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## **Downside Risk Measurement of Thailand Equity Mutual Funds**

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## Abstract

Value at Risk (VaR) is a simple, transparent and consistent measure that summarizes all sources of downside risk. VaR has gained acceptance in the banking industry in accordance to Basel II rules which require banks to use VaR in calculations of market risk. VaR as a risk measure is not as widely accepted in the investment industry. This thesis embraces five different VaR models to 20 equity mutual funds in Thailand. That is done to analyze if these equity mutual funds have considerable downside risk in terms of VaR. A comparative analysis of parametric, semi-parametric and non-parametric approaches is used to find the model that is the most suitable for the sample. The parametric approaches are student-t distribution and log-normal distribution and the non-parametric approach is basic historical simulation. The semi-parametric approaches are EWMA (exponentially weighted moving average model) and volatility weighted historical simulation using a GARCH(1,1) model for volatility. To test robustness and predictive ability three backtesting models are applied on all the approaches and all the equity mutual funds. The backtesting models are Bernoulli trial approach, Kupiec test and Christoffersen framework. Backtesting results for the models demonstrate that volatility weighted historical simulation using a GARCH(1,1) model is the most accurate measure of downside risk for both VaR at 95% and 99% confidence interval.

*Keywords:* Value at Risk, equity mutual funds, Thailand, student-t distribution, log-normal distribution, EWMA, volatility weighted historical, GARCH(1,1), historical simulation, backtesting, Bernoulli, Kupiec, Christoffersen.

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# 1. Introduction

Investors are in general risk averse and therefore try to optimize risk and return. A basic financial risk management principle is not to put all eggs in the same basket. Investors instead divest investments into a variety of assets to diversify risk. One way of diversification is through a mutual fund that collects money from a group of investors with common investment goals and buys for example stocks, bonds, money market instruments or combinations of these. These holdings of securities are known as a portfolio. Mutual funds is popular in Thailand, in recent years the portion invested in mutual funds has increased while bank deposits have become more constant.<sup>1</sup>

Financial risk can be divided into operational risk, market risk and credit risk.<sup>2</sup> This thesis will focus on the market risk or more specifically the downside risk measurement of equity mutual funds in Thailand using Value at Risk (VaR) as a measurement. VaR is a statistical approach that measures the likelihood of loss due to unfavorable changes in market conditions within a specific time horizon and with a specified confidence interval.<sup>3</sup> VaR has gained acceptance in the banking industry in accordance to Basel II rules which require banks to use VaR in calculations of market risk. VaR is not as widely accepted in the investment industry primarily because of the fundamental difference of these industries. VaR as a risk measurement is valuable for investors as well as fund managers. Investors can assess whether they are comfortable with the level of risk that each equity mutual fund exposes and fund managers have better overview of the risk. In this thesis we will take a look at 20 equity mutual funds in Thailand and estimate Value at Risk for each fund using five different VaR models. Our goal is to find the best VaR model that can capture the downside risk. In order to find the most precise model that suits our sample the models are backtested with three different models.

## 1.1 Problem discussion

In this thesis we are going to demonstrate that Value at Risk can be used to measure downside risk in the investment industry. Our sample combines of 20 equity mutual

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<sup>1</sup> <http://www.aimc.or.th>

<sup>2</sup> Jorion (2007) pp. 519

<sup>3</sup> Dowd (2002) pp. 19

funds in Thailand and we are going to find the VaR model that is the most appropriate to capture the downside risk of those funds. The study will use two parametric models, two semi-parametric models and one non-parametric model total of five models. The parametric models used are student-t distribution and log-normal distribution. The semi-parametric models used are EWMA (exponentially weighted moving average model) and volatility weighted historical simulation using a GARCH(1,1) model for volatility. The non-parametric model used is historical simulation. To test for accuracy of the models we will use three back testing methods the Bernoulli trial approach, Kupiec test and Christoffersen framework.

## **1.2 Purpose**

The purpose of this study is twofold first to describe the downside risk of equity mutual funds in Thailand using VaR as a measurement and second to evaluate the performance of the different VaR models.

## **1.3 Delimitation**

There are many VaR models that exist and we have chosen five models as a measure of downside risk and 20 equity mutual funds in Thailand. We are going to find the most accurate VaR model for those funds. Choosing more equity mutual funds and more than five models would have improved our results but due to our short time horizon in our thesis study we have to delimit our study.

Assets allocation for each fund is not disclosed in public. Some of the equity mutual funds might disclose top five or top ten invested assets but not all the assets in the portfolio. Therefore we can not calculate Value at Risk from portfolio weight and covariance metric. With this limitation, we use the net asset value per unit (NAV/unit) to calculate VaR on total return of mutual funds. Due to limited knowledge in programming the coefficients in the GARCH(1,1) model are only estimated once for the sample period of each fund.

## **1.4 Structure**

This paper is divided into 7 chapters we start with introduction and in chapter 2 we provide the theoretical background. In chapter 3 we provide a description of the data and how it was processed. Chapter 4 describes the methodology behind our study and chapter

5 is previous research. Results are presented and analyzed in chapter 6 and concluded in chapter 7.

## 2. Theoretical background

### 2.1 Mutual funds and equity mutual funds in Thailand

Mutual funds collect resources from individual investors and invest in well diversified portfolio of securities. The benefits of investing in mutual fund are that investors are better secured about their investment because of the portfolio diversification and professional fund management. Risk management should be included when an investment portfolio is designed. In designing an investment portfolio four steps should be considered:

- 1) decide which asset classes should be represented in the portfolio
- 2) determine the long term target percentage of the portfolio to allocate to each of these asset classes
- 3) specify for each asset class the range within which the allocation can be altered in an attempt to exploit better performance possibilities in one asset class versus another
- 4) selection of securities within each of the asset classes.<sup>4</sup>

Some mutual funds gain higher return in comparison to others the reason can be that its exposure is higher to risk, it could be attributed to luck or a market boom not necessarily a pure skill. Since Thailand's capital market conditions are less mature compared to e.g. Western countries and fluctuations of the equity market are untamed and awareness among investors are not as much as in more mature capital markets it is especially important to evaluate risk performance in Thailand.

The first asset management company in Thailand was established in 1975 through cooperation between the Thai government and the International Finance Corporation (IFC) which is a division of the World Bank. In 1977 the first fund was established "SinPinYo Fund" with a fund size of 100 million Baht and a 10-year maturity. In 1992 the Ministry of Finance began to issue a permission license for companies to operate on mutual funds management. From 1992 there has been a rapid growth in fund

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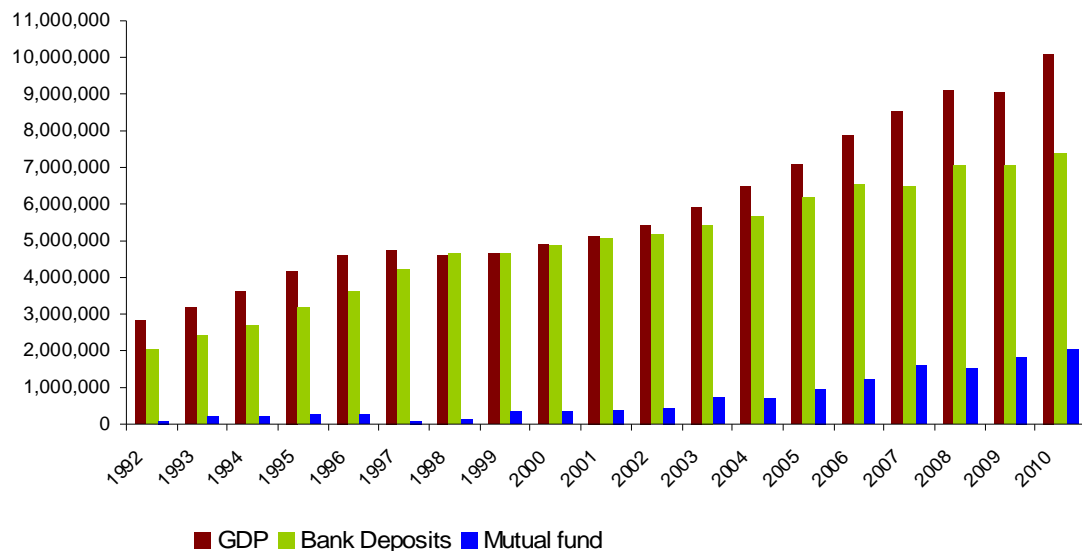
<sup>4</sup> Gibson (2008) pp. 12



management and it has become an important development of capital markets in Thailand.<sup>5</sup>

In April 2011 total asset management companies in Thailand were 21 with 2,020 Trillion Baht including equity mutual funds in total of 432.35 Billion Baht<sup>6</sup>.

### Household investments in mutual funds and bank deposits to GDP 1992-2010<sup>7</sup>



**Table 2.1** The table shows the development of investment in mutual funds.

In 1992 inhabitants of Thailand deposited more in bank accounts compared to investments in mutual funds in term of percentile of gross domestic product (GDP). In recent years the portion invested in mutual funds has increased while bank deposits have become more constant. There are many reasons that can explain this development for example it could be because of more financial knowledge of the inhabitants in Thailand. Investors are informed about the level of risk (high or low) for each mutual fund but do not get information on the downside risk. The performance reports of the funds only report the net asset value (NAV), NAV/unit and return. The report disregards the downside risk of the funds.

<sup>5</sup> <http://www.thaimutualfund.com>

<sup>6</sup> <http://www.aimc.or.th>

<sup>7</sup> <http://www.aimc.or.th>

The traditional risk measurement of mutual funds is by using standard deviation. It is a simple, unambiguous and a low cost method to calculate risk. Standard deviation is a roughly measurement of the average amount by which observations deviate from the mean. Asymmetric or skewed distribution occurs when one side of the distribution does not mirror the other. Applied to investment returns, asymmetric can be either positively skewed or negatively skewed. Our sample data is negatively skewed (long left tail) investors have a greater chance of extremely negative losses. In this case the downside risk such as VaR is a better measurement for asymmetric distribution. In addition downside risk better reflects investors attitude toward risk since investors dislike losses but enjoy receiving unexpected gains.

## **2.2 Risk management**

Institutions are today exposed to more sources of risk and more complex financial instruments than before. The need for global risk management is greater with new sources of risks and greater volatility of new products.<sup>8</sup> A high quality risk management system allows for more efficient deploy of capital and provides a source of comparative advantage.<sup>9</sup> Inherent in the business of equity mutual funds is taking risks and managing risks. It is important to manage risk because of the potential financial loss that may occur. A good way to manage risk is to implement risk principles and an independent risk monitoring as well as to design methods of risk assessment and measurement. To manage risk the risk has to be known, measured and monitored. Financial risk is the prospect of financial loss or gain due to unforeseen changes in underlying risk factors.<sup>10</sup> Financial risk can be separated into operational risk, credit risk and market risk.<sup>11</sup> This study is going to focus on market risk.

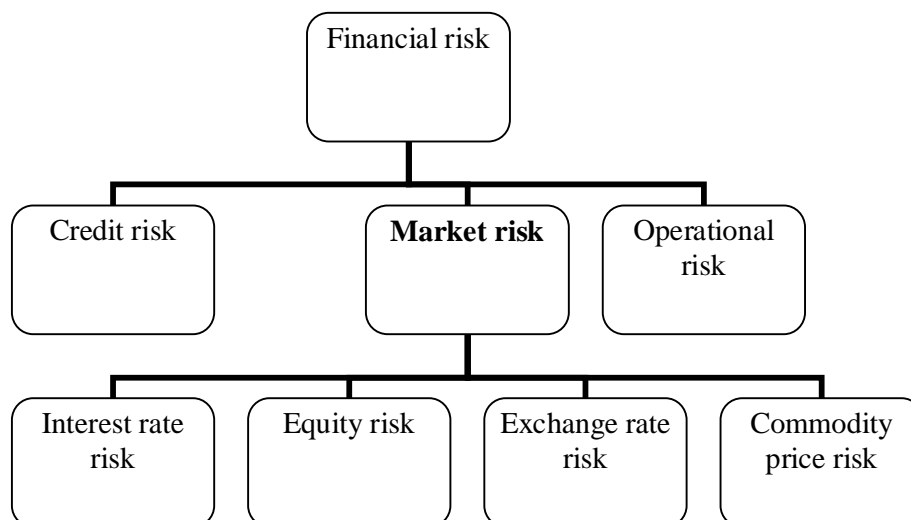
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<sup>8</sup> Jorion (2007) pp. 381

<sup>9</sup> Jorion (2001) pp. 52

<sup>10</sup> Dowd (2005) pp. 1

<sup>11</sup> Jorion (2007) pp. 516



### 2.2.1 Market risk

Market risk is defined as the risk of losses or gain that comes from unexpected changes in market prices (e.g. security prices) or market rates (e.g. interest or exchange rates). It can be divided into interest rate risk, equity risk, exchange rate risk and commodity price risk.<sup>12</sup> Market risk measurement tries to quantify the risk losses due to a combination of two factors the volatility in the underlying financial variables and the exposure to this source of risk. Mutual funds have no control over the volatility of financial variables but they can adjust their exposure to these risks. A widely known and used market risk measurement is Value at Risk (VaR), which can be used to measure, control and manage risk.<sup>13</sup>

Investors that invest in mutual funds will always face risk since mutual fund investments are subject to market risk. Investors should be aware that mutual funds invest in capital market instruments such as stock, debentures and bonds. As investors have their own risk preference they have to select a mutual fund that is equivalent to their own preference, it can be return objectives, risk tolerances and/or time horizon. Equity mutual funds in Thailand is a suitable instrument for retail investors as it offers an opportunity to invest in a well diversified portfolio that is managed by professionals at a relatively low cost. Mutual funds risks depend on the correlation between the bundles of stocks and are highly related with the volatility of the stock market.

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<sup>12</sup> Jorion (2007) pp. 22

<sup>13</sup> Jorion (2007) pp. 425

### 2.2.2 The Bank for International Settlements (BIS) – Basel rules

The Bank for International Settlements (BIS) is an international organization which fosters international monetary and financial cooperation and serves as a bank for central banks.<sup>14</sup> The BIS formulates supervisory standards and guidelines on banking supervisory matters however BIS has no legal power, instead its member countries implement its guidelines as it best suits each country's system. In 1988 the Basel Committee of Banking and Supervision that works under the BIS published minimum capital requirements for banks, Basel I. In a market risk amendment from 1996 to the original Basel I banks with significant trading activities were required to hold a capital to cover the market risk exposure in their trading accounts. This market risk capital requirement was recommended to be based on VaR models generated by the bank's own internal risk management models.<sup>15</sup> The Basel II from the year 2004 set by the Basel Committee of Banking and Supervision requires banks to use VaR in calculations of market risk has been legislated in various countries. VaR has gained popularity in all aspects of finance in recent years because of its simple, transparent and consistent measurement of overall risk.

### 2.3 Value at Risk

Value at Risk can be traced back to Markowitz's work of portfolio choice. Markowitz was a supporter of the standard deviation as an intuitive measure of dispersion and noted that investors should be interested in risk as well as in return.<sup>16</sup> Value at Risk (VaR) can be used as a measurement for market risk. It is a statistical measurement indicating the likelihood of loss due to unfavorable changes in market conditions within a specific time horizon and with a specified confidence interval.<sup>17</sup> VaR is the maximum expected loss for a specific time period under normal market conditions given a certain confidence interval. Mathematical definition of VaR is:<sup>18</sup>

$$\Pr(x \leq VaR) = a$$

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<sup>14</sup> [www.bis.org/about/index.htm](http://www.bis.org/about/index.htm)

<sup>15</sup> Lopez (1998)

<sup>16</sup> Jorion (2007) pp. 113

<sup>17</sup> Dowd (2002) pp. 19

<sup>18</sup> Culp (2001) pp. 342

Where  $x$  is the portfolio return over a specific time horizon with the probability  $\alpha$ . The time horizon must be set before VaR of an exposure is calculated. One week risk horizon is when potential market risk related loss from starting point to end of one week. A risk horizon for VaR calculation can be for example one day, one week, one month or one year. The most applicable time horizon is influenced by several factors: first the frequency of risk reporting requirements, second the frequency of comparisons by firms between actual risk and tolerances and third the time required liquidating or hedging huge losses.<sup>19</sup> The confidence interval also has to be specified before VaR of an exposure is calculated. A confidence interval is the confidence that VaR represents the true worst case loss in the next time horizon. The confidence interval is  $(1 - \alpha) \%$  and the  $\alpha$  (e.g. 1% or 5%) is the amount of probability in the left tail of the risk distribution.<sup>20</sup> If the confidence interval is 99% loss should only exceed the VaR outcome in one day out of hundred.

The attractions and criticisms of VaR are following. The attractions are that VaR combines several sources of market risk into a single quantitative measure of potential value change for a portfolio.<sup>21</sup> It is a common consistent measure of risk and can be applied to any asset for example stocks, bonds and derivatives. VaR can aggregate a lot of positions to one measure therefore a portfolio or a whole firm can be measured and it takes an overall perspective on risk, it focuses on assessment on a complete portfolio not just on individual positions in it. VaR is also a probabilistic measure and is expressed in a simple way in terms of a unit. The criticism of VaR is the sensitivity of underlying assumption, if the estimates are inaccurate a greater risk can be taken and it does not take losses beyond VaR into account that is the size of the loss if a tail event occurs.<sup>22</sup>

### **2.3.1 VaR investment industry versus banking industry**

As mentioned before VaR is widely used within the banking industry however it is not as widely used within the investment industry, primarily because of the fundamental

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<sup>19</sup> Culp (2001) pp. 343

<sup>20</sup> Culp (2001) pp. 343

<sup>21</sup> Johansson et al. (1999)

<sup>22</sup> Dowd (2005) pp. 12-13

difference of the later from the former. Pallotta and Zenti summarize the differences between the banking industry and the investment industry.<sup>23</sup>

<b>Characteristic</b>	<b>Banking</b>	<b>Investment</b>
Horizon	Short time horizon	Horizon is relatively long
Distribution	Normally distributed returns	Not safe to assume that returns are normal
Expected return	Zero expected return	The expected change is not zero
Variance	Constant variance covariance matrix	Volatilities and correlations vary over time and are not inevitably linear
Benchmark	Absence of a benchmark	Usually a benchmark

The trading environment of banks is much faster, the time horizon on trading is 1 day or intraday compared to mutual funds where positions change more slowly, monthly or quarterly. The turnover frequency is also more rapid in the banking sector and the leverage is higher.<sup>24</sup> VaR can be used to measure the risk of an individual instrument or the risk of an entire portfolio it can be increased if VaR is too low or decreased if risk is too high.<sup>25</sup> Even though there are differences between the banking industry and the investment industry VaR can also be applicable for the investment industry since VaR is a forward looking measure of risk. In general banks report its trading VaR for a 1 day horizon that is because of the liquidity and fast turnover in its portfolios. Mutual funds generally invest in less liquid assets and adjust its risk exposure more slowly with a 1 month horizon often selected.<sup>26</sup> The investment industry can also benefit from the discipline that the risk management system incorporating VaR provides.

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<sup>23</sup> Pallotta and Zenti (2000)

<sup>24</sup> Jorion (2007) pp. 426-427

<sup>25</sup> Pritsker (1997)

<sup>26</sup> Jorion (2007) pp. 116

## 3. Data

### 3.1 Sample

The data used are daily NAV/Unit of Thailand equity mutual funds over the period January 2006 to December 2010. The data was extracted from Bloomberg's data feed. The data period has 1275 observations for each equity mutual fund to estimate the models in calculations of VaR. This amount of observations should be enough to give a reasonable estimation of VaR predictions as well as enough backtesting periods. Two criteria were prevailing when we chose the 20 funds, first only funds that did not pay dividend and second only funds that were active the whole period were selected. The entire price is quoted in Thai Baht and daily NAV/Unit is used to calculate daily total return by using percentage change of unit value<sup>27</sup>

The total return of the equity mutual funds is used to calculate ex-ante VaR predictions. Daily returns for 2 years or 510 working days are used as the rolling window period then daily VaR for all the remaining data 765 days is calculated.

For historical simulation, student-t distribution, log-normal distribution and volatility weighted historical simulation using GARCH(1,1) rolling window was applied and for EWMA we used recursive window. The difference between a recursive window and a rolling window is that the recursive forecasting is where the initial estimation date is fixed and additional observations are added one by one to the estimation period. A rolling window is where the length of the in sample period for estimation is fixed and the start date and the end date increases by one observation each time.<sup>28</sup>

Microsoft Excel was used to calculate all the VaR models. It was applied manually by using formulas which will be discussed more precisely in the next section. For volatility weighted historical simulation using GARCH(1,1) Eviews 7 was used to estimate the parameters for the GARCH model. A programming script was created in Visual Basic Application (VBA) in Excel in order to repeat calculation by rolling data for each day (see script in appendix 3). Eviews 7 was used to test for normality and volatility of the returns. Bera-Jarque test was applied for normality and the returns were plotted

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<sup>27</sup> Performance Measurement Standards Acts 2009

<sup>28</sup> Brooks (2005) pp. 246

from Eviews to test for volatility (see appendix 2). All the back testing methods Bernoulli, Kupiec and Christoffersen tests were also calculated in Excel.

### 3.2 Descriptive statistics

To test for normality Bera-Jarque test was applied to the data. The null hypothesis of normality of the data is rejected at 1% significant level. Under the null hypothesis the test assume that the entire distribution is characterized by the first and second moment, the mean and the variance. The third and fourth moments of the distribution are skewness and kurtosis. Skewness measures its variation from the mean to find out if the distribution is symmetric or not, Kurtosis measures how fat the tails of the distribution are. A normal distribution is not skewed and has a coefficient of kurtosis of 3 and it is symmetric about its mean.<sup>29</sup> The returns follow a leptokurtic distribution, the tails are fatter than in the normal distribution and it is more peaked at the mean. Our returns are negatively skewed which means that the distribution is not symmetric. Therefore VaR as a downside risk measurement should be better than variance in prediction of losses as already explained.

