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The Risk Management on Alpha Strategy

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Abstract

During the November and December in 2014, the products with alpha strategy in China, which overrode the stock index during the past few years, encountered huge drawdown and many funds liquidated themselves, bringing in great loss to many investors. In this project, we constructed a simplified portfolio to simulate the trading process of alpha strategy and focus on the exogenous and endogenous reasons for this unusual performance. At last, we take advantage of VaR to manage our risk and criticize the manager's lacking necessary risk management.

1. Introduction

Before 2010, investors in Chinese capital market can only long the stocks in the secondary market, as a consequence of which, the return of their capital positions was closely related to performance of the general market. The single investment approach result in a big exposure of market risk for investors, and made them hardly earn profit during the bear market. In April of 2010, the financial derivatives market entered into a new age as the stock index futures are issued, which activates a new trading approach and investment strategy in China. Investors can earn profit through shorting the index futures during the bear market, which helps stabilize capital positions and reduce the market risk exposure. At the same time, Alpha Strategy, a strategy consisting shorting the index and longing the stocks, becomes more and more popular in China. Many funds turned to invest in the capital market by the alpha strategy, with the claim of risk free and high return, and had attracted a lot of investors. The alpha strategy has performed very well for several years. However, at the end of 2014, the funds with alpha strategy suffered a huge loss and many of them stop their services.

1.1. Alpha strategy

Alpha strategy, as a popular investment method during 1980s in USA, is based on CAPM theory, in which the risk of our position can be separated into two parts. One is the market risk and the other is the special risk of different stocks. Mathematically, we have the following equation.

$$r = \alpha + r_f + \beta(r_m - r_f) + \varepsilon$$

In this equation, r is the return of a stock, r_f is the risk free rate, r_m is the return of market index and ε is the residual. In a perfectly efficient market, alpha is significantly close to zero, meaning that we cannot earn a statistically excess return via any portfolio in this market. In reality, especially in such emerging markets such as China Stock Market, alpha is always unequal to zero caused by the inadequate pricing of the stock price.

We can construct a portfolio by buying stocks whose performances are better than others with similar features and selling stock index futures, whose return can be regarded as market return. Then we adjust the capital allocation to make the beta of the portfolio close to 0 to eliminate the market risk.. Through this portfolio, we can almost surely earn a return overriding the stock index by choosing stocks carefully, and earn alpha cumulatively.

In the aspect of implementation, seeking alpha is kind of statistical arbitrage. Specifically, we can choose some stocks whose performance are better than other stocks with similar features in multi-factor regression analysis based on empirical data, and then make use of stock index futures to hedge away the market risk, namely, the risk that all the stocks tend to go up or down simultaneously to some extent, to achieve a goal of earning absolute excess returns.

1.2. Development of alpha strategy in China

After China Shanghai Shenzhen 300 Stock Index Futures was introduced, more and more quant trading strategies are developed in China and, among varies of quant arbitrage strategies, seeking alpha is one of the most popular market-neutral strategies. The number of products with alpha strategy increased by 200% in 2014 alone comparing with that in 2013, and the capital scale increased by more than 50 billion CNY. Many large hedge funds whose capital were more than one billion, running for more than three years achieved an outstanding annual return of 20% with maximum drawdown of 3% during the past years.

However, most of the fantastic P&L curves of alpha products stopped climbing after 7th Nov 2014. Since 10th Nov, SH&SZ 300 Index presenting most of the blue chips in China started skyrocketing. From the same day on, most of the funds using market-neutral strategies became silent in mass media. Also, they ceased to publish their fund's net value and stopped showing up in most of the roadshows.

The market volatility didn't decline until the second week of December, when the prices of many bull stocks began to consolidate. However, it could be found out that most of the products with alpha strategies showed up a drawdown of 10% within just one month. The net value of some products with high leverage even declined sharply to nearly 0 during this period, resulting in large scale of funds redemption. Therefore, people started to think about this scenario. Our group also focus on this issue and try analysing the reasons of the issue and proposing a risk management method on alpha strategy to reduce the risk.

1.3. Value at risk

The main risk measure of this project is the Value at Risk, which is a widely used risk method on a specific portfolio of financial assets because of ease for using. For a given portfolio, time period and probability, the 100p% VaR is defined as a threshold of loss value, the probability for exceeding which is p. usual parameters selected for VaR are 1% or 5% probabilities, one day or two week horizons.

The risk measured by VaR is easy to understand, use and manage, which establishes a standardized benchmark for risk management area. VaR is a great, ground-breaking method, developed basing on probability and mathematical statistics, not only science-based also has easy access for manipulation. Because of its Mathematics foundation, VaR is used widely in finance market, changing the phenomenon that lack of standard risk measure method. In the other hand, VaR can be calculated in advance instead of measuring risk after loss or crisis, reducing finance market risk in general. As to supervision and financial institutions, a specific value of VaR can reflect the risk profile, which becomes a good tool to manage overall risk for top management of company. Nowadays, VaR is applied in many conditions including interest rate risk, currency risk, equity risk, derivatives risk and also as a basic foundation in Basel Accord set by BIS.

2. Methodology and Implementation

In this chapter, we are going to construct a portfolio based on alpha strategy and simulate the trading process in the period of about one year before 23rd December in 2014. We expect to get a P&L line, which increases relatively stable before Nov 2014, and encounters significant drawdown in November and December.

2.1. Stock Selection

We construct a simplified portfolio with longing some shares of specific stocks and shorting some shares of stock index futures. We refer to the positions of the open funds in China with alpha strategy and choose 13 popular stocks they used in 2014. The ticker symbols of the stocks we choose are 000768, 300002, 300005, 300137, 002390, 002371, 002241, 600340, 600433, 000970, 002049, 002190 and 002400. The time period of weekly data is chosen from Nov 2010 to Dec 2014. According to the rule of separating data to trading portion and regression portion to be 70% versus 30%, we choose 140 weeks as the moving window to estimate all the parameters we need in the trading period, which is from 30th Sep 2013 to 23rd Dec 2014.

2.2 Portfolio Construction

Base on the data we selected above, the CAPM model is as following.

$$r_{k,i} = \alpha_{k,i} + r_f + \beta_{k,i}\left(r_{k,m} - r_f\right) + \varepsilon_k$$

$$r_{k,i} = \frac{\Delta S_{k,i}}{S_{k,i}}, r_{k,m} = \frac{\Delta m_k}{m_k}$$

Because choosing only one stock includes too much uncertainty, we choose a basket of stocks to simulate the alpha strategy. In the equation above, the return $r_{k,m}$ is the weekly return of a basket of stocks with the same proportion of money on each stock so that we can reduce the idiosyncratic risk of each stock and the portfolio performance may benefit from the diversification.

$$\frac{1}{N}\sum_{i=1}^{N} r_{k,i} - r_f = \frac{1}{N}\sum_{i=1}^{N}\left[\ \alpha_{k,i} + \beta_{k,i}\left(r_{k,m} - r_f\right)\right] + \tilde{\varepsilon}_k$$

where $\tilde{\varepsilon}_k = \frac{1}{N}\sum_{i=1}^{N}\varepsilon_i$ and $\tilde{\varepsilon} \sim N(0, \frac{\sigma_{\varepsilon}^2}{N})$

And r_f is the risk free rate, $r_{k,m}$ is the weekly return of SH&SZ 300 Index, m_k is the value per contract of stock index futures at time k, which is the index multiplied by 300 and $\tilde{\varepsilon}_k$ is the total residual. By doing regression of the market data we can get the estimated $\beta_{k,i}$ and $\alpha_{k,i}$ of the basket (Note: we denote i the week index).

