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Asset Selection Model Based on the VaR Adjusted High-Frequency Sharp Index

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Abstract

This paper uses high frequency intraday data to construct the VaR adjusted high-frequency sharp index model as an efficient method of asset selection and portfolio strategy for the optimal portfolio problem. Both asset selection and perfect weight allocation are key processing. This paper constructs the VaR adjusted high-frequency sharp index to choose stocks, and uses several portfolio strategies to allocate stock weight. Through market data of shanghai stock exchange as out-of-sample empirical, we find that VaR adjusted high-frequency sharp index model can have a better result than high-frequency sharp index model and momentum stock choice model, and portfolio strategies based on the VaR adjusted high-frequency sharp index model have a higher risky return.

Key words: High frequency intraday data; VaR; Sharp index; Portfolio

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INTRODUCTION

As modern asset portfolio theory's beginning, Markowitz (1952) has established average value-variance model in the book Portfolio Selection that is published in the year of 1952. The model proposed effective front theory, provided theoretical basis for the investors. Markowitz's most superior investment portfolio relies on the risk asset expectation returns ratio and covariance matrix, which actually cannot be performed by their real values, but only are estimated by the historical market data. The traditional average value-variance model will enlarge the expectation returns ratio error that enables result of optimal portfolio seriously different to real optimal portfolio, in some cases, equal weight portfolio performance surpasses the global superior optimal portfolio. Best et al. (1991) has carried on the sensitive analysis to input variable, and discovers that small perturbation of input variable possibly causes the violent result. Kan et al. (2007) points out that optimal solution from estimators possibly is very bad result, because when we solve the average value-variance problem, first, we need to estimate the covariance matrix of returns ratio, then seek the covariance matrix counter, but the property quantity in the investment portfolio often contain many property and have certain relevance with returns ratios (Kourtis et al., 2012).

Different to previous research, this article uses the high-frequency intra-day data to construct a VaR adjusted sharp index series. This question of total cash limit can be transformed to the return question with punishment, which can be solved effectively. According to this mentality, we put the newly constructed high-frequency Sharp index in the frame of return question to carry on the property choice, then determine the portfolio weight to obtain the most superior asset portfolio. It makes several advantages: First, through constructing new index and adjusting its stock component every day, we can get the index series that can not only catch the momentum effect, but also eliminate the influence of the reversal effect in certain extent; second, we put this index into the return question, our procedure solutions can design the quantity of investment portfolio with any number of stocks, this has very strong practical value; third, the selected stocks according to VaR adjusted high-frequency sharp index series have good risk return characteristic. This article's content arrangement is as follows: The first part introduces that the structure of VaR adjusted high-frequency sharp index series, and takes it as a new property of the market to carry on the property choice; the second part gives the construction of superior asset portfolio strategy; the third part carried on out-of-sample empirical analysis based on our market's stock data; the last part has a summary to this article.

1. MODEL OF VAR ADJUSTED HIGH-FREQUENCY SHARP INDEX SERIES CONSTRUCTION

The Sharp Index is an indicator of the performance of an asset and describes the level of earnings per unit of risk over a period of time. In practice it often sets a benchmark, such as a risk-free rate or market index, and calculates the sharp index with excess return and risk of assets relative to the benchmark.

$$SR_p = \frac{R_p - R_B}{\sigma_p}. \quad (1)$$

Where SR_p denotes Sharp index of the combination, R_p is the return rate of the portfolio during the inspection period, R_B is the benchmark rate of return of the market index during the same time, σ_p is the standard deviation of the asset portfolio during this period.

Consider t = 1, 2... T, for the securities i in the market, using the rate of return of the market index as the basis, and using the daily data to define the Sharp Index securities i in th day:

$$SR_{i,t} = \frac{R_{i,t} - R_{m,t}}{\sqrt{RV_{i,t}}}. \quad (2)$$

Where $R_{i,t}$ is the yield of the securities i in the th day, $R_{m,t}$ is the rate of return of the market index at time t, and $RV_{i,t}$ is the Realized volatility (Andersen et al., 2001) of the securities i in the th day :

$$RV_{i,t} = \sum_{j=1}^{M} {r_{t,j}^{i}}^{2}. \quad (3)$$

$r_{t,j}^{i} = lnP_{t,j}^{i} - lnP_{t,j}^{i}$ is the intraday high frequency yield of the securities i, where $P_{t,j}^{i}(j = 1,2,\dots,M)$ represents the j transaction price data for the th day, and M is the number of sampling in day.