	ABERSL	ABESMF	AJFSCAI	AJFSTDY	AJFSTEQ	K_FEQ	K_SET50	KASRKEC	KASRKF3	KASRKF4
Mean	0.05%	0.05%	-0.01%	0.08%	0.06%	0.06%	0.06%	0.07%	0.03%	0.03%
Median	0.10%	0.10%	0.07%	0.07%	0.07%	0.11%	0.07%	0.08%	0.08%	0.08%
Maximum	8.01%	4.47%	10.34%	10.88%	10.33%	12.25%	11.69%	12.37%	12.34%	12.34%
Minimum	-11.17%	-6.16%	-16.75%	-11.93%	-12.41%	-15.73%	-15.67%	-15.72%	-15.71%	-15.67%
Standard Deviation	1.22%	0.91%	1.78%	1.61%	1.56%	1.79%	1.74%	1.83%	1.92%	1.95%
Skewness	-0.861	-0.711	-1.933	-0.427	-0.493	-0.592	-0.649	-0.546	-0.942	-1.167
Kurtosis	13.989	8.963	20.185	11.878	12.508	13.189	13.725	12.769	13.861	15.413
Jarque-Bera	6573	1997	16483	4226	4855	5590	6200	5134	6455	8475
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
No of observations	1275	1275	1275	1275	1275	1275	1275	1275	1275	1275
	NAKGTHA	SCBDHAA	SCBMH2A	SCBMH3A	SCBMH4A	SCBMH5A	SCBPMOI	SCBTAWA	SCBTS2A	TMBJB25
Mean	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.07%
Median	0.11%	0.08%	0.09%	0.09%	0.08%	0.08%	0.11%	0.09%	0.08%	0.09%
Maximum	7.52%	10.44%	10.01%	10.00%	9.87%	10.39%	8.80%	9.84%	9.84%	12.35%
Minimum	-10.34%	-15.18%	-14.15%	-13.97%	-14.00%	-14.58%	-12.20%	-13.94%	-13.93%	-15.97%
Standard Deviation	1.12%	1.62%	1.59%	1.60%	1.59%	1.60%	1.42%	1.59%	1.59%	1.81%
Skewness	-0.905	-0.666	-0.580	-0.581	-0.573	-0.611	-0.440	-0.572	-0.569	-0.503
Kurtosis	14.253	12.935	11.681	11.581	11.415	12.383	10.254	11.443	11.363	13.377
Jarque-Bera	6902	5337	4075	3984	3832	4756	2837	3856	3784	5775
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
No of observations	1275	1275	1275	1275	1275	1275	1275	1275	1275	1275

**Table 3.2** descriptive statistics parameters and normality test using Jarque-Bera test for the 20 funds

<sup>29</sup> Brooks (2005) pp. 161



## 4. Methodology

### 4.1 Characteristics of financial data

When deciding which approaches to use for VaR calculations we considered the characteristics of financial returns. Normal distribution approach was excluded since our data rejected normality. Absolute and squared financial returns tend to have volatility clusters with high autocorrelation they have high kurtosis resulting in more peaked distribution around the center and fatter tails as well as mild skewness.<sup>30</sup> Using normality simplifies VaR calculation since all percentiles are multipliers of the standard deviation.<sup>31</sup> Because of this, alternative approaches are needed to describe the tails and the possible losses.

The approaches we use are parametric approaches, non-parametric approaches and semi-parametric approaches. For parametric approaches we chose distributions that are better at capturing the possible losses than the normal distribution. Non-parametric approach estimates risk without using predetermined distribution for the returns, instead historical returns are used to forecast risks in the near future. Semi-parametric approach is a combination of the previous two.

**Volatility** A number of important features that is common to financial data:

- *Leptokurtosis* – returns have tendency to have distributions with fatter tails and excess peakedness at the mean.
- *Volatility clustering* – volatility in financial markets have tendency to appear in clusters, that is high returns are expected to follow high returns and vice versa. The reason behind this is that arrival of information which drive price changes occur in clusters that is they do not arrive evenly over time.
- *Leverage effects* – volatility tends to rise more following a large price fall than following a rise of price of the same extent.<sup>32</sup>

The models we use to capture this stylized features of volatility is volatility-weighted historical simulation using a GARCH(1,1) and EWMA (see section 4.4.1.1 and 4.4.1.2).

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<sup>30</sup> Kuester et al. (2005)

<sup>31</sup> Pallotta and Zenti (2000)

<sup>32</sup> Brooks (2005) pp. 380

The disadvantage of GARCH(1,1) is that it cannot capture the leverage effects. An extension of GARCH with an additional term to account for leverage effects is the GJR model named after the authors Glosten, Jagannathan and Runkle.<sup>33</sup>

## 4.2 Parametric approach

The parametric approach estimates risks by fitting a parametric distribution to the data before concluding VaR from the distribution. Parametric distribution is easy to use and creates more accuracy estimates of VaR if the density function fit the data, however the approach is vulnerable to error if the density function does not fit the data sufficiently. When choosing a parametric approach the characteristics in returns have to be taken into consideration. The approaches that we are going to use are student-t distribution and log-normal distribution.

### 4.2.1 Student-t distribution

Returns normally have excess kurtosis and failure to capture this excess kurtosis can lead to an underestimation of VaR. Student-t distribution is a heavy tailed distribution that allows for excess kurtosis along with mean and standard deviation.

The student-t distribution formula for VaR:<sup>34</sup>

$$Var(a) = -m + st(a, v) \sqrt{\left(\frac{(v-2)}{v}\right)}$$

The main parameters for this formula is  $\alpha$  (one minus the confidence interval), mean ( $\mu$ ), standard deviation ( $\sigma$ ) and t which is the t-test statistic at given  $\alpha$  and v. The degrees of freedom (v) indicate the shape of the distribution, how fat the tails are and the height of the kurtosis. If the degrees of freedom are low it results in fatter tails and the vice versa. Kurtosis can be traced to degrees of freedom:<sup>35</sup>

$$v = (4k - 6)/(k - 3)$$

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<sup>33</sup> Brooks (2005) pp. 405

<sup>34</sup> Brooks (2005) pp. 159

<sup>35</sup> Brooks (2005) pp. 160

The advantage of the student-t distribution is its ability to handle excess kurtosis. The drawback is that it cannot respect constraints on maximum possible losses and therefore can produce misleadingly high risk estimates. It also suffers from an additional problem: the sum of two or more t-distributed random variables might not be distributed as the t variable itself.<sup>36</sup> Student-t distribution is a symmetric distribution and cannot capture skewness.

#### 4.2.2 Log-normal distribution

The log-normal distribution assumes that geometric returns are normally distributed. Using geometric returns is a good approach when dealing with returns over long periods. The formula for log-normal VaR is:<sup>37</sup>

$$VaR = 1 - \text{Exp}(m - z_a S)$$

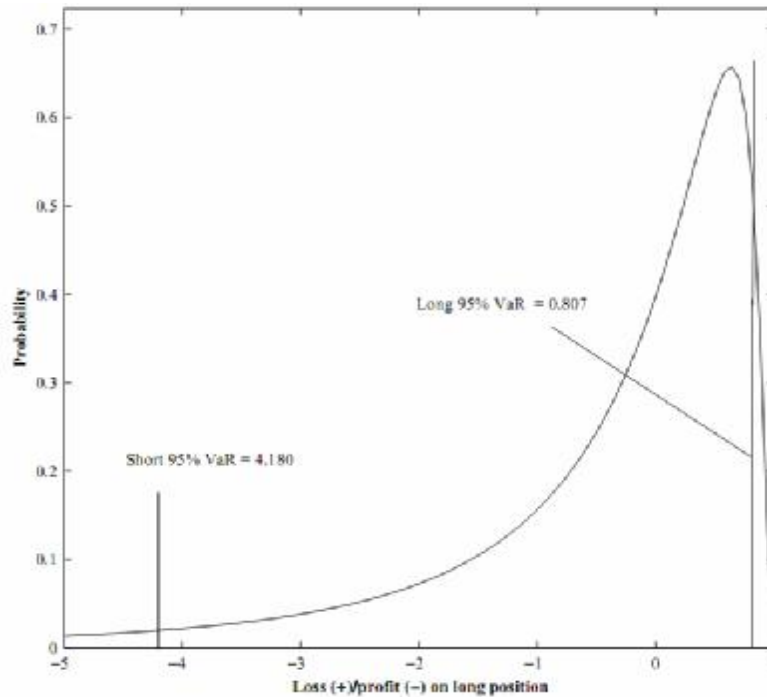
The log-normal distribution is not symmetric like the normal distribution, it is asymmetric and therefore has not the same distance from the mean. The long and short positions have asymmetric risk exposure, meaning that if the market goes down a long position loses and a short position loses if the market goes up. The characteristic of log-normal distribution is at worst the long position can lose all the investment but the short position can make losses exceeding the original investment (see figure 1).<sup>38</sup>

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<sup>36</sup> Dowd (2005) pp. 160

<sup>37</sup> Dowd (2005) pp. 161

<sup>38</sup> Dowd (2005) pp. 161



**Figure 1**

Source: Dowd (2005)

The advantage of the log-normal distribution is that it takes into account the maximum loss restriction on long positions.<sup>39</sup>

### 4.3 Non-parametric approach

Non-parametric approach is of popularity when estimating risk. This approach does not assume about the shape of the distribution of the returns the same way as the parametric approach does. Instead historical data are used under the assumption that events from the near past will be likely to represent the recent future and they do not follow some theoretical distribution.<sup>40</sup> The advantage of the non-parametric approach is that it accommodates non-normal features like kurtosis and skewness. A weakness of this approach is that it depends on historical data and possible events that might occur however it does not take into account events that have not occurred.<sup>41</sup> The non-parametric approach used in this thesis is historical simulation.

<sup>39</sup> Dowd (2005) pp. 162

<sup>40</sup> Dowd (2005) pp. 83

<sup>41</sup> Dowd (2005) pp. 99-100

### **4.3.1 Historical simulation**

Historical simulation assumes that all future event variations have occurred in the past and the historical distribution is identical to the future returns distribution. Taking all historical returns into consideration an empirical distribution can be built. The sample size should be as large as possible to hinder few points in the lower tail of the distribution which at high confidence interval could lead to an imprecise VaR.<sup>42</sup> The distribution can be built from a histogram, if we have 1000 observations of returns (4 years of observations with 250 trading days for each year) and a 95% confidence interval, the VaR is then the 51<sup>st</sup> highest loss value of the observations.<sup>43</sup>

The advantages of historical simulation are that it can accommodate to any type of instruments and can accommodate non-normal features as well it is relatively simple to implement and it accurately reflects the historical multivariate probability distribution. The disadvantage is that it does not incorporate volatility updating.<sup>44</sup> Another drawback of historical simulation is the ghost effect that appears when putting the same weight on all past observations in a sample parallel to the use of a rolling window. Using a rolling window an old observation is dropped out of the sample and that can lead to a significant change in the risk measure.<sup>45</sup>

## **4.4 Semi-parametric approach**

Semi-parametric approach is a combination of both parametric approach and non-parametric approach. Semi-parametric approach is also regarded as weighted historical simulation.<sup>46</sup>

### **4.4.1 Weighted historical simulation**

As discussed above historical simulation puts the same weight on all past observations in the sample and the weight belong to the sample until the observation is dropped out and has no impact after that. The problem with this method is that each observation has the same weight apart from age, volatility or other features. Historical simulation assumes iid (independent and identically distributed), that is observations are treated as they are

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<sup>42</sup> Alexander (2008) pp. 42-43

<sup>43</sup> Dowd (2005) p. 84

<sup>44</sup> Hull (1998)

<sup>45</sup> Dowd (2005) pp. 100

<sup>46</sup> Dowd (2005) pp. 93

equally likely and independent of others over a certain time period. The iid assumption is unrealistic since volatility varies over time together with volatility clusters in high and low volatility periods.<sup>47</sup> Dropping observations out of sample is a loss of information even old observations have valuable information and should not be thrown away.<sup>48</sup> To overcome some of these problems observations are weighted.

#### 4.4.1.1 Volatility weighted historical simulation using GARCH(1,1)

Hull and White suggested weighting data by volatility to compute VaR. If data observed two months ago have lower volatility than today the volatility can be underestimated and vice versa if the data have higher volatility than today the volatility can be overestimated.<sup>49</sup> Volatility weighted historical simulations takes into account recent volatility of returns. In times of high volatility the returns are scaled upwards and vice versa in times of low volatility. This adjustment gives a more accurate measure for tomorrow's VaR and can also predict higher VaR than the historical simulation. The mathematical equation is:<sup>50</sup>

$$r^*_{t,i} = \left( \frac{\sigma_{T,i}}{\sigma_{t,i}} \right) r_{t,i}$$

$\sigma_{T,i}$  most recent forecast of the volatility of asset i

$\sigma_{t,i}$  historical forecast of the volatility of the returns in asset i for day t made at the end of day t - 1

$r_{t,i}$  the historical returns in the sample

Hull's and White's approach to volatility weighted historical simulation is capable of various extensions and combinations of other approaches. In this thesis we exercise with the volatility estimates of GARCH(1,1).

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<sup>47</sup> Dowd (2005) pp. 92

<sup>48</sup> Dowd (2005) pp. 93

<sup>49</sup> Hull (1998)

<sup>50</sup> Dowd (2005) pp. 94

### **GARCH (1,1)**

In 1982 Engle proposed the Autoregressive Conditionally Heteroskedastic or ARCH model to capture the volatility clustering in returns. To model the persistent movements in volatility without estimating a large number of coefficients Bollerslev and Taylor in 1986 independently developed the generalized ARCH or GARCH.<sup>51</sup> The model allows for the conditional variance to be dependent upon previous own lags. It is a one period ahead estimate for the variance, the calculations are based on any past relevant information. The GARCH(1,1) equation is:<sup>52</sup>

$$y_t = m + \alpha y_{t-1} + u_t, \quad u_t \sim N(0, s_t^2)$$
$$s_t^2 = a_0 + a_1 u_{t-1}^2 + \beta s_{t-1}^2$$

$u_t$  is a residual sum of squares in the mean equation.

$a_1 u_{t-1}^2$  give information about volatility during the previous period

$\beta s_{t-1}^2$  give the fitted variance from the model during the previous period

$a$  and  $\beta$  measures the rate of the effect to fade out over time. The closer to 1 the slower the volatility shock fades out.<sup>53</sup>

The advantage of GARCH model is that it can account for volatility clustering and leptokurtosis (fat tails) and it is less likely for non-negativity constraints to be violated. The drawback is that it can not account for leverage effects.<sup>54</sup>

#### **4.4.1.2 EWMA**

Exponentially weighted moving average (EWMA) model improves the shortcoming of the simple moving average, which only uses equally weighted returns for volatility. EWMA takes more consider of recent observations than of older observations by putting a greater weight to the latest data using the parameter  $\lambda$  ( $0 < \lambda < 1$ ) where all the weights must sum to 1. Boudoukh et al. suggested the age weighted historical simulation. The

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<sup>51</sup> Capmell, Lo and MacKinlay (1997) pp. 482-483

<sup>52</sup> Brooks (2005) pp. 395

<sup>53</sup> Cont (2005)

<sup>54</sup> Brooks (2005) pp. 404

intuition is that if the latest observation probability weight is  $w(1)$  then the second latest observations probability weight is  $\lambda w(1) = w(2)$ ;  $w(3)$  can be  $\lambda^2 w(1)$  and so forth.<sup>55</sup> The weight of observation  $i$  days old is<sup>56</sup>:

$$w(i) = \left( \frac{I^{i-1}(1-I)}{1-I^n} \right)$$

The attractions of age weighted historical simulation are:

- 1) provides a nice generalization of traditional historical simulation and is more flexible
- 2) more responsiveness to large losses and better dealing with clusters of large losses which will have greater affect on the next day VaR
- 3) it reduces distortions from events that occur rarely. The ghost effect will be less because when an old observation falls out of the sample the weight falls from  $\lambda^n w(1)$  to zero instead of from  $1/n$  to zero
- 4) increasing efficiency and ghost effect can be eliminated by allowing each new observation to grow with the sample period as a result no valuable information are thrown away.<sup>57</sup>

The exponential rate of decay ( $\lambda$ ) reflects the weight of each observation ( $x$ ). Decay close to 1 designate a slow rate of decay while decay close to 0 designates a high rate of decay. With constant  $\lambda$  between 0 and 1, the forecast volatility is calculated from the following equation:<sup>58</sup>

$$s_t^2 \approx (1-I) \sum_{i=1}^n I^{i-1} x_{t-i}^2$$

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<sup>55</sup> Boudoukh et al. (1998)

<sup>56</sup> Dowd (2005) pp. 93

<sup>57</sup> Dowd (2005) pp. 93-94

<sup>58</sup> Dowd (2005) pp. 130



The RiskMetrics Technical Document recommends  $\lambda$  to be about 0.94 for daily return data.<sup>59</sup>

The advantage of EWMA is that it reacts faster when shocks occur in the market since recent data has more weight than the older. Moreover, after shocks occur, the volatility using EWMA declines exponentially as the weight of the shock falls, it is in contrary with the equal weighted observations which usually take several months to decrease<sup>60</sup>. If data is updated frequently, EWMA captures external shocks better than equally weighted moving average, the exponentially weight gives more realistic measurement of current volatility.<sup>61</sup> Another attractive feature of EWMA model is that it can be written in recursive form. The next period's variance can be predicted by the variance available today (one day earlier) with the equation:<sup>62</sup>

$$s_{t+1}^2 \approx I s_t^2 + (1 - I)x_t^2$$

#### 4.5 Backtesting

Several VaR models have been constructed to disclose the downside risk of equity mutual funds in Thailand. For model validation we are going to check if the models are acceptable. Backtesting is a method used to evaluate the accuracy of VaR models. It is a statistical framework that verifies if the actual losses do not exceed with predicted losses.<sup>63</sup> If the number of exceedances are much more than expected the model may underestimate the losses and cause the model to be rejected. The other way around if the number of exceedances are much less than expected then the model may overestimate the loss. Once VaR models are constructed it is important to test the accuracy and the reliability before used in practice. This study will use three backtesting models to test the validation of VaR at 95% and 99% confidence interval. The models that are used are: Bernoulli trial test, Kupiec test and Christoffersen test. The confidence interval used for backtesting is 99%.

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<sup>59</sup> Risk Metrics – Technical Document (1996) pp. 97

<sup>60</sup> Risk Metrics – Technical Document (1996) pp. 78

<sup>61</sup> Risk Metrics – Technical Document (1996) pp. 80

<sup>62</sup> Risk Metrics – Technical Document (1996) pp. 81

<sup>63</sup> Jorion (2007) pp. 139

#### 4.5.1 Bernoulli trial and failure rate approach

A simple approach to test the accuracy of VaR models is to use a failure rate approach. Jorion describes the approach that gives the proportion of how many times VaR exceeds in a sample as a failure rate. The equation is<sup>64</sup>:

$$f(x) = \binom{T}{x} p^x (1-p)^{T-x}$$

The results are either success or failure if tested consecutive T times. The number of exceedances is x and the failure rate is x/T. As the sample increases the failure rate should converge to p which is the probability of exceedances each day. At a given confidence interval, x can be examined whether it is too small or too large under the null hypothesis at p percent. This approach is fully non-parametric and makes no assumption about the return distribution. This framework for a sequence of success and failures is called Bernoulli trials. The number of exceptions x follows a binomial probability distribution under the null hypothesis that the model is accurately calibrated.

In times when T is large the central limit theorem can be used and approximate the binomial distribution by the normal distribution.<sup>65</sup>

$$Z = \frac{x - pT}{\sqrt{p(1-p)T}} \approx N(0,1)$$

The z test statistic is calculated from the equation above and compared either with the critical value z from the standard normal distribution table with 99% confident interval or p-values with 0.01 to check for bias in VaR. This model focus on the number of violations in the sample period but it ignores the information about the temporal pattern of violations<sup>66</sup>.

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<sup>64</sup> Jorion (2007) pp. 143

<sup>65</sup> Jorion (2007) pp. 143

<sup>66</sup> Cotter and Zhong (2007)

#### 4.5.2 Kupiec test

In 1995 Kupiec introduced a test that can be used to verify the accuracy of a VaR model, the test focuses on the unconditional coverage. It bases its estimations on number of exceedances that is how many times the portfolio loses more than the previous estimated VaR in the backtesting<sup>67</sup>. The non-rejection regions are defined by the log likelihood ratio with the following equation:<sup>68</sup>

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

N is the number of how many times actual loss exceeds predicted one and T is the number of observations. The test statistic is distributed chi-square with one degree of freedom under the null hypothesis that p is a true probability<sup>69</sup>.

The Kupiec test only focuses on the unconditional coverage, it ignores the conditioning coverage or time variation in data<sup>70</sup>. The advantages of this model are that it is simple, easy to apply and does not require much information. The drawbacks are that it can only identify poor models when the sample size is large. It only focuses on the frequency of exceedances and throws away important information about the temporal patterns of exceedances as well as information on the sizes of tail losses that was previously predicted.<sup>71</sup> In addition, the model can fail when applied to unusual surroundings like market crash or other abnormal situations.<sup>72</sup>

#### 4.5.3 Christoffersen test

Christoffersen in 1998 formalized the Kupiec test. The first part in the test is the same as the Kupiec test using likelihood ratio to test the unconditional coverage. The second part tests if the exceedances are serially independent of each other. The combination of the unconditional coverage and independence is the joint test of coverage and independence.