Mathematically, our portfolio balance, or equity is shown as below.

$$P_k = \sum_{i=1}^{N} a_{k,i} S_{k,i} + 0.3 b_k m_k$$

where $a_{k,i} S_{k,i} = a_{k,j} S_{k,j}$, for $i, j \in [1, N], i \neq j$.

In the equation, $a_{k,i}$ is the shares of stock i at time k, b_k is the number of stock index futures contracts at time k, and $S_{k,i}$ is the ith stock price at time k. For the coefficient 0.3, we take into consideration both the margin of 15% of the contract value and cash reserve for margin call at the worst scenario in the history of market index in which the index increased by 15% in one week.

We adjust our portfolio allocation and beta every week. At time k before our portfolio is adjusted, the portfolio market value is as following.

$$F_{k^-} = \sum_{i=1}^{N} a_{k-1,i} S_{k,i} - b_{k-1} m_k$$

After we adjust the portfolio based on the price changes every week, the portfolio market value becomes below.

$$F_{k^+} = \sum_{i=1}^{N} a_{k,i} S_{k,i} - b_k m_k$$

The change of our balance every week, or change of portfolio market value is as following.

$$\Delta P_k = \sum_{i=1}^{N} a_{k,i} * \Delta S_{k,i} - b_k * \Delta m_k$$

Because alpha strategy is beta neutral, our portfolio should have zero beta.

$$X_k \sum_{i=1}^{N} \frac{\beta_{k,i}}{N} = Y_k$$

From the equation above, we can get the recursion and evolution process of our portfolio.

$$\sum_{i=1}^{N} a_{k-1,i} S_{k,i} + 0.3 Y_{k-1} + (m_{k-1} - m_k) * b_k$$
$$= \sum_{i=1}^{N} a_{k,i} S_{k,i} + 0.3 b_k m_k$$

Thus, we can use programmatic method to simulate the whole process of the alpha strategy.

2.3. Risk Management

The main purpose of our group is to identify the exceptions via the performance of the portfolio and propose a risk management method based on the dynamical portfolio VaR.

In fact, as a statistical arbitrage method, alpha strategy is not always risk-free. Basically, we may encounter potential problems such as stock basket choosing, missing high return of market, time choosing to construct portfolio and unperfected hedging.

In our model, we take advantage of how Basel Accord to evaluate the market risk, namely using 99% VaR with normality assumption to do risk management.

Basically, the 99% VaR of our portfolio can be calculated as following.

$$VaR = 2.33 * \sigma_{\Delta p} - \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{\alpha_{k,i} + (1 - \beta_{k,i}) r_f}{N} \times X_k$$

To estimate the portfolio volatility, we can first calculate the volatility of the basket of stocks and carry out regression on the basket and stock index to estimate basket beta. Then we can get the portfolio volatility as following.

$$\sigma_{\Delta p}^2 = \sum_{i=1}^{N} a_{k,i}^2 S_{k,i}^2 \sigma_{r_i}^2 + b_k^2 m_k^2 \sigma_{k,m}^2 + 2 \sum_{1 \le i < j \le N} a_{k,i}^2 S_{k,i}^2 \rho_{k,i,j} \sigma_{k,i} \sigma_{k,j} - 2 \sum_{i=1}^{N} a_{k,i} S_{k,i} b_k m_k \rho_{k,i,m} \sigma_{k,i} \sigma_{k,m}$$

where

$$\rho_{k,i,j} = \frac{\beta_{k,i} \beta_{k,j} \sigma_{k,m}^2}{\sigma_{k,i} \sigma_{k,j}}$$

and

$$\rho_{k,i,m} = \beta_{k,i} \frac{\sigma_{k,m}}{\sigma_{k,i}}$$

During the simulation, we will compare the every-week return with weekly updated 99% VaR to observe the exception.

3. Results and Analysis

We use R code to do the programming and the code is attached in Appendix B.

The flow chart of our alpha strategy is as below.

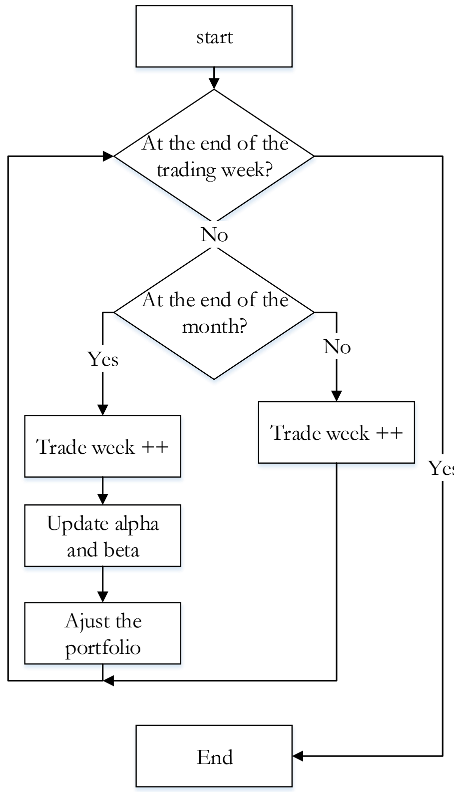

Figure 1: flow chart of alpha strategy

In our trading strategy, we estimate alpha and beta every month and adjust the portfolio allocation to make our portfolio market risk-neutral.

Firstly, we take a glance at the P&L of our portfolio comparing with SH&SZ 300 index. The P&L is shown as following.