For the th day, through the sharp index of each security from the above formula, and we select stocks, the return rate of th day as: $R_{1,t},\dots,R_{n,t}$, at time , the market value of the securities i as $MV_{i,t}$, then based on the Sharp Index we select stocks and build a new rate of return sequence in accordance with the market value:

$$R_{SR,t} = \sum_{i=1}^{n_t} P_{i,t} R_{i,t}, t = 1,2,\dots,T. \quad (4)$$

Where, $P_{i,t} = \frac{MV_{i,t}}{\sum_{i=1}^{n_t} MV_{i,t}}$. Equation (4) is called high-frequency sharp index, because every day the selected securities have a high risk of return, so this index has a higher risk of return.

The market value based on the VaR adjustment is expressed as: $\widehat{MV}_{\text{VaR}}(\gamma)$. The volatility of the stock price is finally reflected in the market value. Assuming that the volatility of the price is subject to the normal distribution, MV is a normal random variable and satisfies the normal distribution: $N\left(\widehat{MV}, \hat{\sigma}^2\left(\widehat{MV}\right)\right)$. Given a lower probability of a probability α (for example, 5%) $\widehat{MV}_{\text{VaR}}(\gamma) = \widehat{MV} - \gamma\hat{\sigma}\left(\widehat{MV}\right)$, it can also be said that the probability of MV falling into this threshold. Less than or equal to α / 2 (Chun et al., 2013; Ma et al., 2015).

The larger γ value penalizes the distant market value and obtains a more credible estimate; on the other hand, if the value of γ is too large, the result of the portfolio may not be credible

Based on the VaR adjusted market value, $\widehat{MV}_{\text{VaR}}$, in fact is to replace the calculation of the MV, other steps just follow the original calculation method, you can calculate VaR adjusted high frequency Sharp index.

$$\hat{R}_{SR,t} = \sum_{i=1}^{n_t} \hat{P}_{i,t} \hat{R}_{i,t}, t = 1,2,\dots,T. \quad (5)$$

Where, $\widehat{P_{i,t}} = \frac{\widehat{MV}_{i,t}}{\sum_{i=1}^{n_t} \widehat{MV}_{i,t}}$.

2. ASSET SELECTION METHOD

2.1 Asset Selection Method Based on VaR Adjusted High Frequency Sharp Index

Considering the variance as a risk function, the optimal combination problem with total position limit is:

$$\min_{\omega} \omega^T \Sigma \omega$$
$$\text{s.t.}\, \boldsymbol{\omega}^T \mathbf{1} = 1, \|\omega\|_1 \le c. \quad (6)$$

The problem can be translated into the regression issue with penalty items:

Under the condition of $\boldsymbol{\omega}^T\mathbf{1}$=1,

$$\text{var}(\boldsymbol{\omega}^T \boldsymbol{R}) = \min_b E(\boldsymbol{\omega}^T \boldsymbol{R} - b)^2 = \min_b E\left(Y - \omega_1 X_1 - \cdots - \omega_{p-1} X_{p-1} - b\right)^2. \quad (7)$$

Where is the rate of return of a certain securities, we can set: the corresponding: $X_i = R_N - R_i$ (i=1,2,⋯, N-1), and $\omega^* = (\omega_1, \omega_2, \cdots, \omega_{N-1})$, at this time the total position limit conditions $\|\omega\|_1 \le c$ can be expressed as $\|\omega^*\|_1 \le d, d = c - \left|1 - \mathbf{1}^T \boldsymbol{\omega}^*\right|$, then the optimal combination of weight problems can be transformed into a least squares problem with constraints:

$$\min_{b,\ \|\omega^*\|_1 \le d} E\left(Y - {\omega^*}^T \boldsymbol{X} - b\right)^2. \quad (8)$$

Where $X = (X_1, X_2, \cdots, X_{N-1})^T$.

It is typical LASSO problem, for $d \geq 0$, Efron el at. (2004) proposed the minimum angular regression (LARS) algorithm can solve this problem efficiently.

The VaR adjusted high-frequency Sharp Index series has a good risk-return feature. It is used as the asset Y in the above equation. Thus, through the LARS-LASSO algorithm, we can select a certain number of securities from the securities to track this index, and then achieve the purpose of asset selection.

