure 3 (see appendix). A noticeable feature of Figures 3 is the lack of dependence in the returns between these two traditional asset classes. The movements of monthly returns from both the assets classes observed from the Figure 3 suggest that when stocks reported their worst monthly return of -27% during the period of global financial crisis, bonds generated a positive monthly return of 8% for that period. The close observations from the scatterplots shown in Figures 1 and Figure 3 emphasized that the tail dependence of the three asset classes is based upon a single worst monthly return observation when mean-conditional value at risk portfolio framework probability level is restraining at 99%. The explanation of the pronounced increase in proportion to the hedge funds in the mean-conditional value at risk portfolio optimization process (see Table 3) at 99% confidence level can be elucidate using Figure 1 and Figure 3. These rare outliers, located at the bottommost left side in Figure 1 and Figure 3, advocate that for the minimum variance portfolio the investors who restrain their portfolio at 99% confidence level CVaR will desire a portfolio mix comprises of bonds and hedge funds instead of a portfolio that comprises stocks and bonds. The reason for this can be explain by a fact that if one can consider the worst case scenario for both hedge funds and stocks then it is evident from the Figure 1 (see appendix) that when hedge funds displays its worst monthly return of -16% then during the same period the stocks also displays its worst monthly return of -27%, which in turn indicates that the investor loose less (16% as compare to 27%) amount of his investment if he holds hedge fund in their portfolio but at the same time pursue conventional rates of return.

To enlighten the attractiveness of hedge funds for investors who entail conventional rates of return, the emphasis will turn to Figure 2 (see appendix). The scatterplot between bonds and hedge fund presented in Figure 2 depicts a very close relationship among these two asset classes. Figure 2 also displays that when hedge funds reported their worst monthly return of -16%, bonds reported positive return of 8%. Moreover, when hedge fund recorded their best monthly return of -24% in May 2009, bond reported negative return of -2%. Because of this inverse behaviour of these two asset classes during the extreme positive and negative months, mean-conditional value at risk investors prefer portfolio comprises of bond and hedge fund instead of a portfolio that comprises stocks and bonds.

CONCLUSION

This paper has focused to find out the diversification benefit by examining the effects of autocorrelation in the selection of portfolio mix when hedge funds are involved in the investment opportunity set. This study compares and contrasts the portfolio selection results of a mean-variance investor and mean-CVaR (Conditional Value at Risk) investor when an investment set comprises stocks, bonds and hedge funds. The empirical results of this study evidently explain that mean-variance investors who wish to minimise portfolio variance, thus visualizing diversification benefit, have a higher hedge fund demand but also bears the undesirable movement of skewness and excess kurtosis. In contrast, a mean-conditional value at risk investor has a hedge funds demand when restraining the left tail region of the portfolio returns distribution. The findings tell that this outcome is because of tail dependency between hedge fund and stock returns. This study also reflects the shifts in portfolio mix caused by biases in the second sample moment from autocorrelation in actual returns. This study used Geltner (1991, 1993) method to account for autocorrelation effects and exhibit the presence of biases in the hedge funds allocation for both mean-variance and mean-conditional value at risk investors and due to this autocorrelation bias both investors may over-distribute their portfolio allocation to hedge fund investments. Also, it is evident that the presence of autocorrelation bias in hedge fund and bond returns in the empirical data series, cause an under-valuation of second sample moment i.e., the variance which always be an vital component in portfolio selection model.

In a nutshell, the purpose of this paper was to expand the novel work of Markowitz (1952, 1959) portfolio optimization model which optimizes the portfolio in the mean-variance framework but because of its basic assumption of normality condition it cannot produced effective results where the asset classes return distribution are non-normal like hedge funds. This study adds to the literature by signifying that natural portfolio choice can cover some of the intrinsic risks in returns that hedge fund generate. This paper offers investor with a model to discover the risks of hedge funds while constructing portfolio by accounting for autocorrelation bias and by determining the tail dependency of hedge fund returns with stock returns in a mean-conditional value at risk model. It is also evident that mean-conditional value at risk model offer enhanced optimization solutions for the developing markets like India, which are open to extreme events (excess kurtosis) and skewed patterns. This study would also offer motivating insights to institutional fund managers, portfolio managers and individual investors who ignore the performance of hedge funds just because of a myth that hedge funds are more risky assets to invest as compare to stocks and bonds.

