Commodity Index Fund Performance Analysis

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Abstract

The fact that many hedge fund returns exhibit extraordinary levels of serial correlation is now well-known and generally accepted as fact. The effect of this autocorrelation on investment returns diminishes the apparent risk of such asset classes as the true returns/risk is easily **camouflaged** within a haze of liquidity, stale prices, averaged price quotes and smoothed return reporting. We highlight the effect *autocorrelation* and *drawdown* has on performance analysis by investigating the results of functions developed during the Google Summer of Code 2013 on **commodity based index** .

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1 Background

The investigated fund index that tracks a basket of *commodities* to measure their performance.The value of these indexes fluctuates based on their underlying commodities, and this value depends on the *component, methodology* and *style* to cover commodity markets
.

A brief overview of the indicies invested in our report are :

- **DJUBS Commodity index** : is a broadly diversified index that allows investors to track commodity futures through a single, simple measure. As the index has grown in popularity since its introduction in 1998, additional versions and a full complement of sub-indices have been introduced. Together, the family offers investors a comprehensive set of tools for measuring the commodity markets.

- **Morningstar CLS index** : is a simple rules-based trend following index operated in commodities

- **Newedge CTI** : includes funds that utilize a variety of investment strategies to profit from price moves in commodity markets. Managers typically use either (i) a trading orientated approach,involving the trading of physical commodity products and/or of commodity derivative instruments in either directional or relative value strategies; Or (ii) Long short equity strategies focused on commodity related stocks.

2 Performance Summary Chart

Given a series of historical returns $(R_1, R_2, ..., R_T)$ from **January-96** to **December-2006**, create a wealth index chart, bars for per-period performance, and underwater chart for drawdown of the 3 funds.
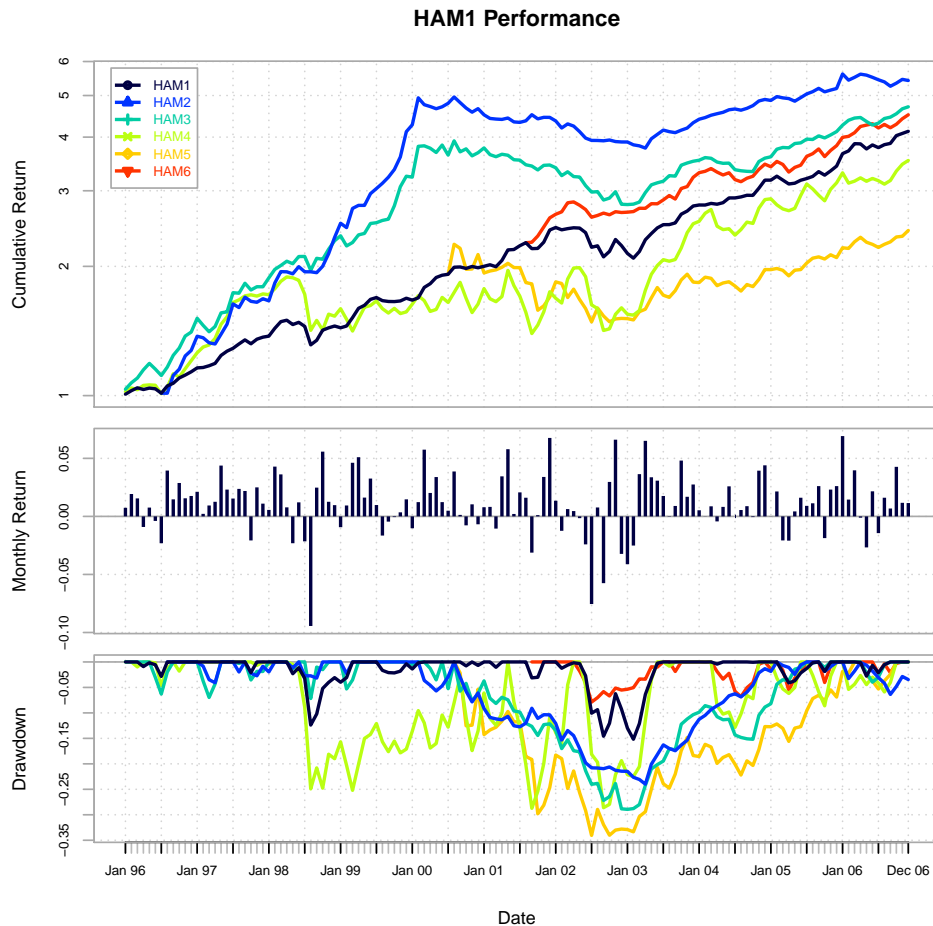
HAM1 Performance

The above figure shows the behavior of the respective fund performance, which is **upward** trending for all the funds till the period of **"January-2008"**. For comparative purpose, one can observe the distinct **drawdown** of **Newedge CTI** since the latter period.