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<sup>67</sup> Alexander (2008) pp. 337

<sup>68</sup> Jorion (2007) pp. 146

<sup>69</sup> Jorion (2007) pp. 147

<sup>70</sup> Jorion (2007) pp. 151

<sup>71</sup> Dowd (2005) pp. 327

<sup>72</sup> Dowd (2005) pp. 328

The test defines as follows:

$$I_{t+1} = \begin{cases} 1, & \text{if } r_{t+1} < VaR_{t+1} \\ 0, & \text{if } r_{t+1} \geq VaR_{t+1} \end{cases}$$

The indicator I is used to identify the number of exceedances. The indicators I is 1 if the return exceeds VaR (lower than VaR) and 0 otherwise. In the unconditional coverage test the order of the 1 and 0 in the indicator sequence does not matter, only the total number of 1 matter.<sup>73</sup>

The second part of the equation examines the independence of exceedances, it detects whether the exceedances tends to cluster or not. The relevant test statistic is:<sup>74</sup>

$$LR_{ind} = -2\ln\left[(1-p)^{T_{00}+T_{10}} p^{T_{01}+T_{11}}\right] + 2\ln\left[(1-p_0)^{T_{00}} p_0^{T_{01}} (1-p_1)^{T_{10}} p_1^{T_{11}}\right]$$

Where  $T_{ij}$  is number of days in state j occurred in one day after state i occurred the previous day.  $\pi_i$  is the probability of observing an exceedance conditional state i the previous day.<sup>75</sup>

$$p = \frac{T_{01} + T_{11}}{T_{01} + T_{00} + T_{10} + T_{11}}, \quad p_0 = \frac{T_{01}}{T_{01} + T_{00}}, \quad p_1 = \frac{T_{11}}{T_{11} + T_{10}}$$

Current day	Conditional Day Before		Unconditional
	No Exceedances	Exceedances	
No Exceedances	$T_{00}$	$T_{10}$	$T(1-\pi)$
Exceedances	$T_{01}$	$T_{11}$	$T(\pi)$
Total	$T_0$	$T_1$	$T = T_0 + T_1$

**Table 4.5.3** An exceedances table

The combination of the unconditional coverage and independence:

$$LR_{cc} = LR_{uc} + LR_{ind}$$

<sup>73</sup> Christoffersen (1998)

<sup>74</sup> Jorion (2007) pp. 151

<sup>75</sup> Jorion (2007) pp. 152

This approach allows testing both coverage and independence hypotheses at the same time. Each part is independently distributed as  $\chi^2(1)$  asymptotically and the sum is distributed as  $\chi^2(2)$ .<sup>76</sup>

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<sup>76</sup> Jorion (2007) pp. 152

## 5. Previous research

Previous research on downside risk analysis using a VaR measure on equity mutual funds and its accuracy is scarce. Our study followed partly the article: “Downside Risk Analysis of Indian Equity Mutual Funds: A Value at Risk Approach”, authors Deb & Banerjee 2009.<sup>77</sup> They used four models namely random walk model, moving average model, EWMA and historical simulation to find the level of downside risk of equity mutual funds in India. The sample was 60 Indian equity mutual funds. The study used a rolling window of past weekly returns to estimate the volatility and to predict a weekly VaR. To test for accuracy they used Kupiec test and Bernoulli trial approach. In their results the moving average model and random walk underestimated VaR. EWMA and historical simulation were just about within the expected range but for a few instances they provided too conservative estimates of VaR.

Various researches have been done on predictive performance of a selection of VaR models. Sinha and Chamu 2000, compared the performance of historical simulation, hybrid method and stochastic method of calculating VaR in volatile markets. They tested these methods with extreme data because emerging economies tend to have volatile stock and bond markets and the produced risk often have fat tails and asymmetry distribution. The hybrid method and stochastic simulation method gave the most precise estimates on VaR.<sup>78</sup> Lee and Saltoglu 2002, evaluated predictive performance of VaR for Japanese stock market data. They used VaR models such as Riskmetrics method, historical simulation, variance-covariance method, Monte Carlo method and various ARCH models however none of the methods exhibited superior predictive ability.<sup>79</sup>

To the best of our knowledge similar study on Thailand equity mutual funds has never been done before. It is our hope that this study will add something to the existing framework of performance evaluation of mutual funds in Thailand.

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<sup>77</sup> Deb and Banerjee (2009)

<sup>78</sup> Sinha and Chamu (2000)

<sup>79</sup> Lee and Saltoglu (2002)

## 6. Results

Our results will be presented in this chapter. The results are obtained from estimation of VaR from five different models and the accuracy of the VaR is evaluated with three different backtesting models as previously described. In appendix 2 the results are presented graphically. The outcomes from backtesting are presented in a table for each VaR model which presents the number of exceedances and the p-values of test statistic in different backtesting methods at 99% confidence interval. The bold values in the tables imply that we do not reject the null hypothesis.

For Bernoulli trial ( $z$ ) the model focus on the number of exceedances in the sample period the null hypothesis is:

$H_0$ : correct model, failure rate =  $a$

$H_1$ : incorrect model, failure rate  $\neq a$

For Kupiec (LRuc) test of unconditional coverage the null hypothesis is:

$H_0$ : correct unconditional coverage,  $H_0 : p_1 = a$

$H_1$ : incorrect unconditional coverage,  $H_1 : p_1 > a$

For Christoffersen (LRind) test of independence the null hypothesis is:

$H_0$ : exceedances are independent,  $H_0 : p_0 = p_1$

$H_1$ : exceedances are not independent,  $H_1 : p_0 \neq p_1$

For Christoffersen (LRcc) joint test of unconditional coverage and independence the null hypothesis is:

$H_0$ : correct conditional coverage,  $H_0 : p_0 = p_1 = a$

$H_1$ : incorrect conditional coverage,  $H_1 : p_0 \neq a, \text{ or } p_1 \neq a$

Not available (NA) in the tables below is traced to the reason that test statistic cannot be calculated if two exceedances following two days in a row do not exist.

## 6.1 Parametric approach

This study uses two parametric approaches to estimate VaR, student-t distribution and log-normal distribution.

### 6.1.1 Student-t distribution

Fund	VaR 95%					VaR 99%				
	Exceed- ences	z	LRuc	LRind	LRcc	Exceed- ences	z	LRuc	LRind	LRcc
NAKGTHA	24	<b>0.018</b>	<b>0.011</b>	0.005	0.001	11	<b>0.223</b>	<b>0.253</b>	<b>0.144</b>	<b>0.179</b>
ABERSL	25	<b>0.028</b>	<b>0.019</b>	0.007	0.002	12	<b>0.114</b>	<b>0.144</b>	<b>0.176</b>	<b>0.138</b>
ABESMF	41	<b>0.648</b>	<b>0.652</b>	0.000	0.000	17	0.001	0.003	0.004	<b>0.000</b>
AJFSCAI	28	<b>0.089</b>	<b>0.075</b>	0.002	0.002	12	<b>0.114</b>	<b>0.144</b>	<b>0.176</b>	<b>0.138</b>
AJFSTDY	31	<b>0.229</b>	<b>0.214</b>	0.007	<b>0.012</b>	9	<b>0.624</b>	<b>0.633</b>	0.000	0.000
AJFSTEQ	34	<b>0.481</b>	<b>0.473</b>	0.003	0.009	13	<b>0.052</b>	<b>0.077</b>	0.000	0.000
KASRKEC	39	<b>0.901</b>	<b>0.901</b>	0.003	<b>0.011</b>	10	<b>0.393</b>	<b>0.415</b>	<b>0.115</b>	<b>0.207</b>
KASRKF3	36	<b>0.709</b>	<b>0.706</b>	0.005	<b>0.020</b>	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
KASRKF4	36	<b>0.709</b>	<b>0.706</b>	0.005	<b>0.020</b>	10	<b>0.393</b>	<b>0.415</b>	<b>0.115</b>	<b>0.207</b>
SCBDHAA	36	<b>0.709</b>	<b>0.706</b>	0.001	0.004	7	<b>0.813</b>	<b>0.811</b>	<b>0.049</b>	<b>0.139</b>
SCBMH2A	29	<b>0.125</b>	<b>0.110</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBMH3A	31	<b>0.229</b>	<b>0.214</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBMH4A	30	<b>0.171</b>	<b>0.156</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBMH5A	30	<b>0.171</b>	<b>0.156</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBPMOI	41	<b>0.648</b>	<b>0.652</b>	0.005	<b>0.017</b>	18	0.000	0.001	<b>0.067</b>	<b>0.001</b>
SCBTS2A	30	<b>0.171</b>	<b>0.156</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBTAWA	31	<b>0.229</b>	<b>0.214</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
TMBJB25	31	<b>0.229</b>	<b>0.214</b>	0.001	0.002	9	<b>0.624</b>	<b>0.633</b>	0.003	<b>0.011</b>
K-SET50	30	<b>0.171</b>	<b>0.156</b>	0.001	0.001	11	<b>0.223</b>	<b>0.253</b>	0.008	<b>0.015</b>
K-FEQ	36	<b>0.709</b>	<b>0.706</b>	0.005	<b>0.020</b>	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>

**Table 6.1.1** The table presents the number of exceedances and the p-values of each backtesting method. When the p-values are higher than 0.01, we do not reject the model. The bold values are the ones that do not reject the null hypothesis.

In the graphs for the student-t distribution (see appendix 2) the approach underestimates VaR during high volatility period and overestimates VaR during stable situations. A high volatility clusters occurred in the financial market in Thailand during 2008. For the Bernoulli methodology it only takes into consideration the number of exceedances as a result for the overall period ex-ante VaR might be overestimated and therefore the model cannot be rejected.

For the unconditional coverage model all of the funds confirm the student-t distribution model by not reject the null hypothesis. The model does not take into account time variation and therefore we cannot conclude that the t-distribution model does not suffer from volatility clustering. The result of independent coverage test rejects the null hypothesis, therefore the model cannot capture the possible volatility clusters and that



could imply for invalidation of the model for VaR 95%. However, seventy percent of funds for VaR 99% do not reject the null hypothesis of independent test. We can imply that the model is acceptable however for a larger confidence interval the probability to validate the model is more as it allows for more room for the downside return. As a result student-t distribution is not a desirable method for estimation of downside risk of equity mutual funds in Thailand.

### 6.1.2 Log-normal distribution

Fund	VaR 95%					VaR 99%				
	Exceed-ences	z	LRuc	LRind	LRcc	Exceed-ences	z	LRuc	LRind	LRcc
NAKGTHA	25	<b>0.028</b>	<b>0.019</b>	0.007	0.002	12	<b>0.114</b>	<b>0.144</b>	<b>0.176</b>	<b>0.138</b>
ABERSL	26	<b>0.042</b>	<b>0.031</b>	0.010	0.004	12	<b>0.114</b>	<b>0.144</b>	<b>0.176</b>	<b>0.138</b>
ABESMF	42	<b>0.534</b>	<b>0.540</b>	0.000	0.000	18	0.000	0.001	0.007	<b>0.000</b>
AJFSCAI	30	<b>0.171</b>	<b>0.156</b>	0.005	0.007	12	<b>0.114</b>	<b>0.144</b>	<b>0.176</b>	<b>0.138</b>
AJFSTDY	31	<b>0.229</b>	<b>0.214</b>	0.007	<b>0.012</b>	12	<b>0.114</b>	<b>0.144</b>	0.000	0.001
AJFSTEQ	34	<b>0.481</b>	<b>0.473</b>	0.003	0.009	15	0.008	<b>0.018</b>	0.000	0.000
KASRKEC	40	<b>0.772</b>	<b>0.773</b>	0.004	<b>0.014</b>	13	<b>0.052</b>	<b>0.077</b>	<b>0.016</b>	<b>0.012</b>
KASRKF3	37	<b>0.836</b>	<b>0.835</b>	0.007	<b>0.027</b>	12	<b>0.114</b>	<b>0.144</b>	<b>0.176</b>	<b>0.138</b>
KASRKF4	38	<b>0.967</b>	<b>0.967</b>	0.010	<b>0.036</b>	12	<b>0.114</b>	<b>0.144</b>	<b>0.176</b>	<b>0.138</b>
SCBDHAA	36	<b>0.709</b>	<b>0.706</b>	0.001	0.004	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBMH2A	31	<b>0.229</b>	<b>0.214</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBMH3A	32	<b>0.300</b>	<b>0.287</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBMH4A	31	<b>0.229</b>	<b>0.214</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBMH5A	31	<b>0.229</b>	<b>0.214</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBPMOI	43	<b>0.431</b>	<b>0.439</b>	0.009	<b>0.024</b>	20	0.000	0.000	<b>0.104</b>	<b>0.000</b>
SCBTS2A	31	<b>0.229</b>	<b>0.214</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
SCBTAWA	32	<b>0.300</b>	<b>0.287</b>	0.000	0.000	9	<b>0.624</b>	<b>0.633</b>	<b>0.089</b>	<b>0.210</b>
TMBJB25	32	<b>0.300</b>	<b>0.287</b>	0.001	0.003	13	<b>0.052</b>	<b>0.077</b>	<b>0.016</b>	<b>0.012</b>
K-SET50	30	<b>0.171</b>	<b>0.156</b>	0.001	0.001	12	<b>0.114</b>	<b>0.144</b>	0.000	0.000
K-FEQ	38	<b>0.967</b>	<b>0.967</b>	0.010	<b>0.036</b>	13	<b>0.052</b>	<b>0.077</b>	0.001	0.001

**Table 6.1.2** The table presents the number of exceedances and the p-values of each backtesting method. When the p-values are higher than 0.01, we do not reject the model. The bold values are the ones that do not reject the null hypothesis.

The outcome of the log-normal distribution model and the student-t distribution is relatively similar. The Bernoulli test accepts the log-normal VaR model for both the 95% and 99%. The unconditional coverage model 100% and 85% of the funds tested confirms the log-normal distribution for VaR 95% and 99% respectively. It implies that the proportion of exceedances (failure rate) is acceptable at the pre-determined  $\alpha$  (one minus the confidence interval). A log-normal model cannot be considered as a reliable model since volatility clustering might occur. For the independence coverage test, 75% of funds do not reject for VaR 99% which means the VaR exceedances are independent. However

VaR 95% do reject the model. As we discussed before in the result for t-distribution VaR 99% has more room to accept the model. The same results applies for the joint test of unconditional coverage and independence, VaR 95% is rejected by the joint test and VaR 99% is qualified by the joint test. Accordingly we reject the log-normal distribution model since it does not capture the volatility clusters at higher confidence interval. At confidence level of VaR 99% the model is more aggressive as it allows for higher maximum loss.

## 6.2 Non-parametric approach

This study uses historical simulation as a non-parametric approach to estimate VaR.

### 6.2.1 Historical simulation

Fund	VaR 95%					VaR 99%				
	Exceed-ences	z	LRuc	LRind	LRcc	Exceed-ences	z	LRuc	LRind	LRcc
NAKGTHA	31	<b>0.229</b>	<b>0.214</b>	0.001	0.002	11	<b>0.223</b>	<b>0.253</b>	<b>0.144</b>	<b>0.179</b>
ABERSL	34	<b>0.481</b>	<b>0.473</b>	0.000	0.000	11	<b>0.223</b>	<b>0.253</b>	0.008	<b>0.015</b>
ABESMF	45	<b>0.263</b>	<b>0.275</b>	0.000	0.000	11	<b>0.223</b>	<b>0.253</b>	0.008	<b>0.015</b>
AJFSCAI	47	<b>0.147</b>	<b>0.160</b>	<b>0.026</b>	<b>0.031</b>	9	<b>0.624</b>	<b>0.633</b>	N/A	N/A
AJFSTDY	40	<b>0.772</b>	<b>0.773</b>	0.004	<b>0.014</b>	10	<b>0.393</b>	<b>0.415</b>	0.000	0.000
AJFSTEQ	44	<b>0.340</b>	<b>0.351</b>	<b>0.012</b>	<b>0.027</b>	13	<b>0.052</b>	<b>0.077</b>	0.000	0.000
KASRKEC	42	<b>0.534</b>	<b>0.540</b>	0.001	0.005	12	<b>0.114</b>	<b>0.144</b>	0.000	0.000
KASRKF3	44	<b>0.340</b>	<b>0.351</b>	0.003	0.007	12	<b>0.114</b>	<b>0.144</b>	0.000	0.000
KASRKF4	42	<b>0.534</b>	<b>0.540</b>	0.001	0.005	13	<b>0.052</b>	<b>0.077</b>	0.000	0.000
SCBDHAA	38	<b>0.967</b>	<b>0.967</b>	0.000	0.000	13	<b>0.052</b>	<b>0.077</b>	<b>0.212</b>	<b>0.096</b>
SCBMH2A	37	<b>0.836</b>	<b>0.835</b>	0.001	0.006	15	0.008	<b>0.018</b>	0.000	0.000
SCBMH3A	38	<b>0.967</b>	<b>0.967</b>	0.002	0.008	15	0.008	<b>0.018</b>	0.000	0.000
SCBMH4A	36	<b>0.709</b>	<b>0.706</b>	0.001	0.004	16	0.002	0.008	0.000	0.000
SCBMH5A	37	<b>0.836</b>	<b>0.835</b>	0.001	0.006	14	<b>0.021</b>	<b>0.039</b>	0.000	0.000
SCBPMOI	43	<b>0.431</b>	<b>0.439</b>	0.009	<b>0.024</b>	16	0.002	0.008	<b>0.338</b>	<b>0.019</b>
SCBTS2A	37	<b>0.836</b>	<b>0.835</b>	0.001	0.006	15	0.008	<b>0.018</b>	0.000	0.000
SCBTAWA	37	<b>0.836</b>	<b>0.835</b>	0.001	0.006	16	0.002	0.008	0.000	0.000
TMBJB25	39	<b>0.901</b>	<b>0.901</b>	0.000	0.002	11	<b>0.223</b>	<b>0.253</b>	0.008	<b>0.015</b>
K-SET50	37	<b>0.836</b>	<b>0.835</b>	0.000	0.001	13	<b>0.052</b>	<b>0.077</b>	0.000	0.000
K-FEQ	40	<b>0.772</b>	<b>0.773</b>	0.001	0.003	12	<b>0.114</b>	<b>0.144</b>	0.000	0.000

**Table 6.2.1** The table presents the number of exceedances and the p-values of each backtesting method. When the p-values are higher than 0.01, we do not reject the model. The bold values are the ones that do not reject the null hypothesis.

The historical simulation model does not depend on parametric assumption like the former two models. The VaR estimation depends on historical data and might not respond to a sudden change in volatility. For VaR 95% the historical simulation model cannot be rejected by both the Bernoulli test and the Kupiec test while 85% of funds for VaR 99% cannot be rejected. In general the proportion of exceedances is acceptable for

the model. Historical simulation model would be satisfactory model for VaR measure if it could imply exceedances that cluster in time but as already discussed financial returns tend to volatility clustering. It is confirmed by the independence test that the model rejects the null hypothesis of no volatility clustering for VaR 95% and VaR 99%. Only few funds at VaR 99% accept the model in the joint test, as a result our sample rejects the historical simulation model as an accurate VaR measurement model.

### 6.3 Semi-parametric approach

The approaches used are EWMA (exponentially weighted moving average) and volatility weighted historical simulation using GARCH(1,1).

#### 6.3.1 EWMA

Fund	VaR 95%					VaR 99%				
	Exceed-ences	z	LRuc	LRind	LRcc	Exceed-ences	z	LRuc	LRind	LRcc
NAKGTHA	39	<b>0.901</b>	<b>0.901</b>	0.000	0.000	14	<b>0.021</b>	<b>0.039</b>	<b>0.272</b>	<b>0.064</b>
ABERSL	38	<b>0.967</b>	<b>0.967</b>	0.000	0.001	14	<b>0.021</b>	<b>0.039</b>	<b>0.272</b>	<b>0.064</b>
ABESMF	42	<b>0.534</b>	<b>0.540</b>	0.000	0.000	15	0.008	<b>0.018</b>	<b>0.028</b>	<b>0.005</b>
AJFSCAI	41	<b>0.648</b>	<b>0.652</b>	0.000	0.000	17	0.001	0.003	<b>0.424</b>	<b>0.010</b>
AJFSTDY	37	<b>0.836</b>	<b>0.835</b>	0.000	0.001	17	0.001	0.003	<b>0.553</b>	<b>0.012</b>
AJFSTEQ	40	<b>0.772</b>	<b>0.773</b>	0.000	0.000	15	0.008	<b>0.018</b>	<b>0.318</b>	<b>0.037</b>
KASRKEC	35	<b>0.590</b>	<b>0.585</b>	0.000	0.000	15	0.008	<b>0.018</b>	<b>0.287</b>	<b>0.035</b>
KASRKF3	32	<b>0.300</b>	<b>0.287</b>	0.000	0.000	16	0.002	0.008	<b>0.333</b>	<b>0.019</b>
KASRKF4	34	<b>0.481</b>	<b>0.473</b>	0.000	0.001	18	0.000	0.001	<b>0.434</b>	0.004
SCBDHAA	40	<b>0.772</b>	<b>0.773</b>	0.003	<b>0.010</b>	14	<b>0.021</b>	<b>0.039</b>	N/A	N/A
SCBMH2A	38	<b>0.967</b>	<b>0.967</b>	0.000	0.000	13	<b>0.052</b>	<b>0.077</b>	N/A	N/A
SCBMH3A	38	<b>0.967</b>	<b>0.967</b>	0.000	0.000	13	<b>0.052</b>	<b>0.077</b>	N/A	N/A
SCBMH4A	38	<b>0.967</b>	<b>0.967</b>	0.000	0.000	13	<b>0.052</b>	<b>0.077</b>	N/A	N/A
SCBMH5A	37	<b>0.836</b>	<b>0.835</b>	0.000	0.000	14	<b>0.021</b>	<b>0.039</b>	N/A	N/A
SCBPMOI	40	<b>0.772</b>	<b>0.773</b>	0.000	0.000	17	0.001	0.003	N/A	<b>N/A</b>
SCBTS2A	38	<b>0.967</b>	<b>0.967</b>	0.000	0.000	13	<b>0.052</b>	<b>0.077</b>	N/A	N/A
SCBTAWA	38	<b>0.967</b>	<b>0.967</b>	0.000	0.000	14	<b>0.021</b>	<b>0.039</b>	N/A	N/A
TMBJB25	33	<b>0.384</b>	<b>0.373</b>	0.000	0.000	12	<b>0.114</b>	<b>0.144</b>	<b>0.191</b>	<b>0.147</b>
K-SET50	36	<b>0.709</b>	<b>0.706</b>	0.000	0.000	14	<b>0.021</b>	<b>0.039</b>	<b>0.272</b>	<b>0.064</b>
K-FEQ	32	<b>0.300</b>	<b>0.287</b>	0.000	0.000	17	0.001	0.003	<b>0.382</b>	0.009

**Table 6.3.1** The table presents the number of exceedances and the p-values of each backtesting method. When the p-values are higher than 0.01, we do not reject the model. The bold values are the ones that do not reject the null hypothesis.

As already mentioned the latest observations have more weight than the older ones and consequently play a more important role in VaR estimation. Our decay factor for daily return is quite high as a result the weight declines more slowly. The results for VaR 95% is the same as for the previous three models. Failure rate is fairly equal to pre-determined  $\alpha$  as the results by the Bernoulli trial test and the Kupiec test reveal. However the model

cannot capture the violation clustering as the result from the independence test shows. For VaR 99% Bernoulli test and Kupiec test verify the EWMA model for the majority of the funds. The independence test cannot reject the model consequently the model fairly well capture the cluster exceedances. A model that accepts the null hypothesis in the independence test needs to be tested again to indicate whether the model is reliable in pre-determine level  $\alpha$  for the joint test. In our case VaR 99% is satisfied by this test.

