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Evaluation of Value at Risk in Emerging Markets

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Abstract

Financial institutions have witnessed numerous episodes of financial crises all over the world during the last four decades. The researchers, academicians and policy makers in the field of finance studied these episodes extensively and to mitigate the risk involved in these crises have proposed several measures in the financial literature, but Value at Risk (VaR) has emerged as a more popular risk measurement technique. Although a number of studies have been undertaken in this area of research for developed markets but very few studies have been conducted in developing and emerging market economies. This study makes an attempt to evaluate the performance of VaR in emerging markets namely Brazil, Russia, India and China by considering Historical, Monte Carlo and GARCH Simulations to calculate VaR for the period 1998 to 2015. The study found that GJRGARCH Simulation is more suitable for Brazil and China while Historical Simulation for Russian and Indian Stock Markets based on the backtesting experiment.

Keywords: Value-at-Risk (VaR), Measurement of VaR, Backtesting, Emerging Markets, Likelihood Ratio, Simulations

JEL Classification: G15, G17, G32

Introduction

During the last 50 years, world economic history has witnessed several episodes of currency and banking crisis. These episodes had a severe impact on the global financial system. There have been a number of suggestions put forward by policy makers, financial institutions and regulatory bodies to minimize the impact of these episodes on the financial system. In the era of new globalized economic and financial system, more emphasis is placed on measurement and management of financial market risks. Given the circumstances of huge macroeconomic changes, lack of liquidity and irrational market behaviour, it becomes vital to measure the level of risk for potential investors and agents even after knowing its presence, in order to survive in the global competitive market in a dynamic manner. Unlike the matured financial markets, the emerging financial markets are characterized with insufficient liquidity, the small scale of trading and asymmetrical and low number of trading days with certain securities (Andjelić, Djaković and Radišić, 2010). In the recent times, the emerging markets have been playing a crucial role due to greater potential in terms of economic growth and investment opportunities. However, the emerging stock markets are relatively young markets and have not developed sufficiently so as to identify all information that affects the stock prices and therefore, do not respond quickly to the publicly disclosed information (Benaković and Posedel, 2010).

After the financial instabilities during 70's and advent of derivative markets, floating exchange rates led to development of several risk measurement methods. Among these Value-at-Risk (VaR) has emerged as a popular measure for assessing the market risk of the portfolio among the trading community. It can be defined as the maximum potential loss of a specific portfolio for a given time horizon. Increasing availability of the financial data and rapid advances in computer technology led to the development of various VaR models that can be applied for the risk management profession.

The application of VaR models and comparing their relative performance gained a momentum in the field of financial economics. However, there is no common model that can give best forecasts of these models see for example, Manganelli and Engle (2001), Christoffersen, et al. (2001), Angelidis, et al. (2004), Wong, et al. (2002), Alexander and Leigh (1997), Harmantzis, et al. (2006). But very few studies have been conducted in the emerging financial markets to evaluate the performance of VaR models.

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In this context this study makes an attempt to evaluate the different VaR models of the emerging markets economies Viz. Brazil, Russia, India and China during the period from 01/07/1998 to 30/11/2015. The rest of the paper is organized as follows. Section two reviews the literature. In section three, we give the data and methodology. In section four we present the empirical findings and section five concludes the paper.

Review of Literature

We reviewed few important studies conducted in the evaluation of the VaR models. An extensive research has been conducted in VaR modelling in recent years and we present here some important contributions in this area of research. Among these, few early studies are: Allen (1994) who compared the performance of historical simulation (HS) and variance-covariance approach; Beder (1995) evaluated the performance of different VaR models; Zangari (1996) investigated the VaR models under non-normality assumption; Jamshidian and Zhu (1996, 1997) studied the efficiency of Monte Carlo methods in comparison with variance-covariance approach;and Ohannes George Paskelian and M. Kabir Hassan (2003) found a major breakthrough in favour of the traditional standard models against the models based on extreme value theory (EVT). The EVT model is more sensitive to the choice of the confidence level than the GARCH-M and Monte Carlo method. Gencay and Selcuk (2004) indicated that EVT-based VaR estimations are more precise at higher quantiles. With respect to estimated Generalized Pareto Distribution parameters, certain moments of the returns distribution don't exist in some countries. In addition, the daily returns distributions have different moment properties at their right and left tails. Therefore, they concluded that risks and rewards are not equally and likely in these economies. Samanta G. P. and Thakur S.K. (2006) found that tail index based methods provide relatively more conservative VaR estimates and possess a greater chance of performing better with the regulatory backtesting. Vanita Tripathi and Shalini Gupta (2007) observed that VaR estimates do not accurately measure the risk in the equity investment in India by overestimating the risk in 24 securities out of 30 securities. They concluded that Portfolio-Normal method does not accurately assess the risk of equity investment in individual securities in Indian securities market. Milad Nozari, Sepideh Mohemmed Raei, Pedram Jahangiri and Mohsen Bahramgiri (2010) found that among the parametric methods, EVT showed relatively better performance and never failed to pass in the 95% confidence level. The GARCH model with t-distribution could take excess kurtosis into account, but failed in 7 out of 21 scenarios. So, they confirmed that it is not a reliable approach. Jung-Bin Su (2015) indicated that the stylized facts that materialized in most of the financial assets are captured effectively by this model and negative returns and volatility spill over effects significantly accomplish to survive from the currency markets to stock markets. Moreover, the stock indices of emerging markets have the higher combination of risk and return.