The findings form this study offer number of prospects for future research. Whereas this study discovers a significant decrease in the hedge fund demand in unrestricted MVA (mean-variance analysis) and M-CVaR (mean-conditional value at risk) portfolio selection model, it is worthy to apply the same in a restricted portfolio choice scenario. Second, the approaches to amount biases in autocorrelation in the actual returns can easily amend to observe these effects on different portfolio selection models. Lastly, this study does not make any attempt to cater the presence of higher moments in the portfolio return distribution, thus leaving the thought-provoking research question for future research.

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BRIEF PROFILE OF THE AUTHOR

Himanshu Gupta is Assistant Professor in Finance and Marketing at IFTM University, Moradabad, India. He has submitted his Ph.D on "Impact of Diversified Investment on Portfolio Performance: A Study on Hedge Funds with special reference to Indian Capital Market" in the Faculty of Management, MLSU (Mohan Lal Sukhadia University), Udaipur, India. He did PGDM in Finance and Marketing from Birla Institute of Management Technology, Greater Noida, India.He has about three years of corporate experience and more than six and a half years of teaching experience. He has attended two international, three national conferences and two FDPs. His research interests are in the area of security analysis, derivatives, investment management and portfolio management.

APPENDIX

Table 4.1: Statistical Summary

This table represents the descriptive statistical analysis of the excess monthly index returns of the three asset classes used in this study. Panel A represents the statistical summary of the monthly index returns of the three asset classes. Panel B and C represents the autocorrelation adjustments for first and second sample moments. Sampled data contains 150 observations from January 2000 to June 2012. * and ** shows the data is statistically significant at the .05 and .01 confidence level, respectively.

Sector	Original Returns			(Geltner) Adjusted Returns		
	Equity India S&P CNX500 Index	Bond_ India_ NSE G-SEC Bond Index	EH_India Hedge Fund Index	Equity India S&P CNX500 Index	Bond_ India_ NSE G-SEC Bond Index	EH_India Hedge Fund Index
Variable						
Panel A: Descriptive Statistical Analysis						
Mean	0.781	0.142	0.572	0.799	0.142	0.563
Standard Deviation	8.569	1.765	5.740	9.463	1.851	7.475
Skewness	-0.229	1.009	0.455	-0.249	0.935	0.288
Kurtosis	1.639	6.920	1.691	1.283	6.798	0.303
Median	1.23	0.02	1.14	0.95	0.01	0.68
Maximum	34.01	9.55	23.81	36.04	9.91	28.91
Minimum	-27.65	-6.11	-16.73	-29.29	-6.41	-21.70
Jarque- Bera Statistic	18.107	324.786	23.047	11.839	310.673	12.693
Jarque- Bera p-value	0.000**	0.000**	0.000**	0.003**	0.000**	0.002**
Panel B: Autocorrelation adjusted for First Moment						
AC1	0.099	0.047	0.224	0.003	-0.007	0.009
AC2	-0.032	0.152	0.157	-0.047	0.149	0.086
AC3	0.045	0.032	0.106	0.041	0.027	0.065
AC6	-0.027	-0.059	0.026	-0.023	-0.054	-0.035
AC12	0.010	0.007	0.011	0.017	0.005	0.052
Panel C: Autocorrelation adjusted for Second Moment						
AC1	0.046	0.113	0.081	0.046	0.118	0.104
AC2	0.021	0.388	0.032	0.030	0.383	0.016
AC3	-0.012	0.006	0.012	0.003	0.019	0.021
AC6	0.092	0.151	-0.015	0.099	0.151	-0.035
AC12	0.003	-0.046	0.005	0.019	-0.047	0.001

