An Empirical Study of Value at Risk in the Chinese Stock Market

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Abstract

Nowadays, value at risk (VaR) has developed into a standard indicator in the financial risk measuring field. The aim of this study is not only to measure the risk of the Chinese stock market using VaR methods, but also to value whether the downside risk is priced in the expected return in the market. This study estimates VaR of six indices using four approaches at both 95% and 99% confidence levels. Then by conducting the Kupiec backtest, we find the best fitted method for each sample. We conclude that the approach of historical simulation with volatility is the best one for most of the samples, and the non-parametric methods fit much better than the parametric ones in the Chinese stock market. Furthermore, this study uses these best VaR estimates to test the intertemporal risk-return trade-off between the downside risk and the expected return. The positive risk-return relation is proved when we consider control variables, which are the one-month-lag return and a dummy variable for financial crisis.

Key words: the Chinese stock market, value at risk, Kupiec test, risk-return relationship

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1. Introduction

Over the past decades, value at risk (VaR) has developed into a standard indicator in risk management, particularly in the financial risk measuring field. For a given portfolio with probability (confidence level α) and time horizon, VaR is defined as the smallest loss value such that the probability of a future loss on the portfolio which is larger than the value, is not more than 1-α over the given time horizon (Jorion, 2007).

In the beginning, people used traditional asset and liability management (ALM) method to manage risk. ALM model depends too much on the analysis of financial statements, and it is quite abstract to use variance and β to measure the risk. In addition, the capital asset pricing model (CAPM) does not take financial derivative products into consideration. The previous conventional methods were unable to define and measure financial risk accurately. Subsequently some major financial institutions started working on aggregate risks into one system, among which, the best known one was come up with by J.P. Morgan in "4:15 report". Thus, value at risk appeared in the early 1990s. Almost at the same time, G30 indicated the interpretation of VaR and its huge potential in its reports. In the following years, VaR developed rapidly and became the industry standard of measuring risk. In 2001, the Basel II actuated banks and other financial institutions to adopt VaR as a reported indicator (Dowd, 2005).

Nowadays, there have been already various methods to estimate VaR, including traditional and modern approaches. Mature methods, such as Weighted Historical Simulation (Boudoukh et al., 1998), Filtered Historical Simulation (Barone-Adesi et al., 1999), Conditional VaR (Rockafellar and Uryasev, 2000), VaR under *t*-distribution and VaR under normal distribution, can already forecast VaR accurately. Meanwhile, there are also some new approaches being developed in recent years. All above methods devote to make VaR more efficient.

With the development of VaR, several researchers go further. For example, some

scholars investigate the intertemporal relationship between VaR and expected return, Bali et al. (2009) strongly proved that VaR and expected return have a positive relation. The original model named intertemporal capital asset pricing model (ICAPM), which was come up by Merton (1973). During the recent years, the model was developed to test risk-return trade-off which in a stock market means that the more a market index fall in value, the higher the expected return.

Plenty of papers (Hendricks, 1996; Linsmeier & Pearson, 2000 and Campbell et al., 2001) estimate VaR for stock markets in US and western countries, using data such as S&P500, Dow Jones Industrial Average Index and NASDAQ Composite Index. However, not so many researchers adopt data from the Chinese stock market. In addition, based on the previous researches, there should be a trade-off between risk and return (Scruggs, 1998). Bali et al. (2009) reported that there is a significantly positive relation between downside risk and expected return in American stock markets. Atilgan and Demirtas (2013) concluded higher expected return with higher downside risk in twenty-seven emerging stock markets, including China. However, although the paper of Bali et al. (2009) is comprehensive and convictive, they adopted a simple method that computing each VaR which is the lowest return observed during the previous targeted period of daily data. In this paper, we will conduct some classical methods to estimate VaR, and test the relationship between VaRs and expected returns in the Chinese stock market.

1.1 The Chinese stock market

Even though many papers study VaR on various markets, they mainly focus on the relatively mature markets, especially American stock market. However, few attempts have been made to estimate VaR on the Chinese stock market. This paper will focus on the Chinese stock market to get insight of the markets.

There are two stock exchanges in mainland China, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). Each exchange has two types of shares,

namely A share and B share. Stocks traded in Renminbi (RMB) in the two stock exchanges are called A shares. B shares, officially named Domestically Listed Foreign Investment Shares, are traded in foreign currencies in those exchanges. B shares are traded in US dollar and Hong Kong dollar in SSE and SZSE respectively.

Shanghai Stock Exchange was built on November 26, 1990 and commenced business on December 19 of the same year. Until now, it has 959 public companies and 1,003 stocks, and its total market capital is about RMB 15,495 million. The main indices are SSE Composite Index, SSE 180 Index, SSE 50 Index, SSE A Share Index and SSE B Share Index (SSE Website, 2014). Shenzhen Stock Exchange opened on December 1, 1990, and it has 1,578 public companies and 2,372 stocks, and its market capital is about RMB 9,387 million. The main indices are SZSE Component Index, SZSE Composite Index, SZSE 100 Index, SZSE Component A and SZSE Component B (SZSE Website, 2014). In order to analyze the Chinese stock market comprehensively, this paper selects six most typical indices in total, three in each exchange respectively: SSE Composite Index (SSEC), SSE A Share Index (SSEA), SSE B Share Index (SSEB) and SZSE Component Index (SZSEC), SZSE Component A (SZSEA), SZSE Component B (SZSEB).

1.2 Purpose of the study

Although many literatures estimate VaR by various methods applying different market data, too few talks about the Chinese stock market clearly. Moreover, previous studies always end at backtesting VaR but this study will do further research. Therefore, the purpose of our study is not only to measure the risk of the Chinese stock market using VaR methods, but also to value whether the downside risk is priced in the expected return in the market. In order to accomplish this, we formulate two research questions:

RQ1: Is there any best fitted VaR method for each index in the Chinese stock market?

RQ2: If yes, is there any risk-return trade-off?

To answer the first question, we firstly estimate VaRs for the six indices separately. For each index, we will conduct four different methods to calculate VaRs. After estimating VaRs, we will implement Kupiec test as the backtest to find the methods that pass the test in order to select the best method for each sample. Thus, our first purpose is to find a best VaR method for each index.

As to the second question, we will examine the intertemporal relation between VaR and expected return by the linear regressions. This relationship should be positive if there is a risk-return trade-off in the Chinese stock market, which is known as a rule: the higher the risk, the higher the expected return.

1.3 Structure of the paper

Based on the two research questions above, we exhibit the structure of our paper as follows: Chapter 2 reviews the theories and approaches for estimating VaR and studying intertemporal relationship between VaR and expected return. After that, we present our methodology in Chapter 3, including data collection and description, calculating VaR using different methods, conducting Kupiec test and testing regression models. Chapter 4 displays and analyzes the empirical results, such as the best methods of VaR we select, and the results from regressing expected return on VaR. Finally in Chapter 5, we draw a conclusion of the study's findings and give some suggestions for further studies.

2. Theory

This chapter contains four sections. The first section defines the VaR and presents some comments on it. The second section reviews the different traditional methods to estimate VaR. After that, it presents Kupiec test to backtest the VaR approaches. The last section is about the theory of risk-return trade-off, which regresses excess return on VaR.

2.1 Value at Risk

The basic idea of VaR presented by Linsmeier and Pearson (1996) is a single and aggregate loss of certain portfolio using statistical methods to estimate, which predicts the loss larger than VaR under a specific probability. VaR can be relatively easily computed as the holistic risk for a certain portfolio under several simple assumptions.

Linsmeier and Pearson (1996) define the VaR as the loss (L) which is expected to be surpassed with a probability of $1-\alpha$ for the following holding period, where α means the confidence level. Mathematically, VaR is:

$$Pr\ (\ L > VaR\alpha(L)\ ) \leq 1-\alpha$$

Under the continuous loss distribution condition, the formula can be rewritten as:

$$Pr\ (\ L > VaR\alpha(L)\ ) = 1-\alpha$$

Furthermore, there are some comments on VaR. Dowd (2005) exhibits various attractions of using VaR as a risk measuring tool. To begin with, VaR can be applied to all kinds of assets, such as bonds, stocks, etc. Moreover, because of its holistic attribution, it can take the complete risk factors into consideration and present us the overall risk for a portfolio. Then, it is based on probability, which gives the information of the likelihood with corresponding loss to users. Finally, VaR is expressed into unit of money that is easy to understand.

However, as Linsmeier and Pearson (1996) argue, VaR is not a panacea although it has

many attractions. Firstly, it is not a coherent risk measure since it is not subadditive in most cases, which is against the risk diversification. Secondly, it tells nothing about the magnitude of loss if the small probability event happens. At last, there are various methods estimating VaR, which gives different VaR values. It is noisy even dangerous for ones who take them seriously, which may enable users to take too much risk and make a huge loss if a tail event occurs (Dowd, 2005).

Because of the general acceptance and widespread adoption of VaR, we are interested in using it to measure the overall risk of the Chinese stock market. Since no consensus of the best VaR method has reached and there are various traditional and modern methods co-existing, we decide to conduct the traditional ones to estimate VaR.

2.2 Traditional VaR Approaches

In this section, we present six VaR approaches. The first two are non-parametric based on historical simulation, and the rest ones are parametric based on the specific distributions.

2.2.1 Non-parametric VaR

The non-parametric approaches, which aim to estimate VaR without the specific assumptions on the loss distribution, are mainly based on historical simulation. The underlying assumption of these methods is the belief that the near future will not change heavily but keep the recent previous trend alike to a large extent, which can be forecasted by using the recent past data (Dowd, 2005).

a) Basic Historical Simulation VaR

The basic historical simulation directly depends on the sample data of the losses and forecasts VaR using the simple moving average method. Specifically, the calculation of VaR is only derived from the empirical sample. According to VaR definition, there are $N(1-\alpha)$ losses larger than $VaR_\alpha(L)$ that we could observe because each observed loss is equal weighted. Therefore, we treat the $N(1-\alpha)+1$ largest loss as the estimation of VaR.

Since it is a discrete distribution, $N(1-\alpha)$ would be a decimal, thus VaR rounds down the nearest unit of $N(1-\alpha)+1$ largest loss. However, when N is sufficiently large, e.g. 500 observations, VaR can also be approximately obtained by α-quantile of the loss distribution. For example, if the size of the estimation is 500 and $\alpha=95\%$, the estimation of VaR is 26th largest loss accounted for 94.8%-quantile of the loss distribution, which is very close to 95%-quantile.

Angelovska (2013) argues that this method would be probably the most widely used method of estimating VaR because of its simple concept and reasonably easy execution. Moreover, Hull and White (1988) state that it can exactly present the market variables' historical multivariate distribution. However, the drawbacks are the lack of consideration of current market condition, and the potentially sudden drop or rise in the VaR when an extreme observation is included or excluded, also called the ghost effect.

b) Historical simulation VaR with volatility

The motivation of this method is driven by the volatility clustering, which is very common in financial market data. Volatility clustering describes a phenomenon that if the volatility of the current condition is higher (lower) than the average, then in the following period it probably continues the trend that the volatility is higher (lower) than the average. Hull and White (1988) introduce the exponentially weighted moving averaging (EWMA) and generalized autoregressive conditional heteroskedasticity (GARCH) models to take the volatility into consideration by rescaling the historical observed sample of losses.

Assume that we observe a sample of T losses denoted by $l_1, l_2, ..., l_T$ and tend to forecast VaR for the time $T+1$, then these losses are rescaled as follows:

$$l_i^* = \left(\frac{\sigma_{T+1}}{\sigma_i}\right) l_i \qquad i = 1, 2, ..., T$$

where $\sigma_1, \sigma_2, ..., \sigma_T$ are the volatilities corresponding to the losses in the estimation period and σ_{T+1} is the forecast one in the period $T+1$. These volatilities are estimated by GARCH or EWMA since they cannot directly be observed.

Brooks (2008) claims that it is generally accepted that using GARCH (1,1) is sufficient enough to catch the volatility clustering for financial data, which is:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad t=1, 2, \dots , T+1$$

This recursion should be initiated by ε_0 and σ_0^2 where we assume that ε_0 equals zero and σ_0^2 equals the sample variance of T observed losses. Furthermore, the unexpected loss $\varepsilon_i = l_i - \bar{l}$, $i = 1, 2, \dots , T$, where $\bar{l}$ equals the sample average. In addition, the parameters of α_0, α_1 and β can be estimated by the Maximum Likelihood method given the T observed losses.