While comparing VaR performance, the modified historical simulation (MHS) and the EGARCH considerably affect the VaR forecast performance for stock indices in the emerging markets when compared with the developed market. Furthermore, the VaR forecast performance of all models with generalized student-t distribution is notable to that with normal distribution only for stock indices of the developed market and only for 99% level. While considering the whole market situation, the VaR forecast performance is almost the same as that of the emerging market. Finally, the MHS-EGARCH model with GT distribution is the optimal model to predict the VaR amongst these eight models, in the three markets that were considered in this study. These findings can provide the financial institutions to appropriately select a model to predict and further control their market risk.

Data and Methodology

We give below the details of data and various methods of measurement of VaR used in this study.

Data

The daily closing prices of the emerging markets' stock market indices are, namely, BOVESPA for Brazil, RTS for Russia, BSE SENSEX for India and SSE for China, which have daily frequency, are considered for the period from 01/07/1998 to 30/11/2015 and used to measure the Value at Risk for the emerging markets. The data has been obtained from the online website of Yahoo finance. The asset returns are calculated by using the formula:

$$r_t = \log_e \left(\frac{P_t}{P_{t-1}} \right) \qquad \ldots\ldots \text{(i)}$$

Where r_t refers to the returns form the portfolio, P_t and P_{t-1} are the closing prices of the portfolio at t^{th} and (t-1) th period.

Methodology: Measurement of Value at Risk

The following methods are employed for estimating VaR in this study

i) Historical Simulation: It is a non-parametric method of calculating Value at Risk. This method is the simplest model for forecasting risk and depends on the notion that history repeats itself, where one of the past observed returns is expected to be the return in the next period. Each historical observation carries the same weight in historical simulation method. The advantage of historical simulation gets clear specifically when working with portfolios as it directly captures nonlinear dependences which other methods cannot. This method does not assume any particular functional distribution of the asset returns. Hence, this method is consistent with the risk factors changes from any distribution. Moreover, it neither involves any statistical estimation and nor it is necessary to generate random numbers.

ii) Monte Carlo Simulation: Monte Carlo simulation in its simplest form is a random number generator that is useful for forecasting, estimation, and risk analysis. Monte Carlo Simulations correspond to an algorithm that generates random numbers that are used to compute a formula that does not have a closed (analytical) form. This is done using pseudo random number generator to produce numbers that for all practical purposes are considered to be random. It deals with a method that randomly produces trails. This is a popular method adopted in the area of finance in the recent times. The steps involved in calculation of VaR are as follows:

1. Fitting the distribution for the estimation window, say 1000 days and decide on the number of holding period of the asset. Let delta be the ratio of number of trading days to the number of trading days in a year.
2. Calculate the annualized mean for the window by multiplying number of trading days by the mean of the window.
3. Calculate the annualized standard deviation of the window by multiplying the standard deviation of the window by the square root of the number of trading days.
4. Now generate random numbers with the values obtained from the fitted distribution of the window. Generally, number of simulation (in financial analysis) is either 10000 or 100000.
5. Create a new series of returns by using the following formula:

   returns = annualised mean*delta+annualised standard deviation * generated random numbers*square root of delta
6. Find the quantile value (to obtain VaR) of the newly generated returns series with respect to the necessary confidence level.
7. Then roll it over to find out the subsequent estimate of VaR