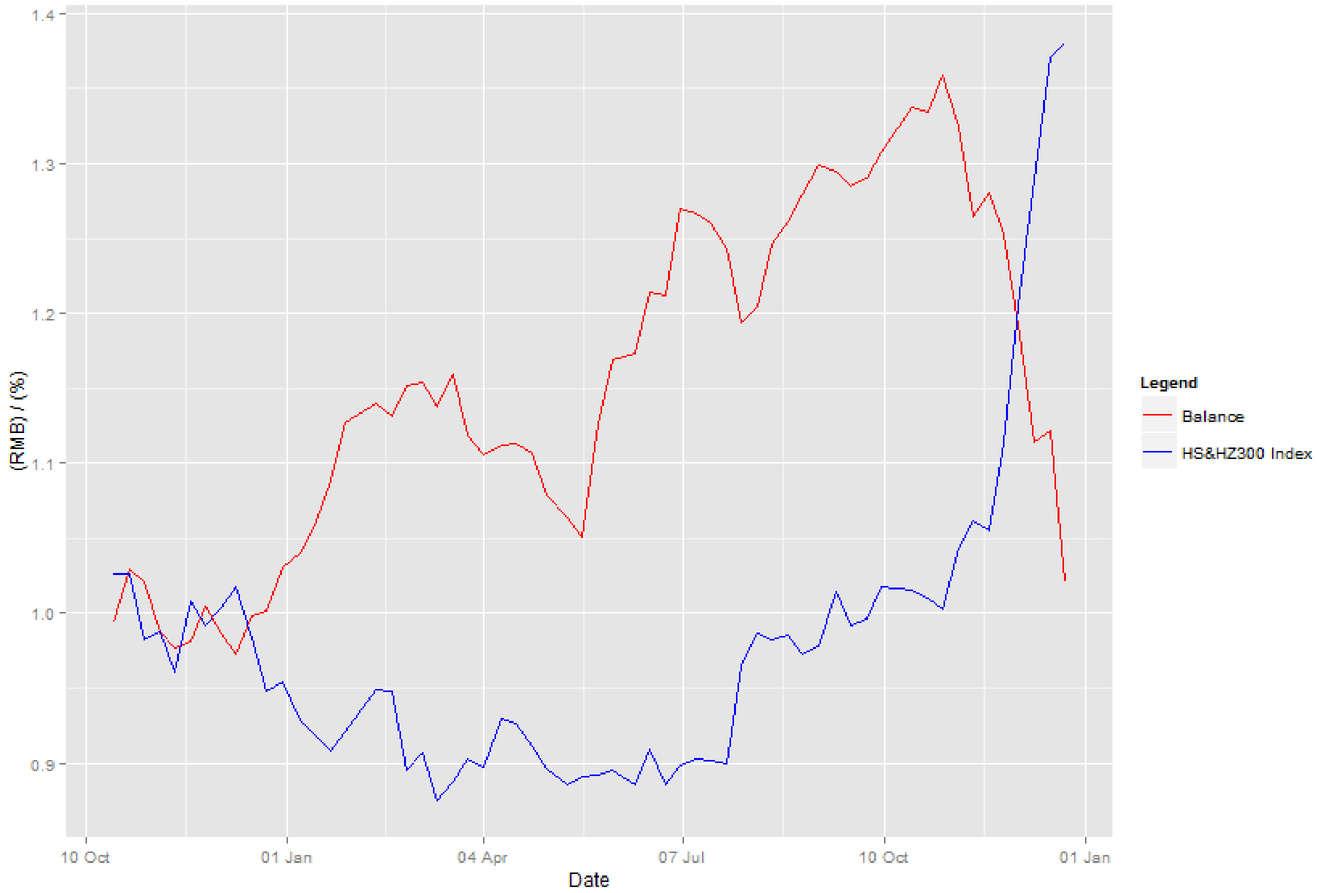

Figure 2: P&L comparing with HS&SZ 300 index

As we can see, before the sharp downside of Nov 2014, our portfolio absolutely overrides the stock index during the corresponding period. During the previous period of the first 40 weeks, when the whole market is weak, we can earn a high return consecutively. Therefore this strategy is indeed efficient and could earn an excess return during the early days of the trading period. As we expect, there is a significant drawdown during Nov to Dec 2014 when the market became bull. It shows that we have successfully reproduced the scenario met by those funds with alpha strategy.

The percentage return of our portfolio is shown below.

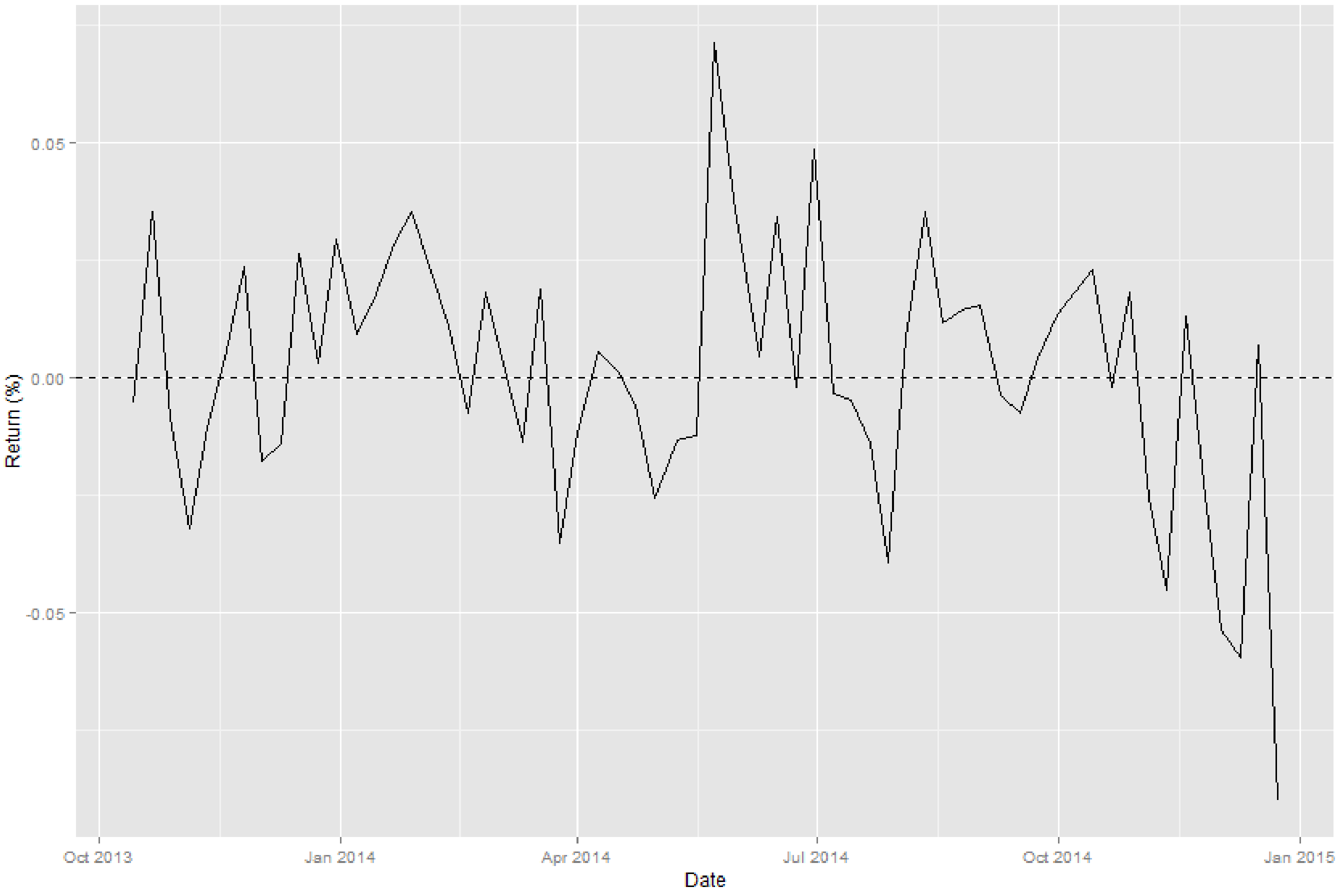

Figure 3: percentage return

From the graph above, we can see the return from the following picture that it stays above zero more than it stays below zero during the simulation period, meaning that we consecutively earn a positive alpha during the trading period. The average annually return of the first 40 weeks is 24.6%. During last 10 weeks of our trading period, the return frequently become a huge negative value, and the average annually return of this 10 weeks is -27.0%

Then, we take a look at the VaR of the portfolio returns comparing with our portfolio return. The comparison of the percentage return and percentage 99% VaR is shown below.