3 Statistical and Drawdown Analysis

A summary of Fund Return series characteristics show that **DJUBS.Commodity** performs worse relatively to it's peers. The most distinct characteristic being highest : **Variance, Stdev, SE Mean** and well as negative **Skewness** . The table shows clearly, that the returns of all the hedge fund indices are non-normal. Presence of *negative* skewness is a major area of concern for the downside risk potential and expected maximum loss.

	HAM1	HAM2	HAM3	HAM4	HAM5	HAM6
Observations	132.0000	125.0000	132.0000	132.0000	77.0000	64.0000

```
NAs                0.0000   7.0000   0.0000    0.0000 55.0000 68.0000
Minimum           -0.0944  -0.0371  -0.0718   -0.1759 -0.1320 -0.0404
Quartile 1         0.0000  -0.0098  -0.0054   -0.0198 -0.0164 -0.0016
Median             0.0112   0.0082   0.0102    0.0138  0.0038  0.0128
Arithmetic Mean    0.0111   0.0141   0.0124    0.0110  0.0041  0.0111
Geometric Mean     0.0108   0.0135   0.0118    0.0096  0.0031  0.0108
Quartile 3         0.0248   0.0252   0.0314    0.0460  0.0309  0.0255
Maximum            0.0692   0.1556   0.1796    0.1508  0.1747  0.0583
SE Mean            0.0022   0.0033   0.0032    0.0046  0.0052  0.0030
LCL Mean (0.95)    0.0067   0.0076   0.0062    0.0019 -0.0063  0.0051
UCL Mean (0.95)    0.0155   0.0206   0.0187    0.0202  0.0145  0.0170
Variance           0.0007   0.0013   0.0013    0.0028  0.0021  0.0006
Stdev              0.0256   0.0367   0.0365    0.0532  0.0457  0.0238
Skewness          -0.6588   1.4580   0.7908   -0.4311  0.0738 -0.2800
Kurtosis           2.3616   2.3794   2.6829    0.8632  2.3143 -0.3489
```