GJRGARCH Simulation:-This is an asymmetric form of GARCH model has the ability to measure the leverage effect on the impact of how a bad or a good news in the market affects the volatility of the stock returns. This model, popularly known as the GJR GARCH (m,s) model because of the econometricians who introduced this model, namely, Glosten LR, Jagannathan R, Runkle DE in 1993 assumes the form

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} (\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \qquad \text{(ii)}$$

Where N_{t-i} is an indicator for negative value of a_{t-i}, that is,

$$N_{t-i} \begin{cases} 1, if\ a_{t-i} < 0 \\ 0, if\ a_{t-i} \geq 0 \end{cases}$$

And $\alpha_0 > 0$ and $\alpha_i, \beta_j > 0$ for $\gamma_i > 0$. From this, we can say that, a positive contributes $\alpha_i a^2_{t-i}$ to σ^2_t, whereas a negative a_{t-i} has a large impact $(\alpha_i + \gamma_i) a^2_{t-i}$ (with $> \gamma_i > 0$. This model uses zero as its threshold to separate the impact of the past shock. After getting the results of the fitted GJRGARCH model, it becomes necessary to check for statistical significance of the parameters especially the parameter that is showing the leverage effect.

The assumptions and specifications of the model that have been used in this study for all the three methods, the estimation windows are the same, that is, 1000. The number of simulations performed is 10000. In case of Monte Carlo Simulations, the value of delta is 1/ 252. In case of GJRGARCH model, GARCH follows the order of (1, 1) with Variance targeting being absent and no external regressor are being employed. The ARIMA model in GRACH framework follows the order of (1, 0, 1). The holding period of the asset is assumed to be one day. The confidence levels considered are: 0.99, 0.95, and 0.90.

Backtesting: Assessment of the accuracy of VaR prediction should be done by tracking the performance of the model in the future using operational criteria. Backtesting is the methodology that is adopted to check how the values have performed in the past. This study employs the joint test of Kupiec and Christoffersen. This test was introduced by Kupiec and Peter Christoffersen to examine whether the excedances are correct and independent or not. This joint test helps in enabling backtesting in the presence of violation clustering. This is based on likelihood test and the test statistic is given as:

$$\text{LR (joint)} = \text{LR (coverage)} + \text{LR (indenpendence)} \sim \chi^2_2 \quad \text{.......(iii)}$$

Let the null hypothesis of the first part of the joint test be H_1 and the later part be $H_{2,}$ then the H_1 is stated as that where the excedances are correct and the H_2 is stated as that where the excedances are correct and independent of each other. For a one percent VaR, we would expect to observe a VaR violation of 1% of the time. If, instead, violations that are observed more (less) of, say, 5% of the time, the VaR model is analytically underestimating (overestimating) the risk at the 1% level. Clustering of VaR violation can lead to a serious problem in the model. Hence, it is necessary to perform the independence test. If VaR violation clustering exists, then we can predict that today there will be a violation, if we have violation yesterday.

VaR violation ratio has also been taken into account for assessing the performance of VaR in forecasting the risk. A violation in VaR is said to have occurred if

$$\eta_t = \begin{cases} 1, \textit{if } y_t \leq \text{VaR}_t \\ 0, \textit{if } y_t > \text{VaR}_t \end{cases}$$

where V_1 is the count of $\eta_t = 1$ and V_0 is the count of $\eta_t = 0$, which is simply obtained by $V_1 = \sum \eta_t$ and $V_0 = W_T - V_1$ .VaR violation ratio is given as the ratio between the observed number of violations and expected number of violations. If violation ratio is more than one, then it tends to under-forecast risk and if it is less than one, then it tries to over-forecast risk. Besides a simple violation ratio analysis, it is important to perform a test of significance of the violation ratio will be more appropriate.

Empirical Results

The Augmented Dickey Fuller Test (ADF) and Phillips Perron (PP) test showed that all the four series are stationary at levels. The Kolmorgovo-Smirnov test (as a Goodness-of fit measure) suggests that all the four indices follow the Student t- distribution. The results of ARCH test imply that the p-values for rejecting the alternate hypothesis is not statistically significant. This indicates that the data has the stylized characteristics of a financial time series of leptokurtic, presence of volatility clustering and fat tails.