Table 2: Mean-Variance Analysis of Original sample

This table presents the mean-variance analysis (MVA) of the original sample for optimizing portfolio, with respect to Indian Capital Market, where the investment opportunity set consists of two assets classes viz stocks and bonds (see left side of the table) and three assets classes viz; stocks, bonds and hedge funds (see right side of the table). This allocation procedure estimates the portfolio weights with a non-negativity constraint. The MVA is executed by minimizing portfolio variance for a specified level of return. Monthly excess returns for the respective indexes were employed during the period from January 2000 to June 2012. The ranges in the MVA efficient set are divided in manner as to make the straight comparison with other investment set. The Eq. CVaR in the table denotes the equivalent Conditional Value at Risk value calculated at the specified probability or the confidence level for each mean-variance portfolio optimization set.

2 Asset Class: Stocks and Bonds **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index**								**3 Asset Class: Stocks and Bonds and Hedge Funds** **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index** **HEDGE FUND: Eureka Hedge Fund India Index Data**								
Portfolio Required rate of return	**S.D**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Eq CVAR at 95%**	**Eq CVAR at 99%**	**Portfolio Required rate of return**	**S.D**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Hedge Funds (%)**	**Eq CVAR at 95%**	**Eq CVAR at 99%**
Panel A: Minimum Variance Portfolio								Panel B: Minimum Variance Portfolio								
0.158	1.747	0.837	6.627	2.4	97.6	-4.03	-5.36	0.181	1.674	0.782	5.798	0.0	91.0	9.0	-4.09	-4.59
Panel C: Efficient Set Calculation								Panel D: Efficient Set Calculation								
0.181	1.775	0.555	5.936	6.1	93.9	-3.98	-5.60	0.234	1.831	0.588	2.469	0.0	78.6	21.4	-4.02	-4.77
0.289	2.480	-0.123	1.779	23.0	77.0	-5.40	-7.66	0.289	2.249	0.519	0.748	3.5	67.5	29.0	-4.24	-5.49
0.344	3.048	-0.173	0.996	31.6	68.4	-6.16	-8.27	0.344	2.792	0.463	0.424	8.8	57.3	33.9	-4.92	-6.15
0.399	3.676	-0.187	0.803	40.2	59.8	-7.64	-9.73	0.399	3.399	0.413	0.592	14.1	47.1	38.8	-6.25	-7.51
0.454	4.339	-0.194	0.851	48.8	51.2	-9.24	-10.82	0.454	4.042	0.366	0.882	19.4	36.9	43.8	-7.80	-9.96
0.509	5.023	-0.200	0.981	57.4	42.6	-10.83	-12.67	0.509	4.706	0.324	1.173	24.7	26.6	48.7	-9.03	-13.00
0.564	5.720	-0.207	1.132	66.0	34.0	-12.42	-14.52	0.564	5.384	0.288	1.431	30.0	16.4	53.6	-11.06	-16.04
0.619	6.426	-0.213	1.279	74.6	25.4	-14.02	-16.37	0.619	6.070	0.256	1.651	35.3	6.2	58.5	-12.81	-19.09
0.674	7.138	-0.219	1.414	83.2	16.8	-16.20	-17.79	0.674	6.776	0.155	1.751	48.8	0.0	51.2	-13.66	-22.06
0.729	7.855	-0.224	1.536	91.8	8.2	-17.87	-19.64	0.729	7.621	-0.058	1.690	75.0	0.0	25.0	-16.93	-19.88
0.781	8.541	-0.229	1.639	100.0	0.0	-19.47	-21.43	0.781	8.535	-0.228	1.639	99.8	0.0	0.2	-19.45	-21.41