Alternatively, estimating volatility using EWMA can be a good candidate, the formula of calculating σ_{T+1}^2 is:

$$\sigma_{T+1}^2 = \frac{1-\lambda}{1-\lambda^T} \sum_{t=1}^{T} \lambda^{T-t} \varepsilon_t^2$$

And it can be simplified and we obtain the approximation when T is reasonably large:

$$\sigma_{T+1}^2 \approx (1 - \lambda)\varepsilon_T^2 + \lambda\sigma_T^2$$

Usually, let $\lambda=0.94$ (according to the standard RiskMetrics available for daily data). This method can release the burden of estimating parameters of α_0, α_1 and β in the method of GARCH (1,1), since the EWMA is the specification of that with the fixed parameter $\alpha_0=0, \alpha_1=0.06$ and $\beta=0.94$.

Dowd (2005) points out that the most attractive merit is that the volatility-weighted method takes the market condition into consideration by rescaling the losses with volatility while the basic equal-weighted method ignores the change of volatility. In addition, we may get the VaR larger than the largest VaR estimated by the basic historical simulation.

2.2.2 Parametric VaR

The parametric approaches assume the fitted loss distribution curves from the empirical sample data and then estimate VaR from those fitted curve. Dowd (2005)

believes that parametric methods are more powerful and convictive than the non-parametric approaches since they obtain additional information from the assumed fitted distribution. However, he points out that it would be biased if the assumed distribution does not match the empirical sample.

a) The normal distribution VaR

The assumption of the normal distribution, e.g. $L \sim N(\mu, \sigma^2)$, is wildly used and plausible due to the central limit theory. Another attraction is that it demands only two parameters, i.e. the mean μ and variance σ^2 (Dowd, 2005).

The probability density function (pdf.) for a normal distribution $X \sim N(\mu, \sigma^2)$ is:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \; exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

According to the VaR definition, we can obtain the VaR under normal distribution:

$$VaR_\alpha(L) = \mu + \sigma Z_\alpha$$

where μ denotes the sample average loss, σ is the sample standard variance and Z_α denotes the α-quantile from standard normal distribution

b) The normal distribution VaR with volatility

The purpose of using parametric approaches is to make the specific distribution consistent with the empirical sample data. However, the unconditional distributions like the normal one ignore the significant information of volatility clustering for financial data, which may not fit the empirical sample well. Thus, a specific distribution adding a conditional EWMA or GARCH volatility can relieve this problem, which takes the current market condition into account (Dowd, 2005).

The normal distribution with volatility VaR is:

$$VaR_\alpha(L) = \mu + \sigma_{T+1} Z_\alpha$$

where σ_{T+1} is the forecast volatility in the period $T+1$ using EWMA or GARCH.

c) The *t*-distribution VaR

A lot of scholars, e.g. Hull and White (1988) and Brooks (2012), believe that many variables in financial data do not comply with normal distribution due to the fatter or heavier tails, where the kurtosis (k) is larger than 3 (the kurtosis of normal distribution). Therefore, student t-distribution can be a proper substitute for that excess kurtosis larger than 0, and the excess kurtosis means the difference between the actual kurtosis and 3.

Although t-distribution has three parameters: the mean μ and variance σ^2 as usual and the additional parameter v called the degree of freedom, Dowd (2005) suggests an approximation relationship between v and k when v is larger than 4 and the number of observations T is sufficiently large:

$$v = \frac{4k-6}{k-3}$$

According to the definition of VaR, we can finally obtain the t-dist. VaR:

$$VaR_\alpha(L) = \mu + \sqrt{\frac{v-2}{v}}\sigma t_{\alpha,v}$$

where $t_{\alpha,v}$ denotes the t-distribution confidence level depends on α and v.

d) The t-distribution VaR with volatility

Similarly, when we consider the current market condition into consideration, the t-distribution VaR with volatility VaR is:

$$VaR_\alpha(L) = \mu + \sqrt{\frac{v-2}{v}}\sigma_{T+1} t_{\alpha,v}$$

where σ_{T+1} is the forecast volatility in the period $T+1$ using EWMA or GARCH.

2.3 Backtesting

After estimating VaR by different methods, it is time to test whether these methods perform well or not. Kupiec test (a basic binomial frequency test) is probably the most widely used backtest, which aims to testify if the empirical frequency of VaR violations is consistent with the expected frequency of VaR violations. Specifically,

the null hypothesis is that the model is fitted. Under that condition, it obeys a binomial distribution and we can obtain the probability of x tail loss given the number of observations N and the expected frequency of VaR violations $p=1-\alpha$:

$$Pr\ (X = x) = \binom{N}{p}\ p^x\ (1 - p)\ ^{N\text{-}x}$$

To apply the Kupiec test, we follow the several steps:

(1) Compute the number of expected exceedances $N(1 - \alpha)$.

(2) Count the number of actual exceedances denoted by x.

(3) Compare whether $x \geq N(1 - \alpha)$ or not, which is conducted by the one-sided test.

   a) If $x \geq N(1 - \alpha)$, test if the actual exceedances are "too large" comparing with the expected exceedances. Thus, computing the $Pr\ (X \geq x)$ under the null hypothesis. Choosing the statistical confidence level, usually 5%, compares with the computed probability. If $Pr\ (X \geq x)\ <$ 5%, the null hypothesis is rejected; otherwise it is not rejected.

   b) If $x \leq N(1 - \alpha)$, examine if the actual exceedances are "too low" comparing with expected ones. Therefore, computing the $Pr\ (X \leq x)$ under the null hypothesis. If $Pr\ (X \leq x)\ <$ 5%, reject the null hypothesis; otherwise not.

(4) Compare the probabilities of different VaR methods, and choose the highest one as the best method.

Apart from the one-sided test, we also can conduct the two-sided test. Since it has two rejection areas due to the rejection of "too large" or "too low" for actual exceedances compared with expected ones. Usually, we take 5% as the confidence level where the rejection areas define the areas of observations lower than bound x_{low} and higher than bound x_{high} are both 2.5%. We can use the expected number of exceedances to compute a 95% confidence interval, which is $[x_{low,}\ x_{high}]$. If the actual exceedances fall outside this interval, the null hypothesis is rejected, otherwise it is not.

After the best fitted approach for VaR was selected via the Kupiec test, it can be used

for further researches. One of ways is to investigate the intertemporal relationship between expected return and VaR.

2.4 The risk-return trade-off theory

It is the relationship between return and risk in respect to the holistic stock market (e.g. market indices) that has become an increasingly hot topic in economics. Markowiktz (1952) presents the mean-variance optimization theory under certain assumptions: (1) the investors all trade based on the quadratic utilities, (2) the returns have a joint normal distribution. He argues that if either of the two conditions is satisfied, this optimization is founded. However, neither of the two is satisfied under the empirical condition since the distribution of returns from the stock market is skewed (Arditti and Levy, 1975; Harvey and Siddique, 2000) and has an excess kurtosis (Pratt and Zeckhauser, 1987) in most situations. Moreover, Merton (1973) formulates the intertemporal capital asset pricing model (ICAPM) that suggests there is a positive relationship between the excess return and volatility under the conditional situation of investors being risk averse.

Based on the previous work, Bali et al. (2009) and Atilgan and Demirtas (2013) conduct the research and demonstrate the intertemporal positive relationship between the downside risks (especially VaR) and the expected returns theoretically and empirically. In detail, the reasons for choosing the downside risk determining the positive risk-return relation theoretically proofed are: (1) the safety-first investors introduced by Roy (1952) are those who minimize the losses for fear of disaster that would select portfolios by the criterion of maximizing their expected return constrained by the downside risk. Therefore, these investors will exert what they can to reduce the chance of disaster. (2) The assumptions of mean-variance optimization promoted by Markowiktz (1952) are not satisfied in the real world. Arditti and Levy (1975), and Harvey and Siddique (2000) suggest that investors show a strong preference of positive skewed portfolios rather than the negative one. Pratt and Zeckhauser (1987) argue that the lower leptokurtic portfolios are more favorable for

investors. Therefore, Bali et al. (2009), and Atilgan and Demirtas (2013) expect the positive relationship between VaR and expected market return if the portfolio distribution is left-skewed/non-skewed and leptokurtic. (3) Numerous financial and non-financial firms (e.g. banks, insurance companies, credit rating firms, etc.) are needed to monitor the potential losses that may happen at the aggregate level over a certain horizon, where the risk tool of VaR can be the best candidate.

In terms of empirical studies, Bali et al. (2009) and Atilgan and Demirtas (2013) formulate two fundamental models that demonstrate the positive risk-return relation in the US and emerging markets, respectively. Specifically, Bali et al. (2009) build a time series regression model to the US market:

$$R_{t+1} = \alpha + \beta\, E_t\, (VaR_{t+1}) + \Upsilon X_t + \varepsilon_{t+1} \qquad (1)$$

where R_{t+1} denotes monthly market excess return (which equals actual return minus corresponding risk-free rate), $E_t\,(VaR_{t+1})$ represents the conditional expected VaR computed from daily index returns and the vector X_t stands for the controlled factors like the macro economic variables, the one-lag excess return and a dummy variable in Oct. 1987.

Followed by that, they conduct the first order of autoregression (AR(1)) of VaR, which is $VaR_{t+1} = \lambda + \rho\, VaR_t + \varepsilon_{t+1}$, and find all parameters are between 0.29 and 0.87 with significance at 1% level. Therefore, VaR is significantly consistent with its lags and they treat VaR_t as a proxy for $E_t(VaR_{t+1})$.

Based on their results, the fundamental test model of Equation 1 can be explicitly rewritten as:

$$R_{t+1} = \alpha + \beta_1 VaR_t + \Upsilon_1 R_t + \Upsilon_2 Dummy + \varepsilon_{t+1} \qquad (2)$$

where the dummy variable takes the value 1 in Oct. 1987 and 0 in others.

Atilgan and Demirtas (2013) test that relationship both in several developed and emerging markets, but they are only significant in emerging markets using the regression of panel data with fixed effects by fundamental and robust models. Their

fundamental test model is:

$$R_{i,t} = \alpha_t + \beta \, VaR_{k,i,t-1} + \varepsilon_{i,t} \qquad (3)$$

where $R_{i,t}$ denotes the excess return for the market indices of country i at month t, $VaR_{k,i,t-1}$ represents the VaR of country i over the k months lagged to month $t-1$. In the latter robust model, they control the factors of dividend yield, price-to-earnings and price-to-cash flow and add into the Equation 3.

3. Methodology

This chapter has four sections: data, VaR methods, Kupiec test and regressions. In the data section, we present the data collection and data description. Then demonstrate how to calculate VaR using the selected methods and how to implement the backtest. At last, we test the regression models.

3.1 Data

3.1.1 Data collection

The paper selects six indices to be tested and analyzed, three in each exchange respectively: SSEC, SSEA, SSEB and SZSEC, SZSEA, SZSEB. The reason is that, at first we estimate the VaRs of the two exchanges at the holistic level, where the SSEC and SZSEC can be the best candidates in practice. Then we estimate the VaRs for different types of shares separately, A share and B share. The three indices of Shanghai Stock Exchange contain all corresponding shares. The number of stocks in each index is changing, and so far, there are 1003, 950 and 53 stocks in SSEC, SSEA and SSEB respectively (SSE Website, 2014). The other three indices of Shenzhen Stock Exchange are component indices, which select the broadly representative stocks, e.g. SZSEB are calculated by 10 B stocks (SSE Website, 2014). Details about the six indices can be seen from the Table 1:

All the six indices are calculated by the formula: *Current Total Market Cap of Constituents/ Base Day Value × Base Value*, and then take the value-weighted average of them. As can be seen from the Table 1, these indices were created in the 1990s, and the latest launch day was January 23, 1995; that is to say the Chinese stock market is emerging. Therefore, we collect the six indices' daily close prices of 12 years from January 1, 2002 to December 31, 2013, which is the relatively longest period up to now for our test. We use the first 500 observations (about two years) as the estimation

period so that we can get a 10-year forecast period with the rolling window.

