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# Application of Realized Volatility Matrix in Asset Allocation Problems – Based on China's Stock Market UHF Data

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**Abstract**

This article explores the realized volatility matrix and its model in the classic asset allocation problems. Update time method using UHF data synchronization China's stock market, using three different correction and noise reduction technology get three volatility matrix sequence; sequence through the matrix modeling portray get yields and volatility matrix vector prediction value and apply to asset allocation problem.

**Keywords:** realized volatility, asset allocation, conditional Wishart distribution, heterogeneous market

## 1. Introduction

Asset Allocation is the core of modern finance. This article is based on realized volatility ideological construct covariance matrix have been achieved as a risk measure introduced asset allocation issues - Risk analysis framework in the past, with the overall volatility (volatility points) as an unbiased estimate of the amount of assets at a time risk measurement within the segment. Establish income-based asset allocation of high frequency data Financial - realized covariance analysis framework. Through the introduction of the common types of correction and noise reduction technology, to obtain the volatility matrix sequence use conditions autoregression Wishart model of realized covariance RCOV (Realized Covariance) modeling portrayed. Then return volatility matrix model and combined model, building model and Mean -CAW -CAW-HAR models. Then, the above model to the asset allocation problem in the past.

## 2. Important Concepts and Basic Assumptions

Consider p-dimensional logarithmic price process $\mathrm{X} = (\mathrm{X}(1), \mathrm{X}(2), \cdots \mathrm{X}(\mathrm{p}))$, which observation time is between [0, T], Hutchison T = 1. For the i-th asset, remember the observation time $t_{1(i),,} t_{2(i),} \cdots t_{N(i),}$ and assuming that the time sequence strictly increasing, at the same time, remember X (i) sequence at the time of observation each is implemented as X (i). Price process X is assumed by the following observation is valid for the number of price process Y drive:

$$Y(t) = \int_0^t a(u)du + \int_0^t \sigma(u)dW(u)$$

Wherein, a is a measurable locally bounded process drift vector, σ is the p × p matrix volatility instant process, W (u) of p-dimensional Brownian motion. This process is called Brown semimartingale process or stochastic volatility with drift process. Typically, assuming the price is based on the observation of the number of valid price Y of market microstructure noise superimposed form, namely

$$X^{(i)}\left(t_j^{(i)}\right) = Y^{(i)}\left(t_j^{(i)}\right) + U\left(t_j^{(i)}\right), j = 0,1,\cdots,N^{(i)}$$

Among them, the impact of $U\left(t_j^{(i)}\right)$ the observed price on behalf of noise is usually assumed expectation is zero and covariance stationary.

Said$\sum(t)=\sigma_t\sigma_t'$ instantaneous volatility matrices, saying its integral form $[Y]=\int_0^1 \sum(u)du$ is the integration matrix volatility, which reflects the price process Y [0,1]the overall changes] period of time, occupy an important position in the financial econometric analysis (see Ghysel et al. (1996)). The actual high frequency data are often faced with asynchronous and microstructure noise problems. Therefore, how to synchronize the data, as well as realized covariance matrix correction noise has become a very real problem.

If not otherwise stated hereinafter, referred $\tau_i$ for the first time i, n is the number of synchronization time, $x^{(i)}(t_j^{(i)})=X^{(i)}(t_j^{(i)})- X^{(i)}(t_{j-1}^{(i)})$represents the i-th asset in the period $(t_{j-1}^{(i)},t_j^{(i)})$in the logarithmic rate of return, $x(\tau_j) = (x^{(1)}(\tau_j),\ldots, x^{(p)}(\tau_j))$ represents$[\tau_{j-1}, \tau_j]$ synchronization period logarithmic yields vector.

**3. Calculation Realized Volatility Matrices**

For intraday high frequency data, resulting in a typical asynchronous Fair Epps effect. This effect leads to the risk portfolio (covariance) is underestimated. Intuitively, the sampling frequency increases, leading to more and more non-synchronized Fair zero return, the zero return realized covariance and correlation statistics gradually dominate, and causes these estimators gradually moving to zero. Therefore, the use of asynchronous high-frequency data to estimate volatility matrix must obtain prior data synchronization process. In this paper, the update time method for asynchronous data synchronization process.