2.2 Construction of Optimal Portfolio

After the choice of assets, we need to determine the investment weight of each asset in the combination. In this paper, the variance is used as the risk measure to determine the optimal combination. Considering the actual situation of China's securities market, our combination strategy adopts the situation that is not allowed to be short. In this section, we use the symbols in the previous section, ω, $\sum$, μ respectively represent the portfolio's weight of the assets, the variance covariance matrix and the expected return vector. Assume that the number of assets selected by the previous section is P.

The optimal mean-variance problem is:

$$\begin{gathered} \min_{\omega} \omega^T \sum \omega \\ \text{s.t.}\, \boldsymbol{\omega}^T \mathbf{1} = 1, \omega^T \mu = r^*, \\ 0 \leq \omega_i \leq up_i, i = 1,2,\cdots,P. \end{gathered} \tag{9}$$

Where r^* is the target return, up_i(i=1,2,⋯,P) is the upper limit of the weight for each stock. The problem can be solved by using the quadratic programming directly. We can remove the $\omega^T\mu=r^*$ in the above optimization problem to obtain the global optimal solution, which is called the global minimization mean-variance combination.

3. EMPIRICAL ANALYSIS

3.1 Empirical Description

In this paper, we use the non-ST stock data of the A-share market of China's Shanghai Stock Exchange from April 2014 to June 2016 for a total of 490 trading days. Taking into account the reference method, we choose the method of momentum strategy of stock selection, compare the high-frequency Sharp Index selection method with the VaR adjusted high-frequency Sharp Index selection method, and select 20,40,60,80 stocks to build a combination. For each stock selection method, the combination strategy uses the methods described in the previous section: global optimization variance combination and equal weight combination.

The stock selection method and portfolio strategy is as follows:

Table 1
Symbols of the Stock Selection Method and Portfolio Strategy

Stock selection method	Symbol
1. Momentum stock selection	MT
2. high-frequency Sharp Index selection method	SR
3. VaR adjusted high-frequency Sharp Index selection method	VARSR
Combination strategy	
Equal weight combination	EW
Global optimization variance combination	GMV

We use the rolling window approach (Dei et al., 2009) to evaluate the out-of-sample performance of the proposed portfolio. Specifically, the weight of the combined strategy is reallocated every month, and for each t, we use the data of t-M, t-M + 1 ... t-1month to calculate the weight of each combination strategy. The first combination uses the data from July 2014 to December 2014 to select the stock and build the portfolio, and then in January 2015 hold the portfolio to record its daily rate of return. As a result of monthly rolling, we use the rolling method from July 2014 to May 2016 data to construct portfolio, and forecast the gains from January 2015 to June 2016.

The mean and standard deviation of the corresponding yield series are expressed by and respectively.$\widehat{\mu_m}$ is the daily average return of the CSI 300 index during the study period. We calculate the performance of the out-of-sample:

Variance: σ $\hat{\sigma}^2$, (10)

Sharp Index: $\widehat{SR}_s = \dfrac{\hat{\mu} - \widehat{\mu_m}}{\hat{\sigma}}$. (11)

In addition, when we calculate the sharp ratio of single stock, we get the volatility from the realized volatility estimated by the intraday high-frequency data, so we need to determine the sampling frequency of the data in day, Zhang et al. (2005) and Bandi et al. (2006) have studied the optimal sampling frequency. Guo et al. (2006) has studied the optimal sampling frequency of the "realized" fluctuation. This article refers to the literature and has selected 15-minute sampling frequency to calculate the "realized" fluctuations (Xu & Zhang, 2004).

3.2 Empirical Result

Based on the above-mentioned method of index construction, the high-frequency Sharp Index and the VaR adjusted high-frequency Sharp Index return rate from July 2014 to May 2016 are obtained. The average return rate of the two series is 4.52×10^{-4} ,3.63×10^{-4}, while the average intraday returns of the CSI 300 are -0.47×10^{-4}. It can be seen that the index series that we construct has a good risk-return feature.