### 6.3.2 Volatility historical simulation using GARCH(1,1)

Fund	VaR 95%					VaR 99%				
	Exceed- ences	z	LRuc	LRind	LRcc	Exceed- ences	z	LRuc	LRind	LRcc
NAKGTHA	35	<b>0.590</b>	<b>0.585</b>	<b>0.296</b>	<b>0.499</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
ABERSL	35	<b>0.590</b>	<b>0.585</b>	<b>0.750</b>	<b>0.819</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
ABESMF	41	<b>0.648</b>	<b>0.652</b>	N/A	N/A	11	<b>0.223</b>	<b>0.253</b>	N/A	N/A
AJFSCAI	40	<b>0.772</b>	<b>0.773</b>	<b>0.946</b>	<b>0.957</b>	8	<b>0.899</b>	<b>0.900</b>	N/A	N/A
AJFSTDY	40	<b>0.772</b>	<b>0.773</b>	<b>0.946</b>	<b>0.957</b>	9	<b>0.624</b>	<b>0.633</b>	N/A	N/A
AJFSTEQ	39	<b>0.901</b>	<b>0.901</b>	<b>0.993</b>	<b>0.992</b>	11	<b>0.223</b>	<b>0.253</b>	N/A	N/A
KASRKEC	40	<b>0.772</b>	<b>0.773</b>	<b>0.946</b>	<b>0.957</b>	9	<b>0.624</b>	<b>0.633</b>	N/A	N/A
KASRKF3	41	<b>0.648</b>	<b>0.652</b>	<b>0.887</b>	<b>0.894</b>	12	<b>0.114</b>	<b>0.144</b>	N/A	N/A
KASRKF4	43	<b>0.431</b>	<b>0.439</b>	<b>0.770</b>	<b>0.711</b>	11	<b>0.223</b>	<b>0.253</b>	N/A	N/A
SCBDHAA	40	<b>0.772</b>	<b>0.773</b>	<b>0.946</b>	<b>0.957</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
SCBMH2A	39	<b>0.901</b>	<b>0.901</b>	<b>0.993</b>	<b>0.992</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
SCBMH3A	38	<b>0.967</b>	<b>0.967</b>	<b>0.932</b>	<b>0.996</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
SCBMH4A	39	<b>0.901</b>	<b>0.901</b>	<b>0.993</b>	<b>0.992</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
SCBMH5A	40	<b>0.772</b>	<b>0.773</b>	<b>0.946</b>	<b>0.957</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
SCBPMOI	41	<b>0.648</b>	<b>0.652</b>	<b>0.586</b>	<b>0.779</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
SCBTS2A	38	<b>0.967</b>	<b>0.967</b>	<b>0.932</b>	<b>0.996</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
SCBTAWA	39	<b>0.901</b>	<b>0.901</b>	<b>0.993</b>	<b>0.992</b>	10	<b>0.393</b>	<b>0.415</b>	N/A	N/A
TMBJB25	37	<b>0.836</b>	<b>0.835</b>	<b>0.871</b>	<b>0.966</b>	9	<b>0.624</b>	<b>0.633</b>	N/A	N/A
K-SET50	38	<b>0.967</b>	<b>0.967</b>	<b>0.465</b>	<b>0.765</b>	9	<b>0.624</b>	<b>0.633</b>	N/A	N/A
K-FEQ	38	<b>0.967</b>	<b>0.967</b>	<b>0.932</b>	<b>0.996</b>	9	<b>0.624</b>	<b>0.633</b>	N/A	N/A

**Table 6.3.2** The table presents the number of exceedances and the p-values of each backtesting method. When the p-values are higher than 0.01, we do not reject the model. The bold values are the ones that do not reject the null hypothesis.

Examining the graphs for GARCH(1,1) they reveal that VaR 95% and VaR 99% follow the volatility acceptably moreover all the backtesting models do not reject the GARCH(1,1) model. Even though GARCH(1,1) model is supported by normal distribution and the fact that we reject normality in our descriptive statistic data the GARCH(1,1) model does capture the risk fairly well. For VaR 99% the Christoffersen independence test and the joint test cannot be calculated because there are no two exceedences following two days in a row. However no existence of cluster exceedances

represents that the volatility weighted historical simulation using GARCH(1,1) model is able to capture the behavior of time series characteristic of the returns both at low and high confidence interval. Accordingly we consider the volatility weighted historical simulation using GARCH(1,1) a satisfactory model for our equity mutual funds returns.

## 7. Conclusion

The intention of this study is to find the model that is the most accurate for estimating VaR for equity mutual funds in Thailand. The sample is 20 equity mutual funds in Thailand and the data are daily returns over five years. The returns are used to calculate ex-ante VaR applied to five different VaR models. The models are student-t distribution, log-normal distribution, historical simulation, EWMA and volatility weighted historical simulation using GARCH(1,1). We have constructed the VaR prediction for all the five models and test for accuracy of the models using three backtesting models. The models are Bernoulli trail, Kupiec test and Christoffersen test. The performance result of each VaR model is discussed in section 5. Our result is that volatility weighted historical simulation using GARCH(1,1) is the most accurate model for our sample. Table 7 represents the number of exceedances beyond VaR for every model.

VaR 95%	Average Failure Rate	VaR 99%	Average Failure Rate
student-t	4.24%	GARCH(1,1)	1.29%
log normal	4.38%	student-t	1.38%
EWMA	4.88%	log normal	1.56%
GARCH(1,1)	5.10%	Historical simulation	1.69%
Historical simulation	5.15%	EWMA	1.93%

**Table 7** The tables show the average failure rate of 20 equity mutual funds in Thailand.

The log likelihood test statistic for unconditional coverage (Kupiec test) is used to test the proportion of exceedances known as failure rate it should be equal to the pre-determined  $\alpha$  (1% or 5%). Consequently a good VaR model should have failure rate close to the pre-determined  $\alpha$ . If numbers of exceedances are far less than the predetermined  $\alpha$  it would indicate that the VaR model overestimates the risk. On the contrary, too many exceedances are an indicator of underestimation of risk. For VaR 95% the model that has failure rate closed to 5% will be the best fit for our sample and failure rate close to 1% for VaR 99%. In our study, the result of volatility weighted historical simulation using GARCH(1,1) has failure rate which is nearest to the pre-determined  $\alpha$  both for VaR 95% and VaR 99%.

Although all the five VaR 95% models are accepted by the Kupiec test the graphs in appendix 2 illustrate the character of VaR prediction for each model. For the student-t distribution, log-normal distribution and historical simulation models it is clear that the ex-ante VaR cannot capture the risk in times of high volatility. As a result the null hypothesis is rejected by the conditional coverage test for all the three models and they are considered as inferior models because volatility clustering might occur and expected loss cannot help users of VaR to manage the downside risk. Historical simulation model got better result in the unconditional test but worse result in the conditional coverage test. Historical simulation model seem to be a good model in general, except that exceedances have a tendency to be highly clustered which can make a large impact on losses in a portfolio. On the other hand EWMA underestimate the VaR showing that the exceedances are more than expected, however exceedances are more evenly distributed over time. As we can see in the graphs EWMA model also capture volatility clustering fairly well. EWMA is commonly used in practice because of its ability to capture the volatility and it's intuitive to implement. For the GARCH(1,1) model three coefficients have to be estimated each time, it could be a problem for daily work routine. However from our statistic test the most accurate model for our sample is volatility weighted historical simulation using GARCH(1,1) model.

Our result agrees with what Jorion stated that VaR can also be applied to asset management. VaR is a valid measurement of downside risk in equity mutual funds in Thailand.

## References

- Alexander, C., 2008. *Value-at-Risk Models, Market Risk Analysis volume IV*. Chichester: John Wiley & Sons.
- Boudoukh, J., Richardson, M. and Whitelaw, R.F., 1998. The Best of Both Worlds: A Hybrid Approach to Calculating Value at Risk. *Working Paper Series (SSRN)*.
- Brooks, C., 2008. *Introductory econometrics for Finance*. 2nd edition. Cambridge: Cambridge University Press.
- Campbell, J.Y., Lo, A.W. and MacKinlay, A.C., 1997. *The Econometrics of Financial Markets*. New Jersey: Princeton University Press.
- Christoffersen, P.F., 1998. Evaluating Interval Forecasts. *International Economic Review*, 39(4), pp. 841-862.
- Cont, R., 2005. Volatility Clustering in Financial Markets: Empirical Facts and Agent-Based Models. *Long memory in economics*, pp. 289-309.
- Cotter, J. and Zhong, Y.P., 2007. Validating the backtests of risk measure. In: University College Dublin, *INFINITI Conference on International Finance*: Trinity College Dublin, 11-12 June 2007: University College Dublin.
- Culp, C.L., 2001. *The Risk Management process: Business Strategy and Tactics*. New York: John Wiley & Sons.
- Deb, G.D. and Banerjee, A., 2009. Downside Risk Analysis of Indian Equity Mutual Funds: A Value at Risk Approach. *International Research Journal of Finance and Economics*, 23, pp. 216-230.
- Dowd, K., 2002. *An Introduction to Market Risk Measurement*. Chichester: John Wiley & Sons.
- Dowd, K., 2005. *Measuring Market Risk*. 2nd edition. Chichester: John Wiley & Sons.
- Gibson, R.C., 2008. *Asset allocation: balancing financial risk*. 4<sup>th</sup> edition. New York: McGraw-Hill.
- Hull, J. and White, A., 1998. Incorporating volatility updating into the historical simulations method for Value-at-Risk. *Journal of Risk*, 1(Fall), pp. 5-19.
- Johansson, F., Seiler, M. J. and Tjarnberg, M., 1999. Measuring Downside Portfolio Risk. *Journal of Portfolio Management*, 26(1), pp. 96-106.



Jorion, P., 2001. *Value at Risk: The New Benchmark for Managing Financial Risk*. 2nd edition. New York: McGraw-Hill.

Jorion, P., 2007. *Value at Risk: The New Benchmark for Managing Financial Risk*. 3rd edition. New York: McGraw-Hill.

Kuester, K., Mittnik, S. and Paolella, M.S, 2005. Value-at-Risk Prediction: A Comparison of Alternative Strategies. *Journal of Financial Econometrics*, 4(1), pp. 53-89.

Lee, T.H. and Saltoglu, B. 2002. Assessing the risk forecasts for Japanese stock market. *Japan and the World Economy*, 14(1), pp. 63-85.

Lopez, J.A., 1998. Methods for Evaluating Value-at-Risk Estimates. *Economic Policy Review*, 4(3), pp. 119-124.

Morgan, J.P. and Reuters, 1996. *RiskMetrics—Technical Document*, 4th edition. New York.

Pallotta, M. and Zenti, R., 2000. Risk analysis for asset managers: historical simulation, the bootstrap approach and value at risk calculations. *Working Paper Series (SSRN)*.

Papadamou, S. and Stephanides, G., 2004. Evaluating the style-based risk model for equity mutual funds investing in Europe. *Applied Financial Economics*, 14(10), pp. 751-760.

Performance Measurement Standards Acts 2009. (c.1), Thailand: Association of Investment Management Companies.

Pritsker, M., 1997. Evaluating Value at Risk Methodologies: Accuracy versus Computational Time. *Journal of Finance Services Research*, 12(2-3), pp. 201-242.

Sinha, T. and Chamu, F. 2000. Comparing different methods of calculating Value at Risk. *Working Paper Series (SSRN)*.

#### **Websites:**

Association of Investment Management Companies  
<http://www.aimc.or.th>

Bank for International Settlements  
<http://www.bis.org/about/index.htm>

Thai Mutual Fund  
[http://www.thaimutualfund.com/AIMC/aimc\\_about.jsp?pg=1](http://www.thaimutualfund.com/AIMC/aimc_about.jsp?pg=1)

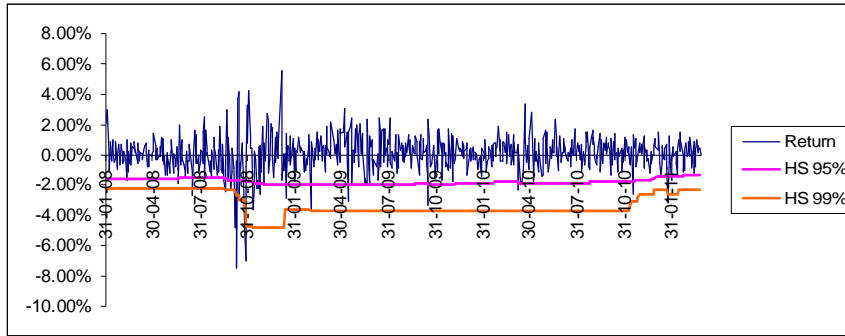
## Appendix

### Appendix 1: Equity mutual funds name list

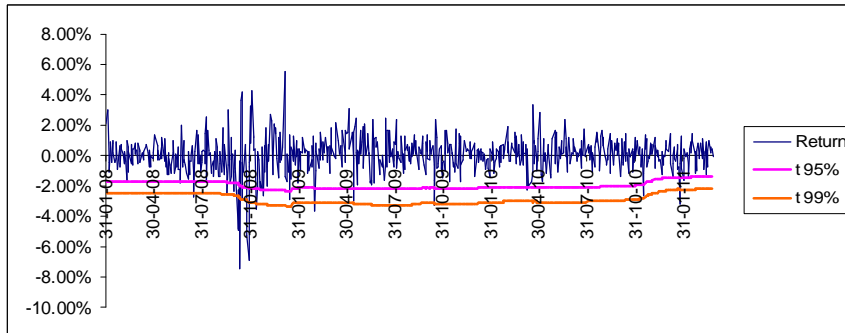
Initials	Fund's Name
NAKGTHA	Aberdeen Growth Fund (ABG)
ABERSL	Aberdeen Siam Leaders Fund (ABSL)
ABESMF	Aberdeen Small Cap Fund (ABSM)
AJFSCAI	AYF Star Capital Fund (AYFSCAP)
AJFSTDY	AYF Star Dynamic Fund (DYNAMIC)
AJFSTEQ	AYF Star Equity Fund (AYFSEQ)
KASRKEC	The Ruang Khao Equity Class Fund (RKEC)
KASRKF3	The Ruang Khao3 Fund (RKF3)
KASRKF4	The Ruang Khao4 Fund (RKF4)
SCBDHAA	SCB DHANA ANANTA OPEN-ENDED FUND (SCBDA)
SCBMH2A	SCB MUNKHONG 2 OPEN-ENDED FUND (SCBMF2)
SCBMH3A	SCB MUNKHONG 3 OPEN-ENDED FUND (SCBMF3)
SCBMH4A	SCB MUNKHONG 4 OPEN-ENDED FUND (SCBMF4)
SCBMH5A	SCB MUNKHONG 5 FUND (SCBMF5)
SCBPMOI	SCB PERMPOL MUNKHONG OPEN-ENDED FUND (SCBPMO)
SCBTS2A	SCB TAWEESUB 2 OPEN-ENDED FUND (SCBTS2)
SCBTAWA	SCB TAWEESUB OPEN-ENDED FUND (SCBTS)
TMBJB25	JUMBO 25 FUND (JB25)
K-SET50	K SET 50 INDEX FUND
K-FEQ	K Flexible Equity Fund

### Appendix 2: Equity mutual funds daily returns & ex-ante VaR

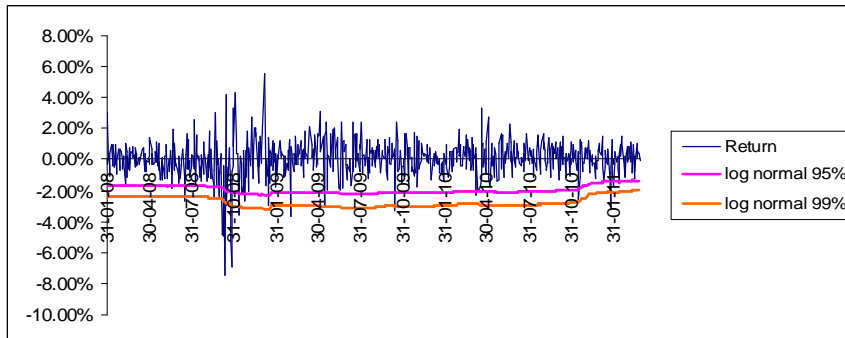
Basic historical simulation approach to estimate VaR for NAKGTHA



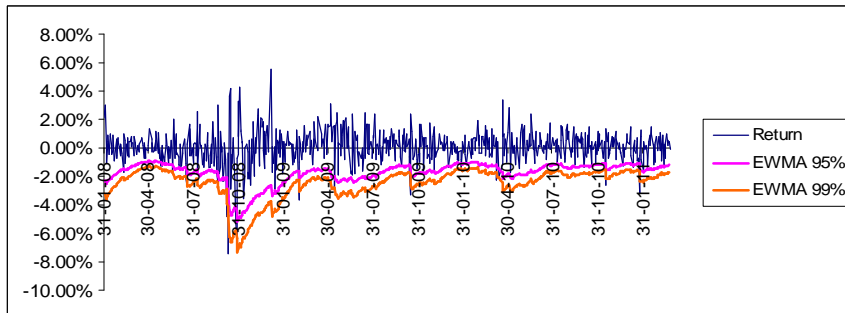
Student-t distribution approach to estimate VaR for NAKGTHA



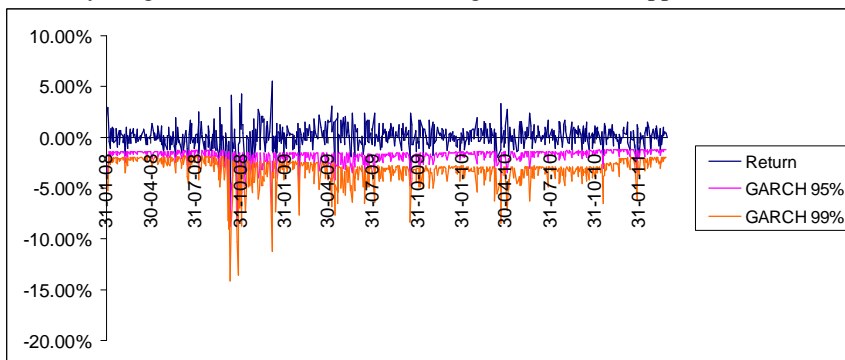
Log-normal distribution approach to estimate VaR for NAKGTHA



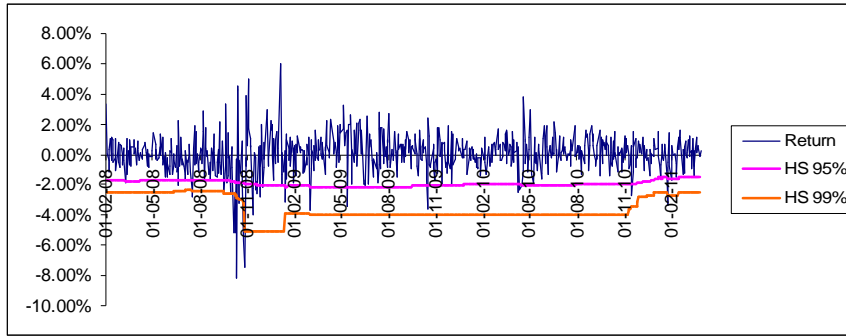
EWMA approach to estimate VaR for NAKGTHA



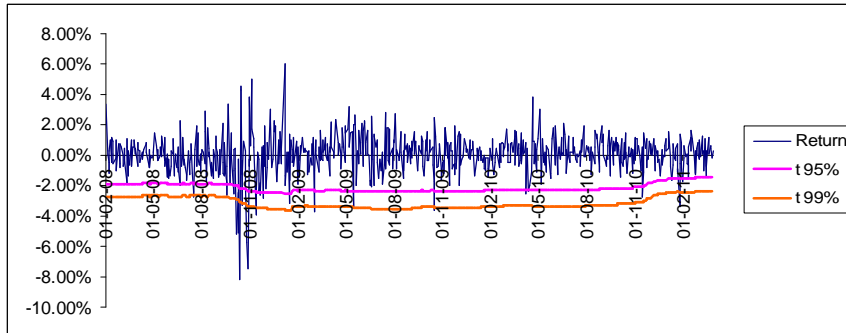
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for NAKGTHA



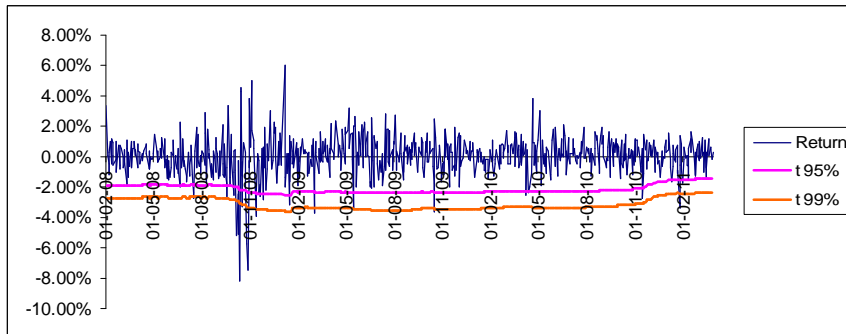
Basic historical simulation approach to estimate VaR for ABERSL



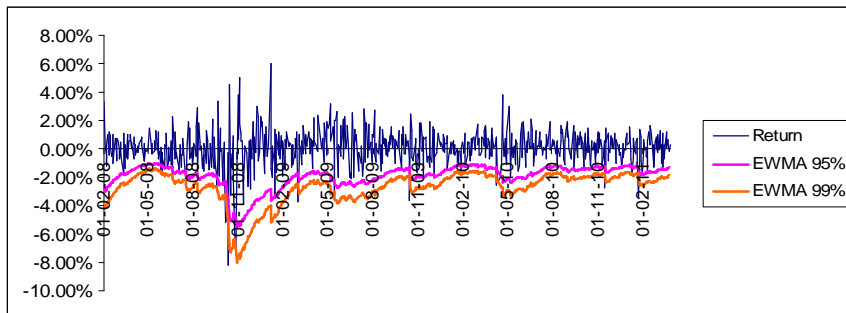
Student-t distribution approach to estimate VaR for ABERSL



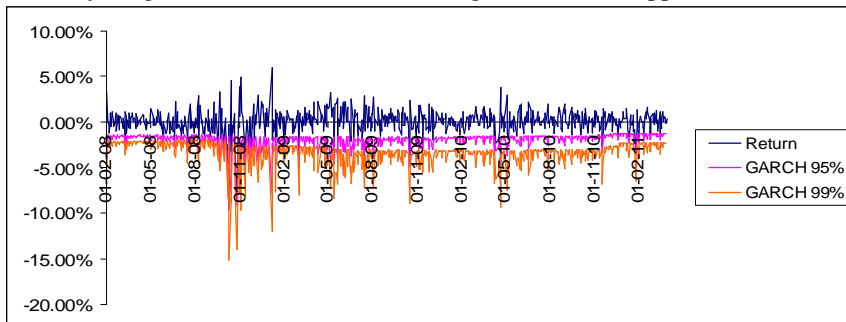
Log-normal distribution approach to estimate VaR for ABERSL