The critical values for the VaR excedances test for the confidence levels 99% and 95% are given as: Unconditional coverage test- (6.634897, 3.841459); Conditional coverage test-(9.21034, 5.991465).The results of the joint test of Kupiec and Christoffersen are shown in tables 1.1-1.3. The following notation are used in the tables 1.1-1.3

EE = Expected excedances,

AE = Actual excedances,

uc.H0 = Null hypothesis of the unconditional coverage test,

uc.LRstat = Estimated Likelihood Ratio of the unconditional coverage test,

uc.LRp= p-value of the Estimated Likelihood Ratio of the unconditional coverage test, uc.Decision = Decision on the unconditional coverage test,

cc.H0 = Null hypothesis of the conditional coverage test,

cc.LRstat= Estimated Likelihood Ratio of the conditional coverage test,

cc.LRp= p-value of the Estimated Likelihood Ratio of the conditional coverage test,

cc.Decision = Decision on the unconditional coverage test and

VR = VaR violation ratio.

Table 1.1: VaR Test Results for Historical Simulation at 99% Confidence Level

Indices	*alpha*	*EE*	*AE*	*uc.LRstat*	*uc.LRp*	*uc.Decision*	*cc.LRstat*	*cc.LRp*	*cc.Decision*	*VR*
BOVESPA	0.01	38	37	0.02898313	0.864818	Fail to Reject H0	7.862665	0.01961751	Fail to Reject H0	0.97368421
	0.05	190	174	1.493257	0.2217118	Fail to Reject H0	16.09351	0.000320139	Reject H0	0.91578947
	0.1	380	350	2.766019	0.09628534	Fail to Reject H0	19.55483	5.67E-05	Reject H0	0.92105263
RTS	0.01	38	35	0.252141	0.6155716	Fail to Reject H0	19.64807	5.41E-05	Reject H0	0.92105263
	0.05	190	159	5.691916	0.01704324	Fail to Reject H0	60.85615	6.10E-14	Reject H0	0.83684211
	0.1	380	355	1.923046	0.1655212	Fail to Reject H0	87.66753	0	Reject H0	0.93421053
SENSEX	0.01	38	41	0.2269011	0.6338312	Fail to Reject H0	16.44007	0.000269205	Reject H0	1.07894737
	0.05	190	152	8.64691	0.003276165	Reject H0	43.42895	3.71E-10	Reject H0	0.8
	0.1	380	314	13.61011	0.000224971	Reject H0	66.54059	3.55E-15	Reject H0	0.82631579
SSE	0.01	38	55	6.712939	0.009571587	Reject H0	13.61456	0.001105696	Reject H0	1.44736842
	0.05	190	203	0.8881015	0.3459923	Fail to Reject H0	30.2365	2.72E-07	Reject H0	1.06842105
	0.1	380	392	0.3895393	0.5325417	Fail to Reject H0	12.05217	0.002414931	Reject H0	1.03157895

Table 1.2: VaR Test Results for Monte Carlo Simulation at 99% Confidence Level

Indices	*alpha*	*EE*	*AE*	*uc.LRstat*	*uc.LRp*	*uc.Decision*	*cc.LRstat*	*cc.LRp*	*cc.Decision*	*VR*
BOVESPA	0.01	38	17	14.81288	0.000118722	Reject H0	NaN	NaN	NA	0.44736842
	0.05	190	117	34.17169	5.05E-09	Reject H0	50.38675	1.14E-11	Reject H0	0.61578947
	0.1	380	231	74.77854	0	Reject H0	94.76371	0	Reject H0	0.60789474
RTS	0.01	38	12	24.57008	7.17E-07	Reject H0	29.35262	4.23E-07	Reject H0	0.31578947
	0.05	190	67	110.7398	0	Reject H0	148.5598	0	Reject H0	0.35263158
	0.1	380	165	168.4349	0	Reject H0	226.7676	0	Reject H0	0.43421053
SENSEX	0.01	38	14	20.24487	6.81E-06	Reject H0	24.41106	5.00E-06	Reject H0	0.36842105
	0.05	190	93	63.91259	1.33E-15	Reject H0	79.45101	0	Reject H0	0.48947368
	0.1	380	183	138.1533	0	Reject H0	174.8218	0	Reject H0	0.48157895
SSE	0.01	38	23	6.99536	0.008172127	Reject H0	14.24883	0.000805204	Reject H0	0.60526316
	0.05	190	98	56.76327	4.92E-14	Reject H0	73.7581	1.11E-16	Reject H0	0.51578947
	0.1	380	216	92.08281	0	Reject H0	113.5434	0	Reject H0	0.56842105