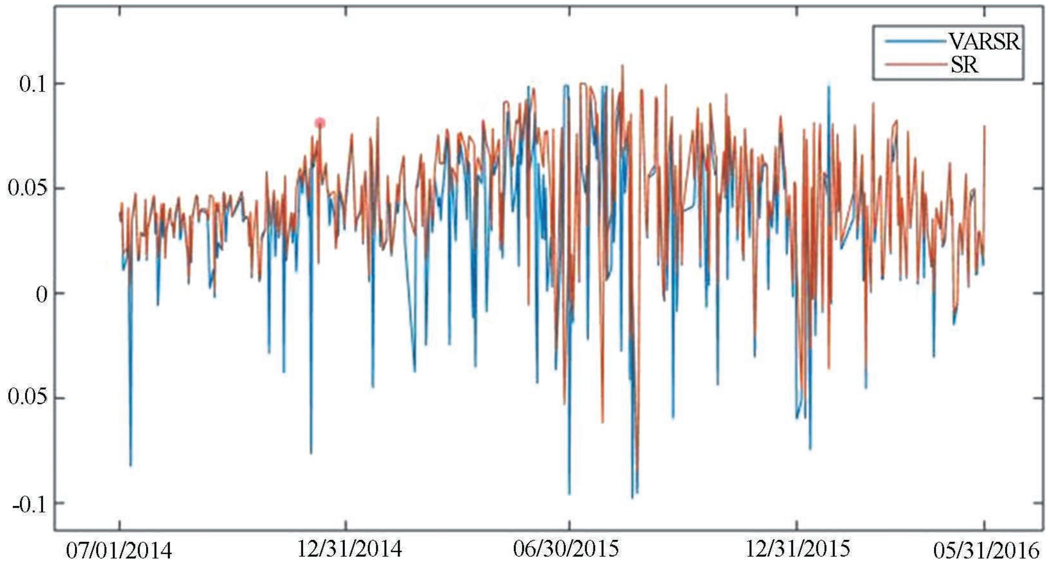

Figure 1
Yield Sequence Based on the SR and VARSR Stock Selection Method

3.3 Out-of-Sample Variance

The table shows the variance of the portfolio with 20, 40, 60 and 80 stocks in different strategy of stock selection method.

Table 2
Variance of Each Combination Strategy

Variance of each combination strategy(%)					
Method	Strategy	20 stocks	40 stocks	60 stocks	80 stocks
MT	EW	0.0798	0.0742	0.0714	0.0705
	GMV	0.0749	0.0694	0.0695	0.0664
SR	EW	0.1050	0.0950	0.0890	0.0752
	GMV	0.0831	0.0679	0.0469	0.0370
VARSR	EW	0.0734	0.0627	0.0638	0.0634
	GMV	0.0596	0.0352	0.0332	0.0311

From the above Table 2, we can find that: a) Compared with momentum stock selection, the optimal combination constructed by equal weight strategy of SR method has a larger variance, but the global optimal combination strategy has lower variance, it shows that SR selection method does have the characteristics of high risk return, and the selected assets still have a high risk. But the equal weight strategy and global optimal strategy of the VARSR stock selection method have smaller variance, which suggests that the VaR adjusted high-frequency sharp index's asset selection method can withstand some potential risks. The momentum stock selection method is based on the early gains of the stock with the possibility of bigger stock fluctuations, so it makes the combination strategy facing greater risk. b) Ccombination strategy, GMV strategy has smaller risk than the combination of EW strategy, GMV combination strategy can reduce the potential risk.

3.4 Out-of-Sample Sharp Index

Now considering the risk gains for each combination strategy. The following table shows the Sharp index of the out-of-sample, where the daily return on the CSI 300 index is for the entire sample period.

From Table 3, we can find that: a) For the EW combination strategy, SR stock selection method is far superior to the momentum stock selection method, VARSR stock selection method is better than the first two methods.

Table 3
Sharp Index of Each Combination Strategy

Sharp index of each combination strategy					
Method	**Strategy**	**20 stocks**	**40 stocks**	**60 stocks**	**80 stocks**
MT	EW	0.0139	-0.0013	0.0078	0.0070
	GMV	-0.0192	-0.0151	-0.0154	0.0090
SR	EW	0.0370	0.0412	0.0469	0.0772
	GMV	0.0217	0.0356	0.0613	0.1316
VARSR	EW	0.0581	0.0744	0.0608	0.0628
	GMV	0.0630	0.0991	0.1126	0.1047

Throughout the inspection period, SR stock selection method has a good overall risky return, VARSR stock selection method makes stock risk gains been further improved, while the momentum stock selection method makes the overall poor performance because of the volatility of the selected stock. b) For the GMV strategy, when the number of selected stock is small, the risk gain of the GMV strategy is less than the risk return of the EW strategy in the momentum stock selection method and SR stock selection method. When the number of selected stocks is large, the GMV strategy gets greater risk return than the EW strategy risk return. In the momentum stock selection method and SR stock selection method, the selected stock volatility is large, and when the number of stocks increases, the overall volatility reduces; in the VARSR stock selection method, the risk return of GMV strategy is significantly higher than that of the EW strategy.