Table 3: Mean-Variance Analysis : Bayes Stein Mean Estimates

This table presents the mean-variance analysis (MVA) with Bayes-Stein mean estimates for optimizing portfolio, with respect to Indian Capital Market, where the investment opportunity set consists of two assets classes viz stocks and bonds (see left side of the table) and three assets classes viz; stocks, bonds and hedge funds (see right side of the table). This allocation procedure estimates the portfolio weights with a non-negativity constraint. The MVA is executed by minimizing portfolio variance for a specified level of return. Monthly excess returns for the respective indexes were employed during the period from January 2000 to June 2012. The ranges in the MVA efficient set are divided in manner as to make the straight comparison with other investment set. The Eq. CVaR in the table denotes the equivalent Conditional Value at Risk value calculated at the specified probability or the confidence level for each mean-variance portfolio optimization set.

2 Asset Class: Stocks and Bonds **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index**								**3 Asset Class: Stocks and Bonds and Hedge Funds** **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index** **HEDGE FUND: Eureka Hedge Fund India Index Data**								
Portfolio Required rate of return	**S.D**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Eq CVAR at 95%**	**Eq CVAR at 99%**	**Portfolio Required rate of return**	**S.D**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Hedge Funds (%)**	**Eq CVAR at 95%**	**Eq CVAR at 99%**
Panel A: Minimum Variance Portfolio								Panel B: Minimum Variance Portfolio								
0.155	1.759	1.009	6.920	0.0	100.0	-4.01	-5.20	0.181	1.674	0.782	5.798	0.0	91.0	9.0	-4.09	-4.59
Panel C: Efficient Set Calculation								Panel D: Efficient Set Calculation								
0.181	2.563	-0.136	1.596	24.3	75.7	-5.81	-7.87	0.199	1.862	0.583	2.197	0.0	77.4	22.6	-4.02	-4.75
0.189	3.072	-0.174	0.980	31.9	68.1	-6.62	-9.01	0.217	2.324	0.509	0.642	4.3	66.0	29.7	-4.32	-5.57
0.199	3.770	-0.189	0.801	41.4	58.6	-7.87	-9.94	0.234	2.879	0.456	0.431	9.6	55.8	34.6	-5.09	-6.46
0.207	4.357	-0.194	0.854	49.0	51.0	-9.28	-11.23	0.253	3.566	0.400	0.664	15.5	44.4	40.1	-6.66	-8.04
0.215	4.960	-0.200	0.968	56.6	43.4	-10.68	-12.50	0.272	4.292	0.350	0.996	21.4	33.0	45.6	-8.38	-11.12
0.222	5.497	-0.205	1.084	63.3	36.7	-11.92	-13.93	0.291	5.040	0.305	1.305	27.3	21.6	51.1	-10.18	-14.51
0.228	5.962	-0.209	1.184	69.0	31.0	-13.41	-15.15	0.311	5.842	0.266	1.582	33.5	9.6	56.9	-12.23	-18.08
0.234	6.431	-0.213	1.280	74.7	25.3	-14.53	-16.38	0.329	6.574	0.214	1.764	41.7	0.0	58.3	-15.12	-21.28
0.245	7.296	-0.220	1.442	85.1	14.9	-16.57	-19.31	0.347	7.426	-0.014	1.703	69.4	0.0	30.6	-16.93	-24.30
0.254	8.009	-0.226	1.560	93.7	6.3	-18.23	-21.28	0.357	7.968	-0.129	1.668	84.8	0.0	15.2	-18.20	-22.46
0.261	8.541	-0.229	1.639	100.0	0.0	-19.47	-22.81	0.367	8.541	-0.229	1.639	100.0	0.0	0.0	-19.47	-21.99

Table 4: Mean-CVaR Portfolio Optimization Analysis of Original sample

This table represents the mean-CVaR portfolio optimizations where the investment set consists of two assets classes viz stocks and bonds (see left side of the table) and three assets classes viz stocks, bonds and hedge funds (see right side of the table). The non-negativity constrained for portfolio weights along with disallowing short sales is followed. The ranges in the Mean-CVaR efficient set are divided in manner as to make the straight comparison with other investment set.