Table 1: Information about selected indices

Index Name	Local Code	Base Day	Base Point	Launch Day	Constituent
SSEC	000001	1990/12/19	100	1992/7/15	All stocks
SSEA	000002	1990/12/20	100	1992/2/21	All A stocks
SSEB	000003	1992/2/21	100	1992/8/17	All B stocks
SZSEC	399001	1994/7/20	1000	1995/1/23	40 stocks
SZSEA	399002	1994/7/20	1000	1995/1/23	40 stocks
SZSEB	399003	1994/7/20	1000	1995/1/23	10 stocks

Source: CNINDEX Website

When collecting these daily data, we first downloaded the data from DataStream and found a problem that DataStream does not get rid of the daily data of Chinese national holiday. For example, in China, January 1, 2 and 3 are a three-day holiday that there will be no trade during those three days, but DataStream automatically fills the prices in with the last workday price (December 31 or before). So the return or loss of these holidays will be 0, which will affect our test results. Then we downloaded the data from one Chinese stock-trade software, namely Tongdaxin (TDX homepage, 2014). After we carefully compared the data between DataStream and Tongdaxin, we are sure about the veracity of the data.

In the latter part of our paper, we will test the intertemporal relation between VaR and expected return, and we use excess return instead of expected return. Moreover, when testing this relation we use monthly data, because daily data are too fluctuant. Thus, we also need the monthly prices of the six indices, as well as monthly risk free rate which we use Chinese 3-month Treasury bill rate instead. When calculating excess return, we define it as the difference between actual index return and risk free rate. Finally, we obtained all the monthly data from DataStream starting from January, 2007 to December, 2013. It is a 7-year test period, because the Chinese 3-month Treasury bill rate in DataStream is only available from January 2007 up to now.

3.1.2 Data description

After obtaining the data of the closed prices for each index, we take the formula of $Ln(P_t/P_{t-1})$ as the returns for these indices. We illustrate the descriptive statistics of daily returns for each market index from January 1, 2002 to December 31, 2013 in Table 2 which shows the samples' mean, median, minimum, maximum, standard deviation, skewness, kurtosis, Jarque-Bera normality test with its corresponding p-value, and the total number of observations.

Table 2: Summary statistics of daily returns

Index	SSEC	SSEA	SSEB	SZSEC	SZSEA	SZSEB
Mean	0.009%	0.010%	0.014%	0.031%	0.033%	0.045%
Median	0.045%	0.046%	0.043%	0.031%	0.034%	0.088%
Minimum	-9.256%	-9.261%	-9.727%	-9.750%	-9.750%	-9.858%
Maximum	9.034%	9.033%	9.382%	9.162%	9.161%	9.563%
Std.Dev	1.639%	1.640%	1.971%	1.829%	1.831%	1.879%
Skewness	-0.155	-0.155	-0.208	-0.188	-0.181	-0.184
Kurtosis	6.781	6.775	8.059	5.900	5.883	6.445
Jarque-Bera	1732.519	1726.714	3102.261	1029.297	1016.148	1444.288
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2902	2902	2902	2902	2902	2902

As can be seen from Table 2, the range of the average daily return in these samples is from 0.009% to 0.045%. Each B share index is the largest one in their corresponding market shares, e.g. the mean of SSEB and SZSEB are 0.0014% and 0.045% respectively that are the largest ones in their group while the mean of the rest two samples is rather similar. Moreover, the interval of minimum for these samples is from -9.858% to -9.256% while the maximum from 9.033% to 9.563%, which shows the similar power of the gains and losses, especially taking the mean of these samples into consideration. As to the volatility, Table 2 shows that the highest standard deviation is 1.971% in SSEB and the standard deviation of each B share index is higher than their counterparts that are rather similar in each market; therefore we

would expect more volatile situations in each B share index and the similar fluctuation for the rest two samples in each exchange.

Furthermore, when it comes to the distribution of these indices, Hull and White (1988) and Brooks (2012) argue that almost financial data are not normally distributed but *t*-distributed. Figure 3 (presented in Appendix) shows the histograms of these samples along with the normal distribution line. Seen from those figures, none of these is fitted into the normal distribution because all of the peaks of the distributions are taller than the normal one and they are fatter in tails than normal one. Also in Table 2, all the skewnesses are close to zero and the kurtoses are far beyond 3, and more importantly, the probabilities of Jarque-Bera normality test are all zero, which indicate that all the indices do not follow the normal distribution. We construct Figure 4 (presented in Appendix) to prove whether they follow the *t*-distribution. Figure 4 presents the Quantile-Quantile (QQ) plot under the theoretical assumption of the *t*-distribution. Except for the several extreme points, most of the dots are in line with the red line in each sample, which shows that the specific *t*-distribution fits the data. Therefore, in terms of estimation of parametric VaR, we conduct the method of the *t*-distribution rather than the normal one.

Since the B index from each exchange is different from the rest two shares in terms of mean, extreme value, standard deviation, kurtosis and value of Jarque-Bera while rest two are rather similar in this regard, we would expect particular performance of B shares and the similar ones for the rest two in each exchange. The reasons for the characteristics are those: firstly, the quantity of B share in each market is relatively small comparing with the A share, thus the holistic index is more influenced by the A share. Secondly, due to foreign currency (i.e. not RMB) trading in B shares, the performance of the B share is distinct from the A share traded in domestic currency in each exchange.

3.2 VaR methods

We introduced six traditional VaR methods in the theoretical chapter; however, according to the analysis of Section 3.1.2, all the indices follow *t*-distribution so that we cannot apply the methods under the normal distribution. Thus, we value VaR using the four approaches: basic historical simulation (HS), historical simulation with volatility (HS-EWMA), *t*-distribution (*t*-dist.) and *t*-distribution with volatility (*t*-EWMA). HS is the most classic and widely used non-parametric method, although HS is theoretically simple, and *t*-dist. is parametric method that is suitable for our data. Then we add volatility into the model, and we have two choices, i.e., GARCH and EWMA. EWMA is a special form of GARCH, and EWMA is of more feasibility for the paper because we will use Excel to calculate VaRs. Therefore, we conduct other two VaR methods: HS-EWMA and *t*-EWMA. In addition, we implement the four methods at both 95% and 99% confidence levels. Almost all previous researches choose 95% or 99%, or both as the VaR confidence levels, thus we choose both 95% and 99% to make our results more comprehensive and viable.

Moreover, we conducted rolling window to estimating VaRs, which means that we use the first 500 daily losses (return*-1) to get one VaR (t=501), and then use the next 500 daily losses to get the second VaR (t=502). Finally, we estimated 2403 VaRs for each sample because each has totally 2902 losses, which are total 48 VaR series due to four methods at both 95% and 99% confidence levels for six indices. As mentioned above, we implement all calculations in Excel.

3.3 Kupiec test

After obtaining VaRs of all samples, we need backtest for the results to find which methods are the best ones. We adopt Kupiec test to examine the 48 VaR series, applying both one-sided and two-sided Kupiec tests. All backtests are judged by 5% confidence level. However, for the two-sided test, the reject region of one side is 2.5%,

which may lead to one model passing the two-sided test but not the one-sided test. Moreover, if we only choose the two-sided Kupiec test and there are more than one passing the backtest, it is hard to distinguish which one is the best. But we can get the cumulative probability of each VaR method by implementing the one-sided Kupiec test so that we can choose the one whose probability is closest to 1. Therefore, we firstly apply the two-sided test to find the passed models, and then apply the one-sided test to get the best one. Also, all backtesting results are calculated in Excel.

3.4 Regressing expected return on VaR

After selecting out the best VaR methods, we test the intertemporal relation between VaR and expected return. According to the reports of Bali et al. (2009), and Atilgan and Demirtas (2013), we test the two fundamental regression models from the simple one to the complicated one: Equation 3 and Equation 2 in Section 2.4.

We name the regression model of Equation 3 as RM-I:

$$R_{i,t} = \alpha_t + \beta \, VaR_{k,i,t-1} + \varepsilon_{i,t}$$

In our regression tests, we only test this model in one country, China, so that i is equal to 1; we apply three month as the lag so that k is equal to 3. As a consequence, R_t denotes the excess return for the market index at month t, and VaR_{t-1} represents the VaR at month t-1 calculated by 3-month lag.

We name the regression model of Equation 2 as RM-II:

$$R_{t+1} = \alpha + \beta_1 VaR_t + \Upsilon_1 R_t + \Upsilon_2 Dummy + \varepsilon_{t+1}$$

This equation is the specification of Equation 1, and it replaces $E_t \, (VaR_{t+1})$ with VaR_t, and replaces X_t with R_t and *Dummy*. Compared to the RM-I, this model adds one-month-lag excess return and a dummy variable into the regression. Since our test period contains this financial crisis, we take the financial crisis of 2007-08 as the

dummy variable, controlling it to be 1 during the financial crisis period and 0 in other periods.

Furthermore, we use the best VaR methods to calculate the monthly VaRs, which we apply latest three-month daily loss (63 losses, since we assume one month has 21 trading days) to estimate the VaR of the current month. Because investors would not consider the too old losses estimate the expected return of the following month. We use the excess return as a proxy for the expected return, and the excess return is calculated by the difference between actual index return and risk free rate of the Chinese market which we use the 3-month Chinese Treasury bill rate. We run all the regressions between VaR and excess return using Eviews.

4. Results and Analysis

This chapter presents the empirical results of our data along with analysis and discussion, which contains three sections. We present the results of daily VaRs by four methods for each index at two confidence levels in the first section. Later on, we conduct the Kupiec test to find the best method of each sample. The last section presents and analyzes the risk-return trade-off by testing two models.

4.1 Estimating VaR

Based on the descriptive data of daily returns, we estimate the daily VaR at 95% and 99% confidence levels in various methods, i.e., HS, HS-EWMA, t-dist., and t-EWMA. By using the rolling window of 500 observations, we obtain 2403 VaRs by each method for each sample. The results are shown in Appendix from Figure 5 to 10.

Seen from these figures, each graph contains the lines of results of four different VaR methods along with a line of the daily returns in the test period. In the graphs, some common characteristics can be found. Firstly, although the average of daily returns in each sample levels off at 0 over these years, these trends fluctuate all the time, especially they drastically fluctuate in the period between 2007 and 2008 due to the financial crisis. We also can see clearly the volatility clustering in that period. Secondly, the VaRs without volatilities are relatively smooth along with a sudden jump or fall called the ghost effect in some points while those with volatilities show more volatile, which reflects the current market conditions. Thirdly, the holistic trends of all the VaR lines are like a bell shape: consistently rise at first, and then reach a plateau, and after that, gradually dip. Moreover, in the period between 2007 and 2008, the crisis period, the trends of VaRs with volatilities change faster than those without volatilities, in which the VaRs with volatilities peak at the beginning of 2008 while those without volatilities reach the peak at the end of 2008. During that period, the HS VaRs are always higher than t-dist. VaRs; similarly, the same results are also founded in the situation with volatilities. Last but not least, in the relatively tranquil period like

in the year from 2004 to 2006 and from 2011 to 2013, the values of different methods of VaRs are relatively similar.

There are also some distinctions drawn from these graphs. Firstly, because the fluctuations of daily returns of each B share are more dispersive than those corresponding two shares in each exchange, the estimated VaRs of each B share are more volatile than their counterparts. Secondly, since the VaRs of each share are estimated at both 95% and 99% confidence levels presented in two figures, the $VaR_{0.99}$ is particularly higher than the corresponding $VaR_{0.95}$ in the crisis year between 2007 and 2008.

4.2 Backtesting

Based on those results, we implement Kupiec test (5% rejection region) to examine whether these estimation approaches pass or not using the two-sided test, and then present the best and the second best methods using the one-sided test.

Table 3: Results of two-sided Kupiec test

Index	SSEC	SSEA	SSEB	SZSEC	SZSEA	SZSEB
Panel A: Volations of VaR 0.95						
HS	133	133	126	133	133	123
HS-EWMA	128	127	123	126	131	129
t-dist.	135	138	122	133	134	139
t-EWMA	145	144	149	152	154	145
Note: Acceptance region from 100 to 142						
Panel B: Volations of VaR 0.99						
HS	32	31	29	34	31	31
HS-EWMA	31	32	26	28	27	26
t-dist.	33	33	40	34	33	33
t-EWMA	36	36	42	29	27	39
Note: Acceptance region from 15 to 34						Passed

Table 3 illustrates the results of violations of VaR using different methods for each sample at 95% and 99% confidence levels given the acceptance region where we

highlight the passed methods.

Panel A shows the computed violations of targeted approaches of VaR at 95% confidence level for each index and presents the acceptance region included from 100 to 142. Seen from the highlights, the approach of t-EWMA is beyond the acceptance region and rejected in each sample while the rest three methods are passed in every sample. This means that t-EWMA is not a proper approach for the Chinese stock market to estimating VaR$_{0.95}$.