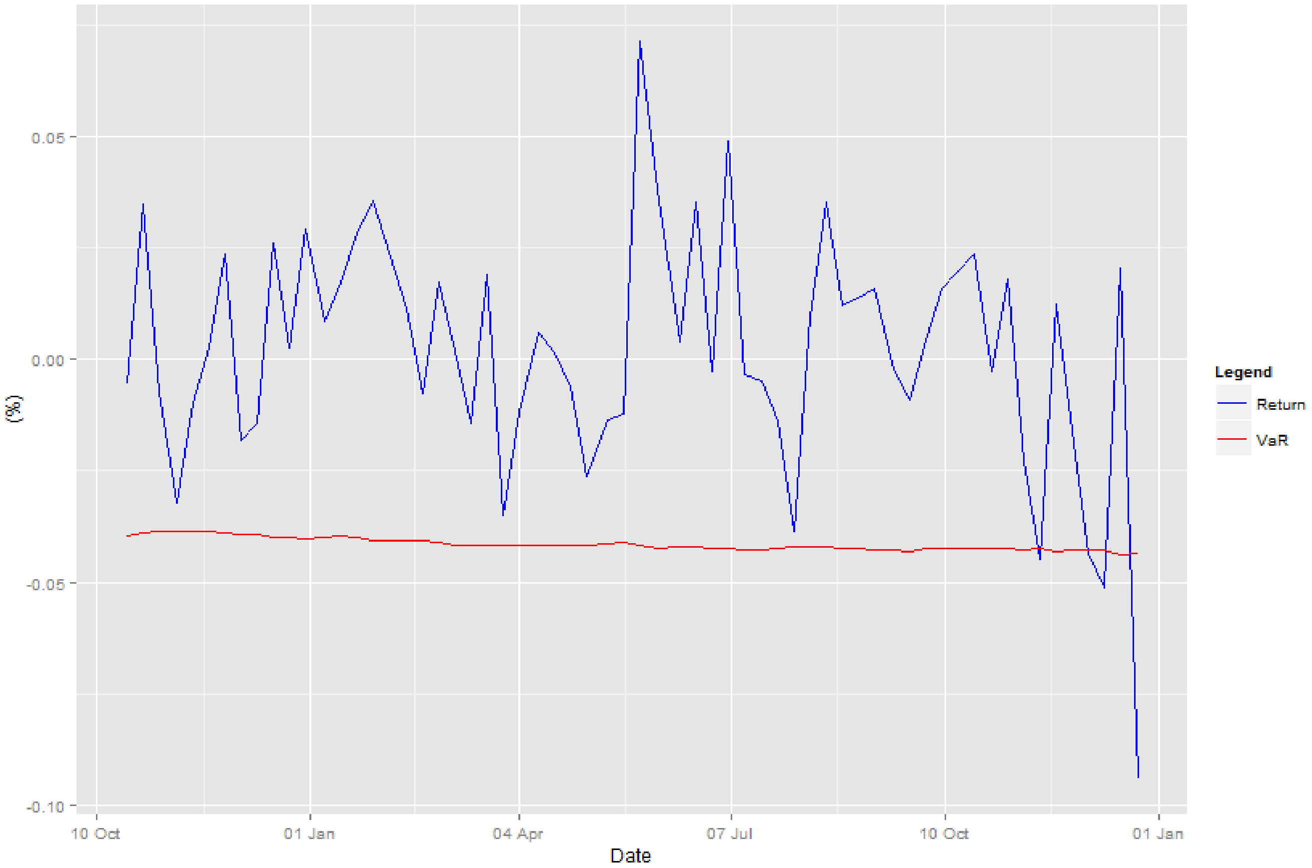

Figure 4: percentage return vs percentage 99% VaR

As we expect, combining with the previous data, there is no VaR exception until November of 2014 and the weekly loss of the portfolio exceeding the corresponding 99% VaR clustered in Nov and Dec 2014. From the chart of last 10 weeks below, we can see that the first exception happens at the 54^{th} week of our trading period, which corresponds to 11th Nov 2014. And after the first exception, another 3 VaR exceptions occur in the next 9 weeks. The frequency of the event of probability of 1% is 40% during the last 10 weeks.

No	Date	Return	VaR	< VaR
51	21/10/2014	-0.00264	-0.04229	FALSE
52	28/10/2014	0.018177	-0.04244	FALSE
53	4/11/2014	-0.02269	-0.04262	FALSE
54	11/11/2014	-0.04484	-0.04241	TRUE
55	18/11/2014	0.012675	-0.04292	FALSE
56	25/11/2014	-0.01775	-0.04257	FALSE
57	2/12/2014	-0.04363	-0.04269	TRUE
58	9/12/2014	-0.05318	-0.04251	TRUE
59	16/12/2014	0.015864	-0.04326	FALSE
60	23/12/2014	-0.09269	-0.04254	TRUE

Data of the whole trading period is in Appendix A.

Scientifically, we can use the conditional coverage model proposed by Christoffersen (1998) to evaluate the validity of the model to see that when we should reject the model and update it.

The formula of the ratio is as following.

$$LR_{uc} = -2\,ln[(1-p)^{T-N}p^N] + 2ln\left[\left(1-\frac{N}{T}\right)^{T-N}\left(\frac{N}{T}\right)^N\right]$$

$$LR_{ind} = -2\,ln[(1-\pi)^{T_{00}+T_{10}}\pi^{T_{01}+T_{11}}] + 2ln[(1-\pi_0)^{T_{00}}\pi_0^{T_{01}}(1-\pi_1)^{T_{10}}\pi_1^{T_{11}}]$$

$$\pi_0 = \frac{T_{01}}{T_{00}+T_{01}} \quad \pi_1 = \frac{T_{11}}{T_{10}+T_{11}} \quad \pi = \frac{T_{01}+T_{11}}{T_{00}+T_{01}+T_{10}+T_{11}}$$

$$LR_{uc} + LR_{ind} \sim \chi^2(2)$$

After simulation, we find that if we refer to this equation, we should reject the null hypothesis that the model is valid at the third time of exceptions, when the $\chi^2(2)$ statistics is 8.67 and the corresponding 95% $\chi^2(2)$ is 5.99. Therefore when the third exception happens, we can infer that the main market features has changed. If we quit this market after the third exception, we can still avoid the fourth exception which leads to -9.41% weekly return and is the biggest loss among our trading period. However, many funds cannot stand the first three huge drawdown at all, which means, some alpha strategy funds may fail after the third exception.

Based on the prudential rule in risk management, we think we should take some measure at the first exception. There should be a lot of methods to deal with the exception occurred. We can evaluate the market and reselect our stocks, or turn to other stable financial investment instruments to reduce the risk exposure. In our trading strategy with risk management, we simply reduce the position on the portfolio and allocate more money on the risk free asset once the exception occurs. The VaR in our trading process is adjusted every week. Every week we will check whether the loss of current week exceeds 99% VaR value. If yes, we will reduce the risky asset and scale out of the risk free asset.

