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Estimation of the market risk exposure of Vietnamese banks' portfolios using VaR approach.

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ABSTRACT

This paper analyses the effectiveness of different methods to estimate Value-at-Risk (VaR) of VN-index, proxy of a Vietnamese bank's portfolio. Both parametric and non-parametric approaches are employed to estimate daily VaRs for two sets of data, one of those sets is 8 months behind the other. We find that non-parametric methods are more reliable than parametric methods when employed to estimate VaR for a bank's portfolio in Vietnamese market. Volatility weighted methods perform better for the first set of data, where there is a sudden jumps in the returns. Meanwhile, Basic historical simulation work best for the data that fluctuates dramatically but have no impulsive jumps over time. Our conclusion is that to correctly estimate the maximum loss of a bank's portfolio, especially in the unstable market like Vietnam, it is important to choose the suitable window size to estimate VaR.

Key words: Market risk, Value-at-Risk, Backtesting, Parametric, Non-parametric

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I. INTRODUCTION

1.1. Background

Market risk has received relatively high interest from financial institutions during the last two decades. Along with the growth of trading activity and liquidity of many financial instruments, the development of new financial products, the explosion of technology, the increased instability in the market environment is the main factor contributing to the interest in market risks. Recently, the financial world is facing increasing risk from the subprime mortgages in the US, which resulted in great losses for enormous financial institutions. Big banks in the US such as Citi-Bank, JP Morgan, Merrill Lynch, Bank of America, and many others reported tens of billions of USD losses in 2007 and even more have been forecasted for 2008. Other banks in Europe, Australia and Asia have also been affected. In April 2008, the International Monetary Fund (IMF) estimated the worldwide losses stemming from the US subprime mortgage crisis to be $945 billion as the impact spreads into the global economy. Looking further back, the financial crisis in the late 1990s in Asia also caused great problems to many of the Asian financial institutions and caused the collapse of many banks. Large changes in the market situation due to currency revaluation and interest rate changes caused banks with inefficient risk management systems to fail badly. At the time, due to the fact that the Vietnamese financial system had not been opened to the world, Vietnamese banks avoided the big losses due to the crisis.

Consequently, managing market risk has become an important part of the risk management program of every financial institution. The ability to estimate exactly the market risk exposure to the investment portfolios is the main contribution to the success of such programs. Measuring market risk can be done in a number of ways but due to its general characteristics, Value-at-risk (VaR) is considered to be the most popular approach to estimate market risk. Various financial institutions, fund managers, and even nonfinancial corporations use VaR to control the market risk in a portfolio of financial instruments. In its various forms, VaR has also gained strong support from industry and regulatory bodies such as the Group of Thirty (G30-1993), the Bank for International Settlements (Settlements 1994), and the European Union. In 1996, the Basel Committee on Banking Supervision (Basel Committee) issued an amendment to the Capital Accord of July 1988 to use VaR for measuring market risk to set capital requirements for banks (Basel Committee, 1988, 1996).

VaR has also gained much attention among academics. There are a number of researchers that have discussed the way to estimate VaR, to test the efficiency of various VaR methods and to improve the ability of VaR model to better reflect the true market risk. Some of them have tried to find an applicable VaR estimating method for different industries and for different investment portfolios. The motive for choosing these methods is subjective to the researcher's belief and the nature of the market. Pérignon and Smith (2007) have based their choice on the survey of popularity of VaR methods currently used in banks and financial institutions. They find that 73% of the firms that disclose their VaR methodology in their 2005 annual reports use Historical Simulation (HS) or related techniques and 23% have used Monte Carlo and other parametric methods. Pérignon and Smith (2008) have also applied both parametric and non-parametric VaR on five international banks and calculated the most efficient methods to derive VaR. Many academics have attempted to overcome problems in measuring VaR in a number of ways, either volatilities or improvement of data selections. Since VaR deals with two important parameters: mean and volatility, the more comprehensive volatility estimation will result in more accurate value at risk. As financial applications typically deal with a portfolio of assets and risk, there are several multivariate GARCH models which specify the risk of one asset as depending on its own past as well as the past behaviour of other assets. Timotheos Angelidis, Alexandros Benos and Stavros Degiannakis (2007) have analysed several volatility models to forecast VaR for two different time periods and two capitalisation weighting schemes. Accurate modelling of volatility is important in finance, particularly as it relates to the modelling and forecasting of value-at-risk (VaR). In another piece of research on VaR analysis, Sang Hoon Kang from the University of South Australia and Seong Min Yoon from Korea (2007) investigated the VaR of the Korean stock market by using the APARCH model with normal and Student t-distribution methods. They believed that the APARCH model can capture clustering and asymmetry in volatility and the assumption of student t-distribution can reflect the fat-tail innovation. Many pieces of research have also focused on the efficiency of VaR measuring methods which are implemented in many different markets. Ngai Hang Chan, Shi-Jie Deng, Liang Peng and Zhendong Xia (2005), in "*Interval estimation of value-at-risk based on GARCH models with heavy-tailed innovations*" introduced the VaR measuring methods in the Hong Kong stock market.

Andrey Rogachev (2007) has considered the problem of using VaR techniques and developed a VaR concept by Swiss private banks. Le Lei (2007) has conducted an empirical reach on the Chinese stock market to find the most appropriate VaR measurement. Sang Hoon Kang and Seong Min Yoon (2007) have concluded that the Student t-VaR models for long and short positions predict critical loss more accurately than the models with normal innovations when applying these methods to the Korean stock market.

Even though there are a good number of researchers in market risk management and VaR in the world and in Asia, it is hard to find any research into these matters with regards to the Vietnamese market. Meanwhile, according to the WTO commitment, Vietnam's financial markets have been open since April 2006, which means that, the Vietnamese banking system has become more and more exposed to market risk, not only domestically but also internationally. Moreover, banks' investment portfolios are more diversified with new financial tools such as stocks, derivatives and funds. Since the Vietnamese financial market is now open to the world, research of risk in the financial market is certainly in need. Developing the VaR system is of great importance to banking regulation and supervision in Vietnam as it helps to limit the risk-taking behaviour of banks and to reduce the likelihood of bank failuresThe Vietnamese financial market is emergent and the knowledge of risk management, its success and failure in developed market and other developing markets, is important to form its own market risk measurement and strategy. The nature of VaR is to measure market risk; hence one VaR measuring method should not yield the same result for all markets. Each market is exposed to different risks and it is important to know which VaR method is the most appropriate one to apply in that particular defined market. Markets in different countries will be influenced by the different macro and micro economic environments which lead to differences in market risk condition. VaR methods that have proven to be superior in the West or in China do not possibly reflect the market risk exposure in Vietnam. In this research, therefore, we attempt to learn the implication of VaR to measure market risk in Vietnamese banks in order to provide interested parties with information about the level of market risk and suggestions of the most efficient method to calculate market risk in this particular market. We based our choice of methods on the improved versions of prior studies in other markets. Both non-parametric such as Basic historical simulation, Age-weighted and volatility-weighted approach and parametric techniques such as the normal distribution and Student's t-distribution are used to capture the Vietnamese banks exposure to market risk. GARCH(1,1) is also employed to estimate the volatility in parametric methods.

1.2. Purpose

The main focus of this study is on empirical research of various VaR evaluation models in estimating the market risk exposure of an investment portfolio of banks in Vietnam and testing the efficiency of backtesting procedures. Different VaR estimation approaches will be employed for two data sets which display different trends. VAR estimates are subjected to testing where we compare with actual return, which provides us a view of our models' predictive accuracy.

1.3. Delimitations

Daily trading revenues of Vietnamese banks' investment portfolios are not publicly available, therefore, the Vietnam index (VN-index) was chosen as a proxy value for the investment portfolio of a bank and then a number of VaR methods were applied to forecast its daily VaRs. The VN-index is a well-diversified portfolio of Vietnamese companies, which makes the VN-index subject to various market risks in both local and the global market. The risk feature of the VN-index is somewhat similar to a Vietnamese bank that exposes itself openly to different financial markets.

1.4. Outline

The next section in this study presents basic theoretical ideas of market risk and value-at-risk. The way we choose the data and data analyses are mentioned in section 3. Section 4 mentions various models used to estimate VaR and backtesting procedures. Empirical findings are analysed in Chapter 6. Section 7 concludes the paper.

II. THEORETICAL FRAMEWORK

2.1. Market risk of bank's portfolio

Risk represents uncertainty in the outcome of a random event. Risk, therefore, indicates a potential loss or gain that an individual or organisation might be exposed to when one particular event occurs. Market risk is one particular form of financial risk, which reflects the risk of loss (or gain) from unexpected changes in market prices or rates. Market risks can be classified into interest rate risks, equity risks, exchange rate risks, commodity price risks, and so on, depending on whether the risk factor is an interest rate, a stock price, or something else[1]. Like traditional credit risk, market risk can lead to significant losses and ultimately to failure if not managed appropriately. However, in contrast to credit-related losses, which can take time to develop, losses due to market risk can occur quickly. Normally, market risk, like any other risks can be measured using absolute or relative terms. Absolute market risk is the amount of shortfall relative to the initial value of the investment and is usually expressed in terms of currency. Relative risk is, on the other hand, measured risk relative to a benchmark index and represents active management risk. Both terms are used by practitioners depending on which type of trading or investment is employed. For bank trading portfolios, market risk is more commonly measured in absolute terms.

2.2. Value-at-Risk (VaR)

Value-at-Risk received its first wide representation as a measure of market risk in July 1993 in the Group of Thirty report. Later, the release of *RiskMetrics*™ by the risk management group at J.P. Morgan in October 1994 provided a means to Value at Risk's growth by attempting to standardise the use of VaR throughout the industry. This is the answer to the search for an internal model to measure and aggregate risks across instruments as a whole which has began in the late 1970s and 1980s: A p-$VaR_{1-n\%}$ equal to m millions dollars means that the most we can expect to lose is m million with the probability of n% from holding a financial asset or a financial portfolio over a certain time period, p. The probability level mostly lie in the range of 95%-99%. The horizon period can be specified as the next day, the next week, month, quarter, etc.

The number of users of Value-at-Risk has increased dramatically since its first announcement. Its popularity is mainly due to its many advantages, which is specified by Dowd (2002). Firstly, using VaR, managers is able to aggregate several components of a firm wide market risk into a single quantitative number which makes it easier for firms to develop appropriate strategy to deal with the potential for losses. Secondly, VaR focuses on the potential for significant loss in a firm's portfolio of assets, a major concern of senior managers, which is different from traditional risk measures that classify both upside and downside potential equally, considering all deviations from the expected return as risk. Finally, it provides a common consistent measure of risk across different position and risk

[1] Dowd, K., (2005), *Measuring Market Risk*, 2nd edition, John Wiley and Sons, Ltd, p.15

factors, enabling us to compare the risk of different portfolios[2]. This advantage allows managers to choose the most suitable portfolio to invest in.