Similarly, Panel B illustrates the computed VaR$_{0.99}$ violations for each sample with the acceptance region from 15 to 34, included. It shows that all of the nonparametric methods pass the test in each sample, which means that they can be proper estimation approaches for the Chinese market. The method of t-EWMA still does not perform well since it is the method that is rejected four out of six times. Except the SSEB index that only pass the non-parametric methods, the rest samples pass the t-dist. method, which shows that t-dist. could be a way to estimate VaR for the stock indices to some extent.

Since each sample has at least two plausible methods to estimate VaR, we conduct the one-sided Kupiec test to find the best and the second best methods for each sample. We show the results of one-sided Kupiec test in Table 4. In this table, we present the computed probabilities of VaR using different approaches at 95% and 99% confidence levels for all samples. Since the acceptance region is no less than 5%, and the higher, the better, we highlight the largest probability with deep blue as our best method and the second largest one with light blue as the second best method for each index at different levels.

Panel A shows the computed probabilities for VaR$_{0.95}$. The most suitable approach is HS-EWMA where the indices SSEC, SSEA, SZSEC and SZSEA have the highest probability among the four methods. Moreover, the indices SSEB and SZSEB, as we expected, show the distinct performance and take the t-dist. and HS method as the best one respectively and only regard HS-EWMA as their second best methods. For

the method of HS, there are only one sample considering it as the best one and four samples as the second best method. For the method of *t*-dist., only one sample takes it as the best method and another one as the second best method while none of the sample takes the *t*-EWMA as neither the best nor second best method.

Table 4: Results of one-sided Kupiec test

Index	SSEC	SSEA	SSEB	SZSEC	SZSEA	SZSEB
Panel A: Computed probability from VaR 0.95						
HS	12.47%	12.47%	30.46%	12.47%	12.47%	40.78%
HS-EWMA	24.34%	27.31%	40.78%	30.46%	16.61%	21.56%
t-dist.	9.13%	5.45%	44.43%	12.47%	10.70%	4.53%
t-EWMA	1.30%	1.63%	0.50%	0.23%	0.13%	1.30%
Panel B: Computed probability from VaR 0.99						
HS	6.76%	9.58%	17.80%	3.12%	9.58%	9.58%
HS-EWMA	9.58%	6.76%	37.01%	23.32%	29.76%	37.01%
t-dist.	4.65%	4.65%	0.17%	3.12%	4.65%	4.65%
t-EWMA	1.30%	1.30%	0.05%	17.80%	29.76%	0.29%

Note: Acceptance region is greater than 5% for the two tests				Best	Second best

In terms of $VaR_{0.99}$, the approach of HS-EWMA is still considered the best method for 5 samples and the second best method for SSEA in Panel B. For the method of HS, there are 4 samples taking it as the second best method and one as the best method. However, SZSEA regards the *t*-EWMA as the best method and SZSEB takes it as the second best one while none of the samples takes *t*-dist. as their best and second best method.

Overall, based on the two kinds of Kupiec tests, we can conclude that the approach of HS-EWMA can be the best candidate for most of the samples. The method of HS can be a relatively good substitution to HS-EWMA for the Chinese stock market indices. However, neither *t*-dist. nor *t*-EWMA method is a proper approach to estimate VaR since most of them are rejected. Therefore, in order to better estimation of VaR, it is the first thing to take non-parametric methods into account, and then we can improve the accuracy of VaR when considering the current market condition (volatility) using

EWMA.

4.3 Implementing regressions

In this section, we present and analyze the results of the two test regressions, namely RM-I and RM-II. Before implementing, we explain the detailed information about the variables from the regressions. After that, we apply the monthly VaRs at 95% and 99% confidence level respectively for each model. We also present some exhibits to show all the results intuitively and give the detailed interpretations.

4.3.1 Interpretation of the regressions

According to the results of the previous section, we obtain the best fitted VaR approach for each sample shown in the Table 5. As can be seen from that table, the method of HS-EWMA is mostly the best one to estimate VaR in the Chinese stock market while for the method of HS, it is the best VaR method for SSEA sample at 99% confidence level and SZSEB sample at 95% confidence level. For the $VaR_{0.95}$ of SSEB, the best VaR method is t-dist. Before applying this method to calculate monthly VaR, we need to check whether the excess return follows t-dist. Thus, we draw the QQ plot under the theoretic assumption of t-dist. to test shown in the Figure 1. Since most of the dots are in line with the red line, it proves that the empirical distribution fits the theoretic assumption well. Therefore, we can use t-dist. method to estimate $VaR_{0.95}$ of SSEB.

**Table 5: VaR models for each sample in regressions**

VaR model	SSEC	SSEA	SSEB	SZSEC	SZSEA	SZSEB
$VaR_{0.95}$	HS-EWMA	HS-EWMA	t-dist.	HS-EWMA	HS-EWMA	HS
$VaR_{0.99}$	HS-EWMA	HS	HS-EWMA	HS-EWMA	HS-EWMA	HS-EWMA

Figure 1: QQ plot of monthly excess return of SSEB under *t*-distribution
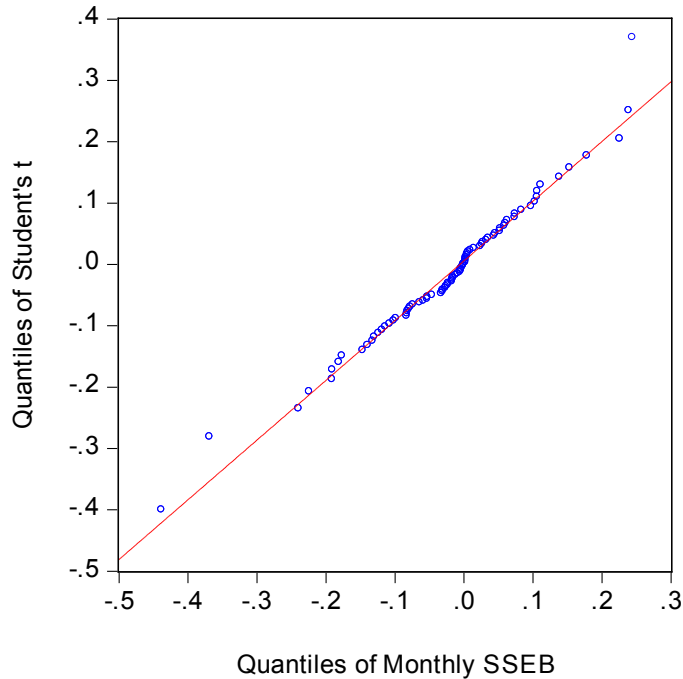
Furthermore, in the regressions, all the observations are monthly data since daily data are too fluctuant which could lead to the results inaccurate. The test period is from January 2007 to December 2013 that there are 84 observations of each variable. In Figure 2, we present the results of monthly excess returns and monthly VaRs which are calculated by the best methods in each sample. As shown in Figure 2, some comments can be drawn. Firstly, the monthly excess returns in these indices experience drastically fluctuation from Oct. 2007 to Oct. 2008, which is in the financial crisis period while the corresponding $VaR_{0.99}$ and $VaR_{0.95}$ fluctuate relatively smoothly. The results suggest that it would be improper if we test the intertemporal risk-return relation without paying attention to this special crisis period. Secondly, although the monthly excess returns of all indices fluctuate sharply in that crisis period, B shares decline consistently while the rest shares experience substantial up and down trends where the upper limits are approximately 0.

Figure 2: Results of monthly VaR and excess return
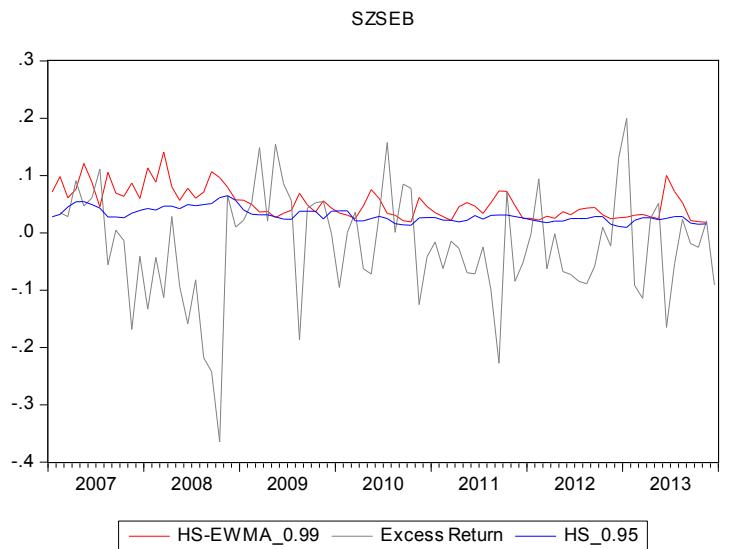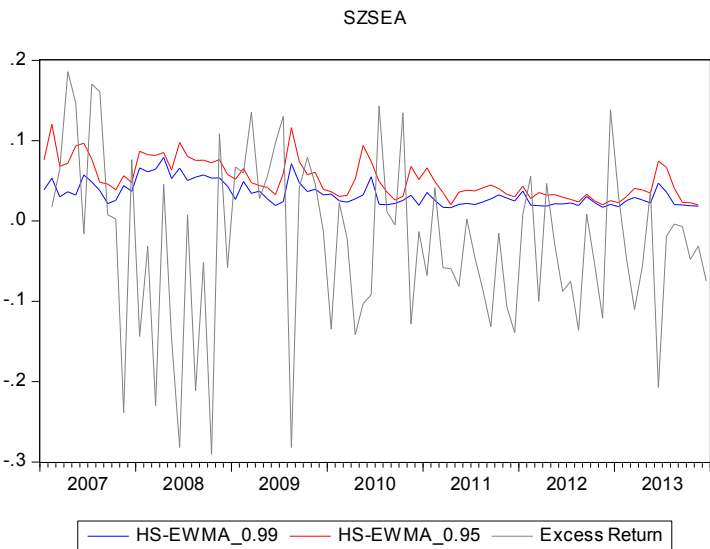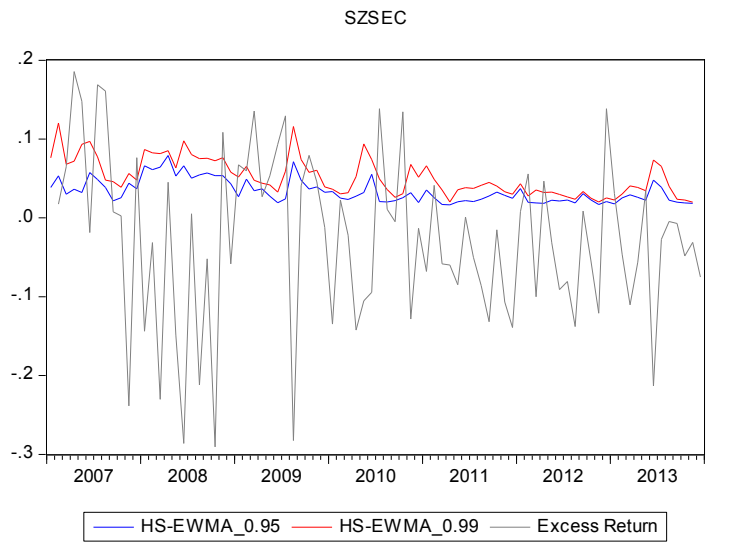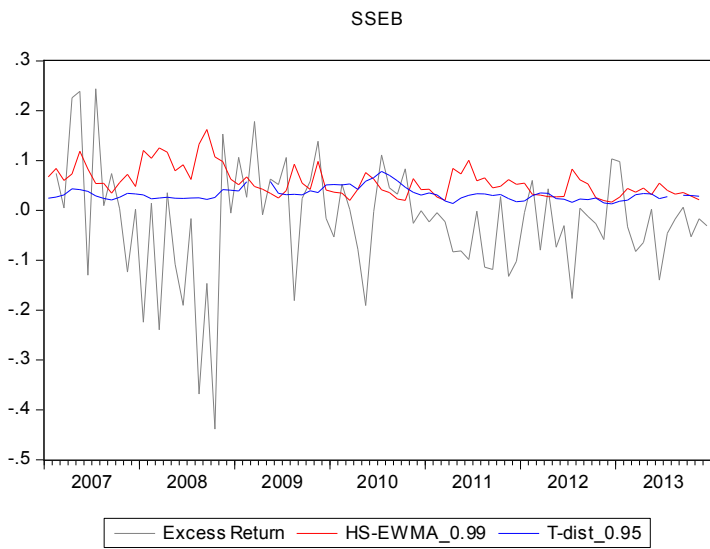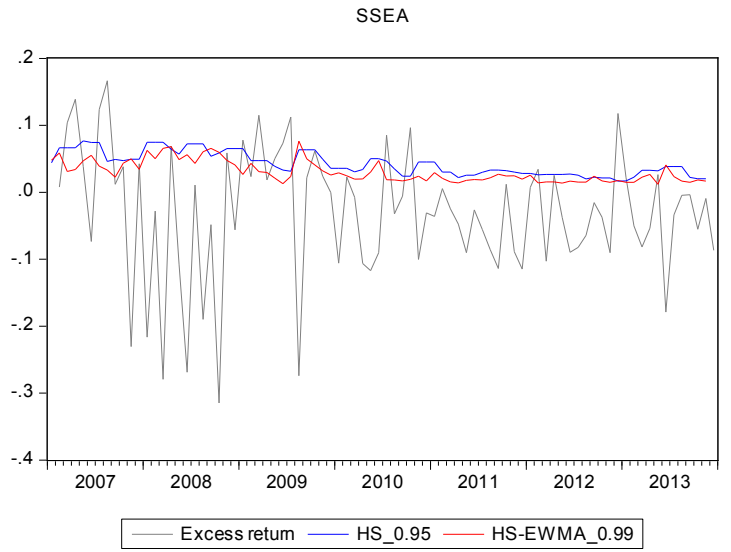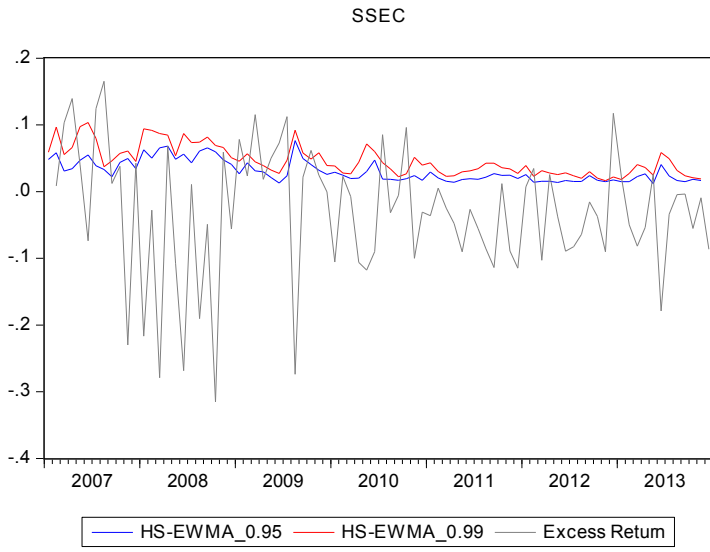
In addition, the second test regression model RM-II contains the dummy variable, and we define it to take value 1 for the crisis period from Oct. 2007 to Oct. 2008 and zero otherwise, which can reflect the situation of the Chinese market properly.