In Barndorff-Nielsen et al. (2011) Update time method, the sample number and synchronization time (ie sampling time) after synchronization is usually the worst assets determine the relative price series by liquidity, which synchronized time formula is:

$$\tau_1 = \max\left(t_1^{(1)},\cdots,t_1^{(p)}\right),\quad \tau_{j+1} = \max\left(t^{(1)}_{N^{(1)}(\tau_j)+1},\cdots,t^{(p)}_{N^{(p)}(\tau_j)+1}\right)$$

Here, $N^{(i)}(\tau_j) = \{t_k^{(i)}\leq\tau_j,1\leq k\leq N(i)\}$ As the time $\tau_j$ for the i-th asset observation samples.

On the basis of the use of the high-frequency data synchronization technology for original high-dimensional high-frequency data synchronization process, the volatility of high frequency noise correction matrix technology is the next address non-synchronous and microstructure of the high-frequency noise volatility matrix estimation major deviation and inefficient way. Here are some common corrective noise reduction technology.

1) Multivariable has achieved nuclear estimates. Barndorff-Nielsen et al. (2011) method using the updated time after the original high-frequency data synchronization, the Barndorff-Nielsen et al. (2008), a one-dimensional correction has been estimated to achieve nuclear technology extended to multidimensional scenario:

$$\mathrm{MRK} = \sum_{h=-\hat{n}}^{\hat{n}-1} k(h/H)\Gamma_h$$

Wherein, k (·) as defined in [0,1] on the kernel, and $k(0)=1,k'(0)=0,x_j=X_j-X_{j-1}, j=1,2,\ldots, \tilde{n}, \tilde{n}=n-2m+1, X_j= X(\tau_j)$, $j=1, 2,\ldots, \tilde{n}-1$, $X_0 = \sum_{i=1}^{m} X(\tau_i)\big/m$, $X_{\tilde{n}} = \sum_{i=1}^{m} X(\tau_{n-m+i})\big/m$

In order to obtain consistency of MRK, the formula on $X(\tau_j)$ the two ends of a mean of m length. MRK mixed asymptotic normality, consistency and noise robustness, and is suitable for serial correlation are endogenous and noise. Optimal convergence rate is $\tilde{n}^{-1/5}$, slightly slower than $\tilde{n}^{-1/4}$when the one-dimensional case. The consistency of the estimated effect chosen by the kernel, and, faced with selecting sensitive parameter window width H's. In general, under the principle of minimum mean square error, the window width is taken as $H\propto\tilde{n}^{3/5}$.

2) Dual realized volatility matrix estimation TSCV. Zhang (2011) to Zhang et al. (2005) proposed a one-dimensional dual Realized Volatility Estimator to a pluralistic situation, to get consistency TSCV estimates (matrix (i, j) non-diagonal elements for example):

$$TSCV(i,j) = [X^{(i)},X^{(j)}]_T^{(K)} - \frac{\widehat{n_K}}{\widehat{n_J}}[X^{(i)},X^{(j)}]_T^{(J)}$$

Wherein, $[X^{(i)},X^{(j)}]_T^{(K)} = \sum_{s=K+1}^{n}(X^{(i)}(\tau_s)-X^{(i)}(\tau_{s-K}))(X^{(j)}(\tau_s)-X^{(j)}(\tau_{s-K}))/K$ , $\tilde{n}_K =(n-K)/K$, $1\leq J\leq K$. $[X^{(i)},X^{(j)}]_T^{(K)}$ is essentially based on the average RC sub-sampling method (see specific description). RC compared to the full sample, the variance is only the original 1 / K. But because there is a biased estimate, so we need to use higher frequencies (J) to estimate the noise variance, whereby the above TSCV estimates. In the absence of endogenous white noise, the estimated while eliminating asynchronous and noise caused by bias. But because TSCV is done based on the difference between two different frequencies RC realization, and therefore can not guarantee its positive definiteness. Actual calculation TSCV, generally take $J$=1, $K=O(n^{2/3})$.

3) The average estimate in advance (Pre-averaging estimators). Independent of the above study, Christensen et al. (2010) through the multidimensional data series and other high-frequency step size average weighted moving average to eliminate non-endogenous sequence independent and identically distributed noise, determined closer to making effective price, At the same tradition of the original sequence synchronous or asynchronous attributes:

$$\bar{x}^{(i)}\left(t_k^{(i)}\right) = \sum_{j=1}^{k_n-1} g\left(\frac{j}{k_n}\right) x^{(i)}\left(t_{k+j}^{(i)}\right), k = 1, \cdots, N_{(i)} - k_n + 1$$