The flow chart of our strategy is shown in the right.

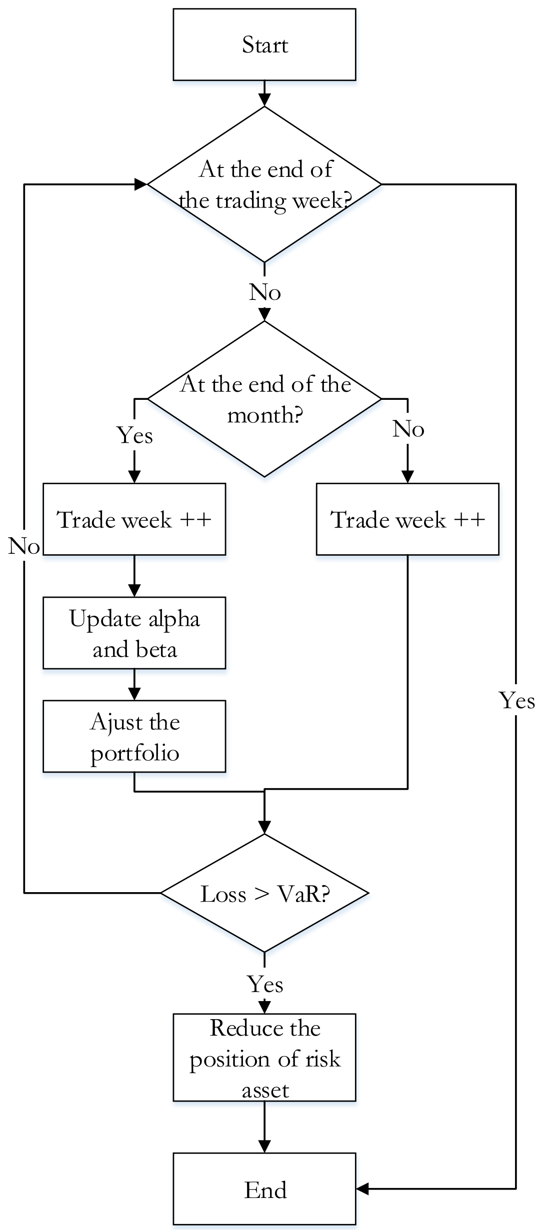

Figure 5: flow chart of alpha strategy with risk management

We suppose that we should transfer 60% of our risky capital into the risk free assets every time the exception happens. The P&L curve with the simple risk control method is shown as below.

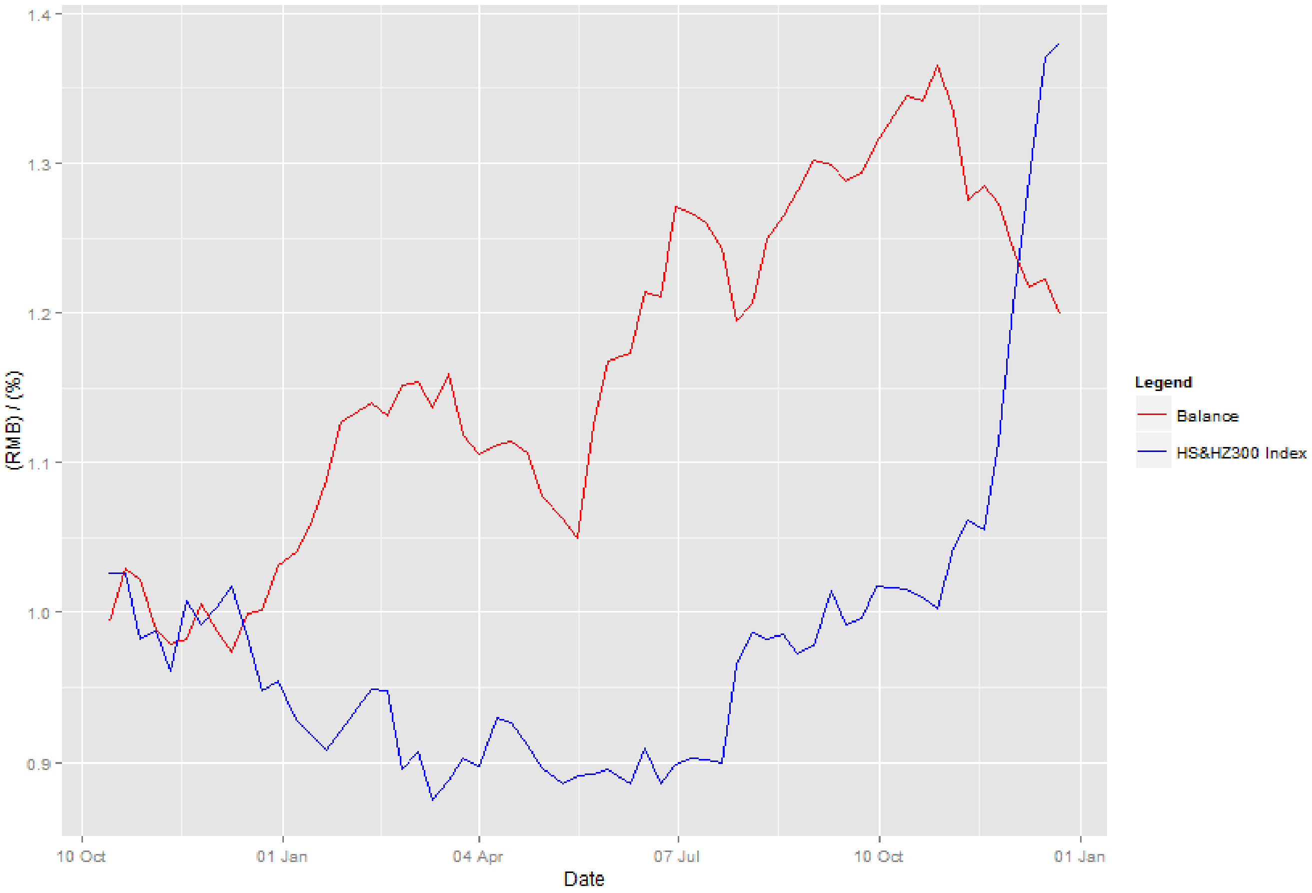

Figure 6: P&L comparing with HS&SZ 300 index with simple risk control method

The final balance of our portfolio is 1.20, much more than 1.06 which is the final balance of the alpha strategy without any risk management.

In a nutshell, the exogenous reason for the significant loss of those funds using alpha strategy is, the market behaviour changed during that period. However, the endogenous reason is the most important trigger for their huge loss, which is that the fund managers didn't take appropriate measure to monitor their market and model risk. In our implementation, we can see that even using some simple risk management method, we can reduce much loss. Thus we think many of the alpha strategy managers didn't have sufficient risk management consciousness or adequate risk control strategy.

4. Conclusion

In our project, we roughly simulate an alpha strategy with shorting SH&SZ 300 index future and longing a basket of 13 stocks to realize the scenario of the alpha strategy funds' performance in China in 2014.