4.3.2 Results and analysis of RM-I

Seen from the Table 6, Panel A presents the regression results (which regress the monthly excess returns on one-month-lag VaRs) when VaRs are at 95% confidence level, and Panel B corresponds to 99%. The numbers with brackets below the coefficients are the corresponding *t*-statistics, and those that statistical significant at the 0.01, 0.05 and 0.10 levels are marked with one, two and three stars, respectively. Seen from the table, the coefficients of VaR of SSEB at 95% and 99% level are significantly positive at the 0.01 level and negative at the 0.10 level respectively whereas the rest test sample regressions are insignificant.

Table 6: Regression results of RM-I

Index	SSEC	SSEA	SSEB	SZSEC	SZSEA	SZSEB
Panel A. Results from regression of VaR at 95% confidence level						
Constant	-0.038	-0.039*	-0.103***	-0.045	-0.044	-0.008
	(-1.643)	(-1.664)	(-2.989)	(-1.524)	(-1.506)	(-0.268)
$VaR_{0.95,t-1}$	0.220	0.233	2.435***	0.504	0.510	-0.486
	(0.328)	(0.348)	(2.502)	(0.636)	(0.645)	(-0.538)
R^2	0.13%	0.15%	7.4%	0.5%	0.51%	0.36%
Panel B. Results from regression of VaR at 99% confidence level						
Constant	-0.039	-0.062**	0.018	-0.063**	-0.062**	-0.011
	(-1.580)	(-2.229)	(0.678)	(-2.230)	(-2.208)	(-0.454)
$VaR_{0.99,t-1}$	0.166	0.727	-0.688*	0.689	0.691	-0.234
	(0.346)	(1.197)	(-1.666)	(1.381)	(1.388)	(-0.589)
R^2	0.15%	1.7%	3.3%	2.3%	2.3%	0.43%

Note: *** Statistical significance at the 0.01 level; ** statistical significance at the 0.05 level; * statistical significance at the 0.10 level.

Overall, the main result of RM-I is that the positive intertemporal relation between excess return and VaR is insignificant, which is not consistent with the researches of Atilgan and Demirtas (2013) who shows the positive relation in emerging markets. The main reason is that the regression model is not comprehensive enough due to the lack of some other important information like ignoring the influence of the financial crisis period in 2007-2008; thus, we test the second fundamental test model RM-II, which adds the control variables, including the one-month-lag excess return and the dummy variable, into the regression to check the intertemporal relation again. In the following part, we illustrate the results and analysis of RM-II in detail.

4.3.3 Results and analysis of RM-II

The test model of RM-II takes the control variables including the one-month-lag excess return and the dummy variable into account. We define the dummy variable that takes value 1 for the period from Oct. 2007 to Oct. 2008 and zero otherwise, which is derived from the empirical results of monthly excess results in Section 4.3.1.

Table 7 presents the results of this regression model, where Panel A and Panel B apply the VaRs at 95% and 99% confidence level respectively, but other factors are the same. In Panel A, all of the coefficients of $VaR_{0.95}$ are significantly positive with its corresponding parameters that are all larger than 1.7. More specifically, the coefficients of $VaR_{0.95}$ of SSEB and SZSEB are significant at the 0.05 and 0.10 level respectively while others are strongly significant at the 0.01 level. In addition, none of the coefficients of R_{t-1} are significant at the 0.10 level while all of the coefficients of the dummy variable are highly negatively significant at the 0.01 level. At last, all of the parameters of R^2 are larger than 20%, which proves that the regression performs well.

In Panel B, the coefficient of $VaR_{0.99}$ of SSEB is insignificant (it is at least not bad when comparing the corresponding one in RM-I with a significant negative coefficient), but the rest samples are highly significantly positive. Among the

significant coefficients of $VaR_{0.99}$, only the sample of SZSEB is significant at the 0.05 level and rest samples are significant at the 0.01 level. Moreover, all of the coefficients of the dummy variable are highly negatively significant at the 0.01 level while four out of six sample coefficients of R_{t-1} are insignificant. Last but not least, all of the R^2 are larger than 17%.

Table 7: Regression results of RM-II

Index	SSEC	SSEA	SSEB	SZSEC	SZSEA	SZSEB
Panel A. Results from regression of VaR at 95% confidence level						
Constant	-0.089***	-0.089***	-0.076**	-0.103***	-0.102***	-0.054*
	(-3.998)	(-4.018)	(-2.150)	(-3.505)	(-3.508)	(-1.910)
$VaR_{0.95,t-1}$	2.734***	2.736***	2.087**	2.985***	3.010***	1.729*
	(3.534)	(3.552)	(2.193)	(3.298)	(3.335)	(1.864)
R_{t-1}	-0.158	-0.159	-0.171	-0.069	-0.074	0.127
	(-1.510)	(-1.518)	(1.453)	(-0.638)	(-0.688)	(1.129)
Dummy	-0.194***	-0.194***	-0.130***	-0.176***	-0.178***	-0.127***
	(-5.657)	(-5.670)	(-3.621)	(-4.612)	(-4.662)	(-3.857)
R^2	29.22%	29.32%	21.62%	22.02%	22.37%	23.30%
Panel B. Results from regression of VaR at 99% confidence level						
Constant	-0.074***	-0.119***	-0.013	-0.084***	-0.083***	-0.047**
	(-3.225)	(-4.748)	(-0.459)	(-3.156)	(-3.133)	(-2.149)
$VaR_{0.99,t-1}$	1.355***	2.574***	0.202	1.478***	1.478***	0.928**
	(2.693)	(4.333)	(0.413)	(2.933)	(2.946)	(2.176)
R_{t-1}	-0.194*	-0.265***	-0.112	-0.091	-0.096	0.170
	(-1.816)	(-2.639)	(-0.963)	(-0.840)	(-0.884)	(1.486)
Dummy	-0.164***	-0.190***	-0.150***	-0.141***	-0.142***	-0.130***
	(-5.060)	(-6.144)	(-3.567)	(-4.130)	(-4.159)	(-4.007)
R^2	24.88%	33.82%	17.02%	19.98%	20.18%	24.46%

Note: ***Statistical significance at the 0.01 level; ** statistical significance at the 0.05 level; * statistical significance at the 0.10 level.

Based on these results, some conclusions can be drawn. Firstly, comparing with the RM-I model with insignificant results in most cases, RM-II model adding the control variables proves the risk-return trade-off, which is consistent with researches of Bali et al. (2009) and Atilgan and Demirtas (2013) that there exists the significantly

positive risk-return relation in stock markets. Secondly, the coefficients of the dummy variable for financial crisis are highly significant negative in all samples, which means that the downside risk is exactly priced in the expected market return in the non-crisis period but not in the crisis period. Due to the negative parameter of this variable, it exerts a negative influence in the crisis period, which means that it decreases the demand for the compensation of the risk premium during the crisis period. The results are also supported by Bali et al. (2009). Thirdly, the coefficients of the control variable, one-month-lag excess return, are insignificant in most cases, which indicate that the excess returns are not influenced heavily by its previous period. Last but not least, the performance of SSEB index differs from the other indices, especially taking the results of data description and RM-I into account. The possible reason for the phenomenon is the traded currency of US dollar because the exchange rate between RMB and US dollar fluctuate heavily during these years.

5. Conclusion

We adopt non-parametric and parametric VaR methods (i.e., HS, HS-EWMA, t-dist. and t-EWMA) to measure the Chinese stock market indices: namely SSEC, SSEA, SSEB, SZSEC, SZSEA and SZSEB. Based on the Kupiec tests, we find out the best fitted model for each index. Then we apply these best methods for these samples to test whether existing positive risk-return relation for each Chinese market index, implementing two regression models. Here are some findings of this study:

1. There is always a best fitted approach estimating VaR for each index in the Chinese stock market, although not existing a model that one size fits all. Most of the samples regard historical simulation with volatility (HS-EWMA) as the best model, and non-parametric methods (HS and HS-EWMA) are much better according to Table 5, but SSEB chooses the parametric method of t-distribution at 95% confidence level.

2. Based on the two regressions, when taking the control variables into consideration, we verify the intertemporal risk-return trade-off in the Chinese stock market except for SSEB using $VaR_{0.99}$. However, the regression model without the dummy viable for financial crisis cannot prove the positive relation between VaR and expected return. These results demonstrate that the downside risk is priced in the expected market return in the non-crisis period but not in the crisis period.

3. According to the data description, it shows that B share is always different from the overall market share and A share in each exchange. Furthermore, when considering the above two findings, we find that the SSEB index performs quite differently from the other indices, which may be caused by the traded currency of US dollar owing to the fluctuation of the exchange rate comparing to RMB.

We hope that all our findings can arouse other researchers to do further studies, especially for the Chinese stock market. Moreover, our time is too limited to do research in depth, e.g. we use some traditional VaR methods; we do not implement

robust test for the regression models. Thus, we give some suggestions for further studies. First, more complicated VaR methods can be used, such as conditional VaR, VaR with GARCH, etc., because these methods may be more suitable than what we have implemented in this study. Second, other backtesting approaches could be applied to check the VaR estimation, for example, Christoffersen frequency test is a good choice since it checks the independence of violations in addition. At last, some other things can be improved in terms of data, including the test period length, the type of indexes, data sources, etc.