Although VaR consept seems to overcome many of the problems associated with traditional techniques to measure market risk, it also contains some great problems that should be taken into account. VaR gives us the loss that will be exceeded with some level of confidence but it does not specify the absolute worst possible losses the may occur. Moreover, VaR also assumes the portfolio remains constant over the entire time horizon. As the composition of the portfolio changes due to normal trading activity within the time horizon that VaR is measured, the accuracy of the VaR estimate declines. Finally, VaR relies on historical price data, and the price risk associated with assets for which historical data are not available is difficult to quantify with VaR. VaR position limits can also lead traders to "game" the system, trading in markets where the historical data resulting in low VaR estimates do not accurately represent the current situation (Jorion, 2001).

III. DATA DESCRIPTION

3.1. Data source and selection

The VN-index data are drawn from the official website of the Ho Chi Minh Stock Exchange (www.vse.org.vn). The first dataset includes 619 daily values of the VN-index from 01/01/2005 to 29/06/2007. The second data set includes 619 daily values from 01/09/2005 to 27/2/2008. As presented in Appendix 1, the Vietnamese stock market is quite stable during the first eight months of 2005, which leads to a fairly stable return during this period. On the contrary, since the beginning of September 2005, the Vietnamese stock market fluctuated dramatically. Therefore, estimating VaR based on different historical data can lead to very different result. Our purpose is to find a method that is predictive for VaR and to determine how the way we choose the data can have an impact on the quality of estimating methods. As the Vietnamese Stock Market is still underdeveloped, the two sets of data will exhibit some abnormal behaviour.

Data processing: From the data collected, we calculate the geometric returns on a bank's portfolio:

$$R_t = \log(P_t/P_{t-1}).$$

[2] Dowd, K., (2005), *Measuring Market Risk*, 2nd edition, John Wiley and Sons, Ltd, p.12

The use of log-returns is especially practical in risk calculations as it considers the daily revenue of the portfolio will be positive. In this thesis log-returns are used in all calculations.

To implement the VaR estimates using different approaches, this study first conducts the moving window procedure, which starts with a window size of 250 observations, to generate the estimate series of mean, standard deviation, and critical value for a given VaR model. We choose to work with a 250 moving window observations as it complies with Basel's requirement that VaRs of banks must be estimated with data of not less than 250 days. Daily one-day ahead VaR is computed using a 250-day moving window covering the sample period t-249 to t. Moving forward by one trading day, the estimation is then repeated for the following trading day. Each method, therefore, will generate 369 VaR estimates. For each VaR estimating approach, we consider three confidence levels p within the range currently employed by banks and regulators: 99%, 97.5% and 95%.

3.2. Data analysis

Descriptive statistics and graphical representation of two data set are presented as the Graph 2 in the Appendix. Both return series skewed to the left, showing that the asymmetric tail extends more towards negative values than positive ones. They also have fat-tails as both kurtosis are greater than 3. However, data set two is closer to the normal distribution. The p-value of the Bera-Jarque test for data set one is lower than 0.05, therefore we can reject the null hypothesis of normality at 5% of confidence, which means that data set one is not normally distributed. Furthermore, as the p-value of the Bera-Jarque test for data set two is greater than 0.05, we can say that data set two follows a normal distribution.

Figure 3.1 Returns from 01/04/2005 to 06/29/2007

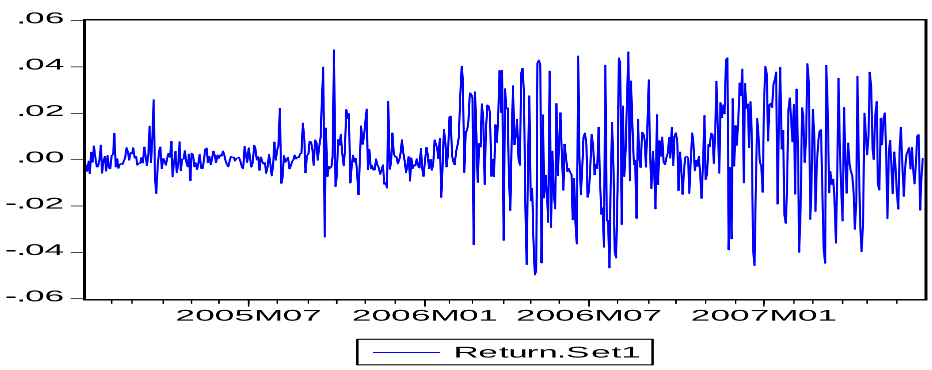
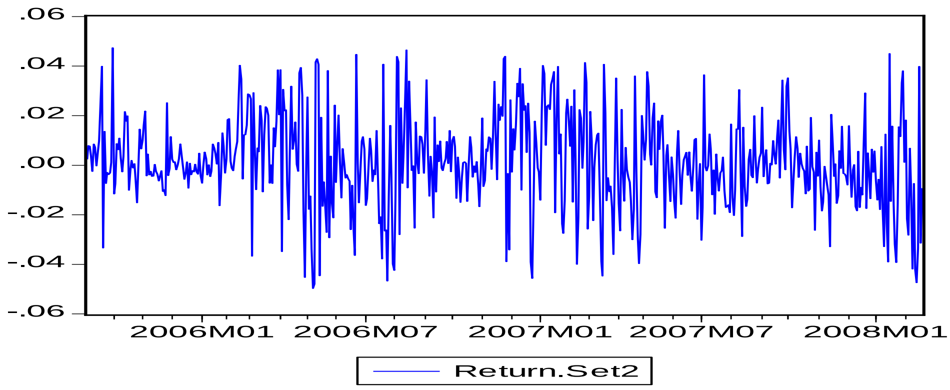


Figure 3.1 and 3.2 shows that daily returns for both data sets are highly volatile. The returns of the price indices have the features of volatility clustering. The absolute value of the minimum returns is greater than the value of the maximum value meaning that the magnitude of the most severe trading losses exceeds the magnitude of the most extreme trading gains. Data set one is fairly stable during the first few months, meanwhile data set two is volatile throughout the whole period. This is due to the time lag of the two data set as in fact, from January 2005 to September 2005, the VN-index is quite stable. This is reflects in performance of Vn-index during these two periods the Graph 1 in the Appendix.

Figure 3.2 Returns from 09/01/2005 to 02/27/2008



IV. MODELLING APPROACH

4.1. Non-Parametric methods

Non-parametric methods make no assumptions about the distributions of returns, and the estimation of VaR is based solely on empirical distributions of returns. These approaches are based on the underlying assumption that the near future will be sufficiently like the recent past that we can use the data from the recent past to forecast risks over the near future. In this study, we only discuss the most popular non-parametric approach - historical simulation. We also consider two other semi-parametric methods which take into account the volatility of the data range.

4.1.1. Basic historical simulation

The most common and the simplest non-parametric method to estimate VaR is Basic Historical Simulation (Basic HS). HS method relies only on minimal distributional assumptions about the return. It assumes that the distribution of the returns is constant over the sample period and the future is sufficiently like the past. Due to this assumption, HS is conceptual simplicity and straightforward implementation. As it is not based on any model assumption, it avoids the model risk - the risk of applying an incorrect statistical model. It also overcome the problems of fat-tailed return series as there is no need to estimate distribution parameters such as volatilities and correlations. A drawback with HS is that it cannot predict losses that occur less frequently than in the sampling period. Even for in-the-sample predictions, the accurate estimation of extreme percentiles is not possible with a small sample size as the returns distribution is discrete and the interval of adjacent observations becomes larger in the tails.

To calculate VaR, we first rank returns of 250-day moving window covering the sample period t-249 to t in order of magnitude and VaR for x level of confidence is the loss that is equalled or exceeded only 1-*X* percent of the time is selected as the VaR statistic. With 250 observations windows, our VaR with the confidence level of 95%, 97.5%, 99% will be the 13^{th}, 7^{th}, and 3^{rd} highest loss value respectively.

4.1.2. Age-weighted historical simulation (Hybrid approach)

Another approach to estimating VaR, which overcomes the weaknesses of basic historical simulation such as the ignorance of ghost effects distortions and unresponsive risk estimations to major events, was proposed by Boudoukh, Richardson and Whitelaw (1998). It estimates the VaR of a portfolio by applying exponentially declining weights to past returns and then finding the appropriate percentile of this time-weighted empirical distribution. The age-weighted historical simulation is the generalization of basic historical simulation. The idea behind this approach is that new observations should be granted higher weights than old observations. This method is the combination of the two most widespread approaches to VaR estimation which are exponential smoothing (e.g., RiskMetrics) and historical simulation (HS). It, therefore, overcomes the disadvantages of the two methods and is classified as a semi-parametric method.

The hybrid approach combines the two approaches by estimating the percentiles of the return directly, using declining weights on past data. While the HS approach attributes equal weights to each observation in building the conditional empirical distribution, the hybrid approach attributes exponentially declining weights to historical returns. Hence, while obtaining the 1% VaR using 250 daily returns involves identifying the third lowest observation in the HS approach, it may involve more or less observations in the hybrid approach. The exact number of observations will depend on whether the extreme low returns were observed recently or further in the past.

The hybrid method involves two steps. Firstly, to each of the most recent N returns: $R_{(t)}$, $R_{(t-1)},\ldots,R_{(t-N+1)}$, assign a weight $[(1-\lambda)/(1-\lambda^N)]$, $[(1-\lambda)/(1-\lambda^N)]\lambda$, ..., $[(1-\lambda)/(1-\lambda^N)]\ \lambda^{N-1}$, respectively. The returns after being multiplied with corresponding weights are called weighted returns. In this study, we choose to work with $\lambda = 0.95$ to reflect the volatility of the Vietnamese market and the great impact of most recent observations on the estimating observations. In this study, N is equal 250 as we use the 250-day moving window to estimate VaR. Secondly, Basic HS are employed to estimate VaR for the weighted returns. Weighted returns are ranked in ascending order. In order to obtain the *x%* VaR of the portfolio, start from the lowest return and keep accumulating the weights until *x%* is reached.

4.1.3. Volatility-weighted Historical Simulation

Hull and White (1998) suggested an alternative approach to historical simulation, which incorporated volatility updating into historical simulation. Volatility-weighted historical simulation will overcome the restrictions of normal historical simulation as it takes in to account volatility changes. The VaR obtained from this method reflects the most recent volatility estimated by updating return information with changes in volatilities. In the traditional historical simulation, the period of high volatility and low volatility are treated with equal weights which leads to an overestimation of VaR compared to the loss in the historical data set. Volatility-weighted historical simulation allows historical returns to scale up in the high volatile period.

The value of risk of return for the VN-index during period t using this method is calculated as followed:

$$r_{ti}^{*} = \left(\frac{\sigma_{Ti}}{\sigma_{ti}}\right) r_{ti} \qquad (1)$$

where σ_{ti} is the historical (in sample) forecast of volatility of the portfolio's return in each period t-249 to t

σ_{Ti} is the next period (out sample) forecast of volatility for portfolio's return.

r_{it} , r_{it}^{*} is the historical return and rescaled return respectively.