Where, g is a continuous function [0,1], and satisfying g (0) = g (1) = 0, $k_n$ is a positive integer. On the one hand, if the average serial asynchronous, it is embedded in the HY estimated obtain asymptotically unbiased HY average estimate in advance (in the off-diagonal elements for example):

$$\mathrm{PAHY}(i,j) = \sum_{k=0}^{N(i)-k_n+1} \sum_{s=0}^{N(j)-k_n+1} \bar{x}^{(i)}\left(t_k^{(i)}\right) \bar{x}^{(j)}\left(t_s^{(j)}\right) I\left(\left(t_k^{(i)}, t_{k+k_n}^{(i)}\right] \bigcap \left(t_s^{(j)}, t_{s+k_n}^{(j)}\right]\right) \Big/ \left(\psi_{HY} k_n\right)^2$$

Among them$\Psi_{HY} = \int_0^1 g(x)dx$. PAHY better combination of pre-noise reduction technology and HY averaging interval estimate synchronization technology to solve the microstructure noise problems faced by the estimated standard HY.

## 4. Mean - Realized Volatility Matrix Model

We use a section of three common correction and noise reduction technology availability of diverse realized volatility matrix sequence, need to use the sequence of multi-dimensional modeling of realized volatility matrix characterization. In order to obtain good performance predictions. This article will use the realized volatility matrices CAW model based on realized covariance RCOV modeled estimates.

Suppose a $n \times n$ random symmetric positive definite covariance matrix have been achieved at time $t$ denoted as $\Sigma_t = (\sigma_{ij,t})$,matrix $\Sigma_t$ at a known value of the pre-conditions, the conditional distribution obedience to the center of the Wishart distribution: . Where $\upsilon > n$, n degrees of freedom, $\upsilon$ and $S_t$ the variance term negative correlation is symmetric positive definite matrix scale. In order to describe the autocorrelation and cross correlation assumed to follow the following linear regression function between the elements: $S_t = CC' + \sum_{i=1}^{p} B_i S_{t-i} B_i{}' + \sum_{j=1}^{p} A_j \Sigma_{t-j} A_j{}'$,. Where, C is the lower triangular matrix is the coefficient matrix. CAW (p, q) model can be interpreted as the state-space model, which is a state variable sequences can be observed by the matrix of the estimated density functions and decisions. This paper will use the maximum likelihood method to estimate the parameters.

Numerous empirical studies have shown that the characteristics of financial assets yield volatility has long memory. Műller et al. (1993) proposed a heterogeneous market hypothesis of the existence of different quality advocates traders on the market, they differ in risk appetite, access to information, etc., and they are bounded rationality. Based on this analysis of behavioral economics to investors Corsi (2004) propose a realized volatility of HAR model that will be on the market investors are divided into three categories, they are different investment behavior in heterogeneous autoregressive model (HAR -RV) are described in the model by different trading session realized volatility to characterize the contribution of trade to the whole different market participants realized volatility.

Bonato et al. (2009) proposed WAR processes and HAR heterogeneity, dynamics together, HAR model will be extended to the multi-dimensional case. In this paper, the idea of drawing Bonato, the CAW HAR model into the model, the parameters of Wishart distribution scale matrix $S_t$ following settings:. $S_t = CC' + A\Sigma_{t-1}A' + A^{(w)}\Sigma_{t-1}{}^{(w)}A^{(w)'} + A^{(m)}\Sigma_{t-1}{}^{(m)}A^{(m)}{}'$,Which $\Sigma_{t-1}{}^{(X)}$ is the time interval for the x-day realized covariance matrix, w represents the time interval of 5 days, representatives of the calendar week; m represents a time interval of 22 days, representatives of the calendar month; C is lower triangular matrix; $A, A^{(x)}$ a dimensional parameter matrix. The model can portray exactly realized covariance matrix of the time series features long memory and so on.

Use reference Xin Jin and John M. Maheu (2010) proposed to build ideas realized volatility yield distribution, the paper will yield volatility matrix vector is introduced into the model has been established to construct -CAW model mean and mean -CAW -HAR model. The yield of the vector is introduced into the realized volatility mean -CAW matrix model constructed model, the expression of the model are:

$$r_t|\Sigma_t \sim N(\mu_t, \Sigma_t^{\frac{1}{2}}\Lambda\left(\Sigma_t^{\frac{1}{2}}\right)')$$

$$\Sigma_t|F_{t-1} \sim w_n(\upsilon, {S_t}/{\upsilon})$$

$$S_t = CC' + \sum_{i=1}^{p} B_i S_{t-i} B_i' + \sum_{j=1}^{p} A_j \Sigma_{t-j} A_j'$$