The results are consistent with Drawdown Analysis in which **DJUBS.Commodity** performs worse relatively to it's peers.

```
                              HAM1    HAM2    HAM3    HAM4    HAM5    HAM6
Semi Deviation                0.0191  0.0201  0.0237  0.0395  0.0324  0.0175
Gain Deviation                0.0169  0.0347  0.0290  0.0311  0.0313  0.0149
Loss Deviation                0.0211  0.0107  0.0191  0.0365  0.0324  0.0128
Downside Deviation (MAR=10%)  0.0178  0.0164  0.0214  0.0381  0.0347  0.0161
Downside Deviation (Rf=0%)    0.0145  0.0116  0.0174  0.0341  0.0304  0.0121
Downside Deviation (0%)       0.0145  0.0116  0.0174  0.0341  0.0304  0.0121
Maximum Drawdown              0.1518  0.2399  0.2894  0.2874  0.3405  0.0788
Historical VaR (95%)         -0.0258 -0.0294 -0.0425 -0.0799 -0.0733 -0.0341
Historical ES (95%)          -0.0513 -0.0331 -0.0555 -0.1122 -0.1023 -0.0392
Modified VaR (95%)           -0.0342 -0.0276 -0.0368 -0.0815 -0.0676 -0.0298
Modified ES (95%)            -0.0610 -0.0614 -0.0440 -0.1176 -0.0974 -0.0390
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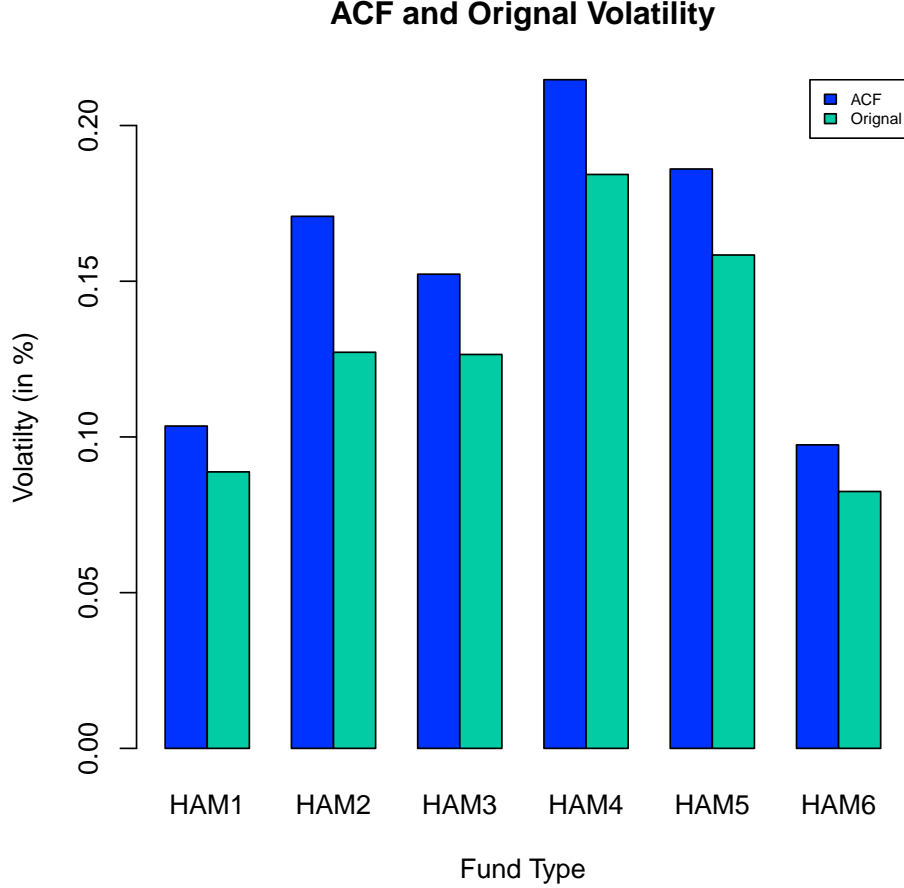
4 Non-i.i.d GSoC Usage

4.1 Auctocorrelation Adjusted Standard Deviation

Given a sample of historical returns $(R_1, R_2, ..., R_T)$, the method assumes the fund manager smooths returns in the following manner, when 't' is the unit time interval, with ρ as the respective term autocorrelation coefficient

$$\sigma_T = \sqrt{\sum_{k}^{n}(\sigma_t^2 + 2*\rho_i)} \qquad (1)$$

ACF and Orignal Volatility

From the above figure, we can observe that all the funds, exhibit **serial auto correlation**, which results in significantly *inflated* standard deviation.

4.2 Andrew Lo Statistics of Sharpe Ratio

The building blocks of the **Sharpe Ratio** : expected returns and volatilities are unknown quantities that must be estimated statistically and are, therefore, subject to *estimation error* .To address this question, Andrew Lo derives explicit expressions for the statistical distribution of the Sharpe ratio using standard asymptotic theory.

The Sharpe ratio (SR) is simply the return per unit of risk (represented by variability). In the classic case, the unit of risk is the standard deviation of the returns.

$$\frac{\overline{(R_a - R_f)}}{\sqrt{\sigma_{(R_a - R_f)}}}$$