We first need to forecast the volatility of returns in each the 250-day moving window. As the return data shows volatility clustering and leptokurtosis, the volatility of returns are estimated using GARCH(1,1) model, by Bollerslev (1986) and Taylor (1986). The GARCH (1,1) model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (2)$$

σ_t^2 : conditional variance

e_{t-1}^2 : one period-ahead conditional error

σ_{t-1}^2 : one period-ahead variance

After getting the daily volatility estimates, the returns are then rescaled using the Equation(1) . Basic HS are employed to estimate the VaR for the rescaled returns.

4.2. Parametric method

Parametric VaR methods includes all approaches to estimating VaR based on the assumptions that the returns follow a certain density function. The parameters of distribution are estimated using a specific estimation procedure, and VaR is obtained as a percentile of the estimated distribution corresponding to the confidence level. Here, we only consider that the returns follow normal and Student's t-distributions.

4.2.1. Normal-distributed returns

Normal distribution is a very popular probability distribution, which is applicable in many fields. It is also common to assume returns data to follow normal distribution. With that assumption, we can estimate VaR at the confidence level α as:

$$VaR_\alpha = -\mu + \sigma z_\alpha$$

Where z_α is the critical value of normal distribution corresponding to α ; μ, σ are the mean and standard deviation of each 250 past return data.

As we assume our data to follow normal distribution, we also recognise some of its weaknesses when applied to returns of data. The normality assumption focuses much on the central value of the density function rather than on its extremes, which is very important in determining the level of loss. Moreover, most financial returns have excess kurtosis, or fatter-tail. Excess kurtosis implies that tails are heavier than normal, and this means that VaRs, especially at the relatively high confidence levels will be bigger. We are, therefore, likely to underestimate our VaRs. The higher the confidence level, the large these underestimates are likely to be.

4.2.2. Student's t-distributed returns

The Student-t distribution has been widely used to model financial time series since it is able to capture at least part of the fat-tailed behaviour. As the data employed in this study is fat-tailed, it would be wise to consider the return to follow Student t-distribution. The Student-t distribution density function for a normalised random variable with zero mean and unit variance is defined as follows:

$$f(r)=\frac{\Gamma((v+1)/2)}{\Gamma(v/2)\sigma_r\sqrt{v\pi}}\left(1+\frac{1}{v}\left(\frac{r-\mu_r}{\sigma_r}\right)^2\right)^{-\frac{v+1}{2}}$$

where 2 <v < ∞ are degrees of freedom and Γ(·) is the Gamma function. The higher the number of degrees of freedom, the thinner the tails of the distribution, the closer of t-distribution to the normal distribution.

For those data that follow Student t-distribution, VaR is estimated as:

$$VaR(\alpha)=-\mu_r+\sqrt{\frac{v-2}{v}}\sigma_r t_{\alpha,v}$$

$t_{\alpha,v}$ is the critical value of Student's t-distribution for probability level α and degree of freedom v. In the VaR-t method, the number of degrees of freedom is derived by calculating the excess kurtosis, using the empirical distribution of 250 estimation returns.

4.3. Backtesting

Testing that the predictions of a VaR model truly reflects the actual, observed outcomes is important to determine the model's quality. Among various techniques to test for the validity of a VaR model, backtesting is most commonly used. Jorion (2001) defines back-testing as a statistical method used to verify that actual losses are consistent with losses predicted by a VaR model. Through back-testing procedures, actual profits and losses are compared with the estimates generated by the VaR model.

Several different back-testing techniques have been developed. Unconditional coverage testing, which was developed by Kupiec (1995) to test whether the actual violation rate is equal to the coverage probability, p is now the most commonly used method of backtesting. The test based on the number of exceptions, or the number of losses that exceed the VaR. The actual violation rate is the number of days when the trading loss is greater than VaR(p) divided by the sample size. If the violation number is significantly higher or lower than p, the VaR model is not valid. Moreover, if VaR violations observed at two different dates for the same coverage rate are not distributed independently, the VaR model is also not valid.

In this study, the Kupiec LR test is used to evaluate the accuracy of different VaR models. The null hypothesis of test is that the failure rate p on each trial equals the specified probability α or the model is good, and the test statistic is:

$$LR = -2\ln\left(\frac{\pi^x(1-\pi)^{T-x}}{p^x(1-p)^{T-x}}\right) \sim \chi^2_{(1)}$$

where: p = x/T, T represents the total number of VaR estimates, x denotes the number of observed failures, which follows a binomial distribution representing the number of exceedances of VaR estimates.

As a result we obtain a typical loss function which takes the value of one if the actual return at time t is lower than the estimated VaR for time t, and

zero otherwise: Let $I_t(\alpha) = \begin{cases} 1 \quad if \quad r_t < VaR_{t|t-1(\alpha)} \\ \quad 0 \quad else \end{cases}$

where $VaR_{t|t-1(\alpha)}$ is VaR estimated for time t and r_t is actual return for the same time.

Given n returns observations and a predicted frequency of tail losses equal to p, the probability of x tail losses is:

$$\Pr(x|(n,p) = \binom{n}{x} p^x(1-p)^{n-x} \qquad \text{where p = 1 - } \alpha.$$

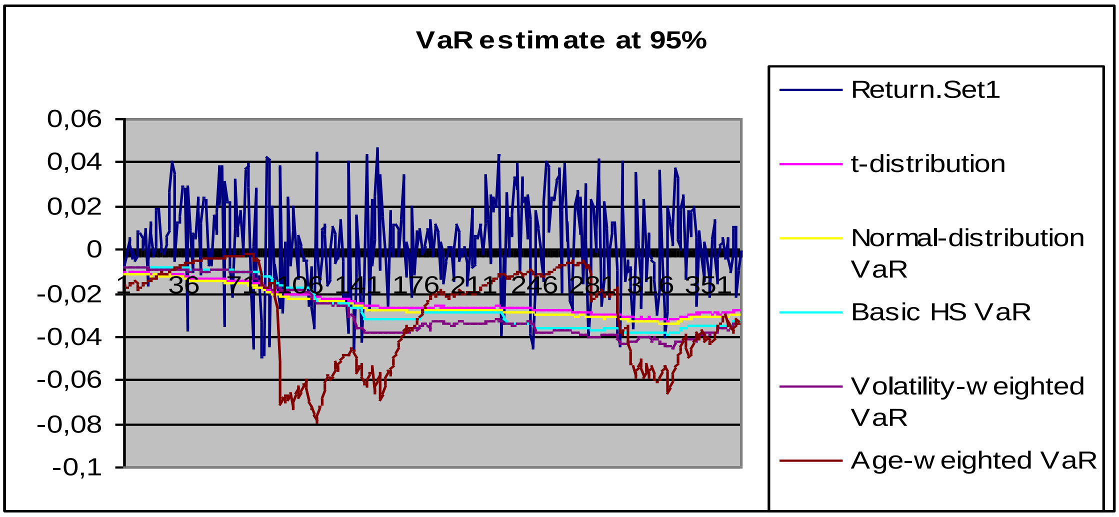
In this study, we test all the model for α =0.05, 0.025, 0.01; n is the number of trading losses that are higher than estimated VaR or the number of 1 in the loss function; x is the sample size, which is equal 369 in this study.

V. RESULTS ANALYSIS

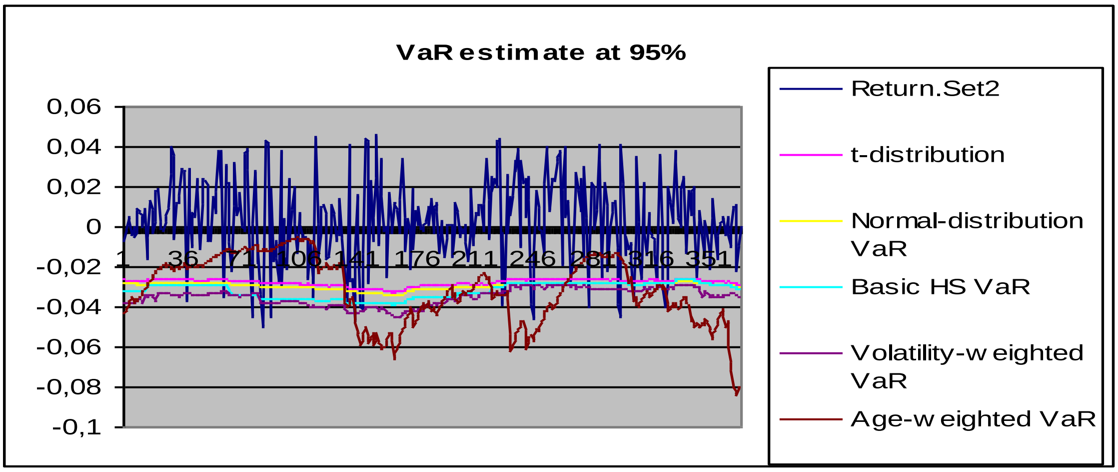
5.1. VaR using five different methods

The graphical representation of VaRs estimated by different methods for two set of data at 95% level of confidence are shown in Graph 5.1 and 5.2. Graphs for other level of confidence can be found in the Appendix. The graphical presentation does not only provide the tendency of VaR over time but also reflects their relevance to the real performance of the portfolio. The first thing to note is the similarity in trends of VaR estimates by five methods for Data set one in three different confidence levels. All VaR estimates, with exceptions from age-weighted reflects three different stage, quite small and stable at first, then increasing dramatically in the second period and again remains stable at a high level in the last period. The main reason for VaR estimates to be rather low and fluctuate very little in the first stage is the small variations of the portfolio price (VN-index) and hence the return value in 2005, the time was used to estimate VaR for this period (See Appendix for the performance of VN-index during this time). As we are moving to a more volatile period in 2006, the VaR increases rapidly. The trend is well reflected in the change of VaR using age-weighted method as it is supposed to carry more weights for more recent development of the market. VaR using age-weighted approach reduced by a large amount compared to the previous period. The next period is also volatile but there is no big difference in violation between this period and the last period in 2006. VaR in this case remains high but only increases slightly. Age-weighted VaR is decreasing and fluctuates around the actual return. As age-weighted VaR is considered to be the most fluctuate, volatility-weighted is in second place. However, unlike the extreme values resulted in age-weighted, volatility seems to incorporate with the real returns of the portfolio.

Graph 5.1 VaR estimates for Returns set 1 at 95% level of confidence



Graph 5.2: VaR estimates for Returns set 2 at 95% level of confidence



For Data set two, except for the age-weighted method, all four other methods show the same trends and fluctuations. Since the second set of data is a lot more stable than in the first set of data and there is no big change amongst different periods. It can be seen in the graphs that VaR results fluctuate less than in the first data set. Even though age-weighted also shows its variations, the level is still a lot lower than it is with the first set of data. This suggests the VaR movement is almost certainly the result of fluctuation and tendency of actually returns. Volatility-weighted VaR counts for the second most fluctuated approach. However, in this case, its VaR values are far from the actual return while historical simulation method seems to result in the most fitted VaR to the actual return.