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Appendix

Figure 3: Histograms of all samples
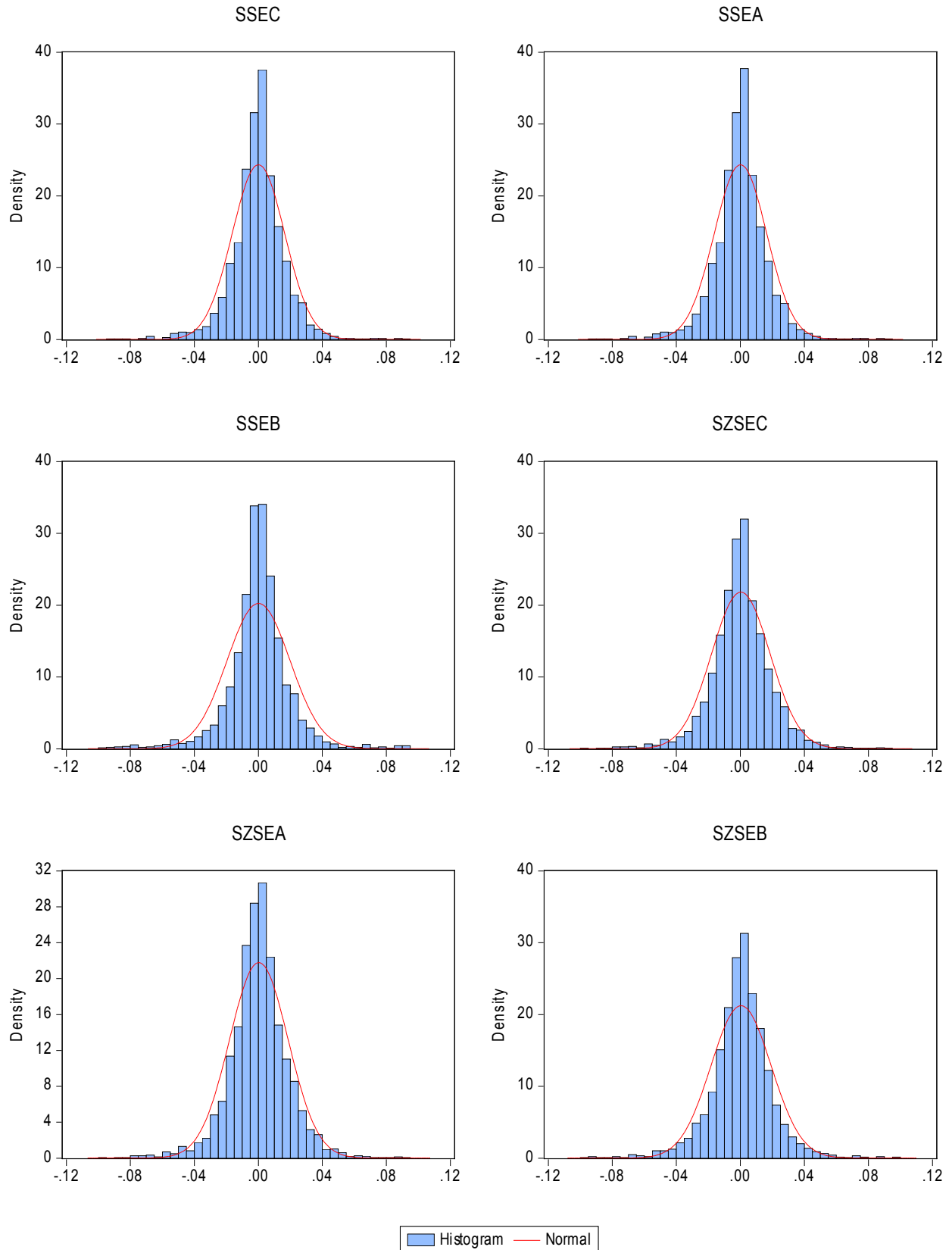
Figure 4: QQ plots of all samples under *t*-distribution
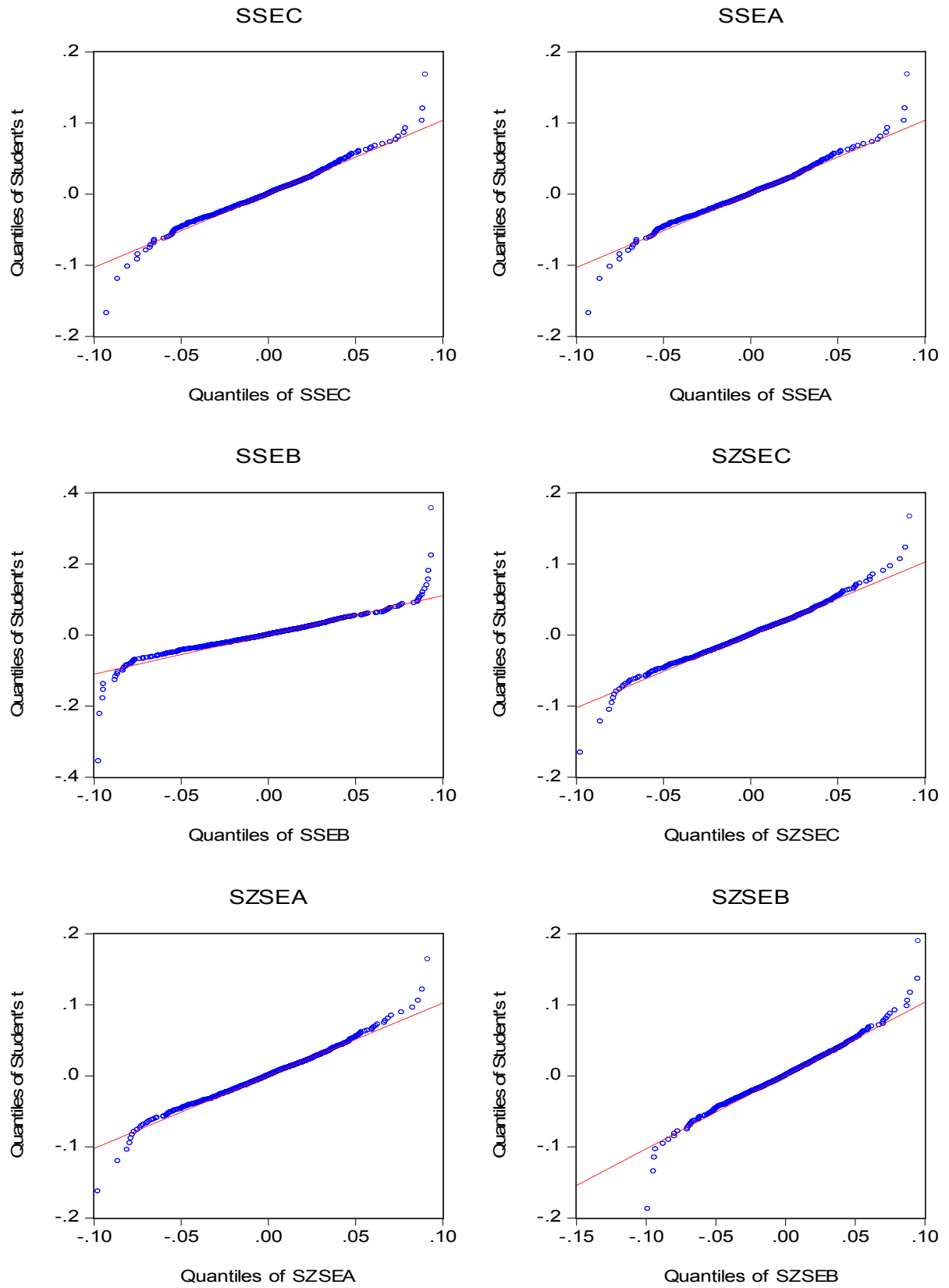
Figure 5: Results of VaR and actual return for SSEC