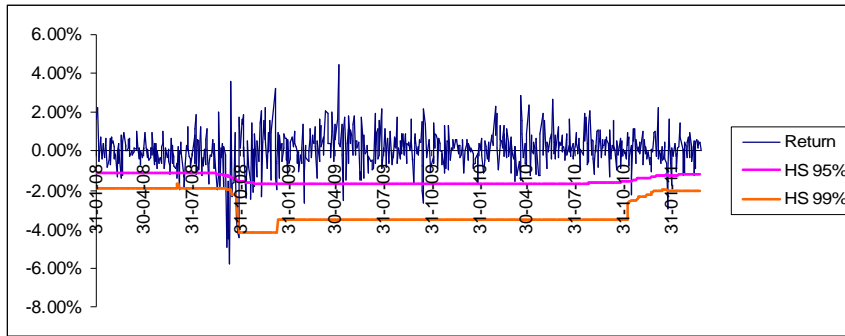
EWMA approach to estimate VaR for ABERSL



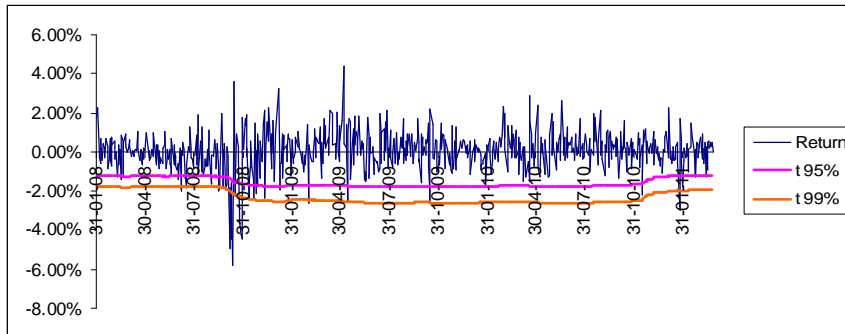
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for ABERSL



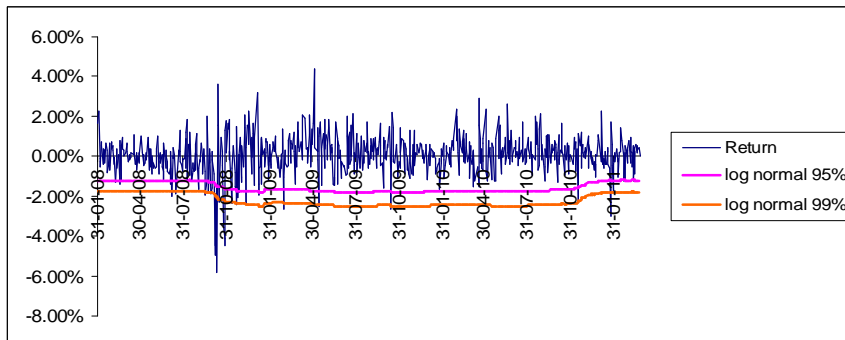
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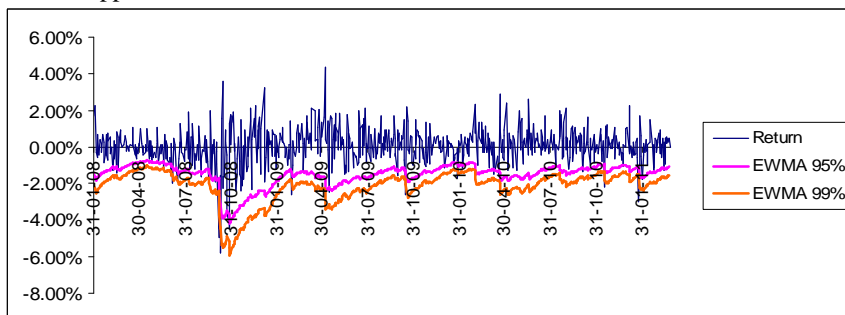
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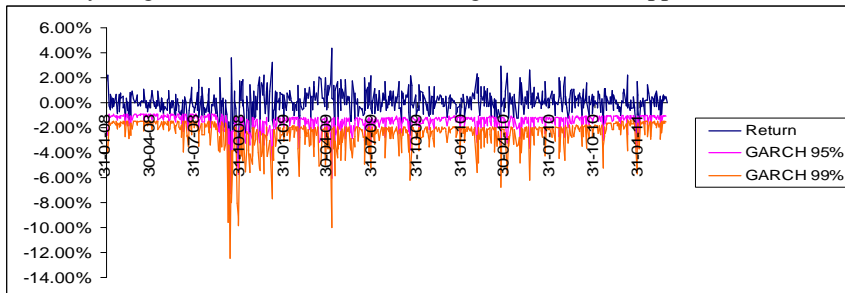
Log-normal distribution approach to estimate VaR for ABESMF



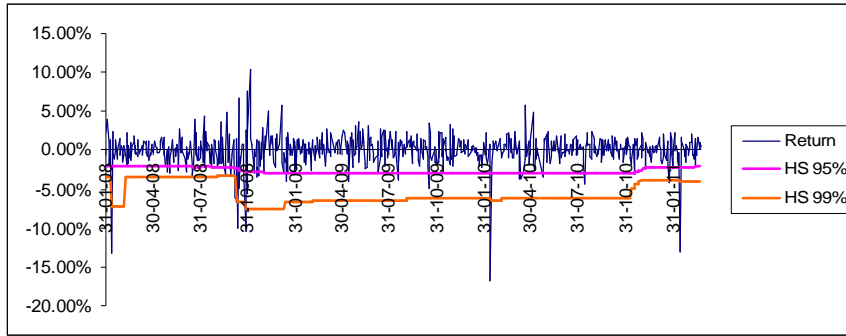
EWMA approach to estimate VaR for ABESMF



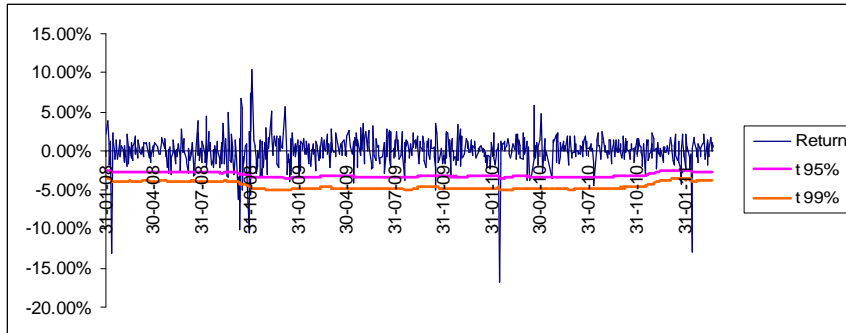
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for ABESMF



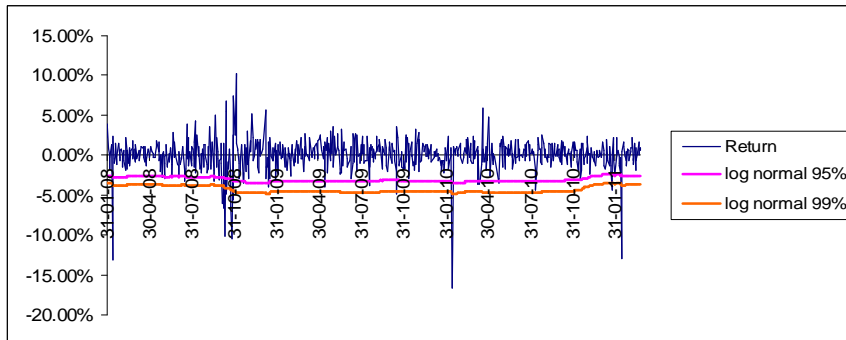
Basic historical simulation approach to estimate VaR for AJFSCAI



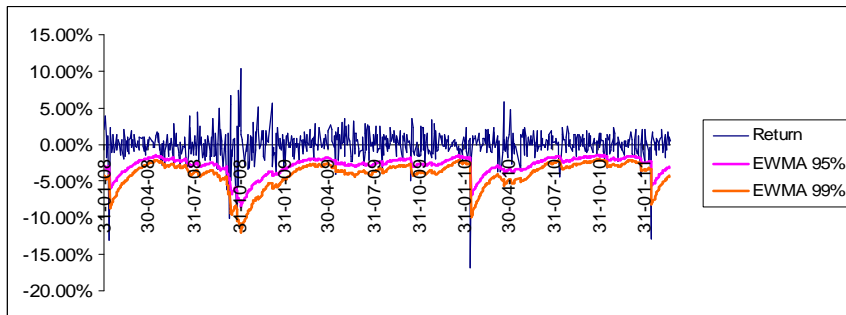
Student-t distribution approach to estimate VaR for AJFSCAI



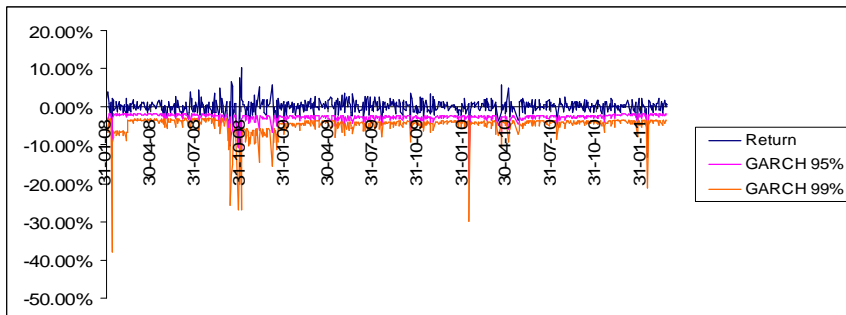
Log-normal distribution approach to estimate VaR for AJFSCAI



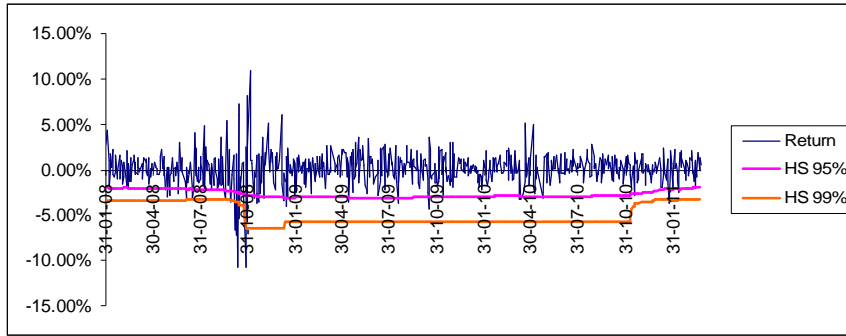
EWMA approach to estimate VaR for AJFSCAI



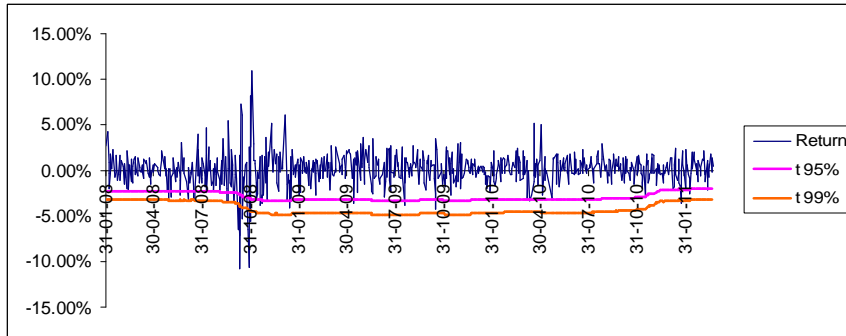
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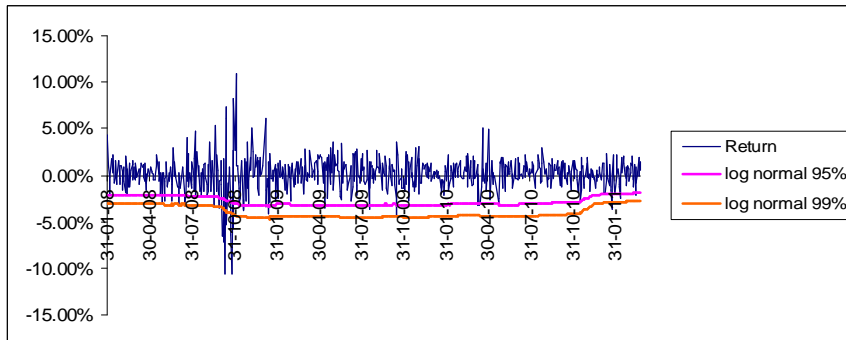
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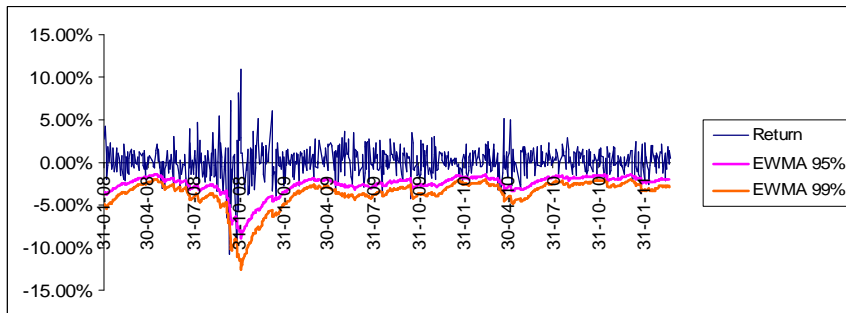
Student-t distribution approach to estimate VaR for **AJFSTDY**



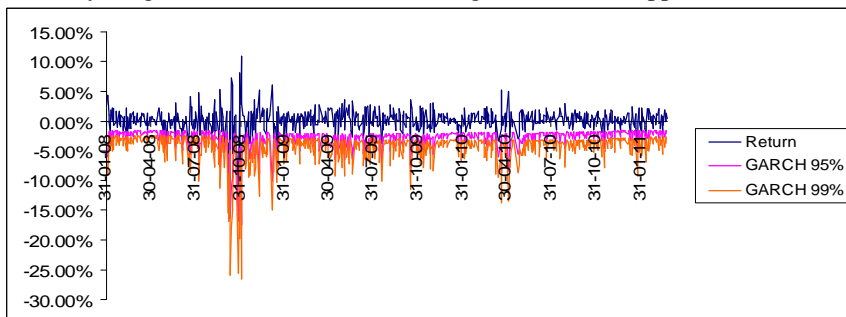
Log-normal distribution approach to estimate VaR for **AJFSTDY**



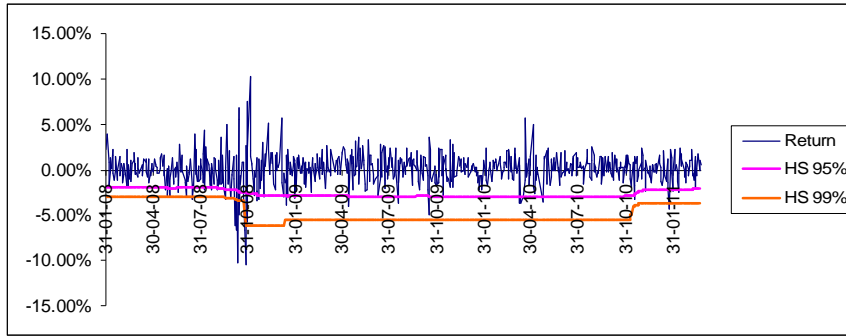
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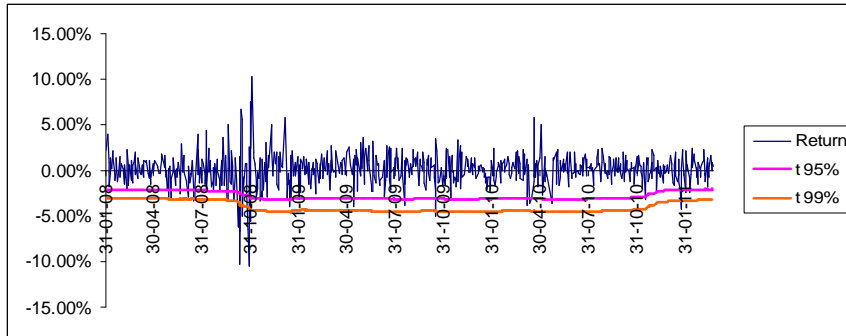
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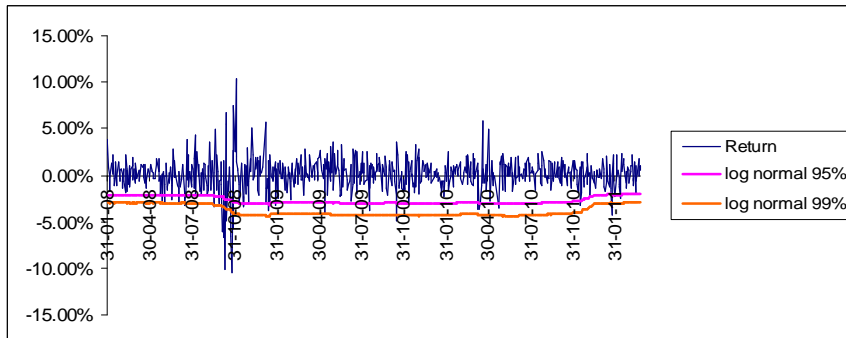
Basic historical simulation approach to estimate VaR for AJFSTEQ



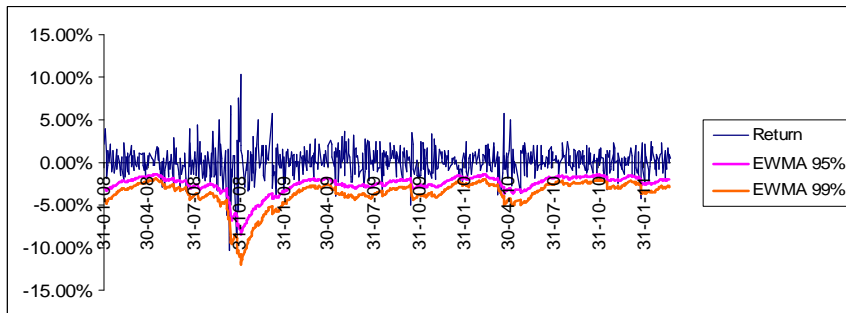
Student-t distribution approach to estimate VaR for AJFSTEQ



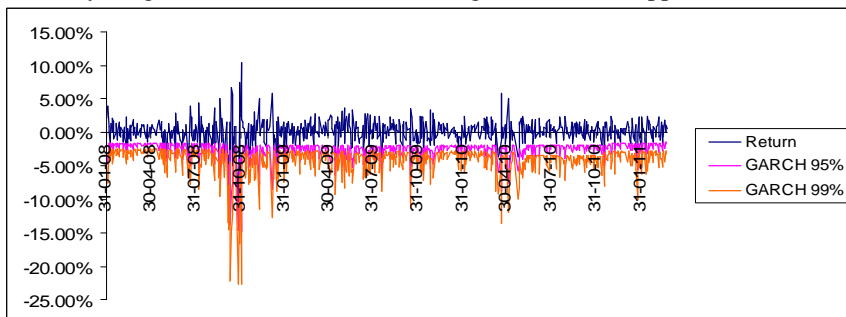
Log-normal distribution approach to estimate VaR for AJFSTEQ



EWMA approach to estimate VaR for AJFSTEQ

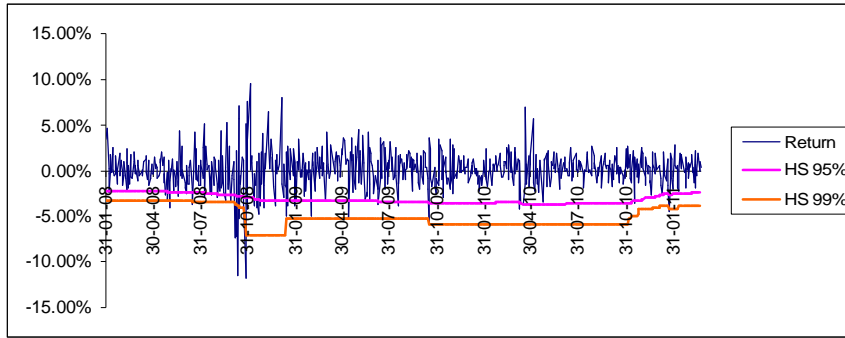


Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for AJFSTEQ

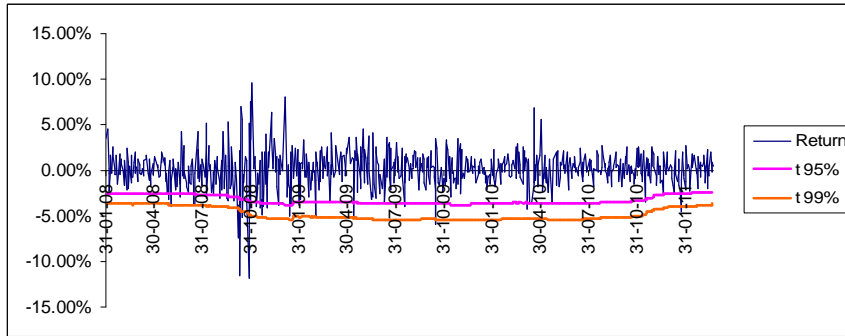




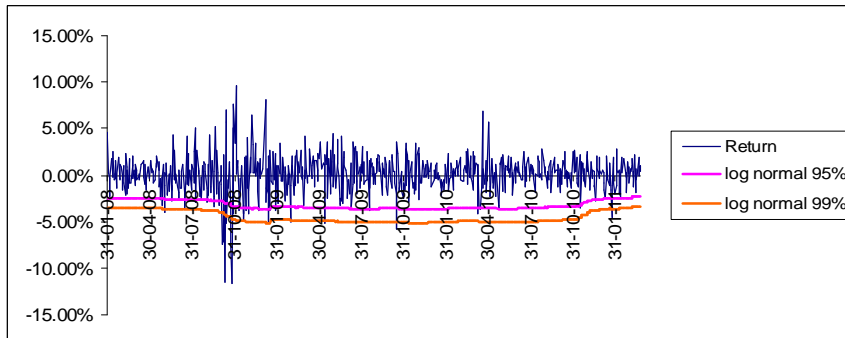
Basic historical simulation approach to estimate VaR for **KASRKEC**