5.2. Back testing result for data set one (from 1/04/2005 to 6/29/2007)

Table 5.1 presents the violation rates and p-values of Kupiec test-statistic for VaRs calculated using five different methods at different level of confidence. According to this backtesting result, there is no single VaR method that performs well in all significance levels. Age-weighted methods and other two parametric methods failed to estimate VaR in every degree of confidence.

Table 5.1 Backtesting result for data set 1

		95%		97.50%		99%	
		Violation rate	p-value	Violation rate	p-value	Violation rate	p-value
Non-parametric	Historical simulation	9.76%	**6.619E-05**	2.17%	0.129329	0.27%	0.091365
	Age weighted	9.49%	**0.0001356**	4.88%	**0.003317**	2.17%	**0.02098**
	Volatility weighted	7.86%	**0.0050436**	2.44%	0.133014	0.81%	0.209831
Parametric	Normal distribution	8.67%	**0.0009626**	5.96%	**0.000122**	3.52%	**8.52E-05**
	t-distribution	9.21%	**0.0002691**	5.96%	**0.000122**	2.17%	**0.02098**

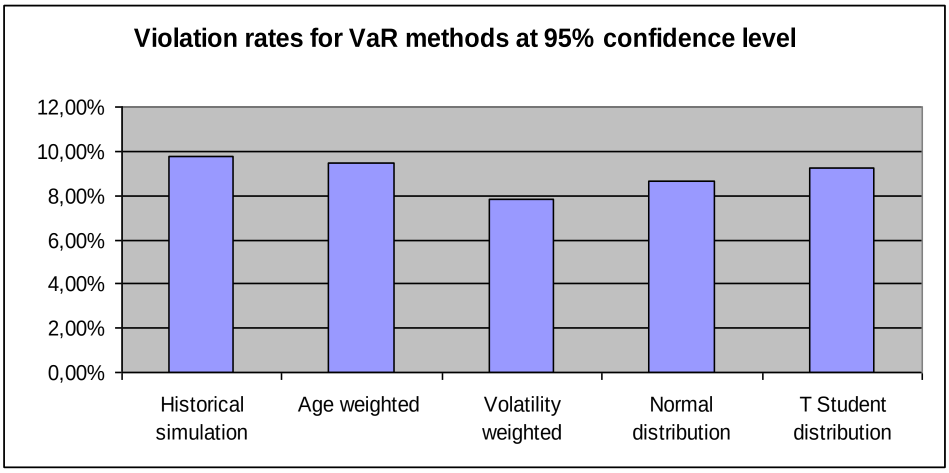
* Null hypothesis: H_0: p = 0.05

** Null hypothesis: H_0: p = 0.025

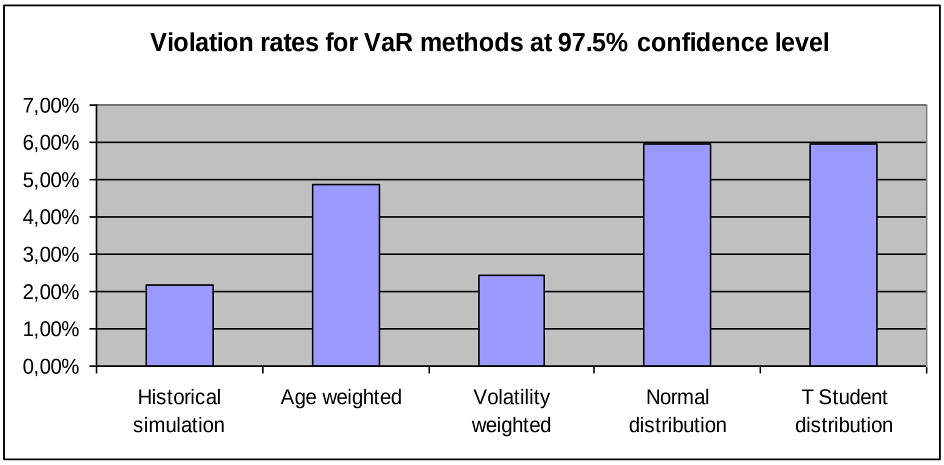
*** Null hypothesis : H_0: p = 0.01

At the confidence level of 95%, according to the p-values of the test-statistic, no methods exhibit the ability to truly reflect the actual losses. All of the violations rates are much higher than the level of 5% (See Graph 4.3). Some methods such as Basic HS and Age-weighted HS even have the violation rate closes to 10%, which is very far from the required significance rate for this level of confidence. Meanwhile, the percentage of exceptions from volatility-weighted method is the closest to 5%. The other two parametric methods all have a quite high exceptional loss rate, between which t-distribution method has a higher rate. The reason can be that at 5% level of confidence, the return data has fatter-tailed than normal distribution, t-distribution therefore reflects more extraordinary losses. Normally, due to fat tail characteristics of t-distribution, it is expected that the parametric VaR model based on the Skewed Student-t distribution to give more realistic and hence more conservative estimates of VaR than the model based on the less flexible Normal distribution. It makes sense, since Skewed Student-t model is able to capture fat tails and skewness which implies more extreme negative events and accordingly a higher absolute VaR than the Normal model. The results of violation rates resulted from Student's t-distribution and normal distribution are consistent with the explanation above at this confidence level. However, they are still too high to be marked as appropriate methods to calculate VaR. At this confidence level, volatility-weighted VaR can count for being the most competent method with the rate of 7.86%.

Graph 5.3. Violation rates of VaR methods for data set 1 at 95% confidence level

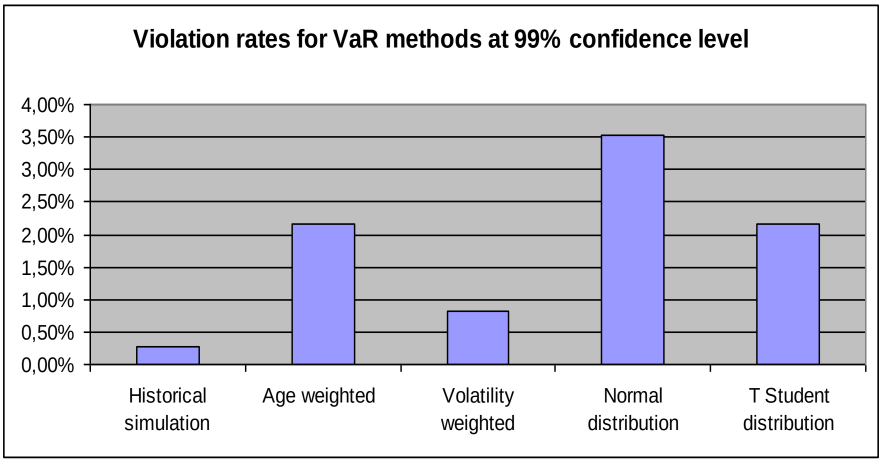


At the confidence level of 97.5%, volatility-weighted stands as the most efficient method to estimate VaR. Its violation rate of 2.44% is the closest value to level of 2.5%. The second best method is the basic HS method, which has violation rate of 2.17%, which is very close to the required significance level. The p-values of the test statistics for these two methods are significant which means that these two methods are good at estimating the maximum loss of the portfolio. The rest of the methods described above are considered to be inefficient ways to estimate VaR as their violation rates are much higher than significance level and the p-values are much lower than the acceptance level of 0.05. For this level of confidence, non-parametric methods seem to outperform the parametric ones. The Age-weighted method is inferior compared with the other two non-parametric techniques but is still better than the results given in the parametric approach. The Normal distribution method and Student's t-distribution method show no difference in VaR estimates, the violation rate of these two methods is very high, more than twice the level of significance.



Graph 5.4 Violation rates of VaR methods for data set 1 at 97.5% confidence level

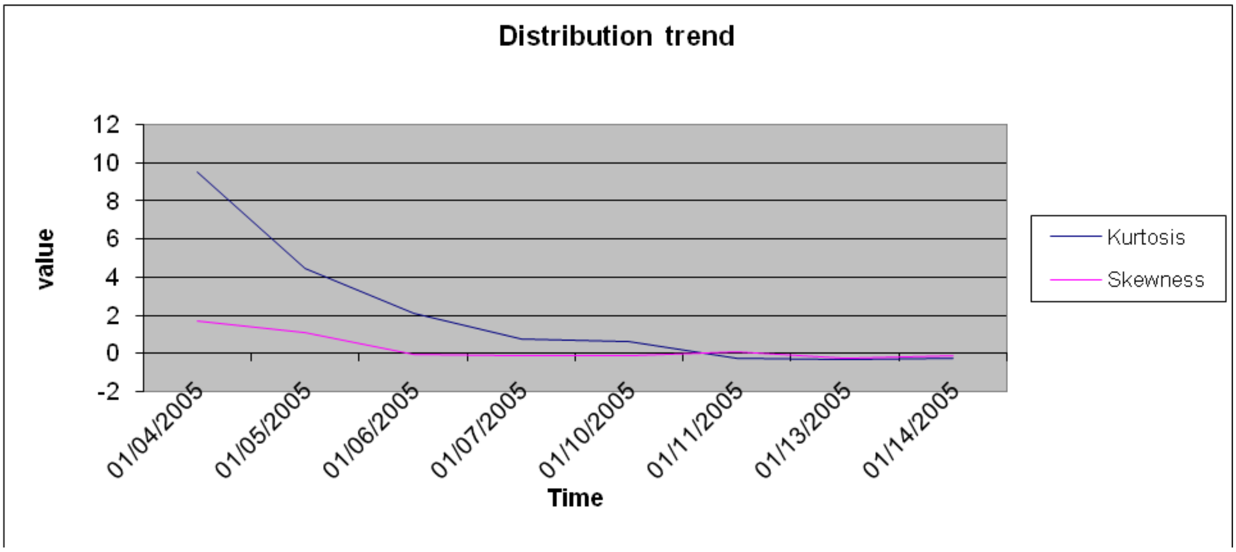
According to table 5.1, at the 99% confidence level, the best performance still belongs to the volatility-weighted technique. The violation rate for the volatility-weighted method is 0.81%, which is very close to 1% and the p-value equals 0.2098 means that this method is significantly good for estimating VaR. With the lowest violation rate of 0.27% (only 1 exceptions), Basic HS remains a good model for VaR calculations at this level of confidence. Among those in the non-parametric approach, age-weighted does not seem to give a competent VaR value. Its violation rate is as high as 2.17% and therefore it is rational that the p-value of this model is insignificant. This is the same with other parametric methods. At the 99% confidence level, it is only allowed for violation rate to be violating around 1%. The normal distribution VaR gives the highest exceptional rate at 3.52%. Based on the level of violation rates and p-values yield from these three methods, it can be said that estimated VaR using age-weighted, normal distribution and T student distribution methods are not reliable. Violation rates for VaR from non-parametric approaches are a lot lower than those ones from parametric approaches.