3.5 Cumulative Return and Excessive Return

The cumulative return of 20, 40, 60, and 80 stocks, and the excessive returns relative to the CSI 300 index during the period of out-of sample.

Table 4
Cumulative Return of Each Combination Strategy

Cumulative return of each combination strategy(%)					
Method	**Strategy**	**20 stocks**	**40 stocks**	**60 stocks**	**80 stocks**
MT	EW	12.59	-3.04	10.93	5.09
	GMV	-20.83	-16.17	-16.52	6.72
SR	EW	41.88	44.46	49.19	75.34
	GMV	21.05	32.08	46.61	90.49
VARSR	EW	55.61	66.13	54.20	55.83
	GMV	54.25	65.97	72.99	65.54

Through Table 4, we can find: a) for the stock selection method, the cumulative return of SR and VARSR stock selection method is better than that of momentum stock selection method, and SR and VARSR stock selection method in the two strategies can get better accumulated return; the overall VARSR stock selection method can have better performance than the SR stock selection method, but when selecting larger number of stocks, SR stock selection method performance is more prominent. b) For the combination strategy, the EW strategy is better than the GMV strategy in the MT and SR stock selection methods. However, in the VARSR stock selection method, the GMV strategy is superior to the EW strategy, which means that in the MT and SR stock selection method, In order to reduce the global risk, the GMV strategy reduces the return, the risk of selected stocks is obvious. In the VARSR stock selection method, GMV strategy obtains higher returns and seeks more effective asset allocation strategy while reducing global risk.

Table 5
Excessive Return of Each Combination Strategy

Excessive return of each combination strategy(%)						
Method	**CSI300 cumulative return**	**Strategy**	**20 stocks**	**40 stocks**	**60 stocks**	**80 stocks**
MT	-1.71	EW	14.30	-1.33	12.64	6.79
		GMV	-19.12	-14.46	-14.81	8.43
SR	-1.71	EW	43.59	46.17	50.90	77.05
		GMV	22.76	33.79	48.31	92.20
VARSR	-1.71	EW	57.32	67.83	55.91	57.54
		GMV	55.96	67.67	74.69	67.25

Through Table 5, we can find: a) In the MT stock selection method, when the number of selected stocks is large, it can outperform the index, but compared with the SR and VARSR stock selection method, poor performance. b) When the number of the selected stocks is small, VARSR selection method has better performance than that of the SR stock selection method. However, when the number of stocks is large, the SR stock selection method is superior to the stock selection method of VARSR.

Figures of cumulative return of selected 20, 40, 60, 80 stocks and CSI300 in different strategy are as follows:

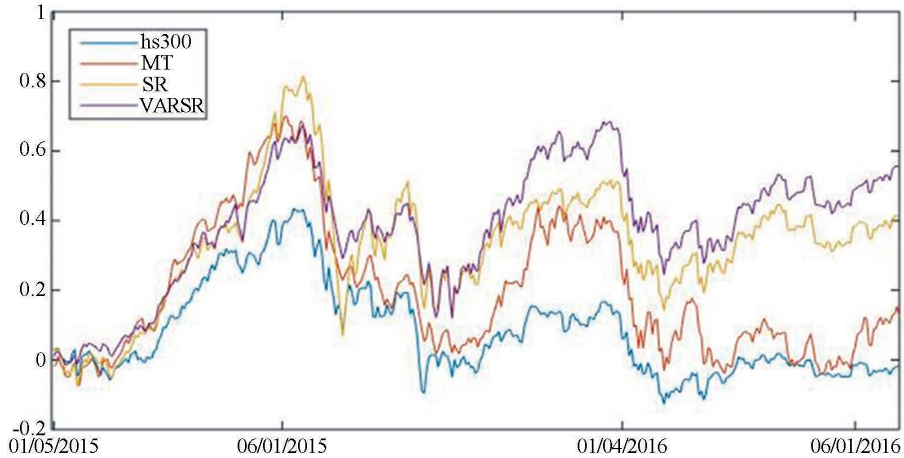

Figure 2
EW Strategy With 20 Stocks

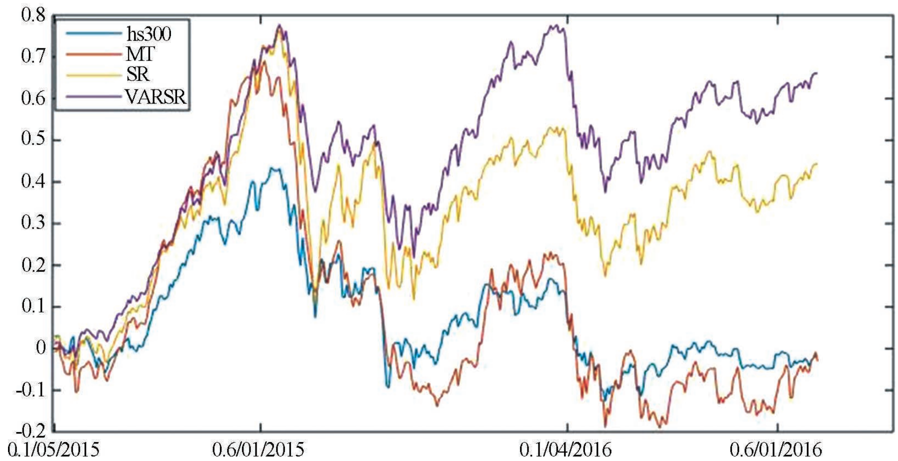

Figure 3
EW Strategy With 40 Stocks

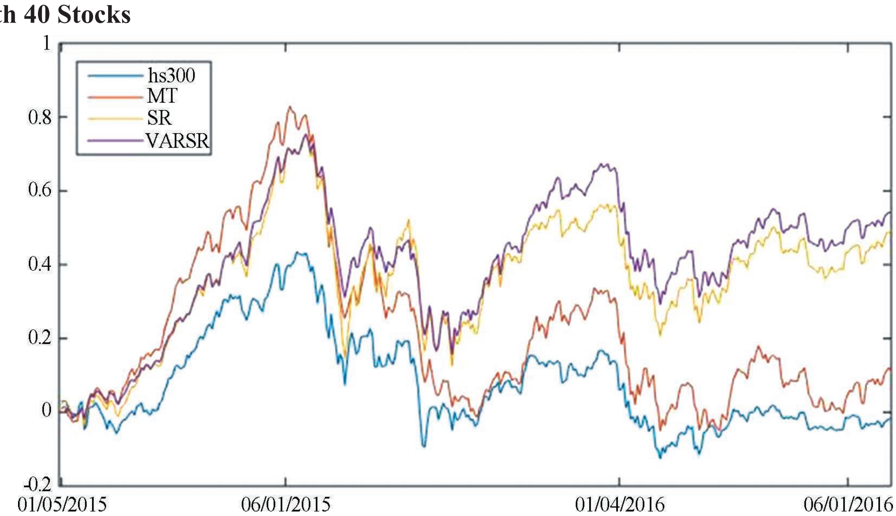

Figure 4
EW Strategy With 60 Stocks

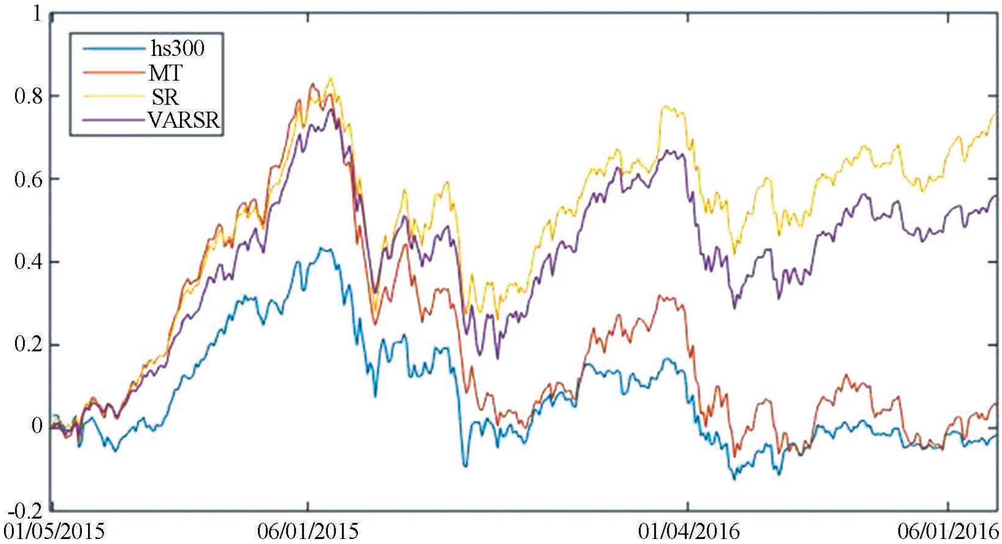

Figure 5
EW Strategy With 80 Stocks

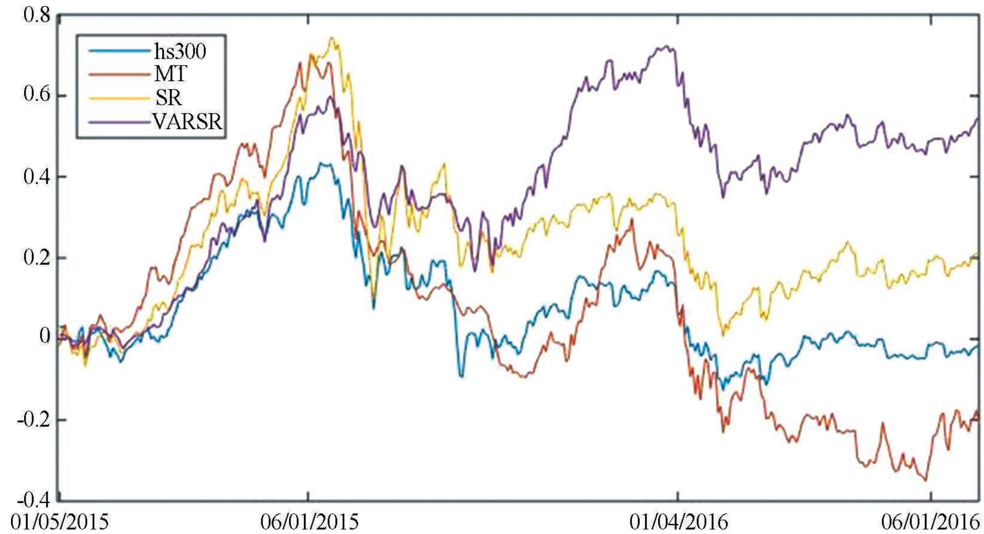

Figure 6
Gmv Strategy With 20 Stocks

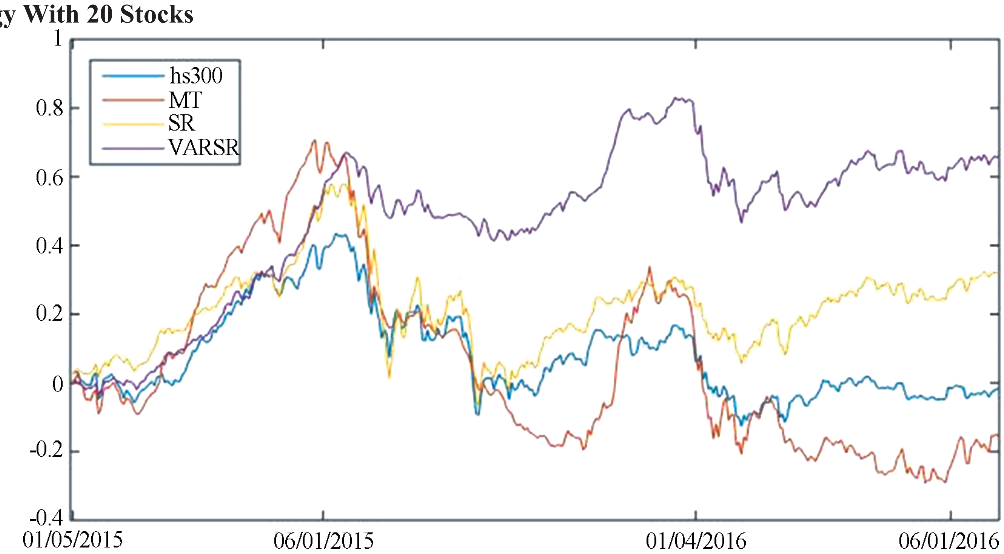