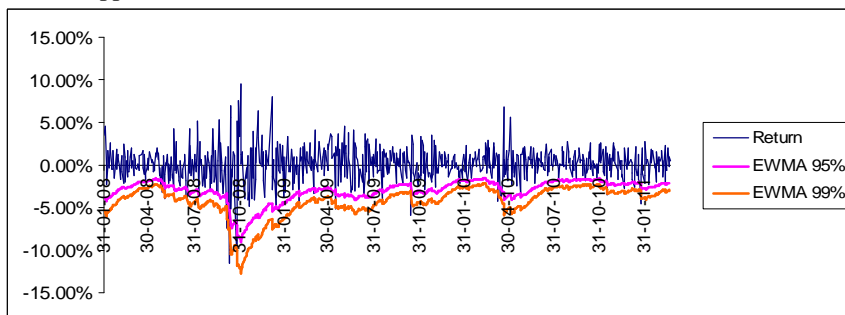
Student-t distribution approach to estimate VaR for **KASRKEC**



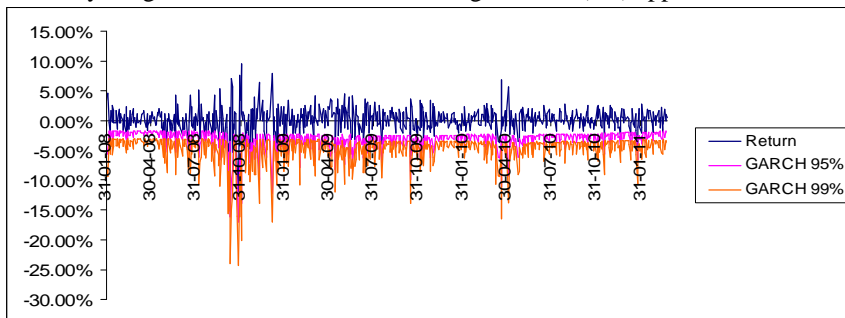
Log-normal distribution approach to estimate VaR for **KASRKEC**



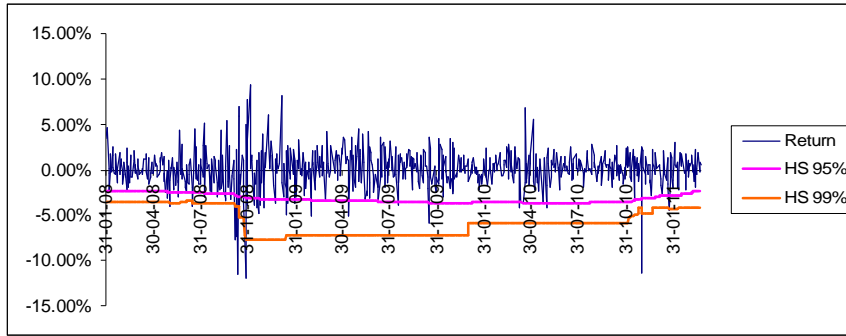
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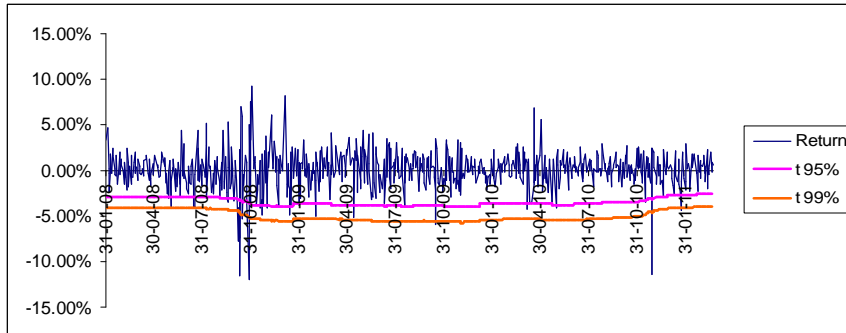
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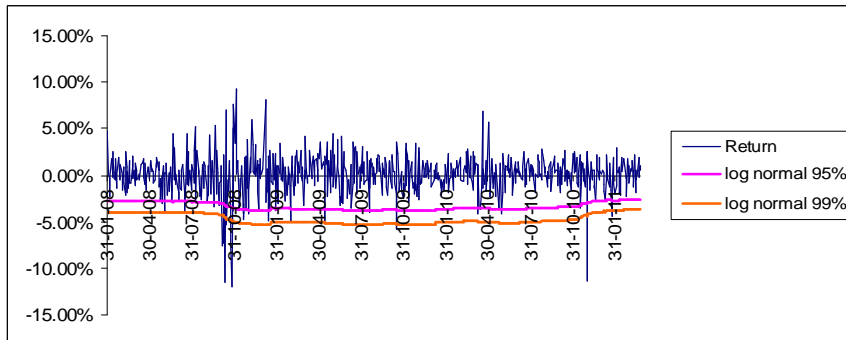
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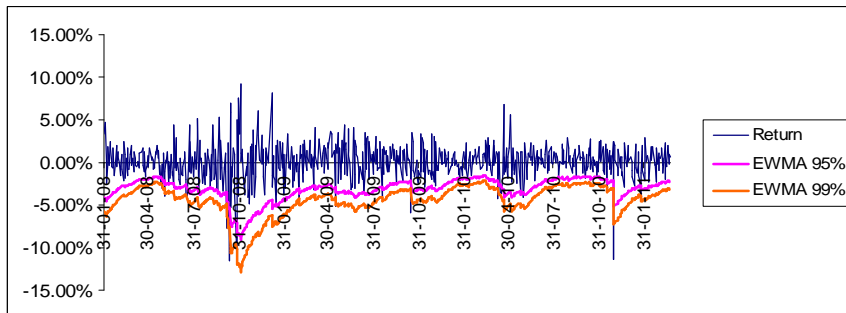
Student-t distribution approach to estimate VaR for **KASRKF3**



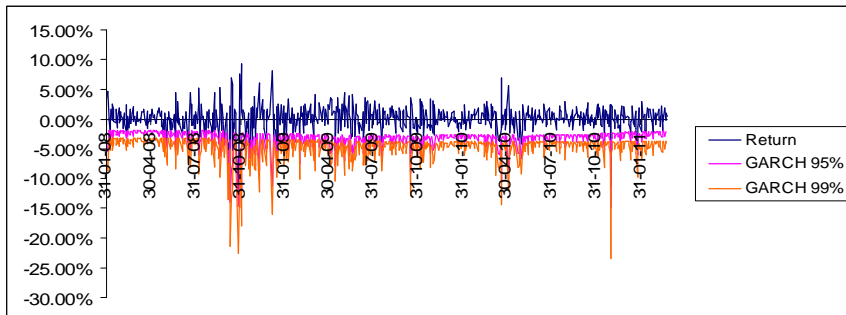
Log-normal distribution approach to estimate VaR for **KASRKF3**



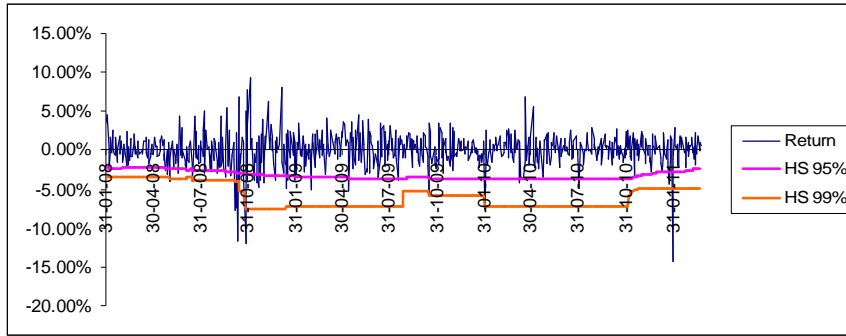
EWMA approach to estimate VaR for **KASRKF3**



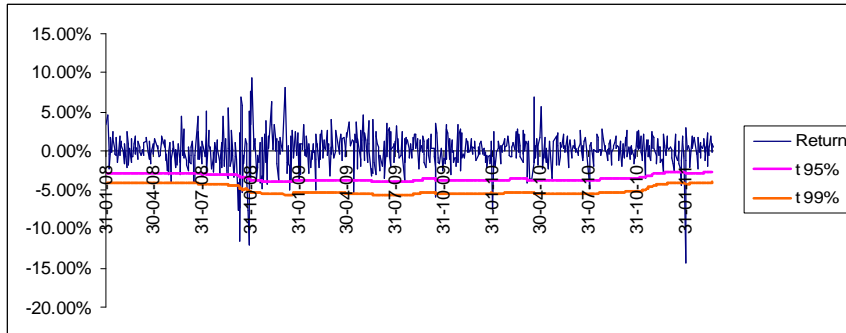
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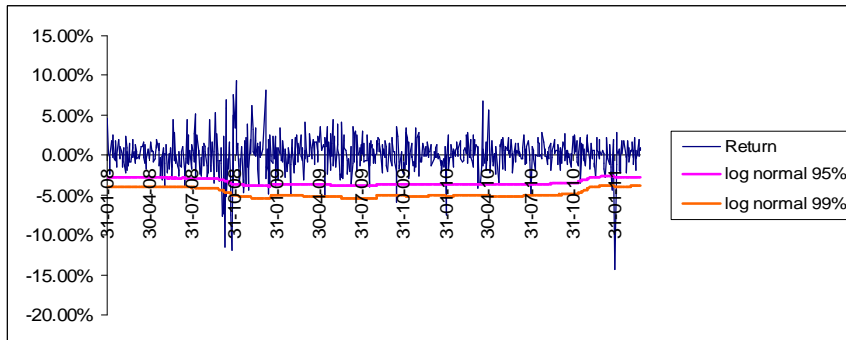
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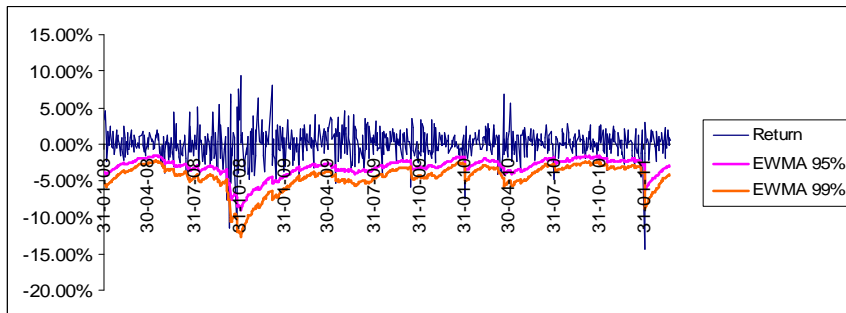
Student-t distribution approach to estimate VaR for **KASRKF4**



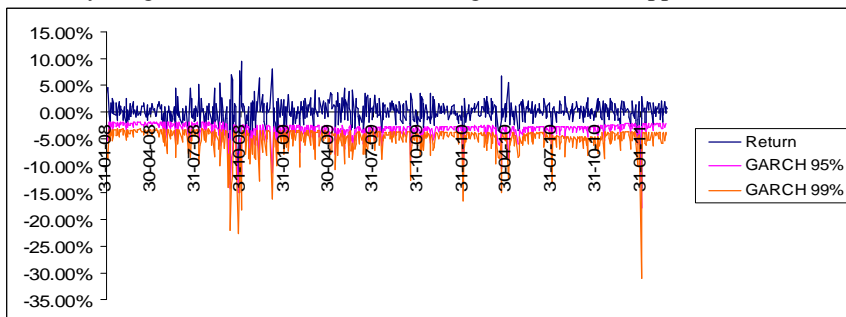
Log-normal distribution approach to estimate VaR for **KASRKF4**



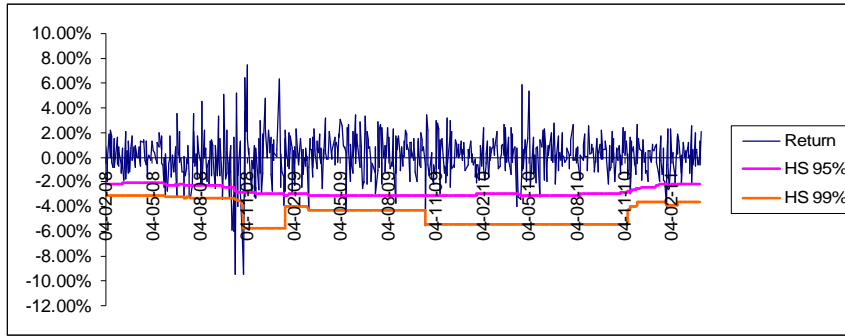
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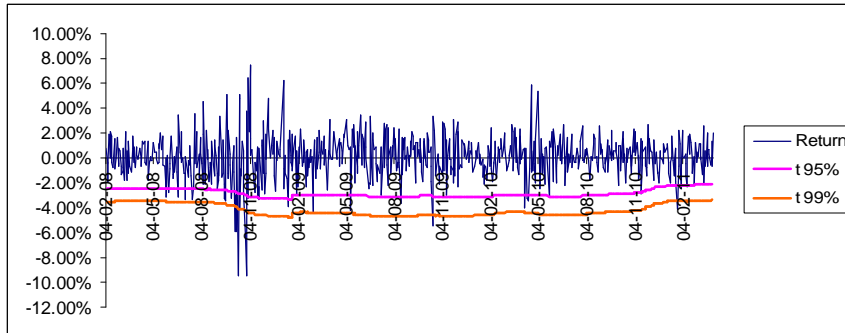
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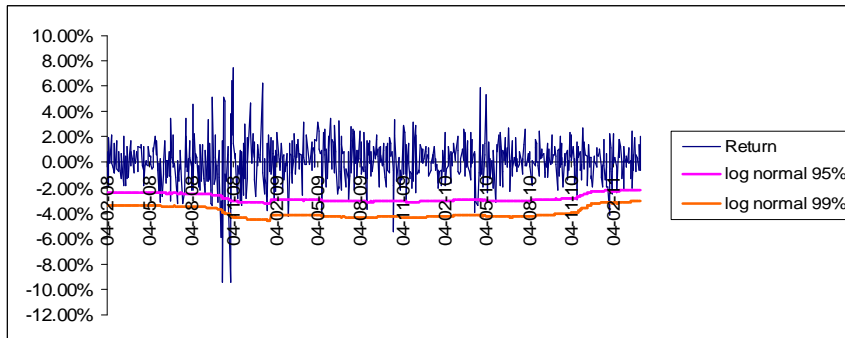
Basic historical simulation approach to estimate VaR for SCBDHAA



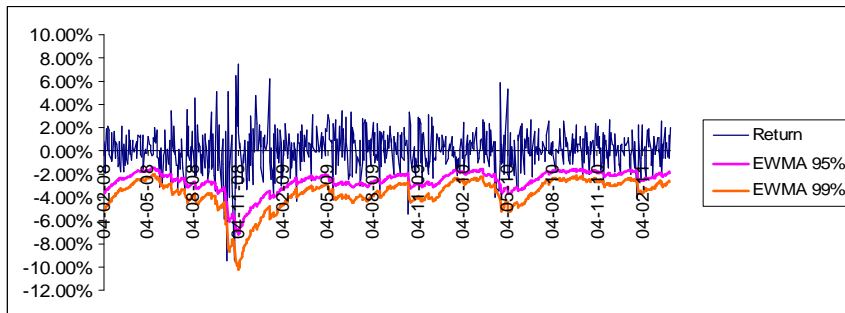
Student-t distribution approach to estimate VaR for SCBDHAA



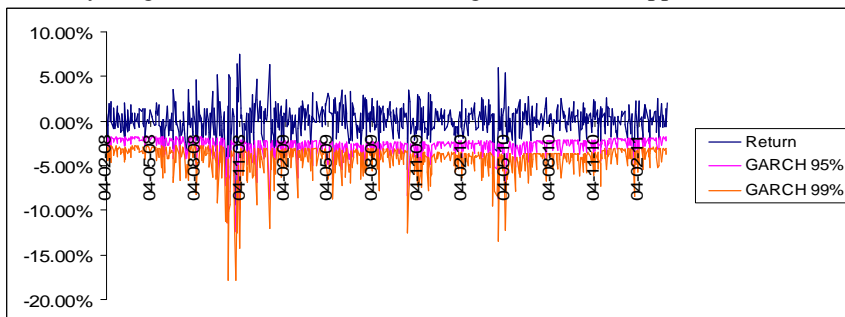
Log-normal distribution approach to estimate VaR for SCBDHAA



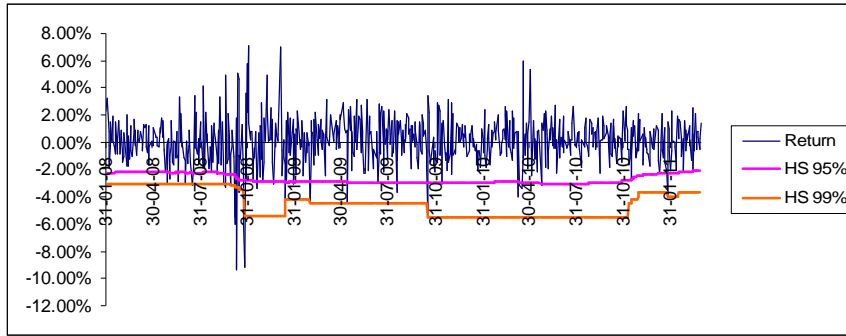
EWMA approach to estimate VaR for SCBDHAA



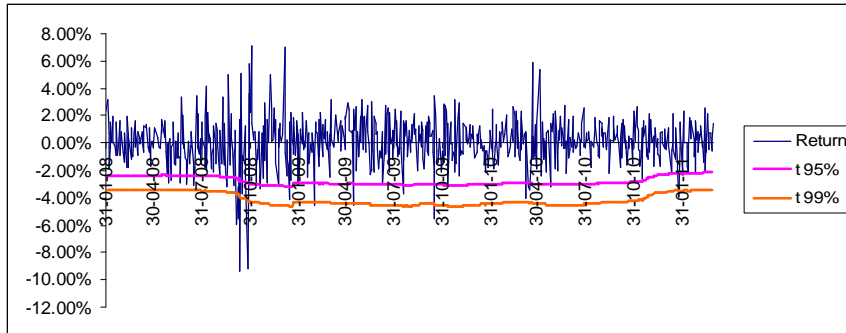
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBDHAA



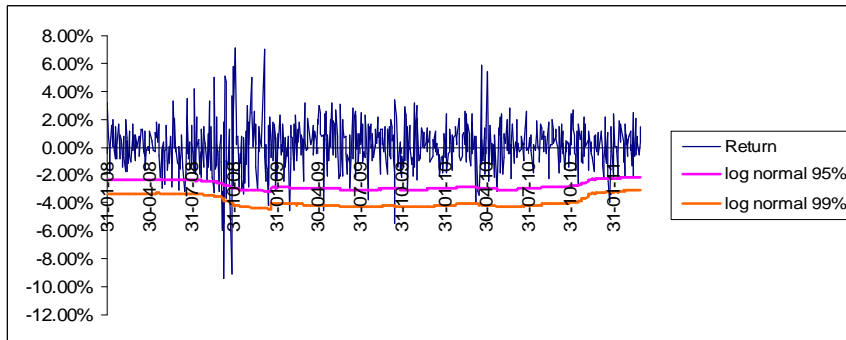
Basic historical simulation approach to estimate VaR for SCBMH2A



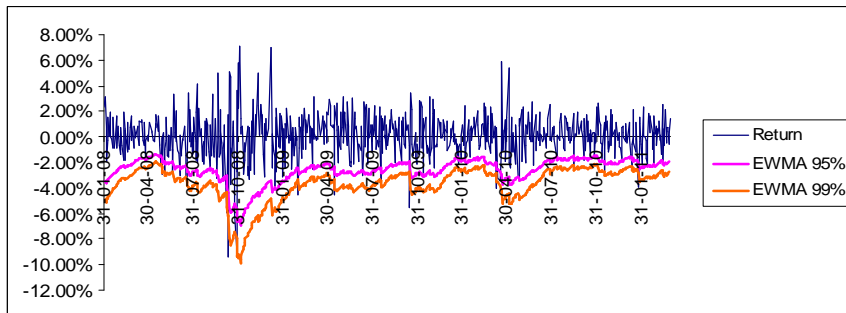
Student-t distribution approach to estimate VaR for SCBMH2A



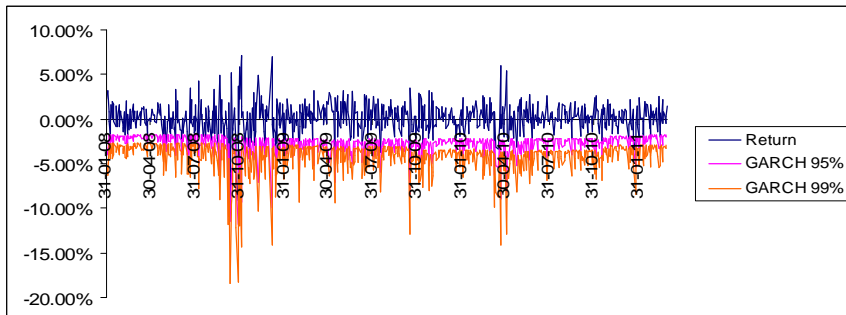
Log-normal distribution approach to estimate VaR for SCBMH2A



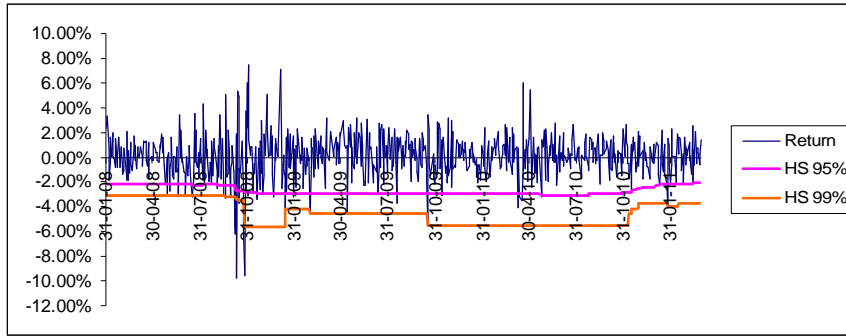
EWMA approach to estimate VaR for SCBMH2A