2 Asset Class: Stocks and Bonds **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index**							**3 Asset Class: Stocks and Bonds and Hedge Funds** **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index** **HEDGE FUND: Eureka Hedge Fund India Index Data**							
Portfolio Required rate of return	**Standard Deviation**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**CVAR (%)**	**Portfolio Required rate of return**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Hedge Funds (%)**	**CVAR (%)**
Panel A: Mean-CVaR constraint at 95%							Panel B: Mean-CVaR constraint at 95%							
0.159	1.747	0.825	6.604	2.6	97.4	-3.81	0.183	1.674	0.772	5.711	0.0	90.6	9.4	-4.08
0.243	2.088	0.019	3.248	15.8	84.2	-4.39	0.243	1.932	0.356	2.599	6.9	79.9	13.2	-4.12
0.303	2.616	-0.143	1.495	25.2	74.8	-5.66	0.303	2.383	0.428	0.634	7.7	66.3	25.9	-4.31
0.363	3.260	-0.180	0.886	34.6	65.4	-6.83	0.363	3.001	0.503	0.491	7.5	52.2	40.3	-5.06
0.423	3.962	-0.191	0.807	43.9	56.1	-8.34	0.423	3.699	0.494	0.835	8.9	38.9	52.2	-6.79
0.483	4.698	-0.197	0.915	53.3	46.7	-10.08	0.483	4.432	0.464	1.199	10.8	25.9	63.2	-8.66
0.543	5.453	-0.204	1.074	62.7	37.3	-11.81	0.543	5.184	0.429	1.504	13.3	13.1	73.6	-10.03
0.603	6.220	-0.211	1.237	72.1	27.9	-13.55	0.603	5.871	0.235	1.557	36.7	10.6	52.7	-11.85
0.663	6.995	-0.217	1.388	81.5	18.5	-15.86	0.663	6.713	0.028	1.577	59.9	8.0	32.1	-14.37
0.723	7.777	-0.224	1.523	90.9	9.1	-17.69	0.723	7.522	-0.036	1.696	72.2	0.0	27.8	-16.56
0.781	8.541	-0.229	1.639	100.0	0.0	-19.47	0.781	8.535	-0.228	1.639	99.8	0.0	0.2	-19.45
Panel C: Mean-CVaR constraint at 99%							Panel D: Mean-CVaR constraint at 99%							
0.142	1.759	1.009	6.920	0.0	100.0	-5.20	0.183	1.674	0.769	5.680	0.0	90.5	9.5	-4.58
0.243	2.088	0.019	3.248	15.8	84.2	-6.58	0.243	1.886	0.581	2.007	0.0	76.5	23.5	-4.73
0.303	2.616	-0.143	1.495	25.2	74.8	-7.99	0.303	2.381	0.548	0.565	2.8	63.9	33.3	-5.24
0.363	3.260	-0.180	0.886	34.6	65.4	-8.77	0.363	2.996	0.446	0.453	10.6	53.8	35.6	-6.61
0.423	3.962	-0.191	0.807	43.9	56.1	-10.36	0.423	3.698	0.255	0.639	23.8	46.2	30.0	-8.18
0.483	4.698	-0.197	0.915	53.3	46.7	-11.79	0.483	4.496	0.043	0.872	40.2	40.3	19.5	-10.72
0.543	5.453	-0.204	1.074	62.7	37.3	-13.81	0.543	5.229	0.031	1.123	47.4	29.8	22.7	-12.68
0.603	6.220	-0.211	1.237	72.1	27.9	-15.83	0.603	6.151	-0.158	1.253	68.0	25.9	6.0	-15.37
0.663	6.995	-0.217	1.388	81.5	18.5	-17.42	0.663	6.960	-0.194	1.401	79.4	17.5	3.1	-17.19
0.723	7.777	-0.224	1.523	90.9	9.1	-19.44	0.723	7.756	-0.211	1.533	89.6	8.5	1.9	-19.30
0.751	8.143	-0.227	1.581	95.3	4.7	-20.02	0.751	8.134	-0.221	1.585	94.7	4.5	0.8	-19.97
0.781	8.536	-0.229	1.638	99.9	0.1	-21.42	0.781	8.535	-0.228	1.639	99.8	0.0	0.2	-21.41