Table 1.3: VaR Test Results for GJRGARCH Simulation at 99% Confidence Level

Indices	*alpha*	*EE*	*AE*	*uc.LRstat*	*uc.LRp*	*uc.Decision*	*cc.LRstat*	*cc.LRp*	*cc.Decision*	*VR*
BOVESPA	0.01	38	65	15.92084	6.60E-05	Reject H0	23.67235	7.24E-06	Reject H0	1.71052632
	0.05	190	221	5.00151	0.02532522	Fail to Reject H0	24.5886	4.58E-06	Reject H0	1.16315789
	0.1	380	378	0.01685595	0.8967006	Fail to Reject H0	14.51701	0.000704161	Reject H0	0.99473684
RTS	0.01	38	59	9.986979	0.00157651	Reject H0	42.66384	5.44E-10	Reject H0	1.55263158
	0.05	190	198	0.3324363	0.564228	Fail to Reject H0	70.20143	5.55E-16	Reject H0	1.04210526
	0.1	380	336	5.969963	0.01455159	Fail to Reject H0	85.02363	0	Reject H0	0.88421053
SENSEX	0.01	38	83	40.1325	2.37E-10	Reject H0	72.26703	2.22E-16	Reject H0	2.18421053
	0.05	190	211	2.315946	0.1280534	Fail to Reject H0	59.02416	1.52E-13	Reject H0	1.11052632
	0.1	380	313	14.03567	0.000179376	Reject H0	125.9033	0	Reject H0	0.82368421
SSE	0.01	38	33	0.7061174	0.4007358	Fail to Reject H0	5.237071	0.07290954	Fail to Reject H0	0.86842105
	0.05	190	120	31.21467	2.31E-08	Reject H0	43.67915	3.27E-10	Reject H0	0.63157895
	0.1	380	245	60.5028	7.33E-15	Reject H0	79.32729	0	Reject H0	0.64473684

The following conditions are considered to be the prerequisites of a good model in selecting the model performance of forecasting risk.

a) VaR Excedances needs to be correct according to unconditional coverage test results.

b) VaR Excedances must be correct as well as independent of previous excedances according to the conditional coverage test.

c) VaR violation ratio should be equal to value one. But, this may be difficult in reality. The range for a good violation ratio can be between 0.8 and 1.2.

The following are the inferences of the backtesting based on the tables from Table 1.1 - 1.3:

The results of the VaR computation based on Historical simulation at 99% confidence level indicate, for $VaR_{0.01}$, indices of BOVESPA, RTS and SENSEX and for $VaR_{0.05}$, indices of BOVESPA, RTS and SSE and for $VaR_{0.1}$, indices of BOVESPA, RTS and SSE, the VaR excedances are within the critical limit, thereby accepting the null hypothesis of unconditional coverage test. Besides, the VaR violation ratio is within the acceptable range, for the mentioned indices and at their respective alpha values. But based on the conditional coverage test, only in the case of BOVESPA, for $VaR_{0.01}$, all the three conditions, that is, the acceptable violation ratio, correct and independence of excedances perform better. So, at 99% confidence level, Historical simulation method is the best method for BOVESPA for $VaR_{0.01}$.

The results of VaR computation based on Monte Carlo simulation at 99% confidence level point out that, for all the three values of alpha, none of the indices are performing well in terms of the acceptable level of VaR violations, correct and independence of excedances. Therefore, VaR computed through Monte Carlo simulation relatively over-predicts the risk under the assumed estimation window.

The outcomes of backtesting results of the VaR computation based on GJRGARCH simulation at 99% confidence level reveal that, for $VaR_{0.01}$, the index of SSE; for $VaR_{0.05}$, the indices of RTS, SENSEX and for $VaR_{0.1}$, the indices of BOVESPA and RTS, the unconditional coverage test fails to reject null hypothesis of correct excedances. It is also observed that the VaR violation ratio is also within the satisfactory level. For $VaR_{0.1}$, BOVESPA is performing well based on the Violation ratio. It can be deduced that only in the case of SSE that all the three conditions are satisfied at alpha being equal to 0.01.

The findings of the back tested VaR models based on the Historical simulation at 95% confidence level suggest that the model is good under the unconditional coverage test for indices of BOVESPA and RTS for alpha equal to 0.01; BOVESPA, SENSEX and SSE for alpha equal to 0.05 and BOVESPA, RTS and SSE for alpha equal to 0.10. These indices at their respective alpha values are even showing VaR violation ratio under the acceptable range. But none of the indices are independent of their previous excedances indicating the failure of conditional coverage test.