The relationship between SR and SR(q) is somewhat more involved for non- IID returns because the variance of Rt(q) is not just the sum of the variances of component returns but also includes all the co-variances. Specifically, under the assumption that returns R_t are stationary,

$$Var[(R_t)] = \sum_{i=0}^{q-1} \sum_{j=1}^{q-1} Cov(R(t-i), R(t-j)) = q\hat{\sigma^2} + 2\hat{\sigma^2} \sum_{k=1}^{q-1}(q-k)\rho_k \qquad (2)$$

Where $\rho_k = \text{Cov}(R(t), R(t-k))/\text{Var}[R_t]$ is the k^{th} order autocorrelation coefficient's of the series of returns.This yields the following relationship between SR and SR(q):

$$\hat{SR}(q) = \eta(q) \qquad (3)$$

Where :

$$\eta(q) = \frac{q}{\sqrt{(q\hat{\sigma^2} + 2\hat{\sigma^2} \sum_{k=1}^{q-1}(q-k)\rho_k)}} \qquad (4)$$

In given commodity funds, we find results, similar reported in paper, that the annual Sharpe ratio for a hedge fund can be overstated by as much as **65** % because of the presence of **serial correlation**.We can observe that the fund "**DJUBS.Commodity**", which has the largest drawdown and serial autocorrelation, has it's Andrew Lo Sharpe ratio , *decrease* most significantly as compared to other funds.

Sharpe Ratio Observed
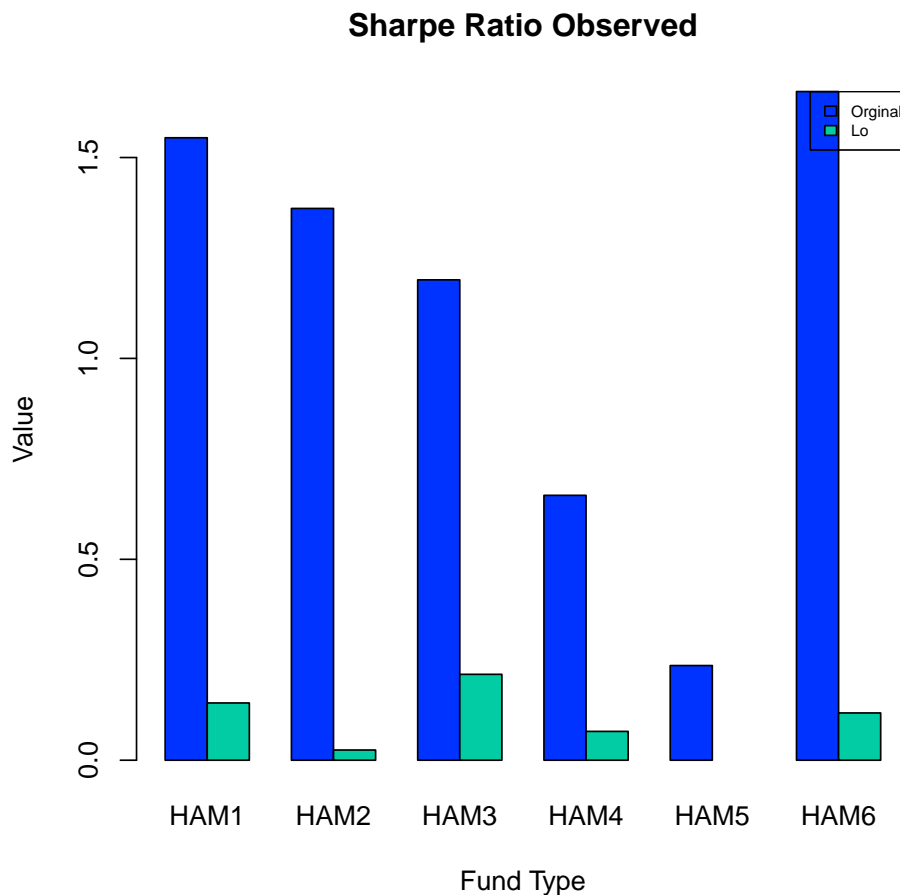
4.3   Conditional Drawdown

A new one-parameter family of risk measures called Conditional Drawdown (CDD) has been proposed. These measures of risk are functional of the portfolio drawdown (underwater) curve considered in active portfolio management. For some value of $\hat{\alpha}$ the tolerance parameter, in the case of a single sample path, drawdown functional is defined as the mean of the worst $(1 - \hat{\alpha})100\%$ drawdowns. The CDD measure generalizes the notion of the drawdown functional to a multi-scenario case and can be considered as a generalization of deviation measure to a dynamic case. The CDD measure includes the Maximal Drawdown and Average Drawdown as its limiting cases.Similar to other cases, **DJUBS.Commodity**, is the worst performing fund with worst case conditional drawdown greater than **50%** and **Newedge.CTI** performing significantly well among the peer commodity indices with less than **15%**.

4.4 Calmar and Sterling Ratio

Both the Calmar and the Sterling ratio are the ratio of annualized return over the absolute value of the maximum drawdown of an investment. equation

$$CalmarRatio = \frac{Return[0,T]}{maxDrawdown[0,T]} \tag{5}$$

$$SterlingRatio = \frac{Return[0,T]}{maxDrawdown[0,T] - 10\%} \tag{6}$$