Table 5: Mean-Variance Analysis (Geltner Adjusted Returns)

This table presents the mean-variance analysis (MVA) with Geltner adjusted returns for optimizing portfolio, with respect to Indian Capital Market, where the investment opportunity set consists of two assets classes viz stocks and bonds (see left side of the table) and three assets classes viz; stocks, bonds and hedge funds (see right side of the table). This allocation procedure estimates the portfolio weights with a non-negativity constraint. The MVA is executed by minimizing portfolio variance for a specified level of return. Monthly excess returns for the respective indexes were employed during the period from January 2000 to June 2012. The ranges in the MVA efficient set are divided in manner as to make the straight comparison with other investment set. The Eq. CVaR in the table denotes the equivalent Conditional Value at Risk value calculated at the specified probability or the confidence level for each mean-variance portfolio optimization set.

2 Asset Class: Stocks and Bonds **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index**								**3 Asset Class: Stocks and Bonds and Hedge Funds** **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index** **HEDGE FUND: Eureka Hedge Fund India Index Data**								
Portfolio Required rate of return	**S.D**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Eq CVAR at 95%**	**Eq CVAR at 99%**	**Portfolio Required rate of return**	**S.D**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Hedge Funds (%)**	**Eq CVAR at 95%**	**Eq CVAR at 99%**
Panel A: Minimum Variance Portfolio								Panel B: Minimum Variance Portfolio								
0.153	1.838	0.814	6.578	1.7	98.3	-4.32	-5.82	0.164	1.803	0.814	6.148	0.0	94.9	5.1	-5.05	-5.61
Panel C: Efficient Set Calculation								Panel D: Efficient Set Calculation								
0.164	1.845	0.680	6.275	3.4	96.6	-4.12	-5.95	0.234	2.145	0.309	2.442	7.6	82.1	10.3	-4.94	-6.11
0.289	2.724	-0.162	1.475	23.0	77.0	-6.00	-8.28	0.289	2.683	0.112	0.865	16.1	73.4	10.5	-5.00	-8.19
0.344	3.368	-0.205	0.765	31.7	68.3	-6.84	-9.02	0.344	3.334	0.024	0.386	24.7	64.7	10.6	-6.26	-9.42
0.399	4.072	-0.217	0.588	40.3	59.7	-8.23	-10.63	0.399	4.044	-0.028	0.370	33.2	56.0	10.8	-7.99	-10.65
0.454	4.811	-0.223	0.623	48.9	51.1	-9.91	-12.25	0.454	4.786	-0.064	0.505	41.7	47.3	11.0	-9.53	-11.41
0.509	5.570	-0.227	0.730	57.6	42.4	-11.93	-13.80	0.509	5.548	-0.091	0.675	50.2	38.6	11.2	-11.29	-13.27
0.564	6.342	-0.232	0.856	66.2	33.8	-13.68	-15.50	0.564	6.322	-0.113	0.839	58.7	29.9	11.4	-13.05	-15.15
0.619	7.124	-0.236	0.980	74.8	25.2	-15.43	-17.53	0.619	7.105	-0.132	0.988	67.2	21.3	11.5	-15.28	-17.83
0.674	7.911	-0.241	1.094	83.5	16.5	-17.82	-19.55	0.674	7.894	-0.147	1.119	75.7	12.6	11.7	-17.11	-20.23
0.729	8.703	-0.245	1.198	92.1	7.9	-19.67	-21.57	0.729	8.687	-0.160	1.234	84.2	3.9	11.9	-18.94	-22.63
0.779	9.431	-0.249	1.283	100.0	0.0	-21.36	-24.04	0.779	9.431	-0.249	1.283	100.0	0.0	0.0	-21.36	-24.04