Nevertheless, we are unable to reproduce the scenario perfectly. We fail to take some factors into consideration when establishing our trading model, such as transaction cost, opportunity cost and liquidity factor in our trading process, and the assumption that stocks and contracts are infinitely divisible cannot be realised in the real scenario, contributing to the bias in the simulation. Also, for simplicity, we use normal distribution applying to VaR empirically instead of doing more research because determining a distribution of return is somewhat difficult, with price limit every day in China stock market.

However, from the result of our simulation, we successfully reduce the loss in November and December of 2014 by applying some simple risk management approach based on VaR. The significant positive effect on the portfolio performance show the importance of VaR. It implies that risk management should be essential, important and need-more-attention in no matter what investment methods, alpha strategy, other arbitrage strategies or our own investment. In the reality, those funds managers have more professional knowledge and risk data source to manage the risk of portfolio, if they take more attention on the risk, they would probably reap more benefits.

Risk would be always behind profit, but with VaR or other risk management methods, we believe the tragedy in November 2014 should be able to be avoided.

Reference

[1] L. Pastor.Portfolio selection and asset pricing models[J]. Journal of Finance, 2000(1):179-223.

[2] Chaperon, Christophe. An empirical approach to long/short equity market neutral portfolio management. Short Equity Market Neutral Portfolio Management[J]. Short Equity Market Neutral Portfolio Management, 2010(11):29

[3] Louis Gagnon, George Andrew Karolyi. Multi-Market Trading and Arbitrage[J]. Journal of Financial Economics, 2010(1):97.

[4] Pole, A. Statistical Arbitrage: Algorithmic Trading Insights and Techniques[M].

[5] Qiuyu, D. Empirical study of the alpha strategy quantitative stock in China SME board[D]. Hebei University of Economics and Business,2014.

[6] Xingchen, Z. The alpha arbitrager research on Chinese stock market based on Guotai Tianqi assets management[D]. Harbin Institute of Technology, 2014.

Appendix A

No	Date	Return	VaR	No	Date	Return	VaR
1	14/10/2013	-0.00559	-0.03975	31	23/5/2014	0.071587	-0.042
2	21/10/2013	0.035269	-0.03997	32	30/5/2014	0.03818	-0.04253
3	28/10/2013	-0.00857	-0.03957	33	9/6/2014	0.00412	-0.04212
4	4/11/2013	-0.03219	-0.03956	34	16/6/2014	0.035373	-0.04227
5	11/11/2013	-0.00957	-0.03866	35	23/6/2014	-0.00285	-0.04225
6	18/11/2013	0.002648	-0.03884	36	30/6/2014	0.049426	-0.04266
7	25/11/2013	0.023886	-0.03898	37	7/7/2014	-0.00324	-0.04276
8	2/12/2013	-0.0181	-0.03875	38	14/7/2014	-0.00473	-0.04273
9	9/12/2013	-0.0141	-0.03919	39	21/7/2014	-0.01406	-0.04269
10	16/12/2013	0.026534	-0.03919	40	28/7/2014	-0.03841	-0.04257
11	23/12/2013	0.003592	-0.0389	41	4/8/2014	0.009503	-0.04209
12	30/12/2013	0.029124	-0.03906	42	11/8/2014	0.035474	-0.04226
13	7/1/2014	0.008768	-0.04004	43	18/8/2014	0.012092	-0.04211
14	14/1/2014	0.017573	-0.03985	44	25/8/2014	0.014021	-0.04209
15	21/1/2014	0.028394	-0.04	45	1/9/2014	0.015848	-0.0429
16	28/1/2014	0.035803	-0.04012	46	9/9/2014	-0.00212	-0.04277
17	11/2/2014	0.011465	-0.04074	47	16/9/2014	-0.00861	-0.04253
18	18/2/2014	-0.00751	-0.04058	48	23/9/2014	0.00431	-0.04227
19	25/2/2014	0.017318	-0.0408	49	30/9/2014	0.015824	-0.04233
20	4/3/2014	0.001831	-0.04108	50	14/10/2014	0.023583	-0.04245
21	11/3/2014	-0.01433	-0.0418	51	21/10/2014	-0.00264	-0.04229
22	18/3/2014	0.019194	-0.04206	52	28/10/2014	0.018177	-0.04244
23	25/3/2014	-0.03505	-0.0415	53	4/11/2014	-0.02269	-0.04262
24	1/4/2014	-0.01166	-0.04182	54	11/11/2014	-0.04484	-0.04241
25	9/4/2014	0.006234	-0.04172	55	18/11/2014	0.012675	-0.04292
26	16/4/2014	0.00144	-0.04163	56	25/11/2014	-0.01775	-0.04257
27	23/4/2014	-0.0061	-0.04149	57	2/12/2014	-0.04363	-0.04269
28	30/4/2014	-0.02607	-0.04136	58	9/12/2014	-0.05318	-0.04251
29	9/5/2014	-0.01366	-0.04136	59	16/12/2014	0.015864	-0.04326
30	16/5/2014	-0.01227	-0.04127	60	23/12/2014	-0.09269	-0.04254