Graph 5.5 Violation rates of VaR methods for data set 1 at 99% confidence level

It is important to notice that all performances in the non-parametric approach seem to be better than the parametric approach. Since the parametric methods assume the returns to be normally distributed or Student's t-distributed while their real distribution does not follow any of these theoretical distributions. The VaR yield from this approach is not as accurate as it is using non-parametric approach which uses real historical distribution.

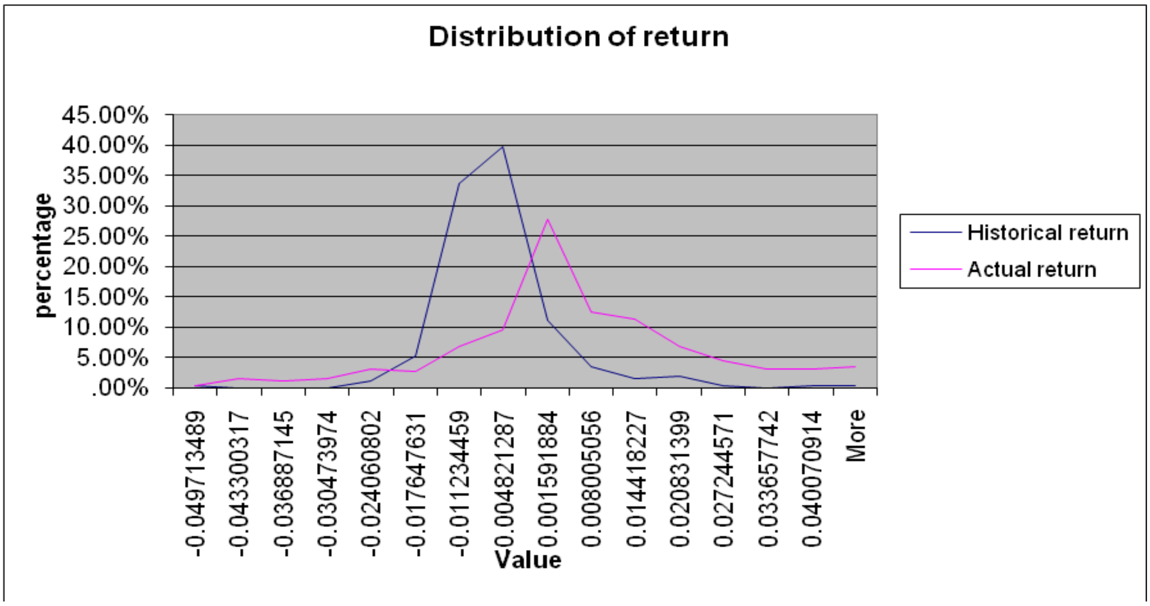
In most cases the VaR shows the significance with lower level of confidence. For example, VaR can be accepted and the exceptional cases would be lower at the confidence level of 95%. As the confidence level increases, the null hypothesis gets harder and it is more difficult to accept the estimated values. However, in this case, the values at risk at 99% and 97.5% of confidence level for basic historical simulation and volatility-weighted methods are highly significant but not in the case of 95% confidence level. The rationale for this situation can be explained by the unusual distribution of the data.



Graph 5.6. Trends of excess kurtosis and skewness of return

Graph 5.6 describes the excess kurtosis and skewness trend of the sample return distribution over time. Each sample consists of 250 observations which were also used to calculate the VaRs for the portfolio. It is indicated in the graph that the excess kurtosis and skewness are decreasing over time. In the first sample ranging from period 01/05/2005 to 12/30/2005, we get kurtosis and skewness of its distribution to be 9.54 and 1.69 respectively. The sample in the period ending in the data range which is from 5/31/06 to 5/30/07 has the distribution kurtosis -0.2589 and skewness -0.1176. According to the definition of kurtosis, it measures the peak or flatness of the data distribution relatively to the normal distribution. On the other hand, skewness is a measure of the asymmetry of the distribution. Hence, from the decreasing trend of kurtosis and skewness of return distribution, it can be said that the distribution of return is flatter over time and leaning more to the right. This fact can be interpreted that there are more extreme values in the period end of 2006 and beginning of 2007 compared to that of 2005 and early 2006. The reduction in the skewness value, especially negative skewness by the end of 2006 and 2007 indicates that there are more data in the left tail of the distribution. These results are consistent in our data analysis. The Vietnam stock index is quite stable in 2005 and the trading quantity is low. This leads to low volatility and low level of extreme values. As the Vietnam market is operating in a new, emergent environment, the market index is getting more volatile which makes it harder to estimate the maximum possible loss for the data. Since VaR relies quite heavily on the distribution of the data, understanding the distribution and tendency of distribution of data would help to find a more proper VaR method to estimate VaR and the reliability of these values at risk.

Since we use 250 observations of historical return to estimate VaR and then use this VaR figure to compare with the actual return to determine the accuracy of this VaR value. The change in distribution of VaR over time will definitely affect the VaR estimation. In the graph below, we are trying to analyse the changes in return distribution which can explain the significant level of VaR at 99% and 97.5% of confidence level, however mistaking the VaR at 95% confidence level. Graph 5.7 illustrates the distribution of 250 historical observations that were used to calculate VaR and the distribution of 250 actual returns of the Vietnam market index. The purpose is to emphasise the difference in distributions of a set used to estimate VaR and the set used to back test VaR. According to our graph, if we use historical returns to estimate VaR, at the level of 5% cumulative, the value in historical sample is lower than the actual return. Therefore, VaR is estimated using historical returns distribution is lower than the real return value. This fact means that there will be more extreme cases where the loss is exceeding the VaR which explains the high violation rates at 95% confidence level. As the confidence level gets higher, in other words, the VaR will move more to the left tail to the distribution. As shown in the graph below, the historical distribution line will cut the actual return distribution and the actual return distribution has a fatter tail. At the cumulative level at 2.5% and 1%, the actual returns are less then VaR in historical sample. As a result, the VaR is acceptable at the level of 97.5% and 99% of confidence using historical simulation and volatility-weighted methods.



Graph 5.7 Movements in distribution of return

5.3. Back testing result for data set 2 (from 9/05/2005 to 2/27/2008)

The back testing results of five different methods using the second set of data are presented in Table 5.2.

		95%		97.50%		99%	
		Violation rate	p-value	Violation rate	p-value	Violation rate	p-value
Non-parametric	Basic HS	5.15%	0.092766	2.17%	0.129329	0.81%	0.209831
	Age weighted	5.96%	0.062220	1.08%	**0.02879**	0.00%	**0.02451**
	Volatility weighted	3.52%	0.045230	1.36%	0.053891	0.27%	0.091365
Parametric	Normal distribution	5.69%	0.074735	3.25%	0.078598	1.08%	0.193935
	t-distribution	5.96%	0.06222	2.98%	0.10275	0.27%	0.091365

Table 5.2 Backtesting result for data set 2

The VaR testing results from the second set of data are more optimistic. At the 95% level of confidence, violation rates from all five methods are much lower of those for data set 1. They range from 3.79% for Volatility-weighted simulation to 5.69% for Normal distribution and Student's t-distribution, which are now quite close to the level of 5%. All the p-values of all the test statistic also show that all the models of estimating VaR are significantly good. In this case, volatility-weighted VaR using this data set is no longer the most efficient VaR method but basic historical simulation. The Volatility-weighted method gained the lowest violation rate which means that the exceptional cases where actual return loss is greater than VaR are at the minimal. It is however far from 5% compared to other methods. All other methods have the violation rate at around 5% and basic historical simulation VaR shows it is very good in violation rate with 5.15% which is the closest to the significance level in this case.

At the confidence level of 97.5% and 99%, except age-weighted method, all other four methods gave low violation rates and significant p-values. All of these four methods can be called as applicable method to measure VaR. The violation rates of VaR in age-weighted approach are noticeably low. The results are at 1.08% and 0% for violation rates at 2.5% and 1% level of significance respectively. This reflects the fact that this method seems to overestimate the maximum losses of the portfolio. Indeed, age-weighted method does not give the accurate VaR values in all three confidence levels compared with other four methods. As volatility-weighted is considered to be the most efficient method to calculate VaR for the first set of data, Basic historical simulation achieves better results in all confidence levels. It is important to understand that there are three major factors which can influence VaR model performance: its inherent flexibility, data quality used and the validity of model assumptions. The flexibility of the model as well as its assumptions reflects model's ability to represent empirical distribution in a precise way. Since we based our research on the improved version of prior studies, the above five methods are considered to be more popular to be applied in risk management of financial firms. The aim of the research is still to find the most efficient VaR method among these to apply for Vietnam bank's portfolio. Quality of data is another important aspect of VaR model. To be comparable with the first set of data, we keep the same number of observations. However, as analyzed in the data analysis section, the second set of data has more volatility but there is almost very little difference between the most volatile period and the least volatile period.

VI. CONCLUSIONS

After estimating and back testing VaR estimates for two different sets of data using different methods, it can be concluded that, non-parametric approaches are more reliable when computing VaR for Vietnamese bank's portfolio than parametric approaches. The volatility-weighted method seems to outperform other methods when applied to data series containing an impulsive jump. Furthermore, in cases when the returns fluctuate dramatically, but there are no big sudden ups and downs, basic historical simulation seems to be the best choice. Another finding is that VaR estimates fails to predict the maximum losses when the characteristics of data used to estimate VaR is different from that of the actual observations. Therefore, it is important to have a good collection of data when computing VaR. In emerging markets like Vietnam, there are always changes in the market and the applications of VaR can not always be appropriate despite calculating methods. It is essential for banks and financial institutions to notice that historical price movements are not the best estimate of future movements and the returns of even the most diverse portfolio can be drastically different from those observed in the past. Various political, structural or economical changes can cause enormous violations. In the case of emergent market like Vietnam, there are more factors that can affect the performance of return on portfolios and these changes make it harder to find the most applicable VaR for this market.