$$\mu_t = \alpha + \beta\mu_{t-1}$$

Construction of the return series introduced mean -CAW-HAR model, the expression of the mode l are:

$$r_t|\Sigma_t \sim N(\mu_t, \Sigma_t^{\frac{1}{2}}\Lambda\left(\Sigma_t^{\frac{1}{2}}\right)')$$

$$\Sigma_t|F_{t-1} \sim w_n(\upsilon, {S_t}/{\upsilon})$$

$$S_t = CC' + A\Sigma_{t-1}A' + A^{(w)}{\Sigma_{t-1}}^{(w)}A^{(w)'} + A^{(m)}{\Sigma_{t-1}}^{(m)}A^{(m)\prime}$$

$$\mu_t = \alpha + \beta\mu_{t-1}$$

In the above two formulas, $\Lambda$ is a symmetric positive definite matrix, the role $\Lambda$ is to be amended $\Sigma_t$. Depending on the nature Wishart distribution, $\Sigma_t$ conditional expectation is: where. $\Sigma_{1:t-1} = \{\Sigma_1, \Sigma_2, \cdots, \Sigma_{t-1}\}$.Yields and realized volatility matrices joint probability distribution of distribution:

$$p(r_t, \Sigma_t|\Lambda, \Theta, \mathrm{r}_{1:t-1}, \Sigma_{1:t-1}) = p(r_t, \Sigma_t|\Lambda, \Sigma_t)p(\Sigma_t|\Theta, \Sigma_{1:t-1})$$

Where , $p(r_t|\Lambda, \Sigma_t)$ is the probability distribution model expression first formula, $p(\Sigma_t|\Theta, \Sigma_{1:t-1})$ is the probability model expression in the second formula of distribution, yield and realized volatility joint probability distribution matrix parameters indicating the estimated rate of return and has parameters realized volatility matrix estimation can be performed separately.

## 5. Mean - Realized Volatility Model in Asset Allocation Problem

Using high-frequency financial data covariance sequences can to. Modeling of the covariance matrix and further characterization of the covariance matrix for prediction. Covariance matrix based on the predicted and expected rate of return, the right to receive the next issue of the portfolio of each stock's weight by classical optimization objective function. By mean -CAW model and mean -CAW-HAR model volatility matrix and vector yields forecast. The stock asset allocation on the basis of yield volatility matrix and vector basis. That dual objective function to find the optimal solution:

The objective function: $\min\delta^2(r_p) = \sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j\, Cov(r_i,\ r_j)$

$$\max(r_p) = \sum_{i=1}^{N} x_i r_i$$

Constraints: $\sum_{i=1}^{N} x_i = 1,\ x_i \geq 0$

Wherein, $r_p$: portfolio return; $r_i$: first i only yield securities; $x_i$, $x_j$ securities i, j proportion of investment in the portfolio of; $\delta^2(r_p)$: Investment portfolio variance, used to represent a combination of total risk; $Cov(r_i,\ r_j)$: covariance between the two securities; $N$: represents the type of portfolio securities. Because then the China Stock Markets Based on empirical data analysis, it does not allow short selling restrictions here.

## 6. Empirical Analysis

### *6.1 Calculated Realized Volatility Matrix Estimation*

China High Frequency Data Based on case by case basis in Shanghai and Shenzhen stock markets, the use of multi-dimensional nuclear estimate has MRK, dual realized volatility matrix estimation TSCV, the average estimate in advance the three correction noise reduction technology is the covariance matrix sequence. Then use to obtain covariance matrix sequence CAW CAW-HAR model and model parameter estimation and correlation test. While establishing the yield vector VAR (1) model and parameter estimation and relevant inspection. After the volatility matrix model and revenue model combines vector construct model and Mean Mean -CAW -CAW-HAR models. And use this model to the covariance matrix and vector yield forecast, obtained pursuant to predict and forecast the covariance matrix yields vector stock asset allocation. Brought it into asset allocation objective function, to obtain the weight of each security. Finally, a comparative analysis.