Appendix B

```
# equal weighted portofolio
# train period:2010-11-05 ~ 2014-12-23
# trading period: 2013-10-14 ~ 2014-12-23
setwd("~/accomplishment/work/risk management")
# basic parameters
risk_free_rate <- 0.03/52
margin_percent <- 0.3 #margin and reserve
init_wealth <- 1 #initial wealth
init_reserve <- 0
adj_period <- 4
z <- 2.33
reduce_percent <- 1

# basic data processing
week_data = read.csv(file="output_st13.csv", header=T,sep=";")
row_num <- nrow(week_data)
# c("st7","st10","st11","st12","st13")
st_col_name <-
c("st1","st2","st3","st4","st5","st6","st7","st8","st9","st10","st11","st12","st13")
sh_col_name <- c("sh")
st13_data <- week_data[1:row_num,st_col_name]
row_num <- nrow(st13_data) #221
col_num <- ncol(st13_data) #ranges from 1 - 13
sh_data <- week_data[1:row_num,sh_col_name]
date <- week_data[1:row_num,c("date")]

# basic index and numbers of time line
ret_row_num <- row_num - 1
train_begin_ind <- 1
train_end_ind <- 140
train_num <- train_end_ind - train_begin_ind + 1  #104-1+1=104
trad_begin_ind <- train_end_ind + 1
trad_end_ind <- ret_row_num - 20  #200
trad_num <- trad_end_ind - trad_begin_ind + 1 #316-105+1=212

# calculate simple return of sh
sh_diff <- diff(sh_data)
sh_ret <- sh_diff[1:ret_row_num]/sh_data[1:ret_row_num]
ex_sh_ret <- sh_ret - risk_free_rate #316
# calculate simple return of st
st13_ret <- matrix(c(1:(col_num*ret_row_num)),nrow=ret_row_num)
ex_st13_ret <- matrix(c(1:(col_num*ret_row_num)),nrow=ret_row_num)
for (k in 1:col_num)
{
  st_diff <- diff(st13_data[,k])
  st13_ret[,k] <- (st_diff[1:ret_row_num])/st13_data[1:ret_row_num,k]
  ex_st13_ret[,k] <- st13_ret[,k] - risk_free_rate #220
}
st_ret <- c(1:ret_row_num)
ex_st_ret <- c(1:ret_row_num)
for (k in 1:ret_row_num)
{
  st_ret[k] <- sum(st13_ret[k,])/col_num
  ex_st_ret[k] <- st_ret[k]-risk_free_rate
}
#
adj_num <- ceiling((trad_end_ind - trad_begin_ind + 1)/adj_period)

#
st_price <- st13_data[2:row_num,] #2:221,
```

```
sh_price <- sh_data[2:row_num]#2:221
alpha_vec <- 0
alpha_mat <- matrix(c(1:(adj_num*col_num)),nrow=adj_num)
beta_vec <- 0
beta_mat <- matrix(c(1:(adj_num*col_num)),nrow=adj_num)
st_wealth <- 0
sh_wealth <- 0
wealth <- 0
ret_vec <- 0
sigma_st_mat <- matrix(c(1:(trad_num*col_num)),nrow=trad_num)
sigma_mar_vec <- c(1:trad_num)
sigma_port_vec <- c(1:trad_num)
var_vec <- c(1:trad_num)
var_per_vec <- c(1:trad_num)
var_loss_vec <- c(1:trad_num)
wealth_ret_vec <-c(1:trad_num)
reserve <- 0 #once exception happens, we should allocation some money into reserve
account
total_wealth <- 0
total_ret <- 0
for(k in 1:trad_num)
{
  total_wealth[k] <- 0
}
for (k in 1:trad_num)
{
  reserve[k] <- 0
}
variance_sum1 <- c(1:trad_num)
variance_sum2 <- c(1:trad_num)



###### trading simulation starts #####
for(i in 1 : adj_num)
{
  (trad_end_ind - trad_begin_ind + 1)/adj_period
  out_begin_ind <- adj_period*(i-1)+1
  out_end_ind <- out_begin_ind + train_num - 1
  alpha_sum <- 0
  beta_sum <- 0
  for (k in 1:col_num)
  {
    lm_model <-
lm(ex_st13_ret[out_begin_ind:out_end_ind,k]~ex_sh_ret[out_begin_ind:out_end_ind])
    alpha_mat[i,k] <- lm_model$coefficients[1] #intercept-alpha
    beta_mat[i,k] <- lm_model$coefficients[2] #slope-beta
    alpha_sum <- alpha_sum + alpha_mat[i,k]
    beta_sum <- beta_sum + beta_mat[i,k]
  }
  alpha_vec[i] <- alpha_sum/col_num
  beta_vec[i] <- beta_sum/col_num
  #
  in_begin_ind <- (adj_period*(i-1)+1)
  in_end_ind <- in_begin_ind+adj_period-1 #212

  for (j in in_begin_ind : min(in_end_ind,trad_num))# j ranges from 1 to 212, but 4
times each iteration
  {
    beta <- beta_vec[i]
    # construct a portfolio
    if ( j == 1)
```

```
    {
      # at the beginning of the week, we have:
      st_wealth[j] <- init_wealth/(margin_percent*beta + 1)
      sh_wealth[j] <- init_wealth*margin_percent*beta/(margin_percent*beta + 1)
      # at the end of the week
      wealth[j] = init_wealth+st_wealth[j]*st_ret[j+train_num]-
(sh_wealth[j]/margin_percent)*sh_ret[j+train_num]
      ret_vec[j] = (wealth[j] - init_wealth)/init_wealth
      wealth_ret_vec[j] <- init_wealth*ret_vec[j]
      total_wealth[j] <- init_reserve*(1+risk_free_rate)+wealth[j]
      total_ret[j] <- (total_wealth[j] - init_wealth)/init_wealth
    }
    else
    {
      st_wealth[j] <- wealth[j-1]/(margin_percent*beta + 1)
      sh_wealth[j] <- wealth[j-1]*margin_percent/(margin_percent + 1/beta)
      wealth[j] <- wealth[j-1]+st_wealth[j]*st_ret[j+train_num]-
(sh_wealth[j]/margin_percent)*sh_ret[j+train_num]
      ret_vec[j] <- (wealth[j]- wealth[j-1])/wealth[j-1]
      wealth_ret_vec[j] <- wealth[j-1]*ret_vec[j]
      ## for risk management strategy
      reserve[j] <- reserve[j-1]*(1+risk_free_rate)
      total_wealth[j] <- wealth[j] + reserve[j]
      total_ret[j] <- (total_wealth[j]-total_wealth[j-1])/total_wealth[j-1]
      ###############################
    }
    # calculate the Value at Risk
#     # 1.static VaR
#     if(j == 1)
#     {
#       ## calculate the sigma of stocks
#       variance_sum1[1] <- 0
#       variance_sum2[1] <- 0
#       for(kk in 1:col_num)
#       {
#         sigma_st_mat[1,kk] <- sd(st13_ret[1:(1+train_num-1),kk])
#         variance_sum1[1] <- variance_sum1[1] +
(sigma_st_mat[1,kk]^2)*((st_wealth[1]/col_num)^2)
#       }
#       ## calculate the sigma of the market
#       sigma_mar_vec[1] <- sd(sh_ret[1:(1+train_num-1)])
#       variance_sum1[1] <-
variance_sum1[1]+((sh_wealth[1]/margin_percent)^2)*(sigma_mar_vec[1]^2)
#       ## calculate sum2
#       for (k in 1:col_num)
#       {
#         variance_sum2[1] <- variance_sum2[1]-
2*beta_mat[i,k]*(sigma_mar_vec[1]^2)*st_wealth[1]*sh_wealth[1]/(col_num*margin_percen
t)
#       }
#       for (m in 1:(col_num-1))
#       {
#         for (l in (m+1):col_num)
#         {
#           #variance_sum2[1] <-
variance_sum2[1]+2*((st_wealth[1]/col_num)^2)*sigma_st_mat[1,m]*sigma_st_mat[1,l]*Cor
relation(st13_ret[1:(1+train_num-1),m],st13_ret[1:(1+train_num-1),l])