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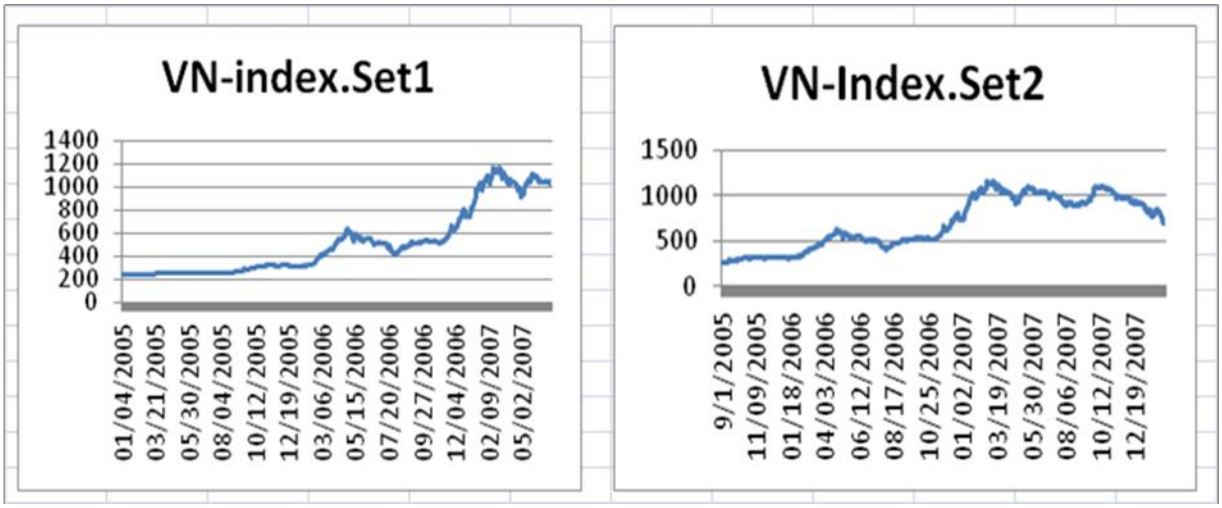
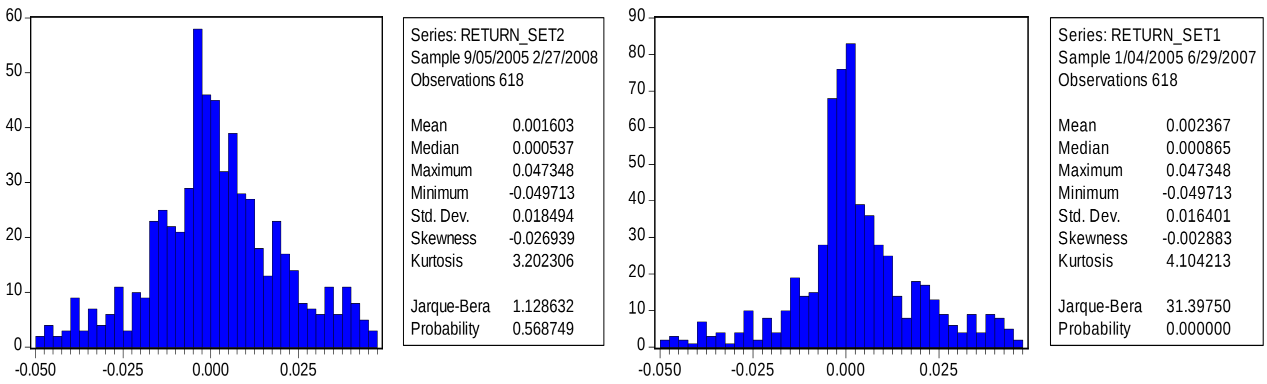
APPENDIX

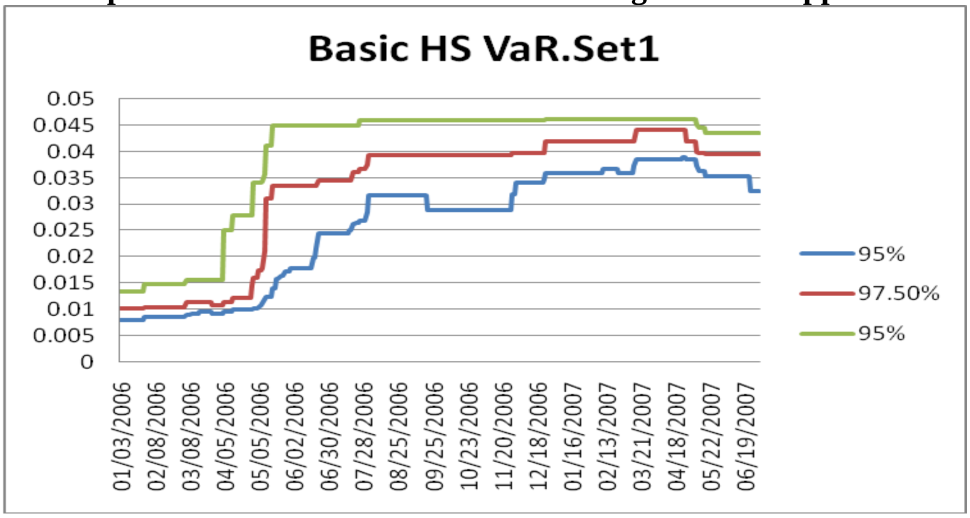
Graph 1. Two data sets



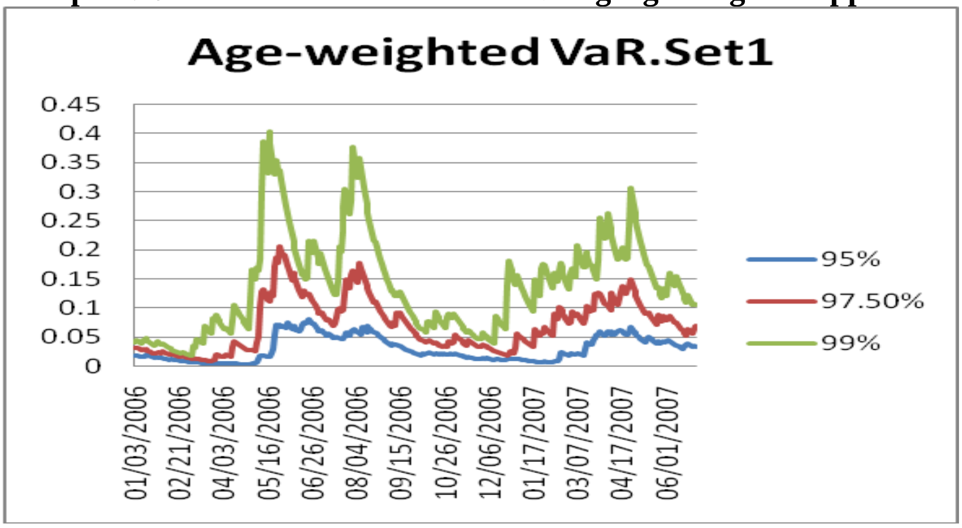
Graph 2. Descriptive statistics of returns of two data sets



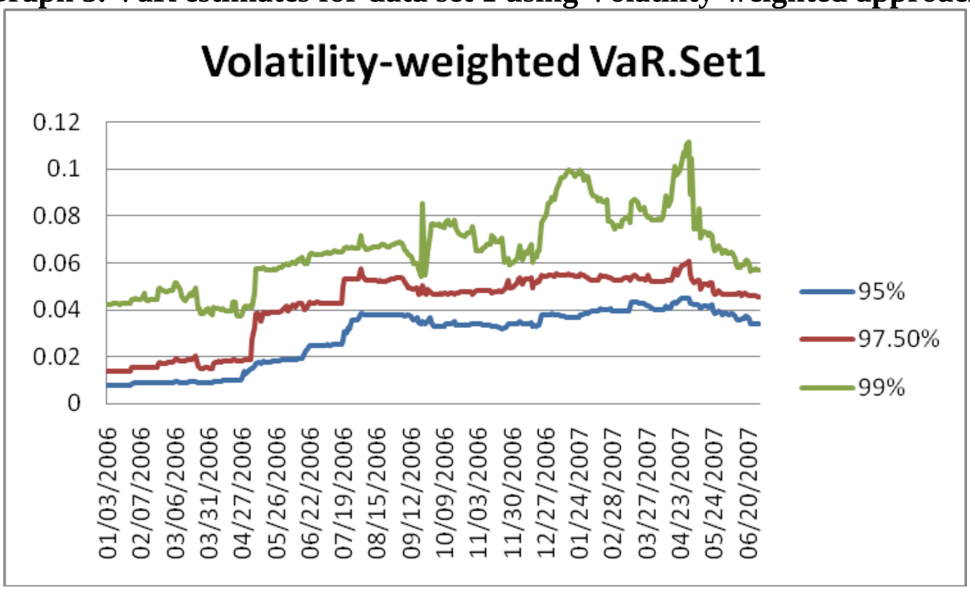
Graph 3. VaR estimates for data set 1 using Basic HS approach



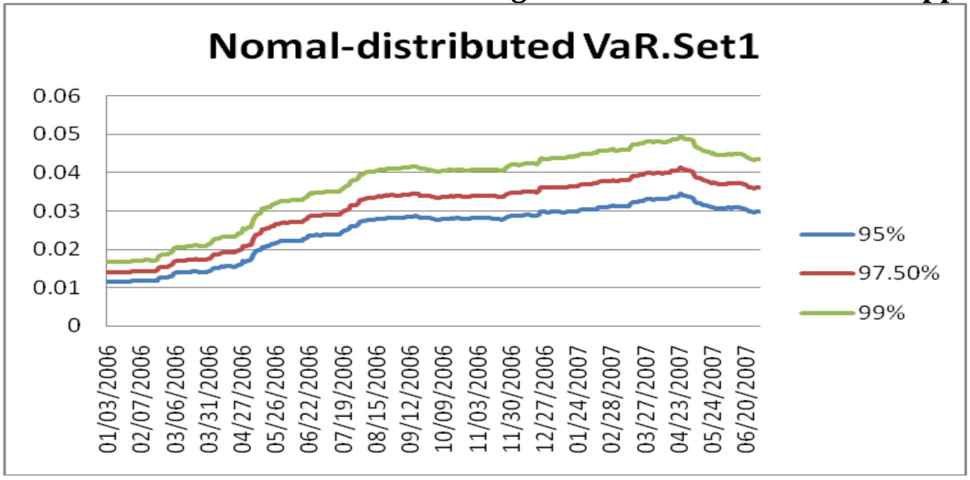
Graph 4. VaR estimates for data set 1 using Age-weighted approach



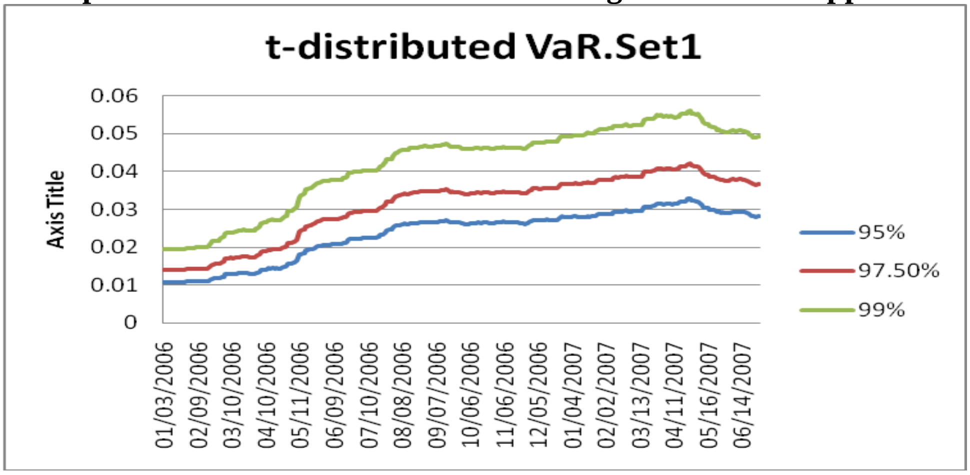
Graph 5. VaR estimates for data set 1 using Volatility-weighted approach