Figure7
Gmv Strategy With 40 Stocks

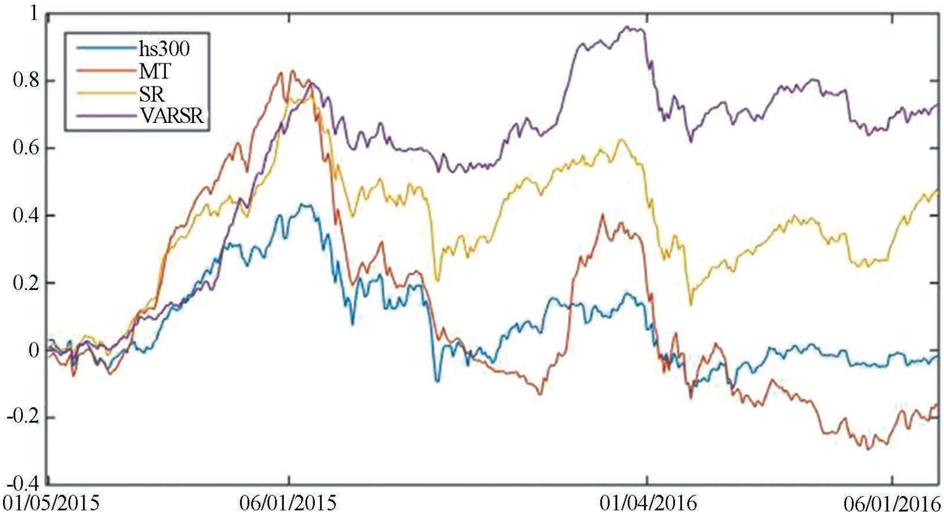

Figure 8
Gmv Strategy With 60 Stocks

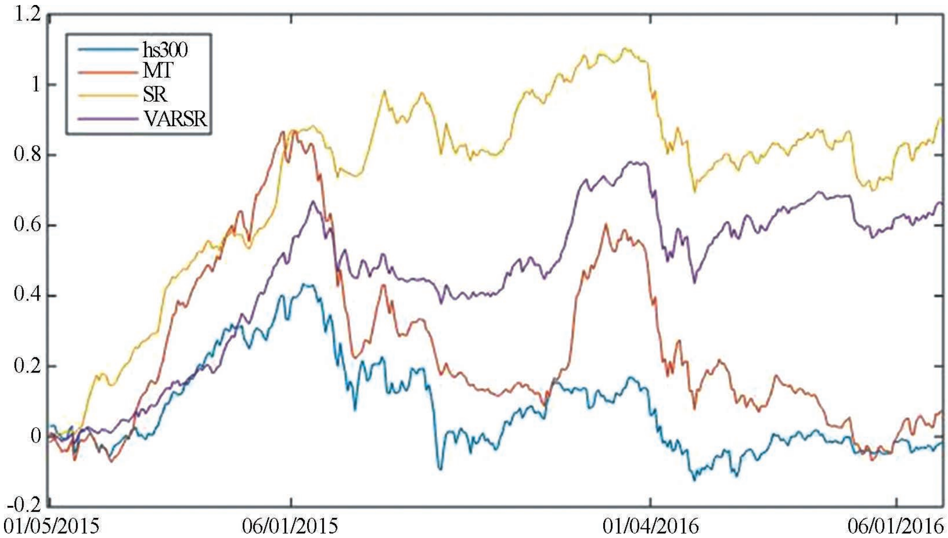

Figure 9
Gmv Strategy With 80 Stocks

CONCLUSION

For investors, how to choose the right assets and build a portfolio is very important and basic problem. In this paper, the whole process is divided into two steps: The first step, we construct the high frequency Sharp index series based on VaR adjustment, and put this index sequence as the typical asset into the market for asset selection; the second step, the optimal portfolio is constructed. Through the out-of-sample empirical study, we find that the stock selection method based on VaR adjusted high-frequency Sharp Index obtains stable and significant excess returns in various combination strategies.

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