VaR_0.95 of SSEC

| | HS | HS-EWMA | t-dist | t-EWMA | RETURN |

VaR_0.99 of SSEC

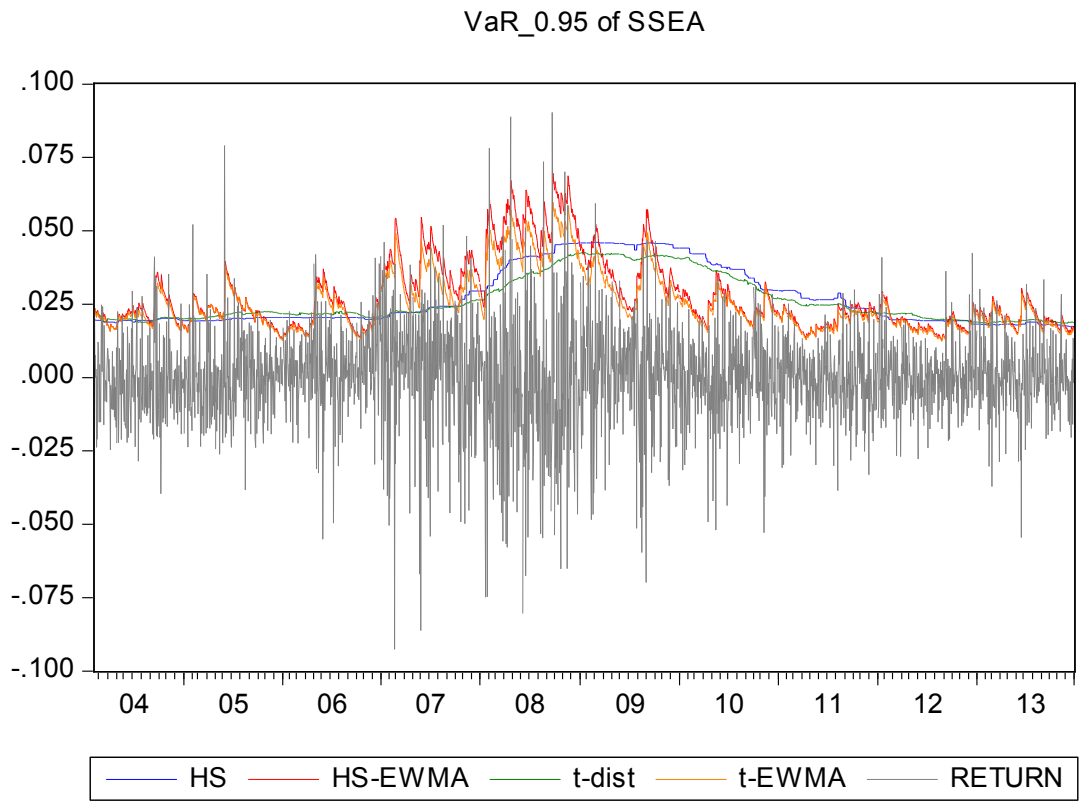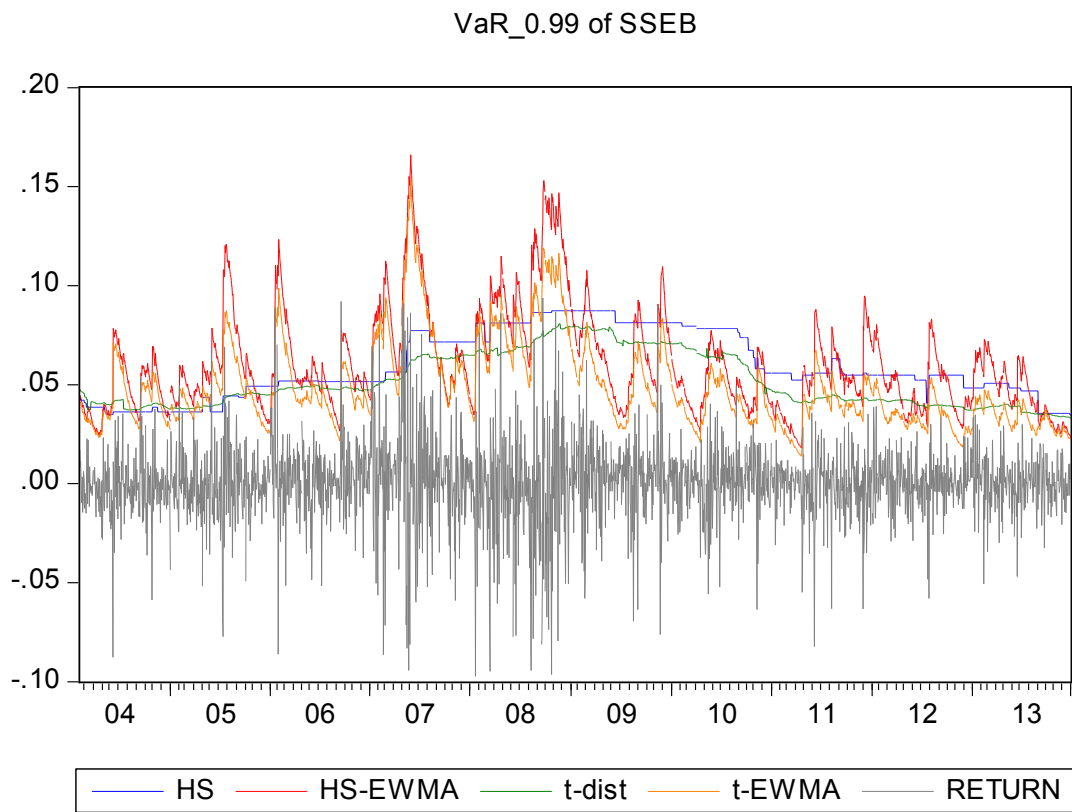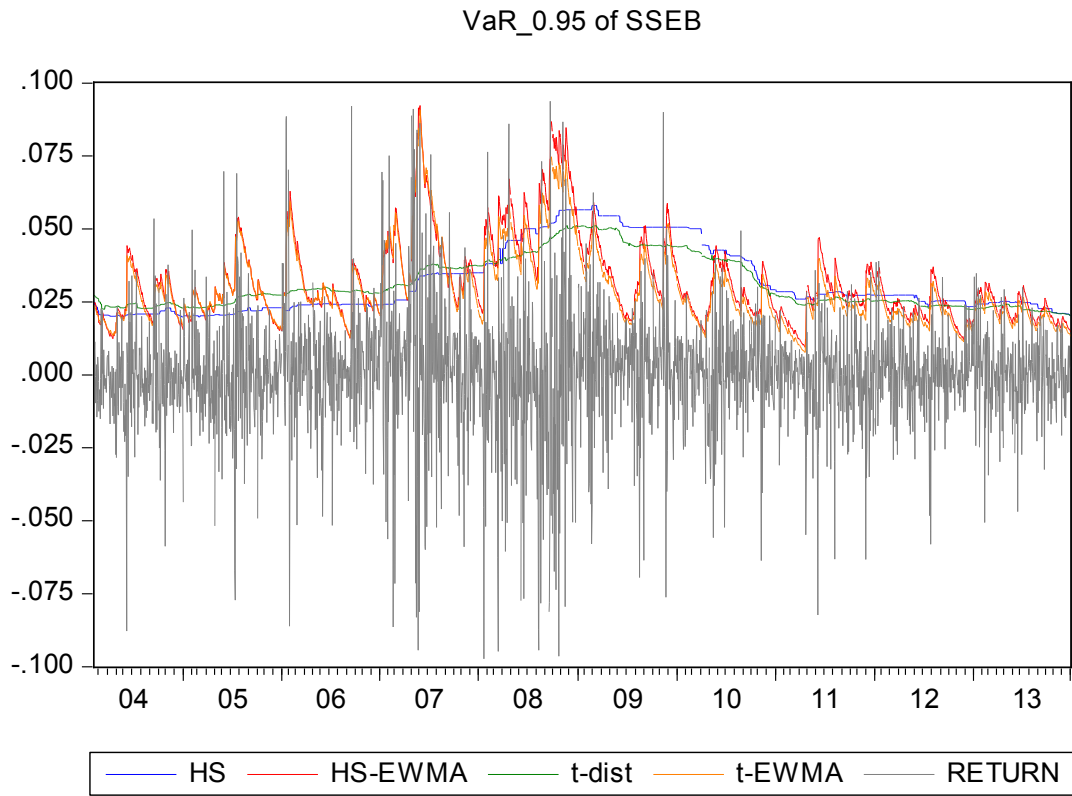| | HS | HS-EWMA | t-dist | t-EWMA | RETURN |
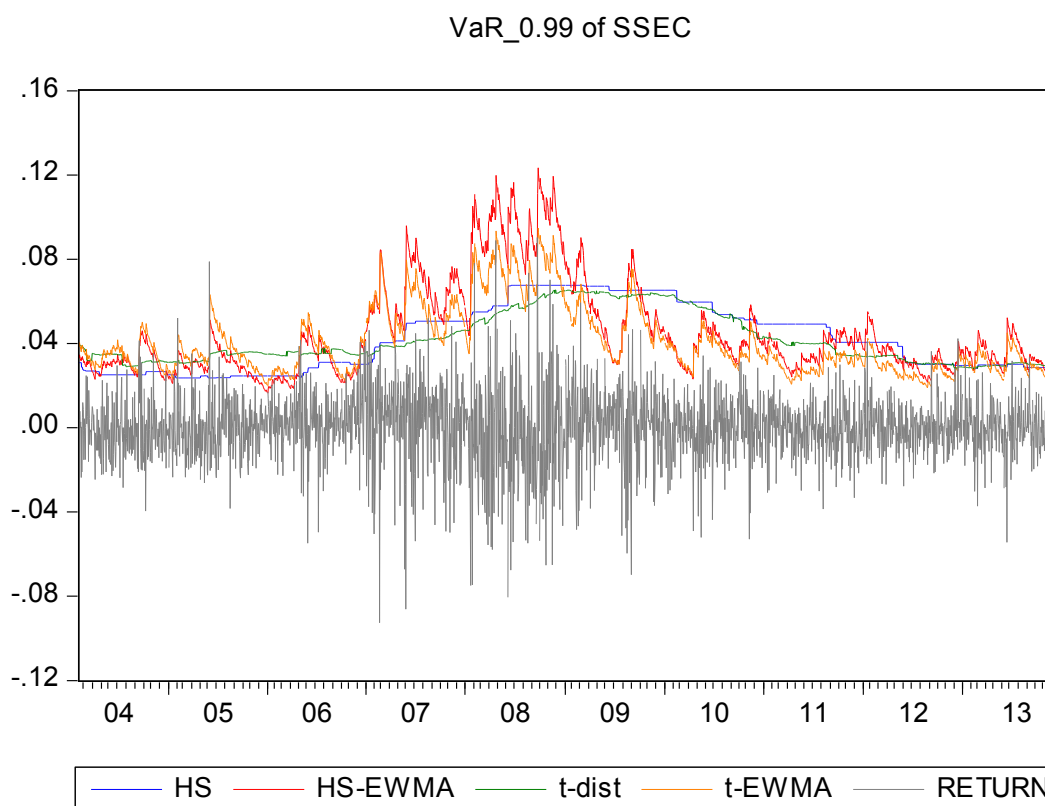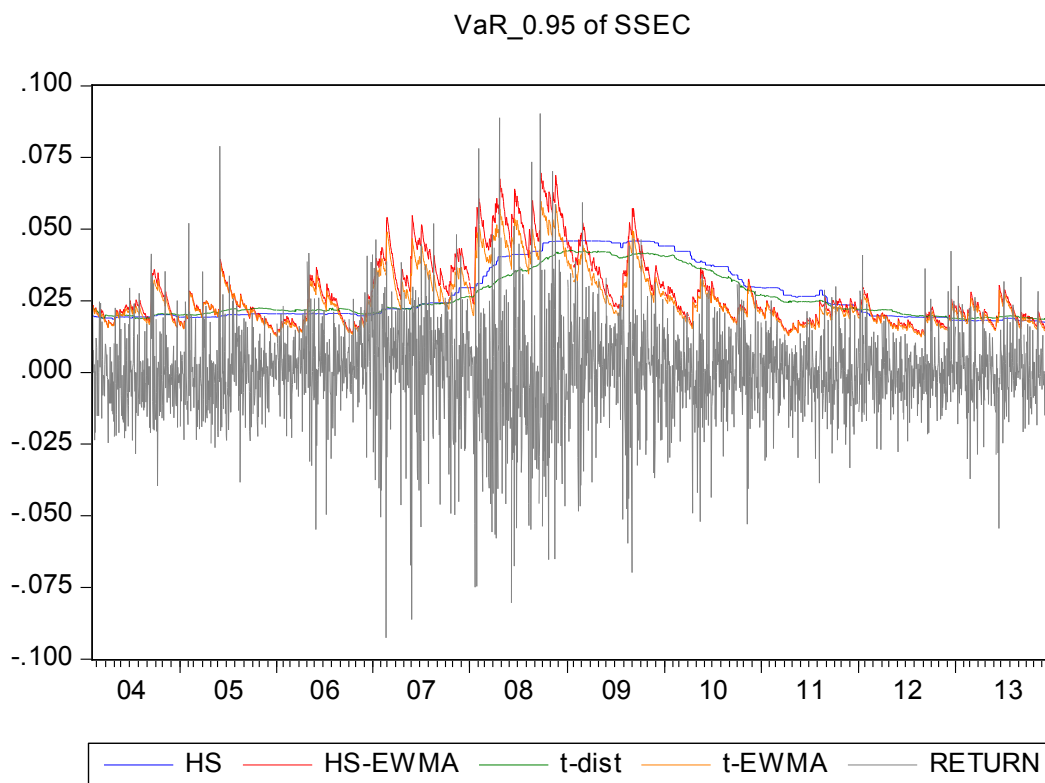
Figure 6: Results of VaR and actual return for SSEA

VaR_0.95 of SSEA

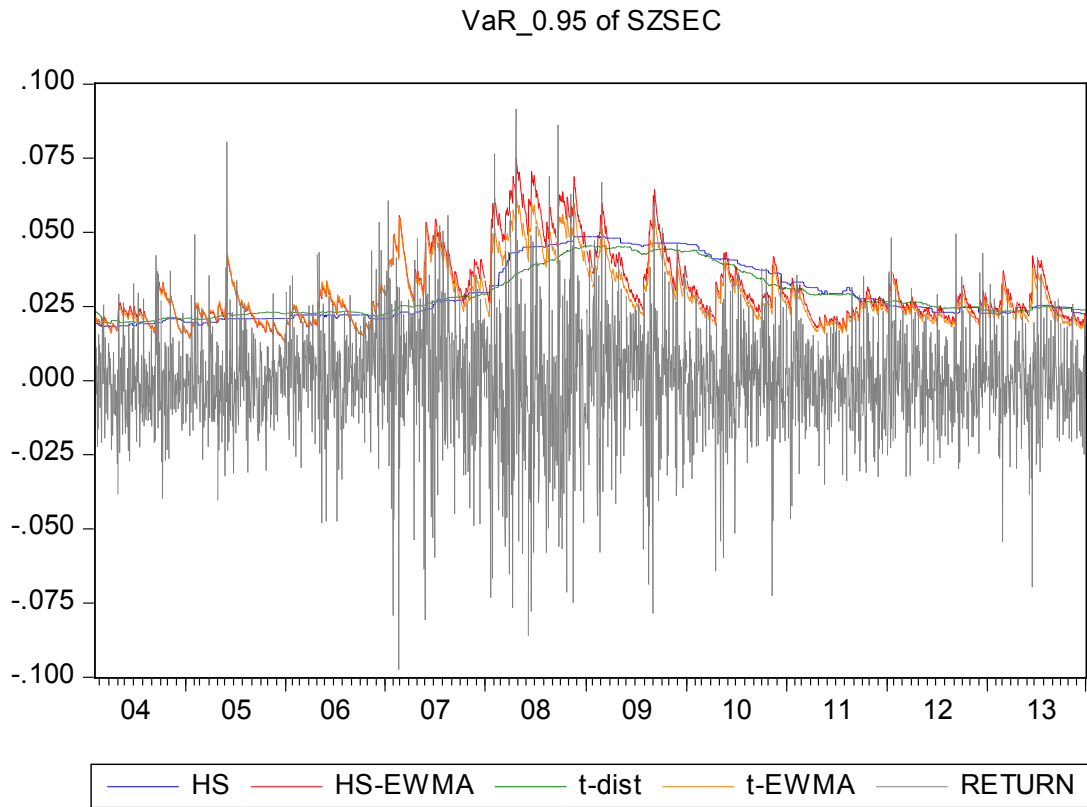| HS | HS-EWMA | t-dist | t-EWMA | RETURN |