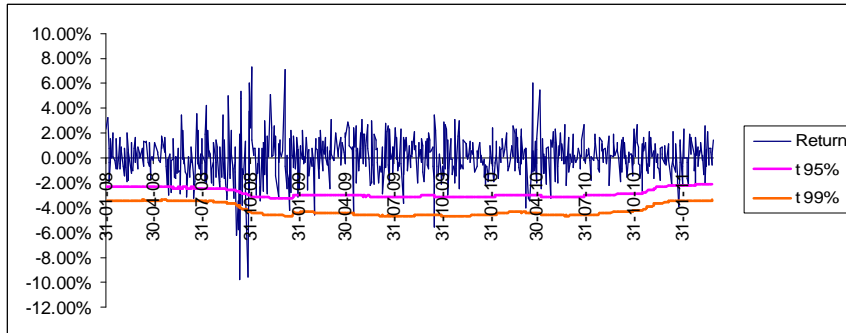
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBMH2A



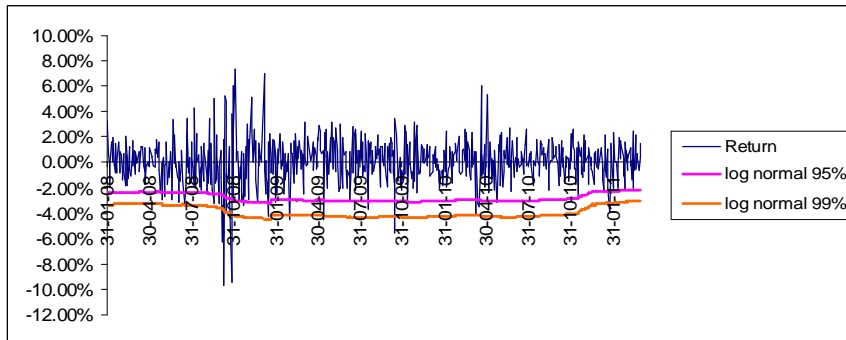
Basic historical simulation approach to estimate VaR for SCBMH3A



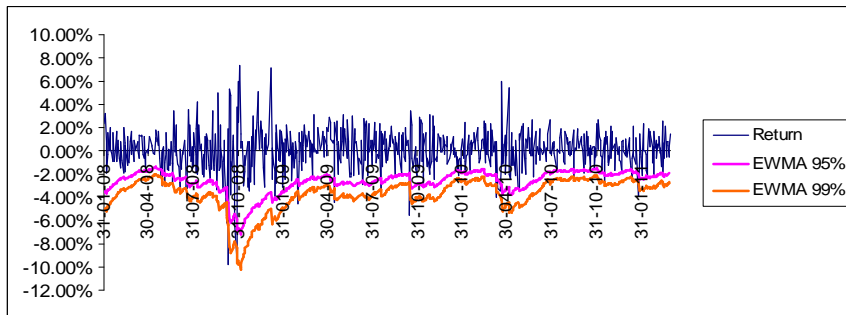
Student-t distribution approach to estimate VaR for SCBMH3A



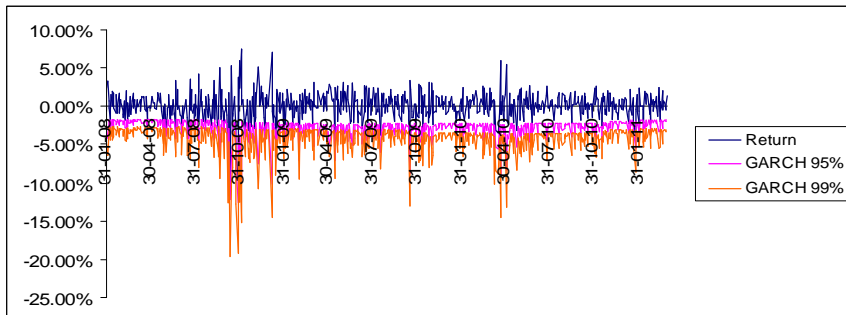
Log-normal distribution approach to estimate VaR for SCBMH3A



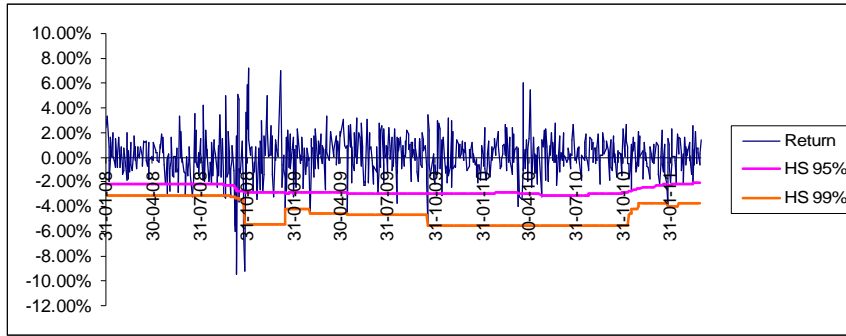
EWMA approach to estimate VaR for SCBMH3A



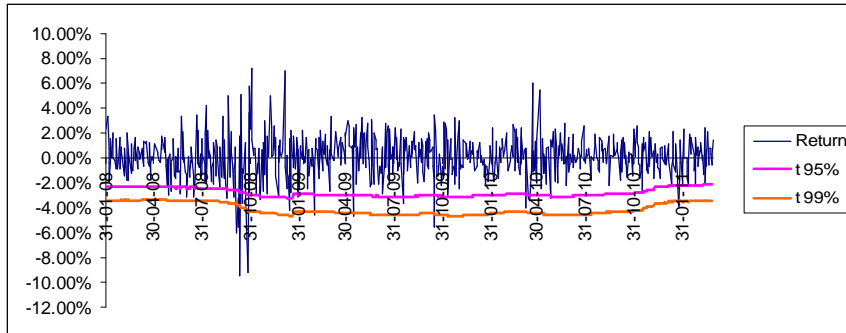
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBMH3A



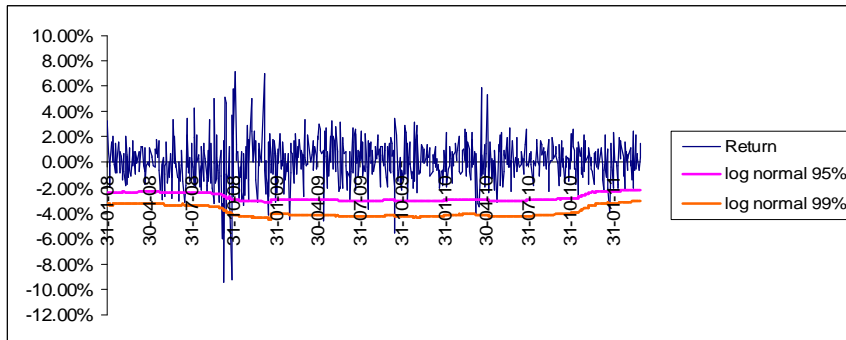
Basic historical simulation approach to estimate VaR for SCBMH4A



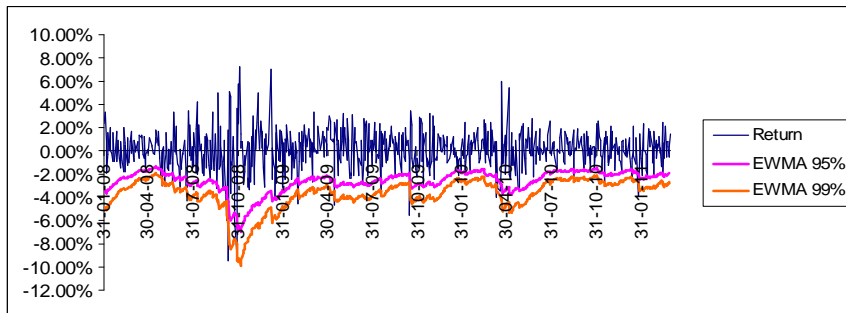
Student-t distribution approach to estimate VaR for SCBMH4A



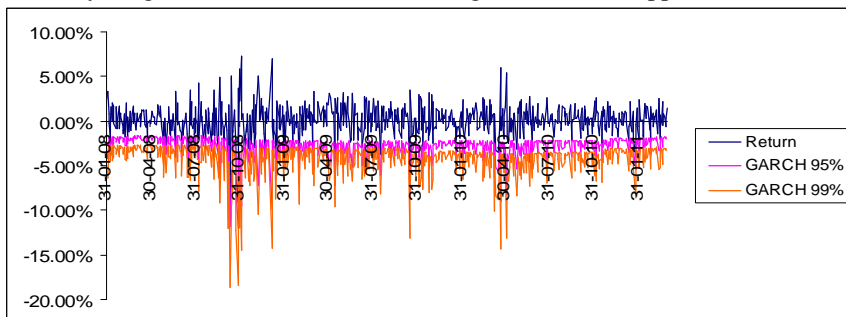
Log-normal distribution approach to estimate VaR for SCBMH4A



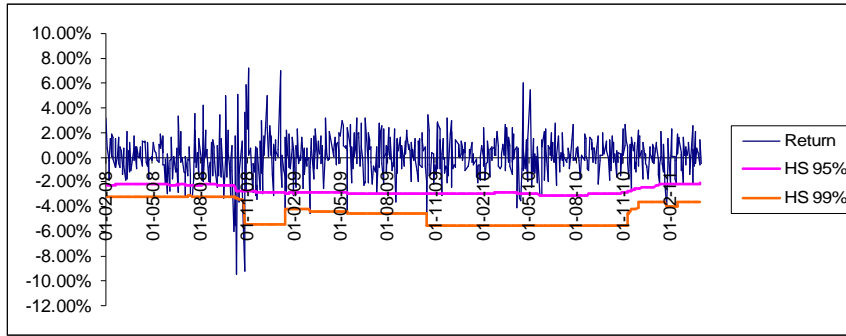
EWMA approach to estimate VaR for SCBMH4A



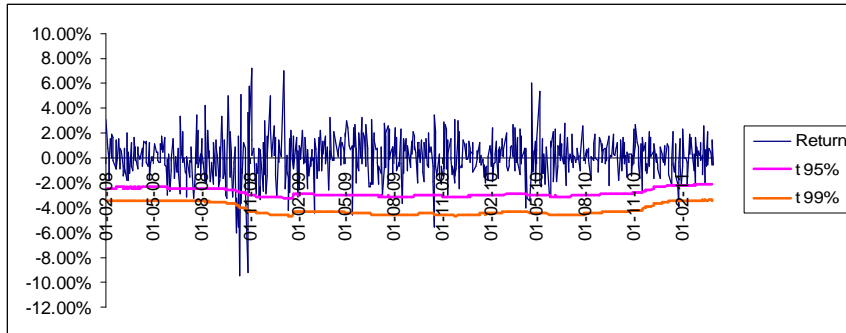
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBMH4A



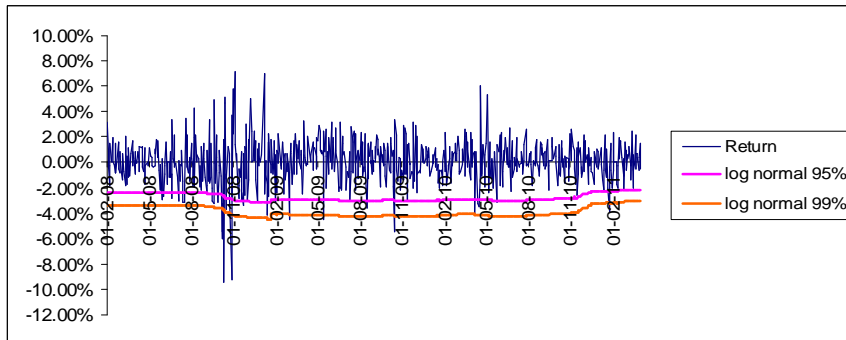
Basic historical simulation approach to estimate VaR for SCBMH5A



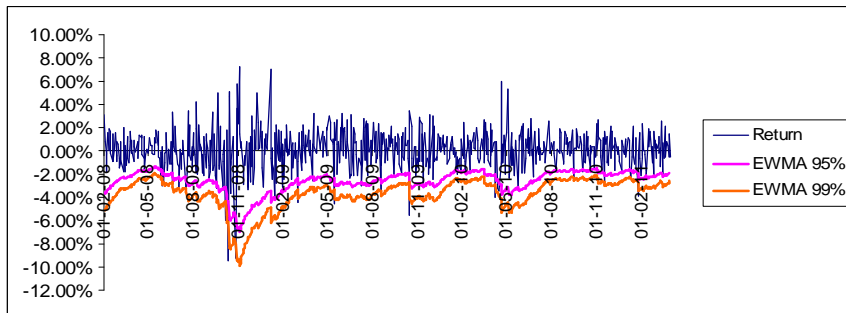
Student-t distribution approach to estimate VaR for SCBMH5A



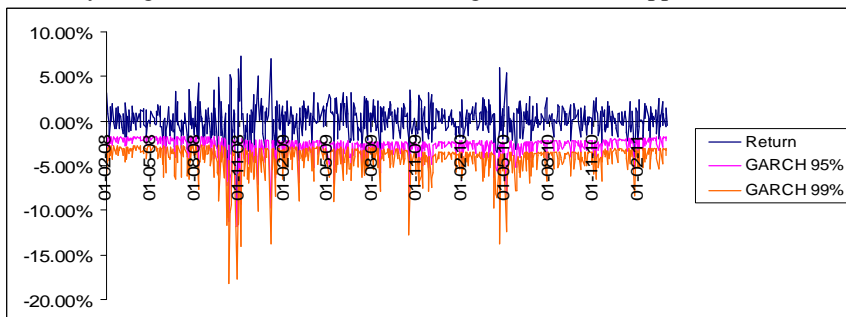
Log-normal distribution approach to estimate VaR for SCBMH5A



EWMA approach to estimate VaR for SCBMH5A

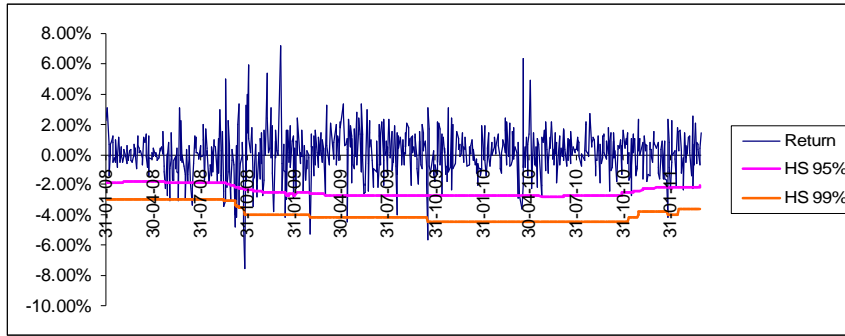


Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBMH5A

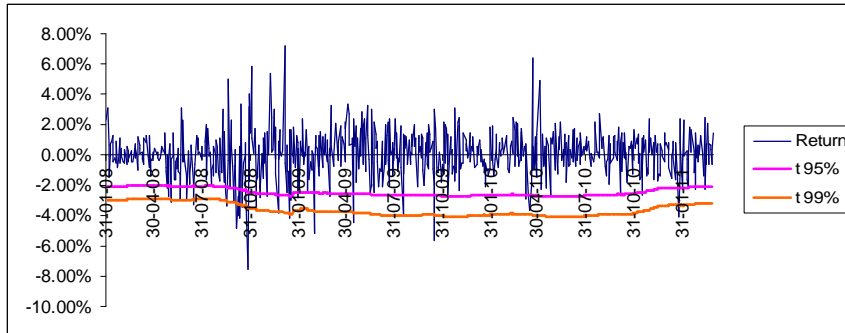




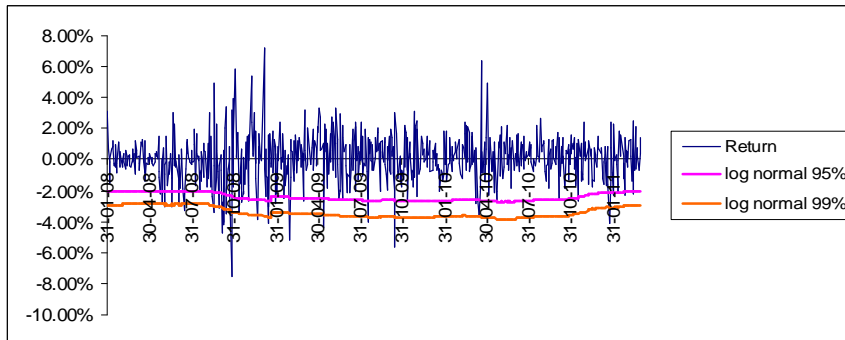
Basic historical simulation approach to estimate VaR for SCBPMOI



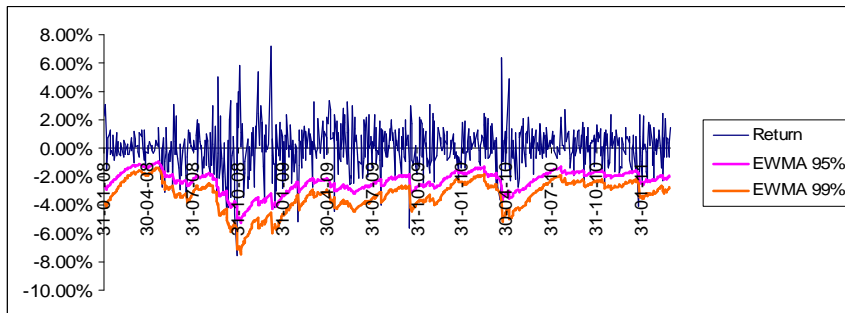
Student-t distribution approach to estimate VaR for SCBPMOI



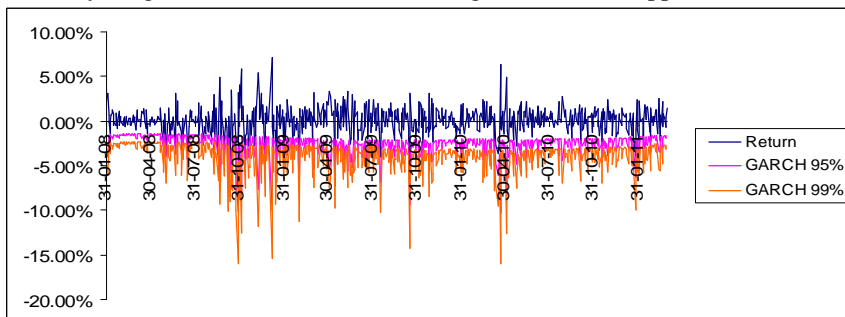
Log-normal distribution approach to estimate VaR for SCBPMOI



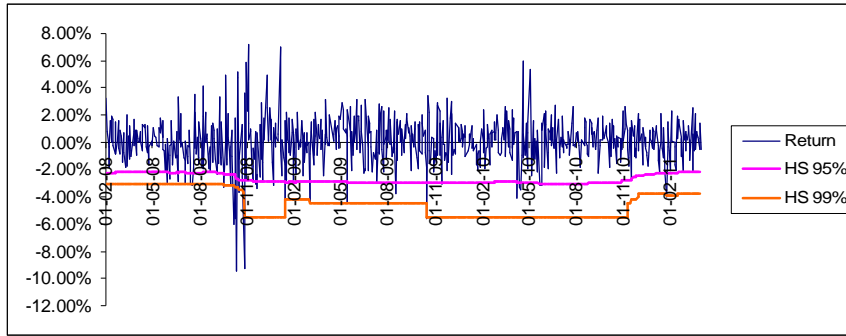
EWMA approach to estimate VaR for SCBPMOI



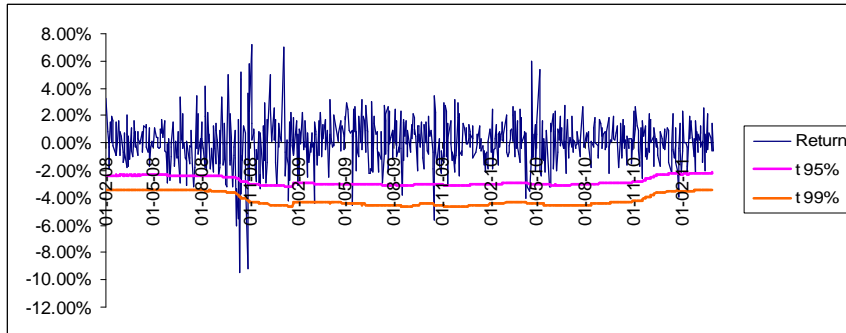
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBPMOI



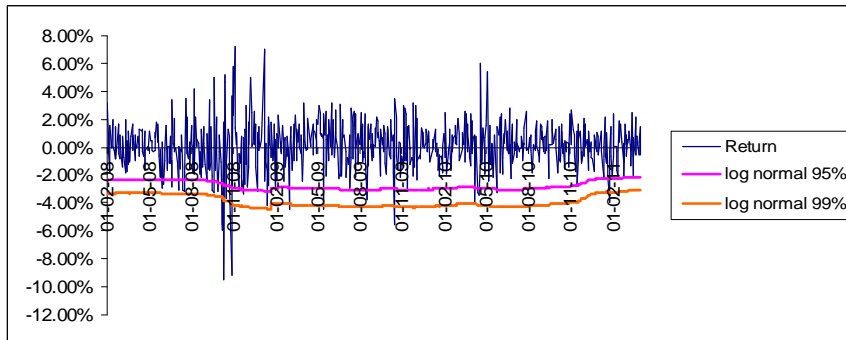
Basic historical simulation approach to estimate VaR for SCBTS2A



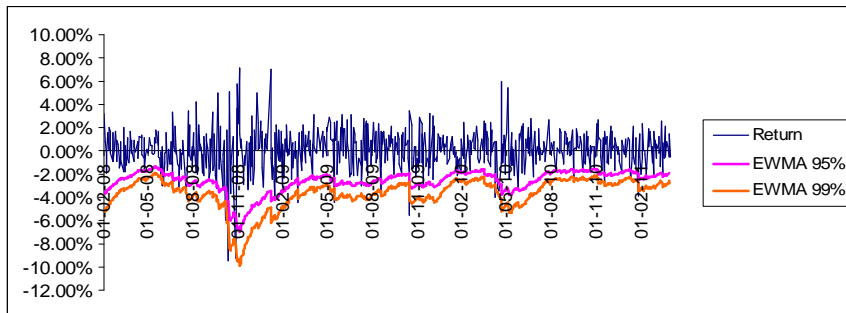
Student-t distribution approach to estimate VaR for SCBTS2A