In this paper, October 2012 stock markets in Shanghai and Shenzhen stock markets from 8 to 30 September 2013 238 days of high-frequency data individually. In order to ensure that each trading day has optimized our portfolio necessary to simplify the stop plate with dates in various different stocks in different announcement caused disturbances; focusing discussions on our asset allocation model of thinking problems. Our special selection super-market stock 9: China's Sinopec (600028), China Shenhua (601088), Agricultural Bank (601288), China Ping An (601318), Bank of Communications (601328), China Construction (601668), China Construction Bank (601939) Bank of China (601988), Industrial and Commercial Bank (901,398). Because the large amount of data and can only use the PC operation, in order to reduce the computational estimation we will 9 stock into three groups. DATA1 data set: Bank of Communications (601328), China Construction (601668), China Construction Bank (601939). DATA2 Data set: China Sinopec (600028), China Shenhua (601,088), China Ping An (601318). DATA3 Data set: Agricultural Bank (601288), Bank of China (601988), (ICBC) 901398. Once the data is grouped, on the one hand to retain a large amount of data, on the other hand because of the reduced dimensionality is reduced in the process of parameter estimation computation. While direct comparisons of different data sets, look at our model structure for different data sets of robustness.

Let synchronized data calculated based on the obtained data preprocessing realized volatility matrix sequence. We were using several multidimensional-case realized volatility calculated matrix correction method volatility matrix sequence. Volatility matrix sequence of statistical analysis. Table 3 shows the volatility of each matrix sequence volatility matrix (1,1) element sequence features related statistics, data were DATA1. MRC5 for the MRC kn = n1 / 2 estimates; preavehy representatives HY average estimate in advance; rk representatives have nuclear estimated Realized Kernel; Rv15s representatives 15s based on calculated data synchronization realized covariance matrix; hy representatives calculated based on the original data HY estimate; rvm representatives 15m synchronized data based on the calculation of realized covariance matrix and 5m synchronized data calculations realized covariance matrix of the average; tscv1 representatives dual estimate calculated the longer the process step c = 0.8 dual covariance matrix calculation. ADF test can be seen realized volatility matrix sequences are stationary series. The abbreviations below also represent the same meaning.

Table 3. Realized volatility matrix statistical characteristics

| | mrc511 | preavehy11 | rk11 | rv15s11 | hy11 | rvm11 | tscv0811 |
|---|---|---|---|---|---|---|---|
| mean | 0.2759 | 0.2203 | 8.8642 | 1.9379 | 7.4041 | 0.2351 | 0.1450 |
| std | 0.4013 | 0.3304 | 133.1969 | 0.7096 | 5.9685 | 0.2640 | 0.2411 |
| skewness | 11.8217 | 10.5764 | 15.3297 | 8.7841 | 10.6078 | 6.6862 | 4.8302 |
| kurtosis | 164.4478 | 139.5547 | 236.0004 | 111.1524 | 143.1431 | 65.2684 | 34.4606 |
| ADF-t | -7.986 | 7.263 | 7.652 | 7.908 | 7.5698 | 7.4812 | 7.4423 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

Note: Figures in brackets denote the p-value statistics, the ADF test, the confidence level of 1% of the critical value -3.439319,5% critical value -2.865389,10% of the critical value of -2.568876.

### *6.2 Multidimensional Mean-Realized Volatility Matrix Model Estimation and Testing*

This section next parameter estimation, to estimate the average date of the adoption equation yields sequence data, date of return series from the closing price minus the previous day's closing price, the yield from the first trading day of the date of closing minus the opening price obtained; volatility matrix model parameters were estimated using various types of correction obtained on the festival realized volatility matrix sequence. VAR structure mean equation delay take one step; CAW (p, q) model (p, q) takes (1,1). Take 1 order delay mean equation by vector analysis of serial correlation yields conclusions,

Table 4 data3 using volatility data set based on the calculated correction and noise reduction technology tscv1 matrix sequence and vector sequences yields -CAW model parameters mean and mean -HAR-CAW model yields VAR part of the estimation results. Table 5 uses data3 genome sequence data and vector sequence matrix yields mean -CAW model parameters and mean -HAR-CAW volatility model estimation results are based on part of the volatility tscv1 calculated correction noise reduction technology.