Table 6: Mean-CVaR Portfolio Optimization Analysis (Geltner Adjusted Returns)

This table represents the mean-CVaR portfolio optimizations with Geltner adjusted returns where the investment set consists of two assets classes viz stocks and bonds (see left side of the table) and three assets classes viz stocks, bonds and hedge funds (see right side of the table). The non-negativity constrained for portfolio weights along with disallowing short sales is followed. The ranges in the Mean-CVaR efficient set are divided in manner as to make the straight comparison with other investment set.

2 Asset Class: Stocks and Bonds **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index**							**3 Asset Class: Stocks and Bonds and Hedge Funds** **STOCK: S&P CNX 500 Equity Index Data** **BONDS: NSE G-SEC India Bond Index** **HEDGE FUND: Eureka Hedge Fund India Index Data**							
Portfolio Required rate of return	**Standard Deviation**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**CVAR (%)**	**Portfolio Required rate of return**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Stocks (%)**	**Bonds (%)**	**Hedge Funds (%)**	**CVAR (%)**
Panel A: Mean-CVaR constraint at 95%							Panel B: Mean-CVaR constraint at 95%							
0.158	1.840	0.756	6.455	2.5	97.5	-4.09	0.199	1.907	0.575	4.043	1.6	87.3	11.0	-4.18
0.243	2.269	-0.036	2.863	15.8	84.2	-5.02	0.243	2.230	0.368	1.788	6.2	79.2	14.6	-4.54
0.303	2.880	-0.179	1.215	25.2	74.8	-6.07	0.303	2.922	0.370	0.337	8.2	66.0	25.7	-5.11
0.363	3.606	-0.211	0.665	34.7	65.3	-7.36	0.363	3.707	0.327	0.268	13.1	54.3	32.7	-6.47
0.423	4.392	-0.220	0.588	44.1	55.9	-8.96	0.423	4.503	0.260	0.466	20.5	43.8	35.7	-8.26
0.483	5.209	-0.225	0.675	53.5	46.5	-11.10	0.483	5.337	0.212	0.715	27.5	33.2	39.3	-10.15
0.543	6.046	-0.230	0.807	62.9	37.1	-13.01	0.543	6.119	0.118	0.886	39.7	25.1	35.2	-11.96
0.603	6.896	-0.235	0.944	72.3	27.7	-14.92	0.603	6.995	0.102	1.102	45.8	14.0	40.2	-13.79
0.663	7.753	-0.240	1.072	81.7	18.3	-17.45	0.663	7.751	-0.060	1.142	66.8	10.6	22.6	-15.65
0.723	8.616	-0.245	1.187	91.2	8.8	-19.46	0.723	8.617	-0.074	1.282	75.2	0.6	24.2	-17.50
0.779	9.426	-0.249	1.282	99.9	0.1	-21.34	0.779	9.425	-0.248	1.283	99.8	0.0	0.2	-21.33
Panel C: Mean-CVaR constraint at 99%							Panel D: Mean-CVaR constraint at 99%							
0.142	1.845	0.935	6.798	0.0	100.0	-5.69	0.199	1.913	0.622	3.787	0.0	86.5	13.5	-5.48
0.243	2.269	-0.036	2.863	15.8	84.2	-6.41	0.243	2.305	0.519	1.281	0.0	76.0	24.0	-5.31
0.303	2.880	-0.179	1.215	25.2	74.8	-8.65	0.303	2.906	0.349	0.348	9.3	66.6	24.2	-6.46
0.363	3.606	-0.211	0.665	34.7	65.3	-9.57	0.363	3.614	0.208	0.226	19.7	57.6	22.7	-8.05
0.423	4.392	-0.220	0.588	44.1	55.9	-11.34	0.423	4.385	0.091	0.379	30.7	49.0	20.3	-9.78
0.483	5.209	-0.225	0.675	53.5	46.5	-12.85	0.483	5.193	-0.003	0.587	42.1	40.7	17.3	-12.11
0.543	6.046	-0.230	0.807	62.9	37.1	-15.04	0.543	6.026	-0.132	0.779	57.1	34.1	8.9	-14.25
0.603	6.896	-0.235	0.944	72.3	27.7	-16.94	0.603	6.879	-0.162	0.941	67.2	25.1	7.7	-16.52
0.663	7.753	-0.240	1.072	81.7	18.3	-19.14	0.663	7.739	-0.188	1.080	77.6	16.1	6.3	-18.80
0.723	8.616	-0.245	1.187	91.2	8.8	-21.35	0.723	8.611	-0.228	1.192	89.6	8.1	2.3	-21.22
0.751	9.021	-0.247	1.236	95.5	4.5	-22.38	0.751	9.020	-0.244	1.237	95.3	4.3	0.4	-22.36
0.779	9.426	-0.249	1.282	99.9	0.1	-24.03	0.779	9.425	-0.248	1.283	99.8	0.0	0.2	-24.02