```
> round(CalmarRatio.Norm(managers[,1:6],1),4)

                        HAM1   HAM2   HAM3   HAM4    HAM5   HAM6
Normalized Calmar Ratio 0.1744 0.1495 0.1175 0.2493 -0.0048 0.3244

> round(SterlingRatio.Norm(managers[,1:6],1),4)

                                        HAM1   HAM2   HAM3  HAM4    HAM5
Normalized Sterling Ratio (Excess = 10%) 0.1052 0.1055 0.0873 0.185 -0.0037
                                        HAM6
Normalized Sterling Ratio (Excess = 10%) 0.1429
```

For a 1 year *horizon* return, we can see that Newedge.CTI is the clear performer in this metric as well.However, a **surprising** observed result, is negative *Sterling* and *Calmar* ratio for Morningstar.CLS .

4.5 GLM Smooth Index

GLM Smooth Index is a useful parameter to quantify the degree of autocorrelation.It is a summary statistic for measuring the concentration of autocorrelation present in the lag factors (up-to 6) , which can be defined by the below equation as :

$$\xi = \sum_{j=0}^{k} \theta_j^2 \tag{7}$$

This measure is well known in the industrial organization literature as the Herfindahl index, a measure of the concentration of firms in a given industry where θ_j represents the market share of firm j. Because ξ_t is confined to the unit interval, and is minimized when all the θ_j 's are identical, which implies a value of 1/k+1 for ξ_i ; and is maximized when one coefficient is 1 and the rest are 0. In the context of smoothed returns, a lower value of implies less smoothing, and the upper bound of 1 implies pure smoothing, hence we shall refer to θ_j as a **smoothing index**.

GLM Smooth Index
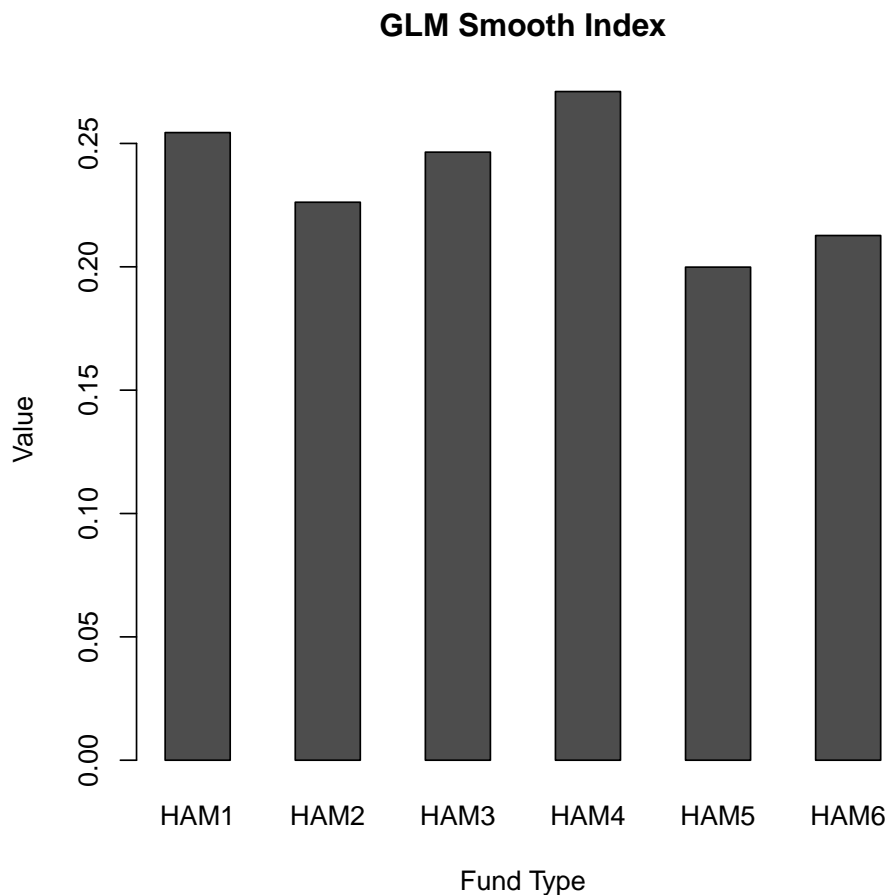
For the given chart, we can observe that **all the funds** have significant level of smooth returns.