The outcomes of the Monte Carlo simulation at confidence level being equal to 95% indicate the same inference of that of the results based on the 99% confidence level.

The results of the GJRGARCH simulation at confidence level 95% indicate that, for BOVESPA at alpha equal to 0.10; RTS for alpha at 0.05 and SSE for alpha at 0.01, the unconditional coverage test accomplish the acceptance of null hypothesis. The VaR violations are under the suitable level. But in meeting all the three requirements of a good forecasting model, it is only the SSE that performs the best for $VaR_{0.01}$.

But, there is no satisfactory method for the indices of SENSEX and RTS. In the case of the former, inferring from the VaR violation ratios, for $VaR_{0.01}$ and $VaR_{0.05}$, Historical simulation method and GJRGARCH simulation methods perform moderately well at both 95 as well as 99 percent confidence level of the joint test. In the context of the latter, for $VaR_{0.05}$and $VaR_{0.1}$, GJRGARCH simulation performs moderately well. For all the three considered values of alpha, historical simulation is moderately good at 99% confidence level. At 95% confidence level, the same is the implication for the results under 99% for GJRGARCH simulation. Nevertheless, Historical simulation holds moderately good only for 1% and 10% VaR. All these results have been compiled with a favourable conclusion based on the unconditional coverage test.

So, there is no unique method that is performing well for all the indices in this study. However, Monte Carlo Simulation is not performing well for any of the indices. BOVESPA and SSE are relatively better in forecasting the risk under Historical and GJRGARCH simulation respectively under both 99 as well as 95 percent Confidence level.RTS is moderately well in terms of correct excedances under GJRGARCH method at 0.01 significance level. SENSEX is also performing moderately well under Historical simulation at 0.05 and 0.01 significance level.

Conclusion

Recent episodes of financial crises in almost all the economies have necessitated the risk management techniques in reducing the risk of these financial crises. Value at Risk (VaR) is widely accepted measurement of risk to mitigate the risk involved in financial management. In this study we have taken up evaluation of VaR methods in emerging economies viz., Brazil, Russia, India and China. We used the daily data of the indices BOVESPA, RTS, SENSEX and SSE during the period 01/07/1998 to 30/11/2015.

Here we considered three methods Historical Simulation, Monte Carlo Simulation and GJRGARCH Simulation methods to evaluate VaR. The results of unconditional and conditional coverage test of Kupiec and Christoffersen and backtesting experiment showed that the GJRGARCH Simulation method performed better when compared to Historical and Monte Carlo Simulations.

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Appendix: VaR Exceedances Plots