Table 4. Data3 calculated based on the average part tscv1 model parameter estimation results

| Parameters | The estimates of the mean -CAW Model | The estimates of the mean -CAW –HAR Model |
|---|---|---|
| $\Lambda$ | $\begin{pmatrix} 1.5262 & -0.3177 & 0.2267 \\ -0.3471 & 2.5268 & -0.2429 \\ 0.1840 & -0.3301 & 1.5328 \end{pmatrix}$ | $\begin{pmatrix} 1.4180 & -0.3177 & 0.2267 \\ -0.3178 & 2.4604 & -0.2429 \\ 0.2267 & -0.2429 & 1.4419 \end{pmatrix}$ |
| $\alpha$ | $\begin{pmatrix} 0.0006^* \\ 0.0004^* \\ 0.0006^* \end{pmatrix}$ | $\begin{pmatrix} 0.0005^* \\ 0.0006^* \\ 0.0004^* \end{pmatrix}$ |
| $\beta$ | $\begin{pmatrix} 0.0817 & -0.0949 & 0.1527 \\ 0.1262 & -0.0715 & 0.1743 \\ 0.0649 & -0.0149 & 0.1145 \end{pmatrix}$ | $\begin{pmatrix} 0.1167 & -0.1012 & 0.1060 \\ 0.1668 & -0.0507 & 0.1121 \\ 0.0923 & -0.0149 & 0.0790 \end{pmatrix}$ |
| Q(50) | 219.4251(0.0193) | 492.1089(0.0150) |

Note: * indicates at the 10% confidence level parameter estimates is not significant. * Represents the same meaning as below, no one explained.

Table5. Calculation model based on volatility tscv1 data3 some parameters estimation results

| Par | The parameter estimates volatility equation model under mean --CAW | Par | The parameter estimates volatility equation model under mean –CAW-HAR |
|---|---|---|---|
| ν | 4.0377 | ν | 4.1762 |
| C | $\begin{pmatrix} 0.0076 & 0 & 0 \\ 0.0053 & 0.0050 & 0 \\ 0.0053 & 0.0025 & 0.0057 \end{pmatrix}$ | C | $\begin{pmatrix} 0.0047^* & 0 & 0 \\ 0.0036^* & 0.0040^* & 0 \\ 0.0040^* & 0.0026^* & 0.0037^* \end{pmatrix}$ |
| B | $\begin{pmatrix} 0.0100 & 6.97E-09^* & 9.79E-09 \\ -1.18E-08 & 0.0100 & -1.59E-09^* \\ 3.20E-09 & -5.25E-09 & 0.0100 \end{pmatrix}$ | A | $\begin{pmatrix} 0.0419 & -0.1653 & -0.0550 \\ -0.0961 & 0.1858 & -0.0246 \\ 0.3534 & -0.5304 & 0.1493 \end{pmatrix}$ |
| A | $\begin{pmatrix} 1.0021 & -0.5738 & -0.1921 \\ 0.3266 & 0.3334 & -0.3928 \\ 0.2929 & -0.2094 & 0.1236 \end{pmatrix}$ | $A^w$ | $\begin{pmatrix} 0.6052 & 0.1323 & -0.2543 \\ 0.0964 & 0.7945 & -0.2903 \\ 0.0636 & 0.2770 & 0.1383 \end{pmatrix}$ |
| | | $A^m$ | $\begin{pmatrix} -0.33960 & 0.9686 & 0.2138 \\ -0.0785 & 0.2946 & 0.0600 \\ -0.1799 & 0.1680 & 0.4785 \end{pmatrix}$ |

*6.3 Assets in the Target Sample Configuration Function Effectively Solving Portfolio Frontier*

Based on the multi-dimensional mean - parameters volatility matrix model estimation results have been achieved. Conditions were forecast in the sample yields vector and matrix conditions volatility, which began into the sample on September 30, 2013 JCP predictive value of 216 trading days from November 7, 2012 (ie, 23 days). The predictive value of the asset allocation into question the objective function solved for all the efficient frontier portfolio.

Previous issues of asset allocation research focuses on empirical analysis model constructed asset allocation of superiority; different scholars based on different data to prove their model or asset allocation strategy is more advantageous. But the conclusions are strictly dependent on the use of data collection and asset portfolio performance evaluation system. So far there is not a framework for different asset allocation strategy or model of the same standard evaluation. The author believes the asset allocation strategy constructed with the existing asset allocation strategy comparative analysis and conclusions drawn merits. The actual meaning of this line of analysis has little, so this article is to compare different conception of volatility algorithm, especially different correction noise reduction has been achieved volatility by volatility model; the impact on the final asset allocation issues.