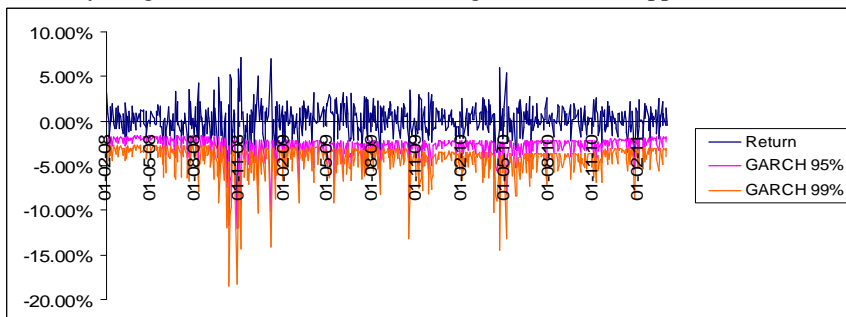
Log-normal distribution approach to estimate VaR for SCBTS2A



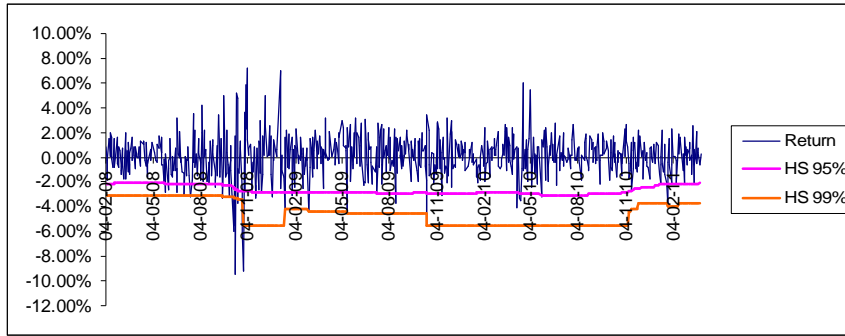
EWMA approach to estimate VaR for SCBTS2A



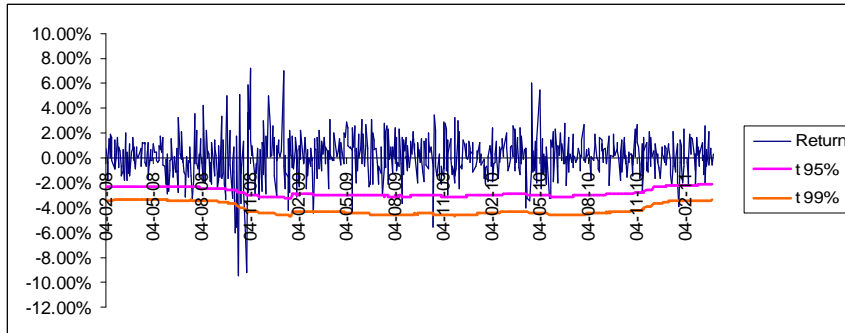
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBTS2A



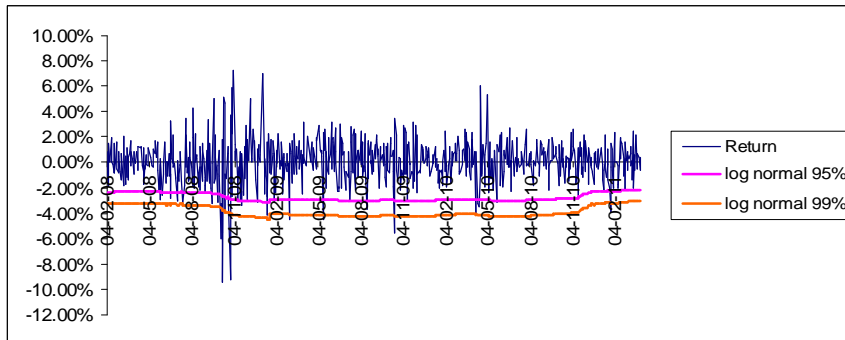
Basic historical simulation approach to estimate VaR for SCBTAWA



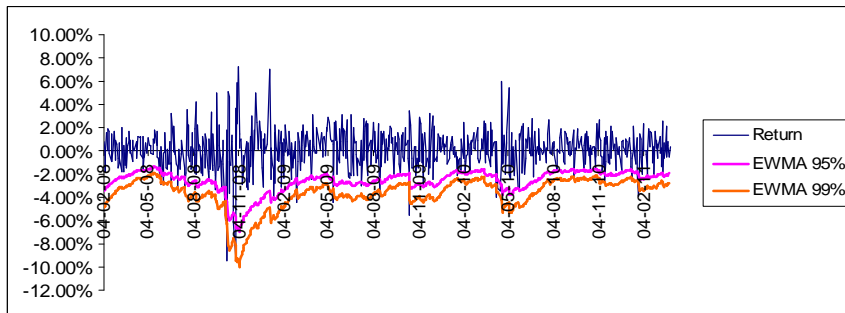
Student-t distribution approach to estimate VaR for SCBTAWA



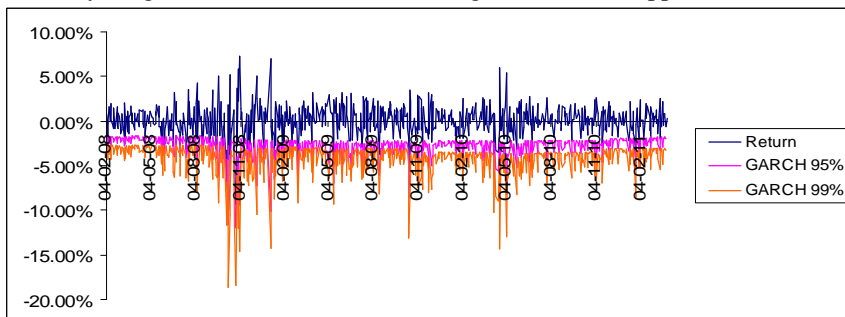
Log-normal distribution approach to estimate VaR for SCBTAWA



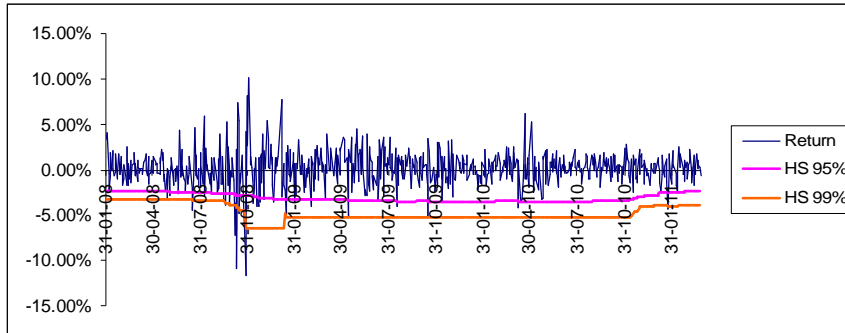
EWMA approach to estimate VaR for SCBTAWA



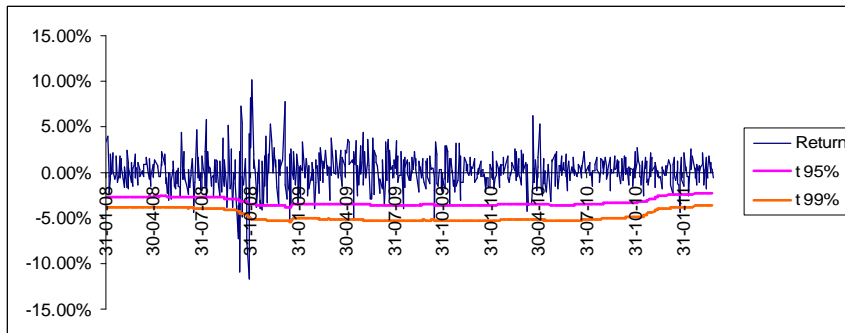
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for SCBTAWA



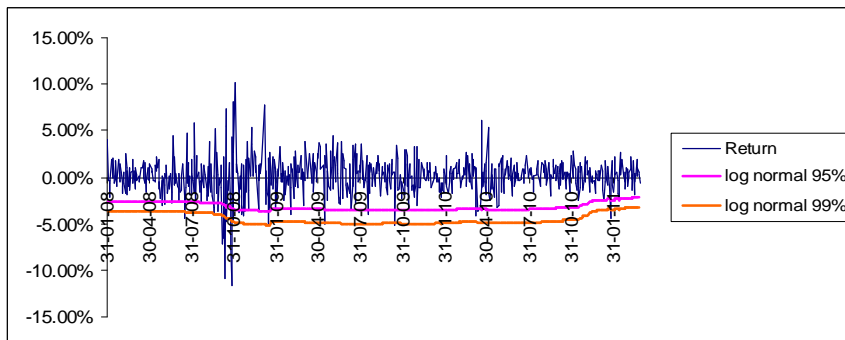
Basic historical simulation approach to estimate VaR for TMBJB25



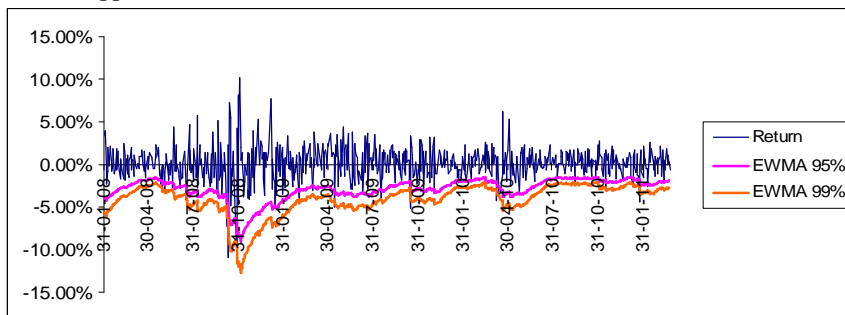
Student-t distribution approach to estimate VaR for TMBJB25



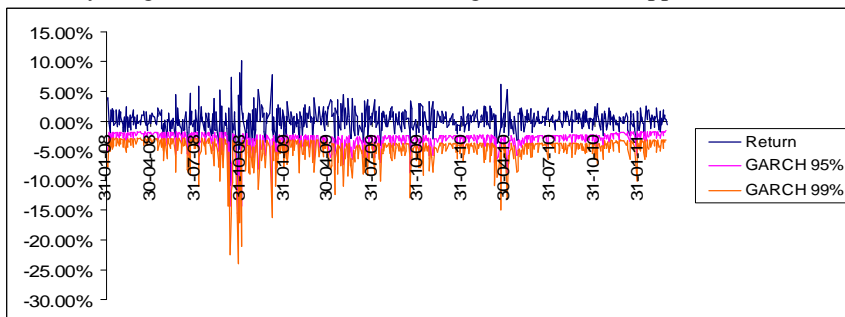
Log-normal distribution approach to estimate VaR for TMBJB25



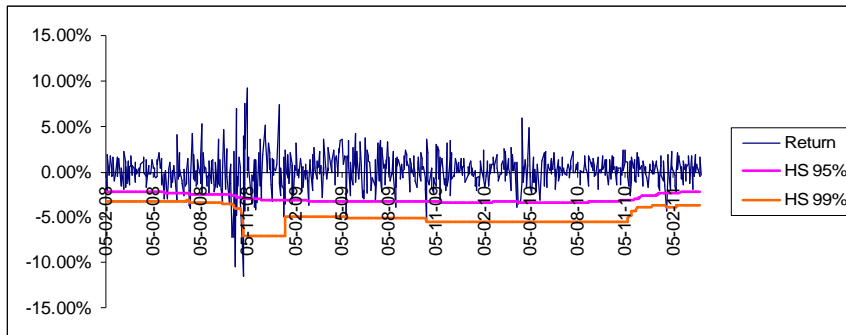
EWMA approach to estimate VaR for TMBJB25



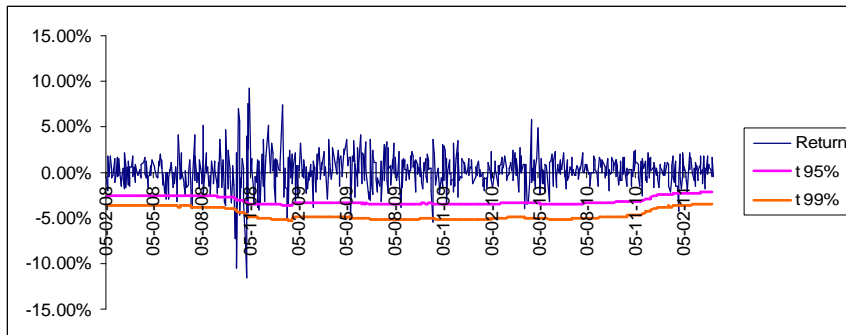
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for TMBJB25



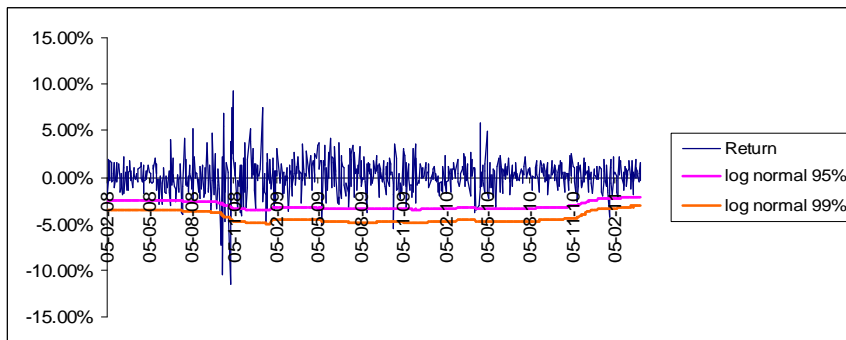
Basic historical simulation approach to estimate VaR for **K-SET50**



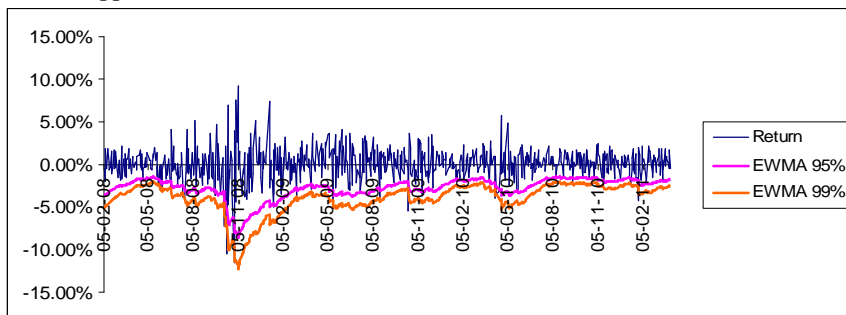
Student-t distribution approach to estimate VaR for K-SET50



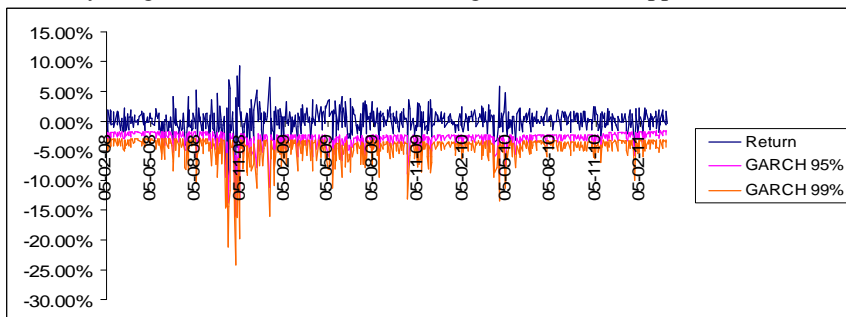
Log-normal distribution approach to estimate VaR for K-SET50



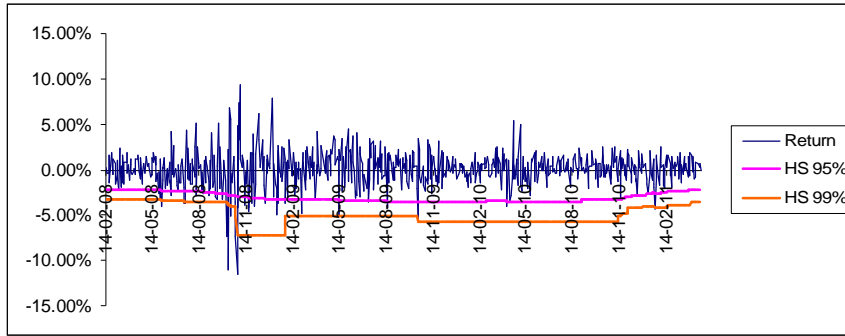
EWMA approach to estimate VaR for K-SET50



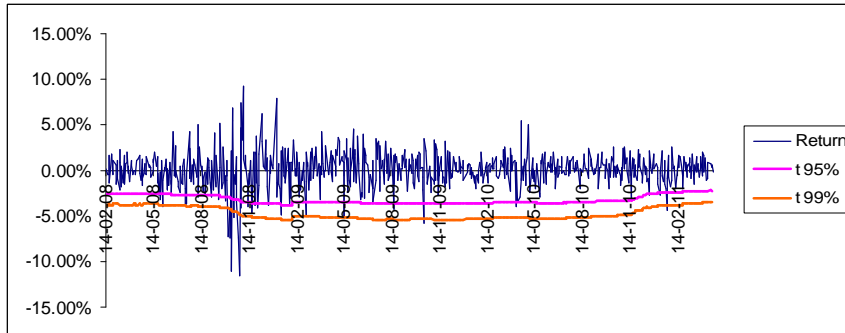
Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for K-SET50



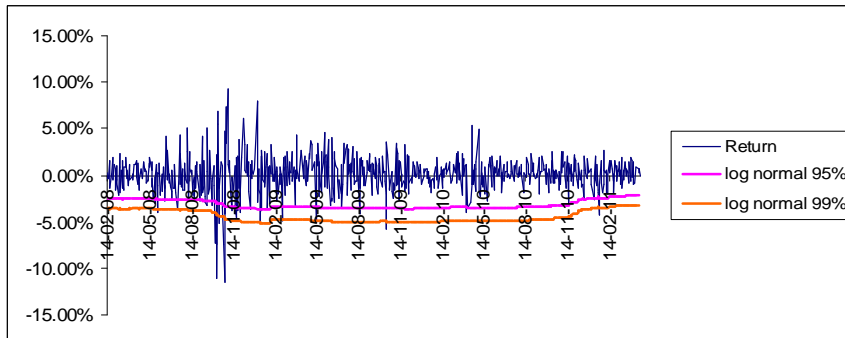
Basic historical simulation approach to estimate VaR for **K-FEQ**



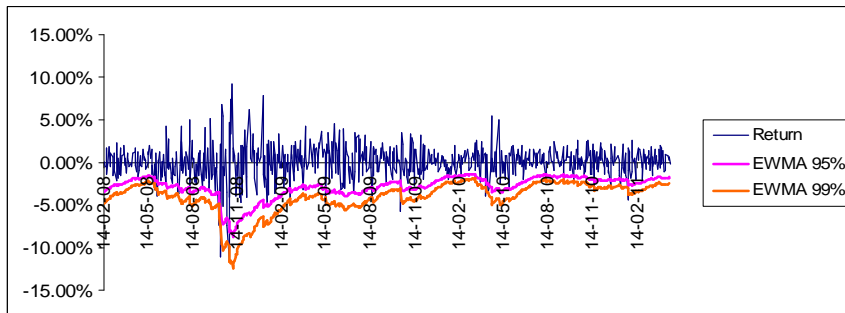
Student-t distribution approach to estimate VaR for K-FEQ



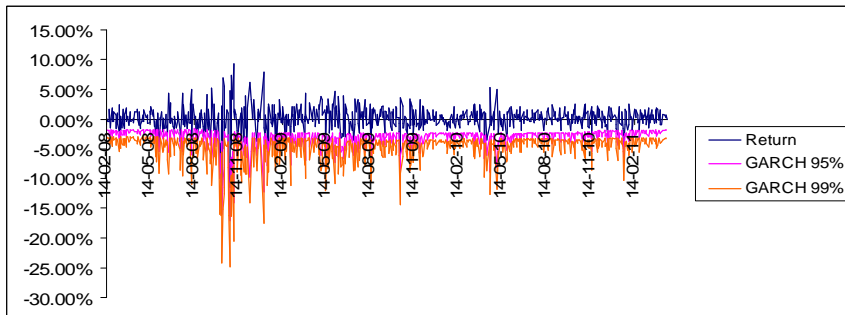
Log-normal distribution approach to estimate VaR for K-FEQ



EWMA approach to estimate VaR for K-FEQ



Volatility weighted historical simulation using GARCH(1.1) approach to estimate VaR for K-FEQ



### Appendix 3: Programming scripts

#### Visual Basic Application (VBA) for estimating volatility weighted historical simulation using GARCH(1,1) model

```
Sub VAR()  
Dim RangeOfDat, Vardat  
Dim Drow, Nrow, Krow, myConst, VarRow, Amnt As Integer  
ActiveSheet.Select  
If Range("Amt") = 0 Or IsEmpty(Range("Amt").Value) Then  
Amnt = InputBox(Prompt:="Please check for the amount of data for calculation ", _  
Title:="Amount of Data", Default:=510)  
Range("Amt").Value = Amnt  
End If  
myConst = Range("Amt")  
Application.ScreenUpdating = False  
Set RangeOfDat = ActiveSheet.Cells(1, 1).CurrentRegion  
Drow = RangeOfDat.Rows.Count - myConst - 3  
For i = 1 To Drow  
Set RangeOfDat = ActiveSheet.Cells(1, 1).CurrentRegion  
Nrow = RangeOfDat.Rows.Count  
Set Vardat = ActiveSheet.Cells(1, "J").CurrentRegion  
VarRow = Vardat.Rows.Count  
Range("A514").Select  
Application.CutCopyMode = False  
Selection.Copy  
Range("J" & (VarRow + 1)).Select  
ActiveSheet.Paste  
Range("G514:H514").Select  
Selection.Copy  
Range("K" & (VarRow + 1)).Select  
Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _  
:=False, Transpose:=False  
If Range("A" & Nrow).Value = Range("J" & VarRow).Value Then Exit Sub  
Range("A4:B" & Nrow).Select  
Application.CutCopyMode = False  
Selection.Copy  
Range("A3").Select  
ActiveSheet.Paste  
If IsEmpty(Range("A" & Nrow).Value) Then Exit Sub  
Range("A" & Nrow & ":C" & Nrow).Select  
Selection.ClearContents  
Next  
Set Vardat = ActiveSheet.Cells(1, "J").CurrentRegion  
VarRow = Vardat.Rows.Count  
Application.ScreenUpdating = True  
End Sub
```