#           variance_sum2[1] <-
variance_sum2[1]+2*((st_wealth[1]/col_num)^2)*(sigma_mar_vec[1]^2)*beta_mat[i,m]*beta
_mat[i,l]
#         }
#       }
```

```
#        ## calculate VaR
#        sigma_port_vec[1] <- sqrt(variance_sum1[1] + variance_sum2[1])
#        var_vec[1] <- sigma_port_vec[1]*z - alpha_vec[i]*init_wealth
#
#        for (k in 1:(trad_num-1))
#        {
#          var_vec[k+1] = var_vec[k]
#        }
#      }


        # 2.dynamic VaR
        ## calculate the sigma of stocks
        variance_sum1[j] <- 0
        variance_sum2[j] <- 0
        for(k in 1:col_num)
        {
          sigma_st_mat[j,k] <- sd(st13_ret[j:(j+train_num-1),k])
          variance_sum1[j] <- variance_sum1[j] +
(sigma_st_mat[j,k]^2)*((st_wealth[j]/col_num)^2)
        }
        ## calculate the sigma of the market
        sigma_mar_vec[j] <- sd(sh_ret[j:(j+train_num-1)])
        variance_sum1[j] <-
variance_sum1[j]+((sh_wealth[j]/margin_percent)^2)*(sigma_mar_vec[j]^2)
        ## calculate sum2
        for (k in 1:col_num)
        {
          variance_sum2[j] <- variance_sum2[j] -
2*beta_mat[i,k]*(sigma_mar_vec[j]^2)*st_wealth[j]*sh_wealth[j]/(col_num*margin_percen
t)
        }
        for (m in 1:(col_num-1))
        {
          for (l in (m+1):col_num)
          {
            #variance_sum2[j] <-
variance_sum2[j]+2*((st_wealth[j]/col_num)^2)*sigma_st_mat[j,m]*sigma_st_mat[j,l]*Cor
relation(st13_ret[j:(j+train_num-1),m],st13_ret[j:(j+train_num-1),l])
            variance_sum2[j] <-
variance_sum2[j]+2*((st_wealth[j]/col_num)^2)*(sigma_mar_vec[j]^2)*beta_mat[i,m]*beta
_mat[i,l]
          }
        }
        ## calculate VaR
        sigma_port_vec[j] <- sqrt(variance_sum1[j] + variance_sum2[j])
        if (j ==1)
        {
          var_vec[j] <- sigma_port_vec[j]*z+alpha_vec[i]*init_wealth+(1-
beta_vec[i])*st_wealth[j]*risk_free_rate
          var_loss_vec[j] <- -var_vec[j]
          var_per_vec[j] <-var_loss_vec[j]/init_wealth
        }
        else
        {
          var_vec[j] <- sigma_port_vec[j]*z+alpha_vec[i]*wealth[j]+(1-
beta_vec[i])*st_wealth[j]*risk_free_rate
          var_loss_vec[j] <- -var_vec[j]
          var_per_vec[j] <- var_loss_vec[j]/wealth[j-1]
        }
        #risk management strategy based on VaR
        if (wealth_ret_vec[j]<(-var_vec[j]))
```

```
        {
          temp_wealth <- wealth[j]
          wealth[j] <- wealth[j]*reduce_percent
          reserve[j] <- ifelse(j==1,0,reserve[j-1])+temp_wealth*(1-reduce_percent)
        }
        else
        {
          reserve[j] <- ifelse(j==1,0,reserve[j-1])*(1+risk_free_rate)
        }

  }
}

##### trading simulation ends #####


plot(1:length(sigma_port_vec),sigma_port_vec,'l')
plot(1:length(total_wealth),wealth,'l')
plot(1:length(alpha_vec),alpha_vec,'l')
plot(1:length(ret_vec),ret_vec,'l')

# graph 1
plot(c(1:trad_num),ret_vec,ylim=c(min(ret_vec,var_per_vec),max(ret_vec,var_per_vec)),
col='red','l')
points(c(1:trad_num),var_per_vec,col='green','l')

# graph 2
plot(c(1:trad_num),total_wealth,ylim=c(min(total_wealth,(sh_price[trad_begin_ind:trad
_end_ind]/sh_price[trad_begin_ind-
1])),max(total_wealth,(sh_price[trad_begin_ind:trad_end_ind]/sh_price[trad_begin_ind-
1]))),'l')
points(c(1:trad_num),sh_price[trad_begin_ind:trad_end_ind]/sh_price[trad_begin_ind-
1],col='red','l')
total_wealth

# for chi test
for (i in 10:length(wealth_ret_vec))
{
  result[i] <- chi_test(ret_vec[1:i],var_per_vec[1:i])
  if (result[i] == 1 && first_oberve_ind==0)
  {
    first_oberve_ind <- i
  }
}

# calculate monthly return
month_ret_vec <- 0
for (k in 1:(trad_num/4))
{
  month_ret_vec[k] <- mean(ret_vec[(4*(k-1)+1):(4*k)])*12
}

# the function to calculate the correlation
Correlation<- function(x,y) {
  len<-length(x)
  if( len != length(y))
    stop("length not equal!")

  x2 <- unlist(lapply(x,function(a) return(a^2)))
  y2 <- unlist(lapply(y,function(a) return(a^2)))
  xy <- x*y
```

```
  a <- sum(xy)*len - sum(x)*sum(y)
  b <- sqrt(sum(x2)*len - sum(x)^2)*sqrt(sum(y2)*len - sum(y)^2)
  if( b == 0)
    stop("data is incorrect!")
  return(a/b)
}

# the function for chi-square test
# x <- wealth_ret_vec
# y <- var_loss_vec
chi_test <- function(x,y)
{
  # x <- wealth_ret_vec[1:10]
  # y <- var_loss_vec[1:10]
  p <- 0.01
  chi_test_result <- 0
  len<-length(x)
  T <- len
  T00 <- 0
  T11 <- 0
  T10 <- 0
  T01 <- 0
  index <- 0
  index <- ifelse(x<y,1,0)
  N <- sum(index)
  if( len != length(y))
    stop("length not equal!")
  for (i in 2:len)
  {
    if (index[i] == 1)
    {
      if (index[i-1] == 1)
      {
        T11 <- T11 + 1
      }
      if (index[i-1] == 0)
      {
        T01 <- T01 + 1
      }
    }
    if (index[i] == 0)
    {
      if (index[i-1] == 0)
      {
        T00 <- T00 + 1
      }
      else
      {
        T10 <- T10 + 1
      }
    }
  }
  a <- T10 + T11
  b <- T01 + T11
  uc_1 <- ((1-p)^(T-N))*(p^N)
  uc_2 <- ((1-N/T)^(T-N))*((N/T)^N)
  lr_uc <- -2*(ifelse(uc_1==0,-1000,log(uc_1)))+2*(ifelse(uc_2==0,-1000,log(uc_2)))
  lr_ind <- 0
  pi1 <- ifelse(a==0,0,(T11/a))
  pi0 <- T01/(T00+T01)
  pi <- b/(T00+T01+T10+T11)
  if(pi != 0 &&pi1 !=0 && pi0!=0)
```

```
  {
    ind_1 <- ((1-pi)^(T00+T10))*(pi^(T01+T10))
    ind_2 <- ((1-pi0)^T00)*(pi0^T01)*(1-pi1)^T10*(pi1^T11)
    lr_ind <- -2*ifelse(ind_1==0,-1000,log(ind_1))+2*ifelse(ind_2==0,-
1000,log(ind_2))
  }
  ratio=lr_uc+lr_ind
  print(ratio)
  #   if (lr_uc > 3.84)#3.84
  #   {
  #     chi_test_result <- 1
  #   }
  if(ratio > 5.99)
  {
    chi_test_result <- 1
  }
  return(chi_test_result)
}
first_oberve_ind <- 0
result <-0
result[1:9] <- 0

# variables to be observed
first_oberve_ind
total_wealth

# write to xlsx
# library(xlsx)
# ifelse(ret_vec[1:60]<var_per_vec[1:60],1,0)
# return_data <- data.frame(ret_vec,-var_per_vec,(ret_vec<var_per_vec))
# write.xlsx(return_data,"~/accomplishment/work/risk management/return_data.xlsx")
```