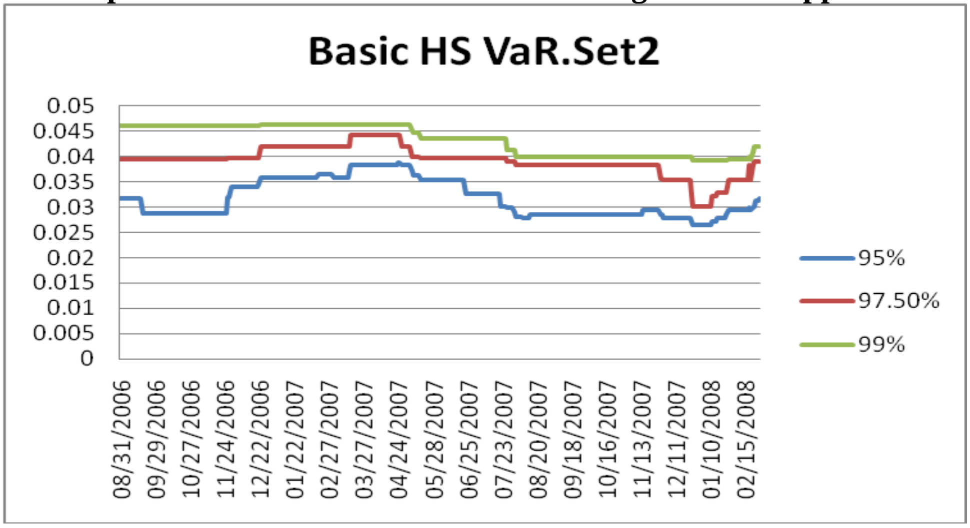
Graph 6. VaR estimates for data set 1 using Normal-distributed return approach



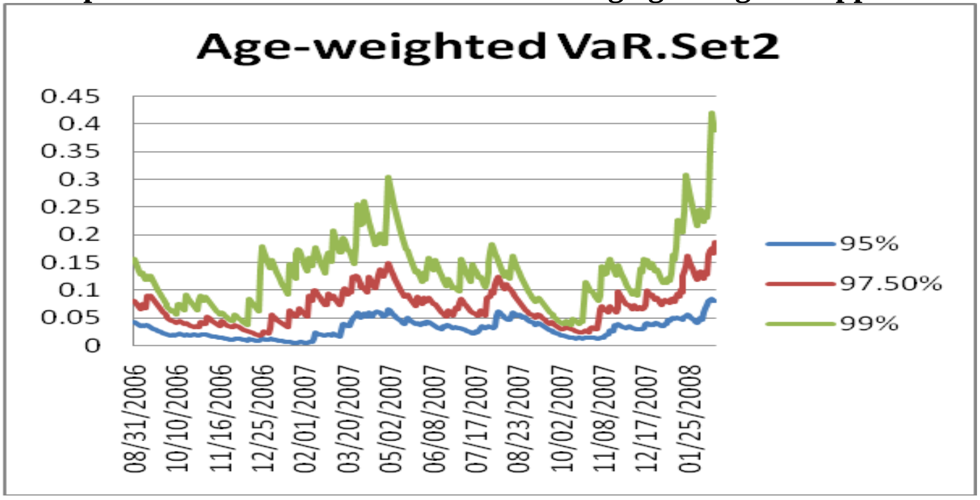
Graph 7. VaR estimates for data set 1 using t-distributed approach



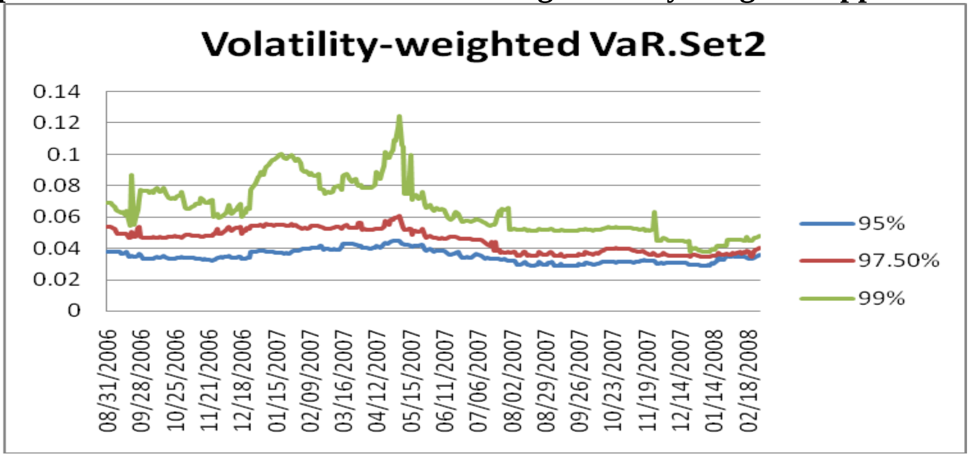
Graph 8. VaR estimates for data set 2 using Basic HS approach



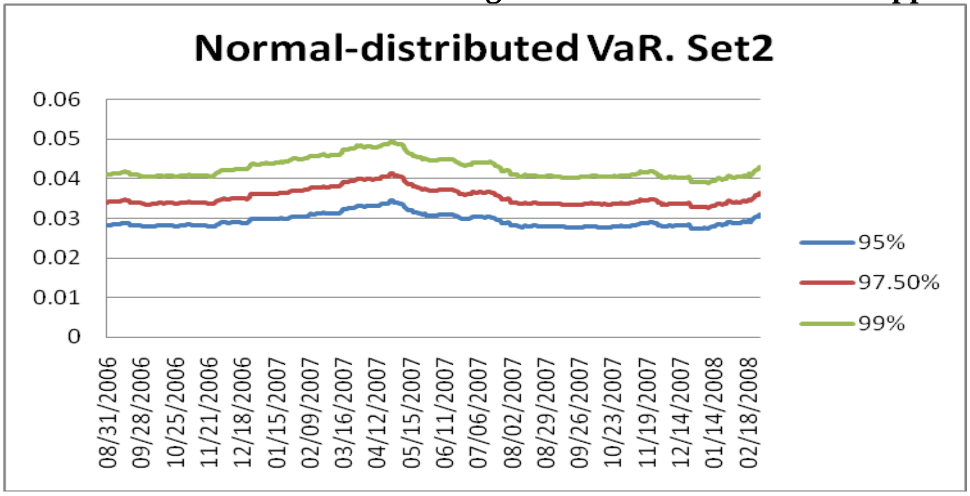
Graph 9. VaR estimates for data set 2 using age-weighted approach



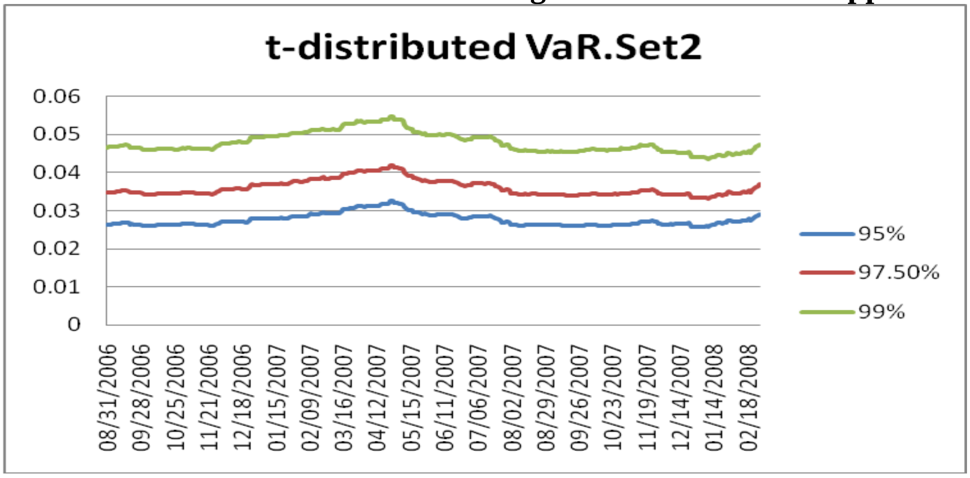
Graph 10. VaR estimates for data set 2 using volatility-weighted approach



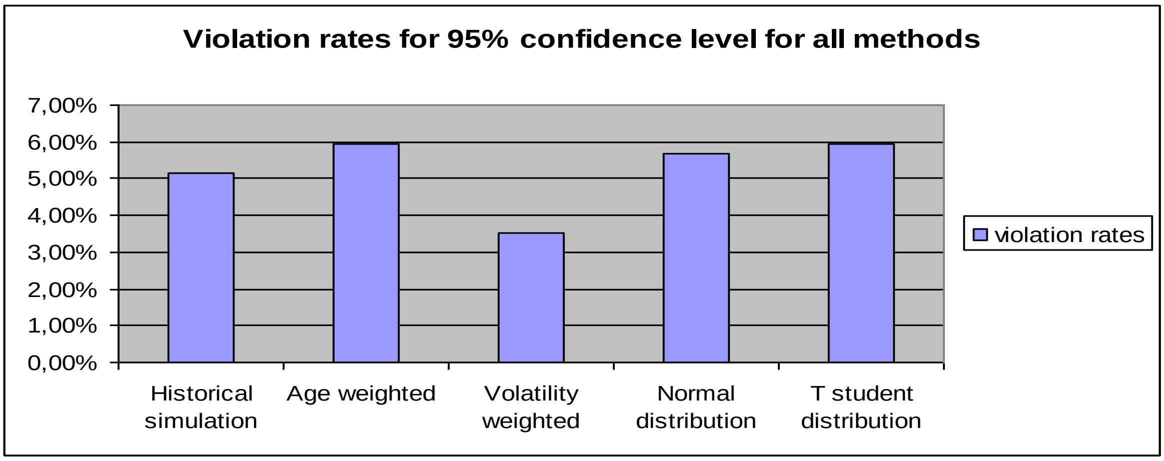
Graph 11. VaR estimates for data set 2 using normal-distributed return approach