The following figure shows the efficient frontier combination track this 216 days in 9 trading days. This article only take 50 daily efficient frontier portfolio, his paintings make visual image displayed in the drawing. Prediction results are as follows:

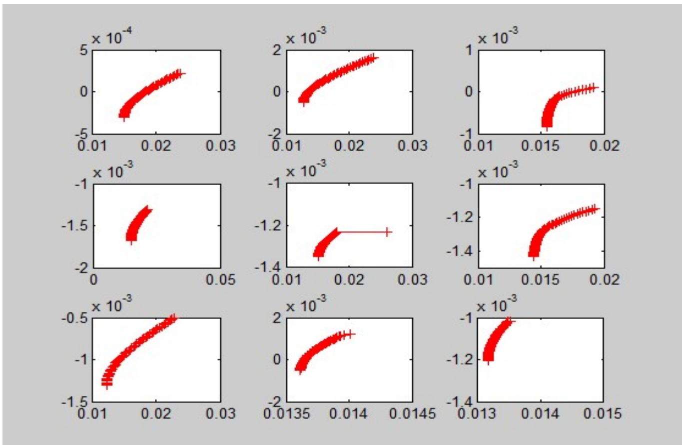


Figure1. Efficient portfolio frontier

Note: The figure, the horizontal axis represents the portfolio risk; vertical axis represents the portfolio yield. Each following figures have the same axis, not setting them.

Figure 1 Calculation based on a combination of the efficient frontier Mean - CAW (data1rk) model within the sample daily return vector and 216 days of the date the condition has been predicted covariance matrix implementation.

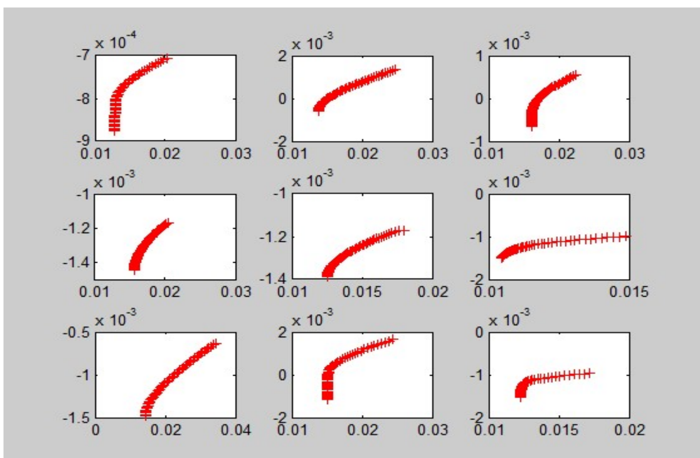


Figure2. Efficient portfolio frontier

Figure 2 is based on the efficient frontier of computing the mean - HAR-CAW (data1rk) model to date of the return vector and day conditions within 216 days of the predictive value of the sample covariance matrix have been achieved.

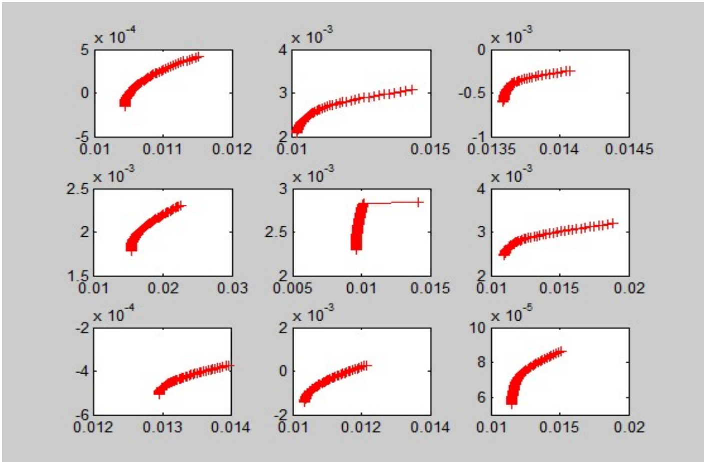


Figure3. Efficient portfolio frontier

Efficient Frontier is calculated in Figure 3. Mean -HAR-CAW (data3tscv1) model based on the predicted value of the covariance matrix of the date of the return date of the conditions within the sample vector and 216 days have been achieved.