4.6 Acar Shane Maximum Loss

Measuring risk through extreme losses is a very appealing idea. This is indeed how financial companies perceive risks. This explains the popularity of loss statistics such as the maximum drawdown and maximum loss. An empirical application to fund managers performance show that **very few investments** exhibit *abnormally high or low drawdowns*. Consequently, it is doubtful that drawdowns statistics can be used to significantly distinguish fund managers. This is confirmed by the fact that predicting one-period ahead drawdown is an almost impossible task. Errors average at the very best 27% of the true value observed in the market.

The main concern of this paper is the study of alternative risk measures: namely maximum loss and maximum drawdown. Unfortunately, there is no analytical formula

to establish the maximum drawdown properties under the random walk assumption. We should note first that due to its definition, the maximum drawdown divided by volatility is an only function of the ratio mean divided by volatility.

$$MD/\sigma = Min\frac{\sum_{j=1}^{t} X_j}{\sigma} = F(\frac{\mu}{\sigma}) \tag{8}$$

Such a ratio is useful in that this is a complementary statistic to the return divided by volatility ratio. To get some insight on the relationships between maximum drawdown per unit of volatility and mean return divided by volatility, we have proceeded to Monte-Carlo simulations. We have simulated cash flows over a period of 36 monthly returns and measured maximum drawdown for varied levels of annualized return divided by volatility varying from minus two to two by step of 0.1. The process has been repeated six thousand times.