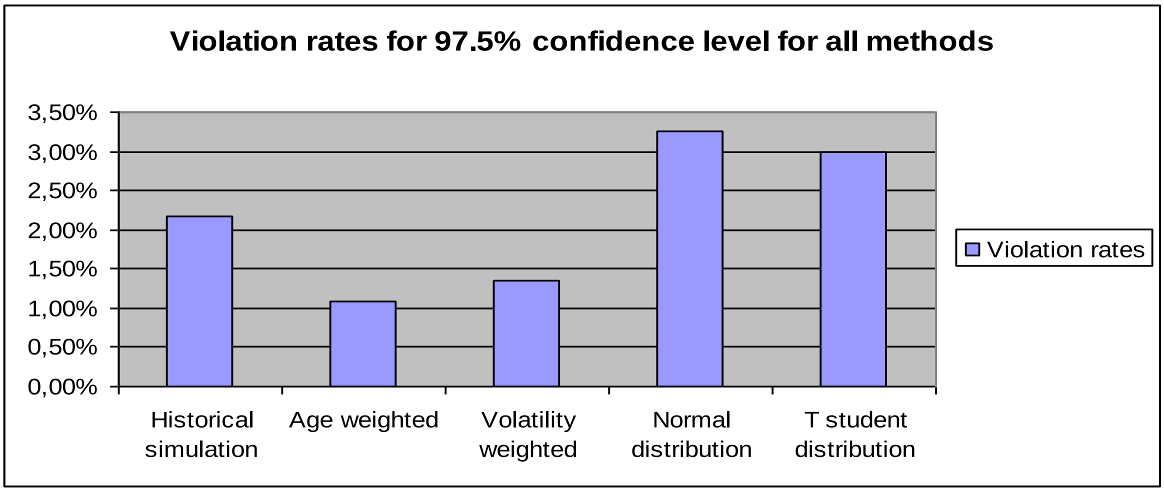


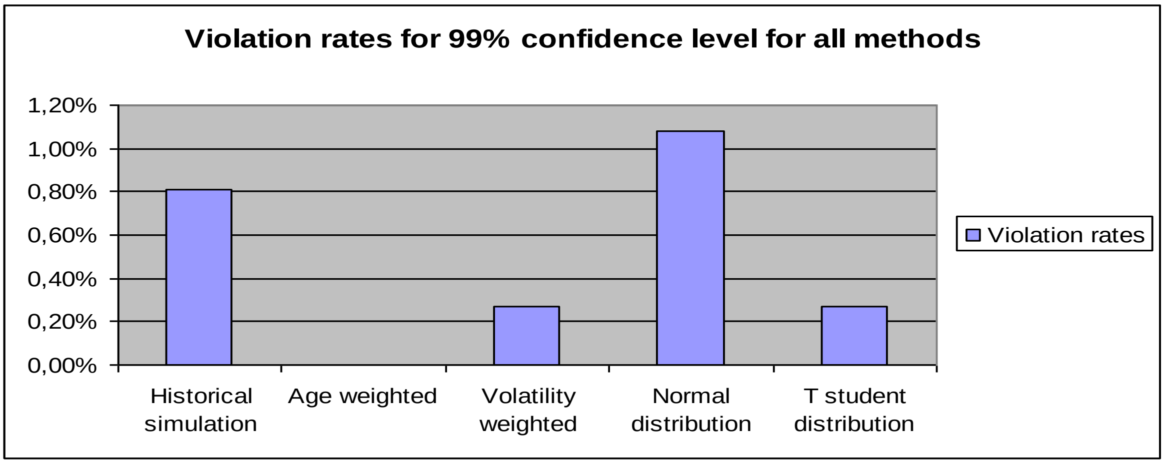
Graph 12. VaR estimates for data set 2 using t-distributed return approach



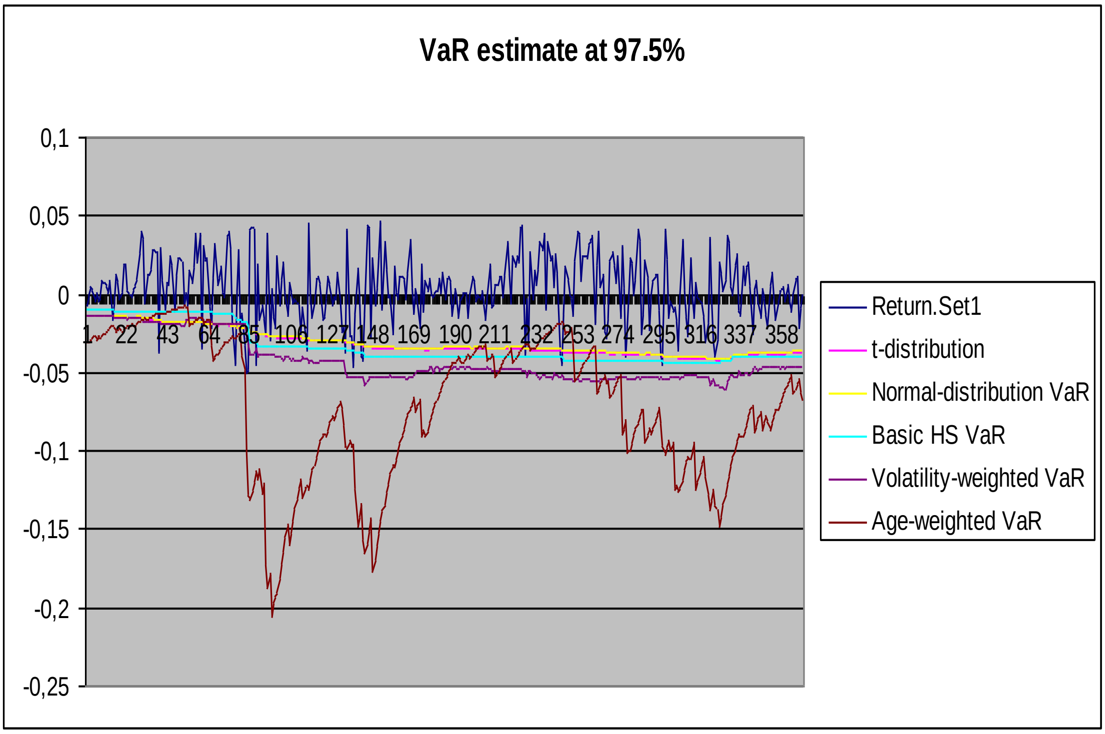
Graph 13. Violations rates of data set 2 at different level of confidence



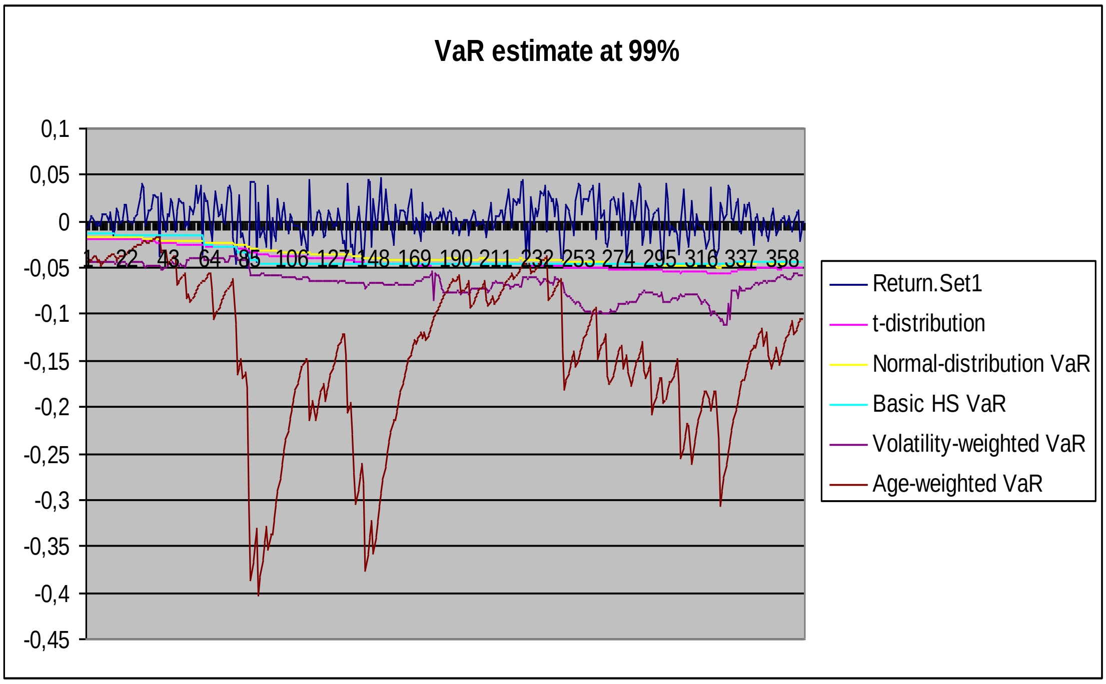




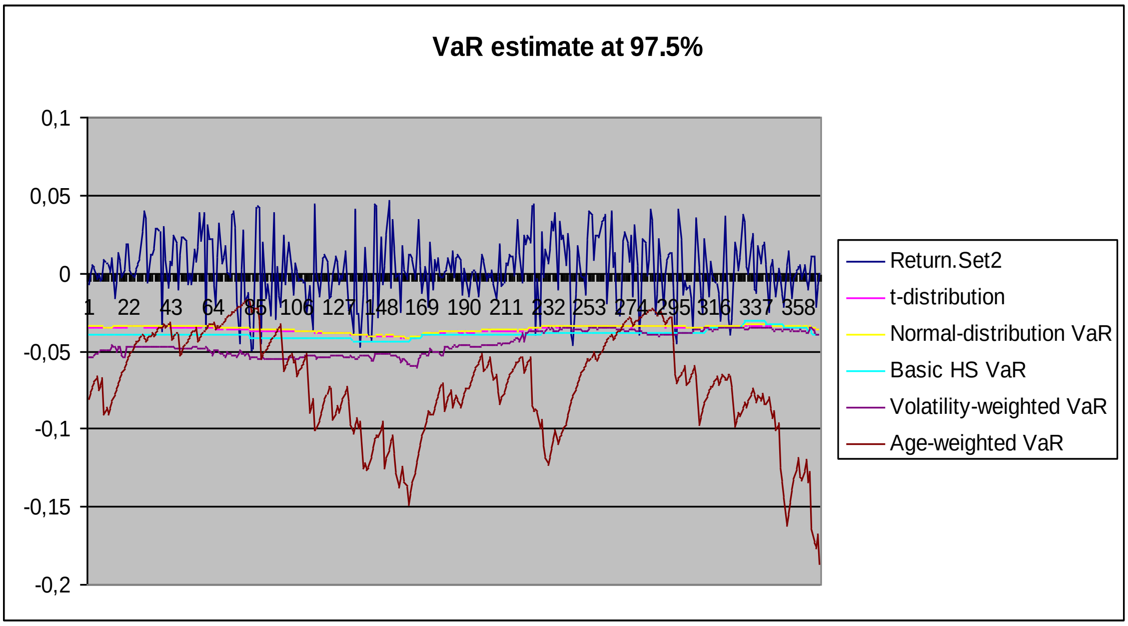
Graph 14. VaR estimates by different methods for data set 2 at level of 97.5%



Graph 15. VaR estimates by different methods for data set 2 at level of 99%



Graph 16. VaR estimates by different methods for data set 2 at level of 97.5%



Graph 17. VaR estimates by different methods for data set 2 at level of 97.5%