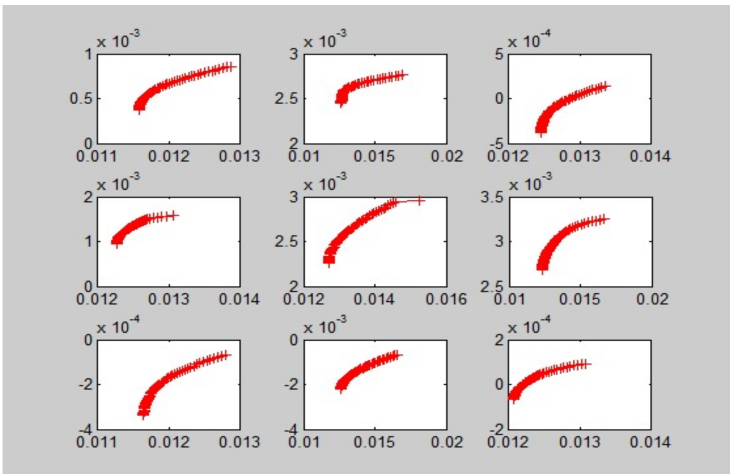


Figure4. Efficient portfolio frontier

Efficient Frontier is calculated in Figure 4 Mean -CAW (data3tscv1) model based on the predicted value of the covariance matrix of the date of the return date of the conditions within the sample vector and 216 days have been achieved.

Comparison Figure1 and2, and 3 and 4 comparison chart. Found different effects on the efficient frontier volatility model portfolio is obvious. So choose a suitable volatility model and then get a more accurate predictive value volatility matrix condition is an important part of the asset allocation problem. The selection of appropriate volatility model is beyond the scope of this article writing, not in this repeat.

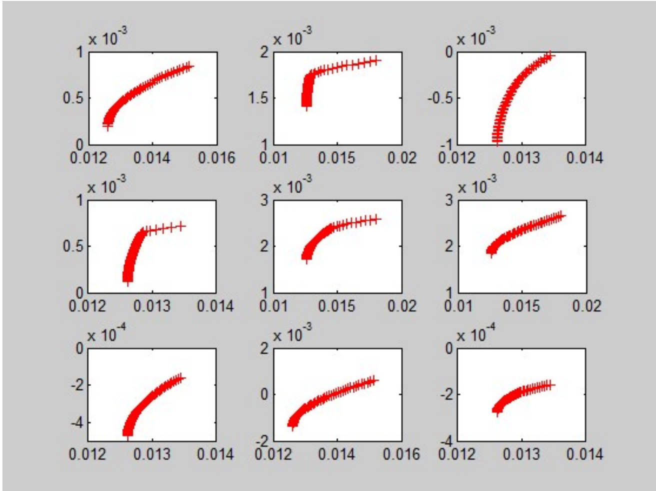


Figure5. Efficient portfolio frontier

Figure 5 is calculated based on the efficient frontier of mean -HAR-CAW (data3rk) model to date of the return vector and day conditions within 216 days of the sample covariance matrix has been predicted to achieve.

Comparison Chart 2 and 4, and the comparative Figure 3 and Figure 5. You can find different Realized Volatility correction and noise reduction technology, by realized volatility models on the objective function of the optimal configuration of assets is significant. This illustrates the importance of reasonable correction and noise reduction technology for asset allocation research questions. The literature and empirical methods to measure different volatility associated direct comparison has been a lot of analysis, this is no longer described in this article.

From Figure1to Figure 5 can be seen: the effective combination of different trading day frontier trajectory changed greatly. When low-frequency data to adjust the asset portfolio, we adjust the frequency of the portfolio is low, because many of our more than enough data to calculate parameters related; without consideration of transaction costs, based on high frequency data for volatility Further characterization of the effective rate of the portfolio is adjusted to achieve timely portfolio adjustments. Also in the same trading day, except realized volatility matrix calculation methods have been effective combination achieve greater volatility matrix sequence differences resulting frontier, the difference is greater than the differences between the volatility matrix model; it illustrates the volatility rate the importance of matrix estimation, and in the Allocation of assets in the past, mostly focused on the study of asset allocation strategy or volatility model at the expense of volatility calculation method of inspection. We find that the volatility matrix calculation method has been implemented a fundamental role in asset allocation in question by empirical analysis.

## 7. Summary

Different sequences realized volatility Volatility matrix correction and noise reduction technology was quite different; and then the parameters of the model and Mean Mean -CAW -HAR-CAW model estimates vary widely. Finally, the objective function obtained by solving an effective portfolio also varies greatly. This conclusion between different arrays have been verified. This shows that the process of making asset allocation, analysis of the process of asset prices is crucial; conventional literature and empirical analysis are the pros and cons of a particular kind of analysis or methods of asset allocation strategy, at the expense of these strategies and analysis of asset prices depend on the characteristics of the establishment of the method. To construct a variety of strategies it is difficult to practice.

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