Do Hedge Funds still Offer Diversification Benefit?
Evidence from the Indian Capital Market

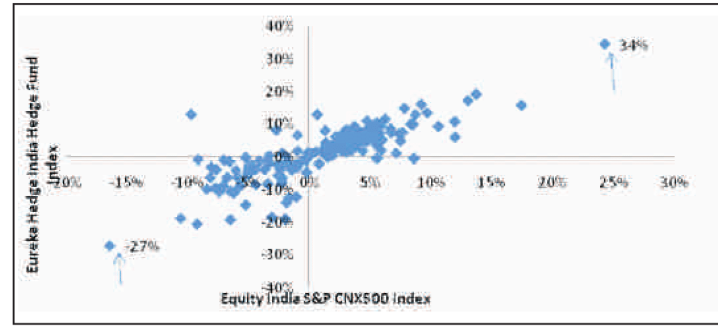
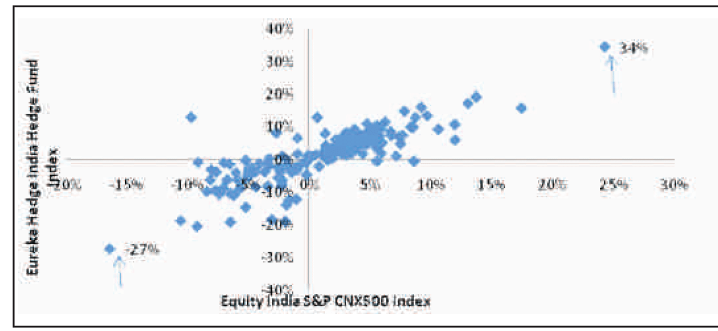


Figure 1: Eureka Hedge India Hedge Fund Index vs. Equity India S&P CNX500 Index



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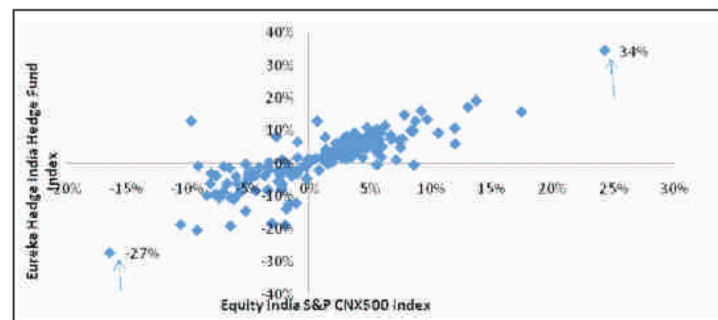

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