For instance, an investment exhibiting an annualized return/volatility equal to -2 should experience on average a maximum drawdown equal to six times the annualized volatility.

Other observations are that:

- maximum drawdown is a positive function of the return/volatility ratio

- confidence interval widens as the return/volatility ratio decreases

This means that as the return/volatility increases not only the magnitude of drawdown decreases but the confidence interval as well. In others words losses are both smaller and more predictable.

Maximum Drawdown/Volatility as a function of Return/Volatility
36 monthly returns simulated 6,000 times
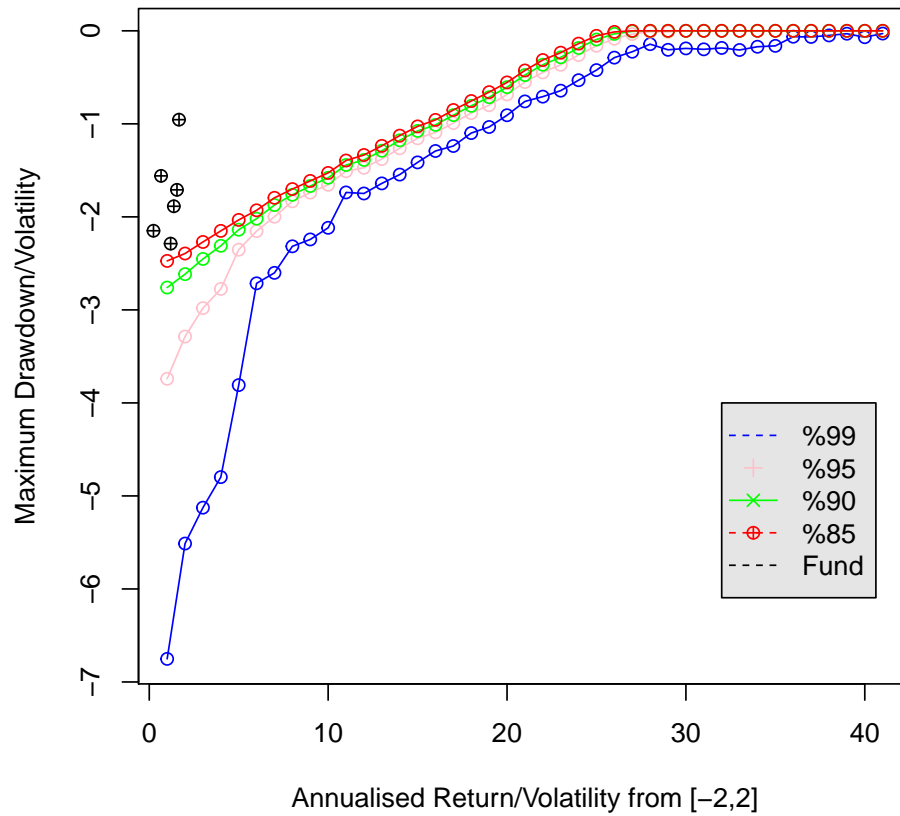
As we can see from the *simulated chart*, DJUBS.Commodity comes at the bottom , which imply a *lower* **return-maximum loss** ratio.

ACF Lag Plot
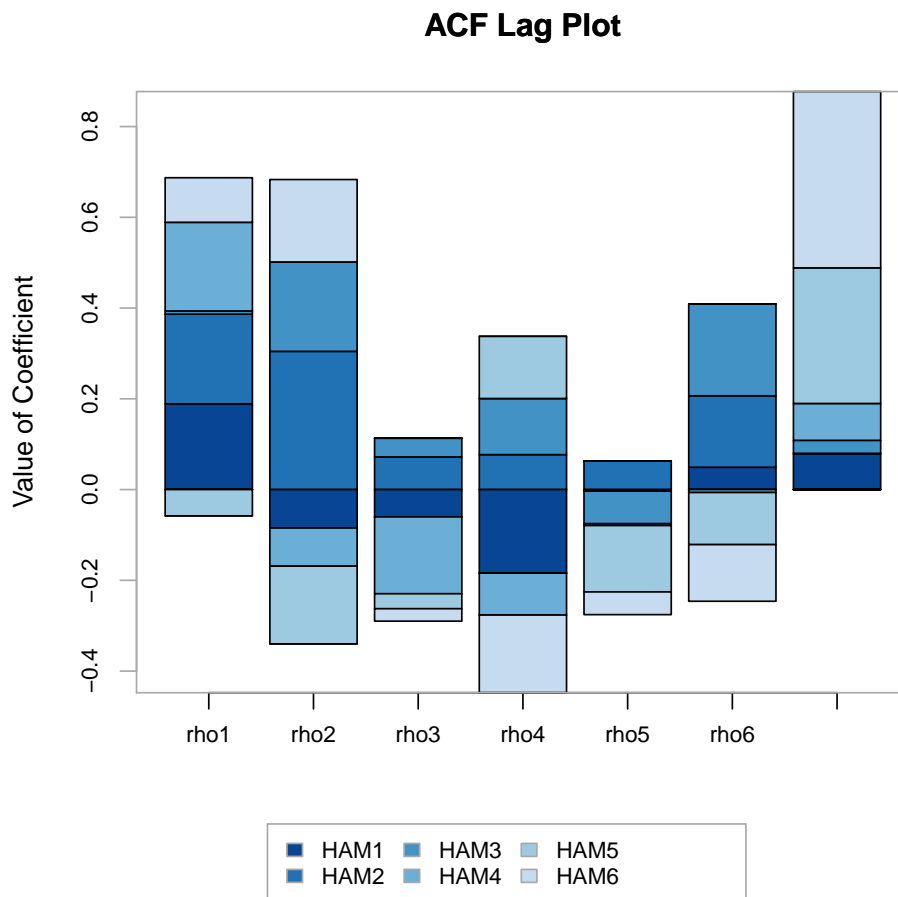
Finally, from the autocorrelation lag plot, one can observe, significant **positive** autocorrelation for **Newedge.CTI**, which is a *warning* signal in case drawdown occurs, in an otherwise excellent performing fund.

5 Conclusion

Analyzing all the function results, one can clearly differentiate **Newedge.CTI**, as a far superior fund as compared to it's peer.**MorningStar.CLS**, exhibits highest autocorrelation as well as lowest Calmar/Sterling ratio, but compared on other front, it distinctly outperforms **DJUBS.Commodity**, which has performed poorly on all the tests.

The above figure shows the characteristic of the respective fund performance, which is after the period of analysis till **"July-2013"**.At this moment, we would like the readers, to use the functions developed in the R **"PerformanceAnalytics"** package, to study ,use it for analysis as well as for forming their own opinion.

HAM1 Performance