VaR_0.99 of SSEA

| HS | HS-EWMA | t-dist | t-EWMA | RETURN |
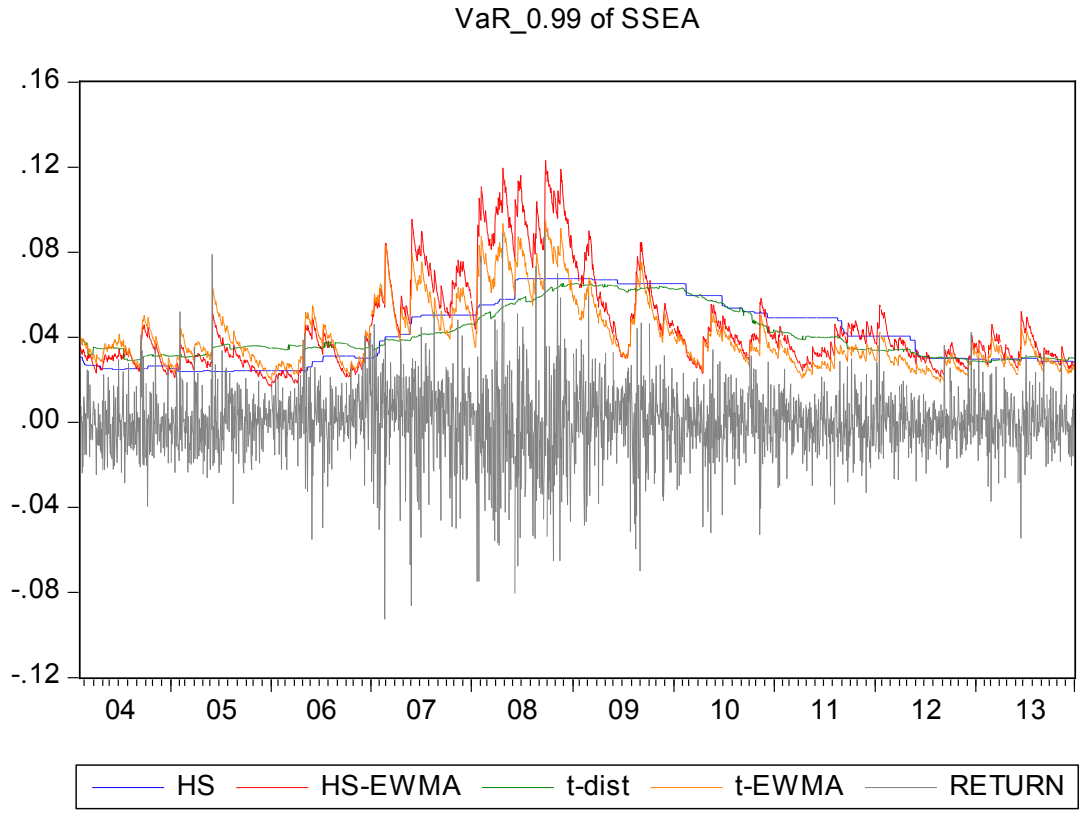
Figure 7: Results of VaR and actual return for SSEB

VaR_0.95 of SSEB

VaR_0.99 of SSEB

Figure 8: Results of VaR and actual return for SZSEC

VaR_0.95 of SZSEC

HS ——— HS-EWMA ——— t-dist ——— t-EWMA ——— RETURN

VaR_0.99 of SZSEC

HS ——— HS-EWMA ——— t-dist ——— t-EWMA ——— RETURN
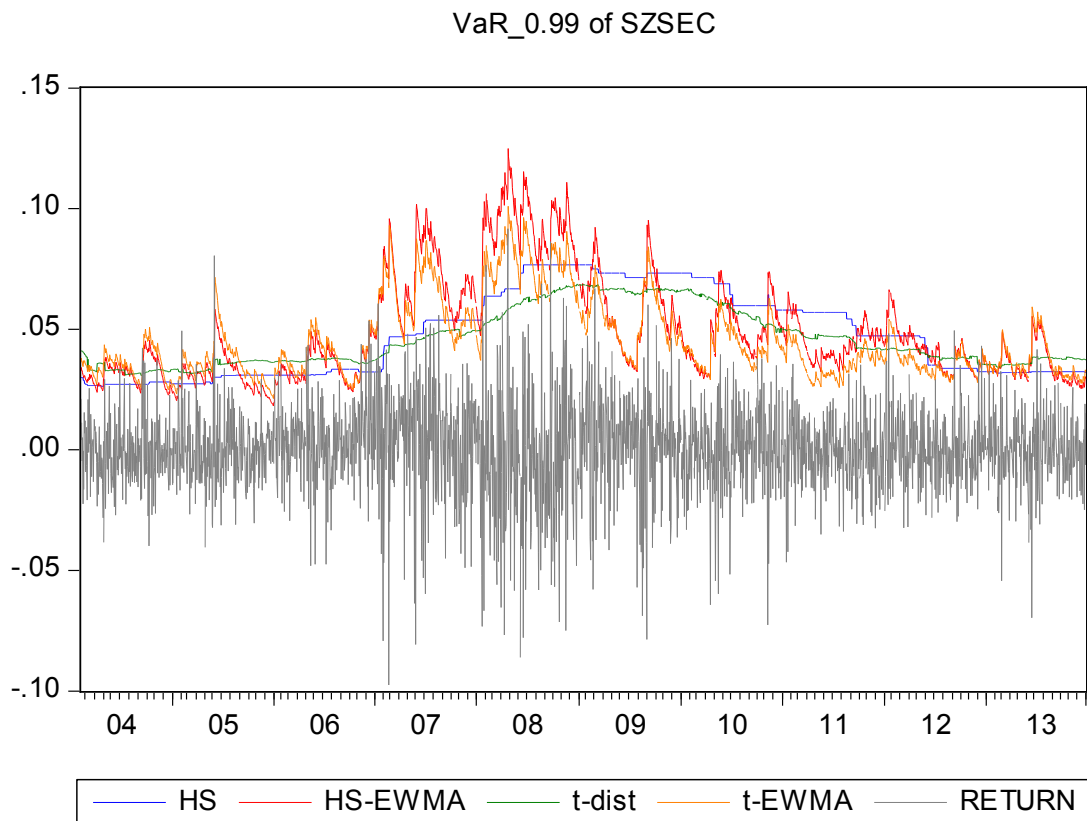
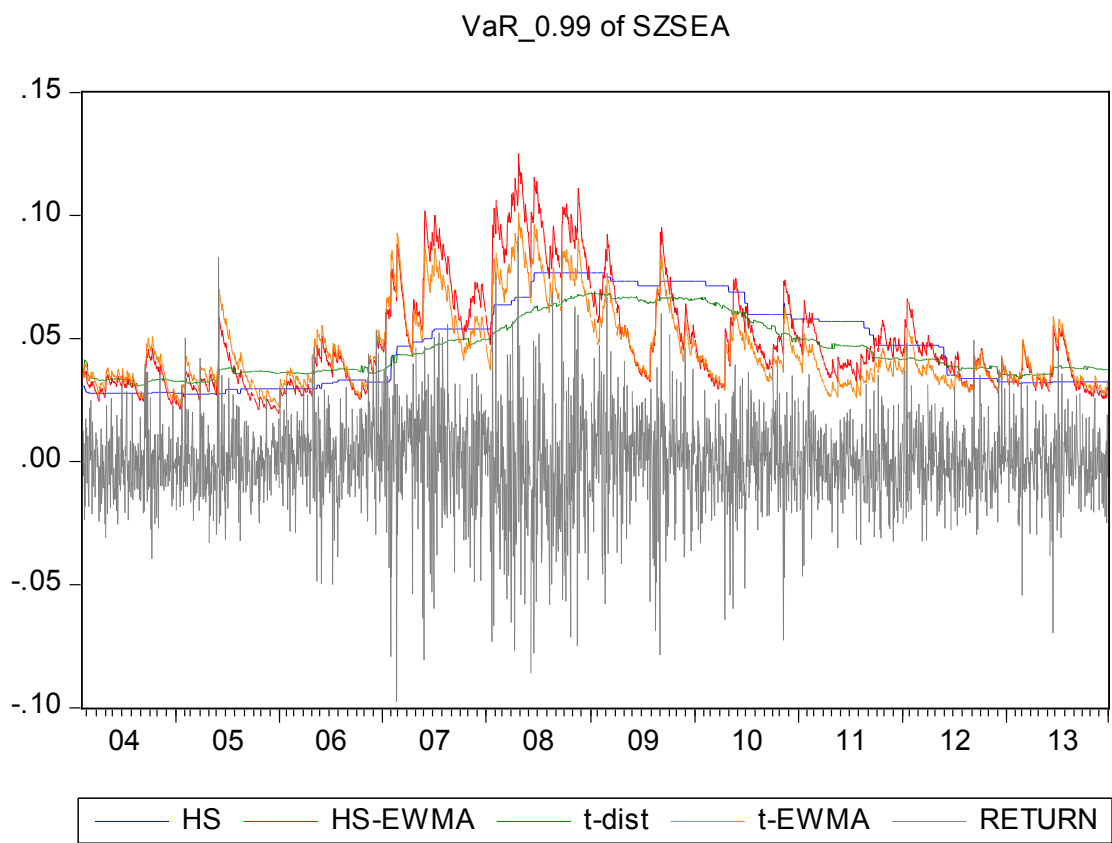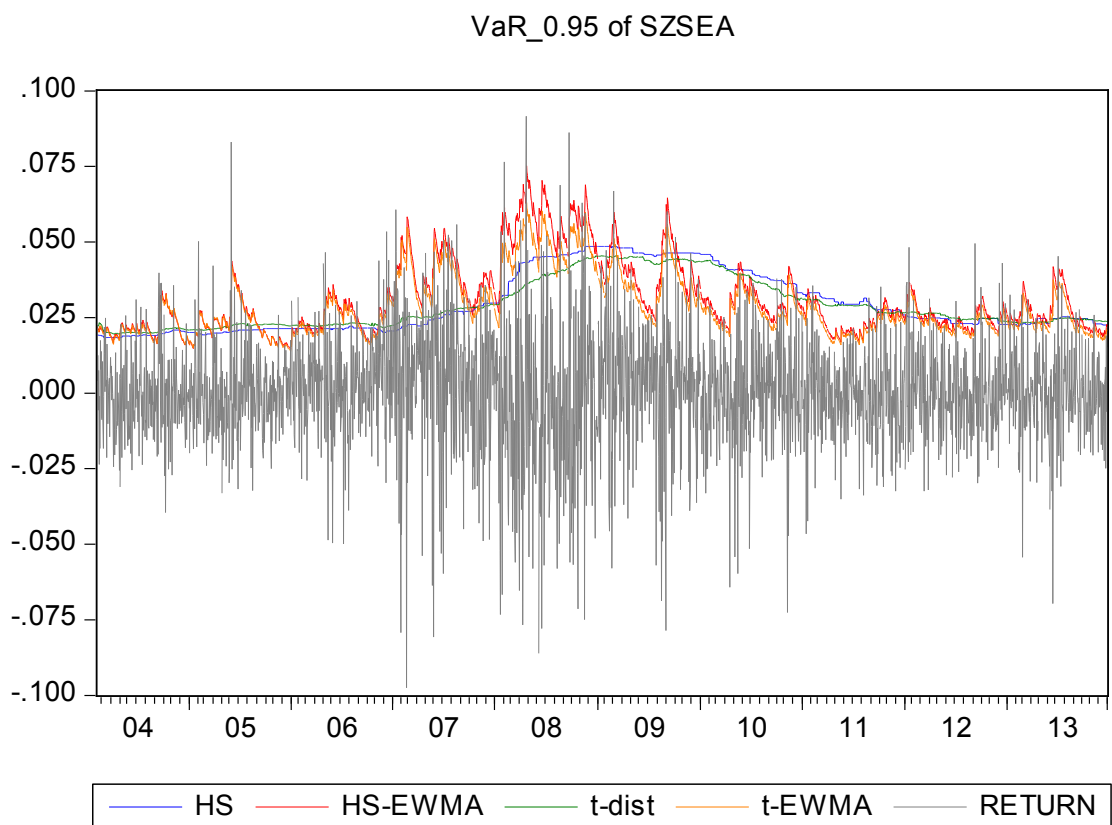**Figure 9: Results of VaR and actual return for SZSEA**

VaR_0.95 of SZSEA

VaR_0.99 of SZSEA

Figure 10: Results of VaR and actual return for SZSEB

VaR_0.95 of SZSEB

VaR_0.99 of SZSEB