Fig. 1: VaR Excedances Plots for GJRGARCH Simulation model

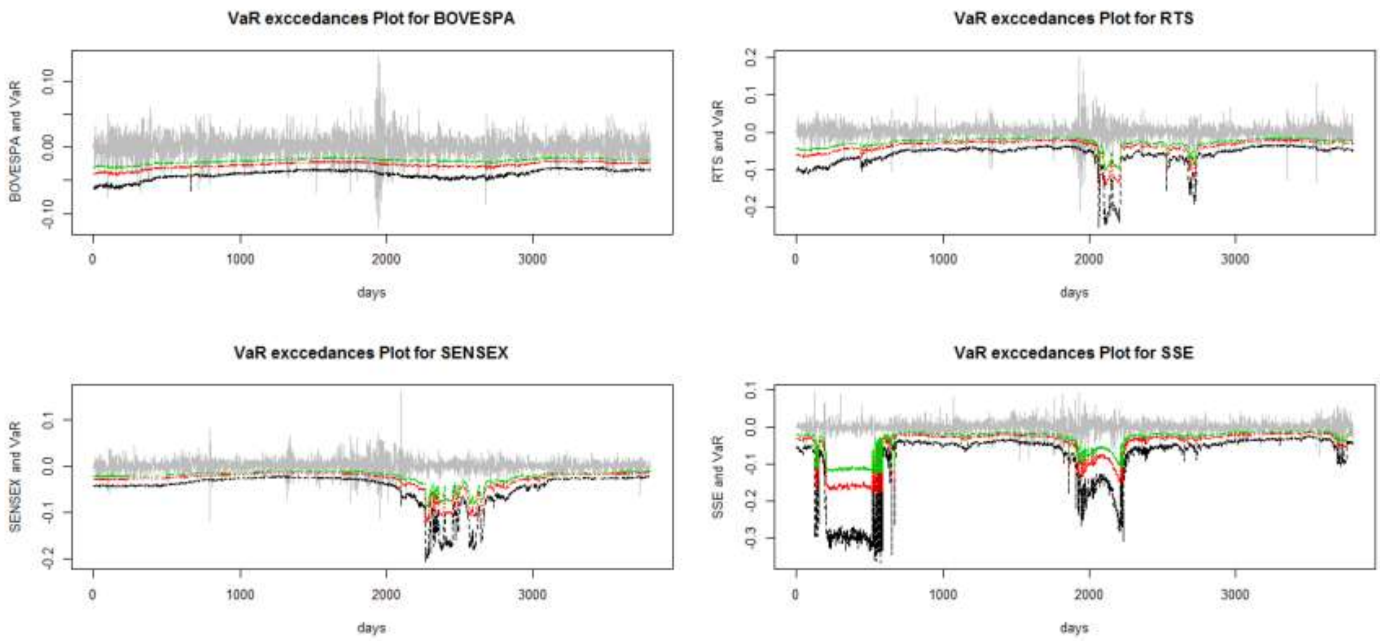

Fig. 2: VaR Excedances Plots for Monte Carlo Simulation Model

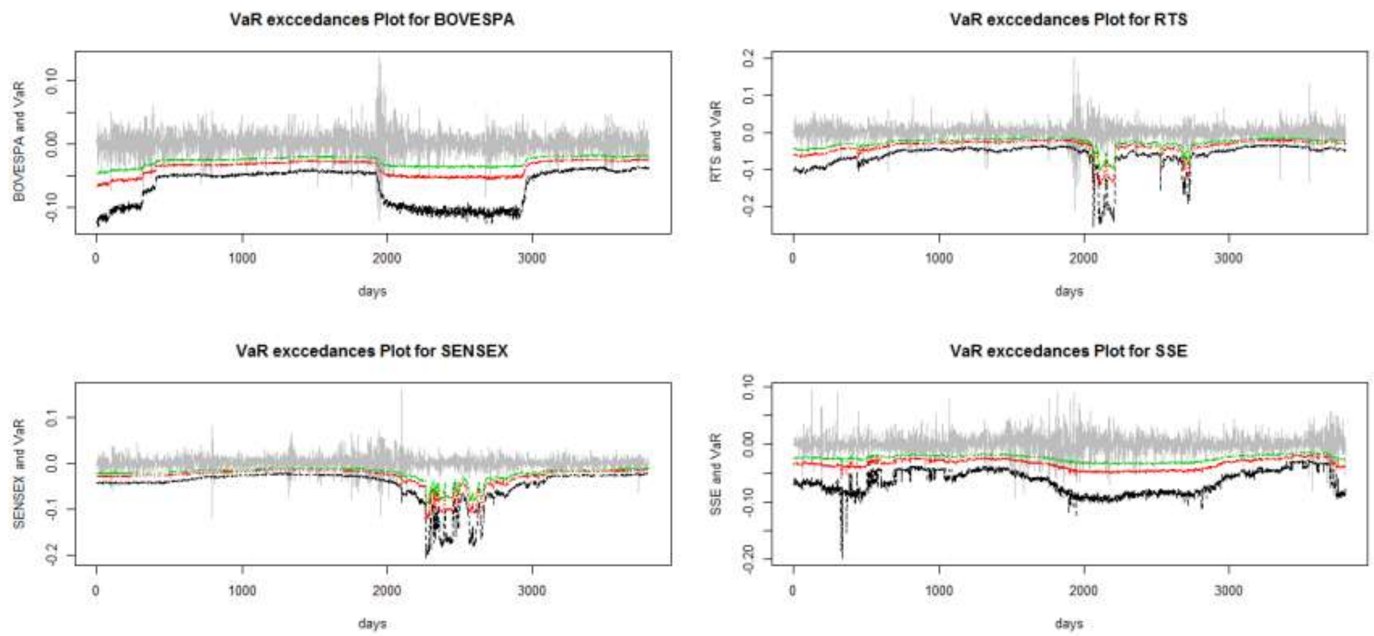

Fig. 3: VaRexcedances Plots for Historical Simulation model