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# VaR & CVaR of Indian stocks using Simulation model and Back testing

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***Abstract:***
*Value at risk (VaR) is one of the widely used risk-measure of market risks. It basically measures the possible loss in single number on given investment, with given probability called confidence level for given time horizon. Conditional Value at Risk (CVaR) quantifies the expected losses that occur beyond the VaR breakpoint. It is an expected value of losses bigger then VaR value. In this paper, our aim is to estimate VaR and CVaR using Monte-Carlo Simulation. Using these approaches in Indian stock market, we have calculated VaR and CVaR for some stocks. We have also included some back testing methods and back tested predicted VaR and CVaR values with binary back-testing.*

***Key Word**: Monte Carlo simulation, Value at risk (VaR), Conditional Value at Risk (CVaR), Back-testing.*

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## I. Introduction

Now a days humans' ability to make business decisions is increasing tremendously with the changing time. Getting more computational power has resulted in the venture in computational finance. Risk management is defined by the assessment of risk and regulating its magnitude within a risk resistant framework. As competition among financial sector has increased, so has the risk that financial institutions bear. In addition to domestic risks, financial institutions must deal with new risks associated with international financial market transactions. Risky assets are assets that are vulnerable to risk, such as value of stocks, bonds, and loans. Risky assets value rises and falls irregularly at times, these variations are correlated.

VaR is one of the Statistical measures which is used to quantify the amount of risk associated with risky assets. Individual and institutional investors face market risks because of price volatility in equity and derivative markets. Asset returns volatility raises the importance of accurate market risk measurement. It is highly important to many investing parties to focus on measuring of financial markets risk, especially downside risk. Basel-I (1988), Basel-II (1999), Basel-III (2007) are the Basel accords published by Basel Committee on Banking Supervision (BCBS). These accords provide recommendations on banking regulations concerning to credit risks, market risks and operational risks. The purpose of these accords is to ensure that financial institutions keep enough capital on account to manage market risks, to meet the obligations, and absorb unexpected losses.

Because the BCBS at the Bank for International Settlements require a financial institution to meet the capital requirements on the base VaR estimates, permitting them to use internal models to calculate their VaRs, this methodology has become a basic market risk management tool of financial institutions.

JP Morgan was the first to implement the modern definition of downside risk of portfolio in 1994. They called it "Value at risk". JP Morgan's value at risk aims to calculate market risk and report the findings in a consistent manner. While value-at-risk is not a perfect solution for estimating market risks, it does play an important role in communicating other risk studies and enhancing investors' risk awareness.

Yawalkar and Rao (2004) tested various methods for estimating value at risk. According to Hull and White analytical method is better than historical simulation method. Aymen, Ousama and Jalellidin (2012) estimated the value at risk relative to the currencies in the Tunician exchange market. For the calculation of VaR they used methods, variance covariance, historical simulation, & Monte Carlo simulation with bootstrapping. The results indicated that Euro is least risky currency and Yen is the riskiest currency. Olle, Bjorn, Birger, and Andres (2009) have worked on portfolio VaR estimation with parametric and nonparametric approaches. For the parametric approach they used normal and student-t distribution. Implied volatility models, GARCH (1,1) and GARCH (1,1)-t applied for parametric approach. For non-parametric approach they used historical simulation, age weighted historical simulation, volatility weighted historical simulation by using EWMA and GARCH

(1,1). Result indicated that value at risk assuming non normality and time varying volatility performs the best. Also, for 250-time windows historical simulation performs well. Jascha (2015) has worked on Monte Carlo simulations techniques with exponentially weighted moving average.
In this paper VaR & CVaR are estimated using Monte Carlo simulation and using back testing methods compared with actual returns with estimated VaR & CVaR. This paper is divided into three sections, firstly VaR & CVaR are discussed with methodologies. Secondly, calculation of VaR and CVaR with Monte Carlo Simulation is done with Data analysis. And, at last Back-testing is discussed along with results and conclusion.

## II. Value at risk and Conditional Value at risk

The Main objective of investment is to make profit, but it is also necessary to understand the possible risk of loss on an investment. If one can quantify possible loss on an investment, it can help to choose the best assets to invest. For the prediction of loss, the Value at Risk and conditional value at risk are most efficient risk measures.

To calculate VaR and CVaR; two parameters, time horizon T and confidence level C are used. Suppose if a portfolio has a VaR value v=0.001 or 0.1% for one an investment period T with the confidence level of $a = 95\%$, it means that the portfolio has 5% chance of losing equal or more than 0.1% on given investment over time period T. Alternatively, we can say that there is 95% probability that the loss for the specified portfolio will not exceeds 0.1% in time period T. CVaR simply measures the expected loss when loss crosses the VaR limit.

The VaR is a conditional quantile of the asset return loss distribution. The main advantage of VaR is its wide applicability and simplicity. Let $a_1, a_2\, a_3, \ldots\, a_n$ be independent and identically distributed random variables representing the portfolio returns. Let $F(a)$ denote the cumulative distribution function, $F(a) = Pr(a < a|\, I_{t-1})$ conditionally on the information set $I_{t-1}$ that is available at time $(t - 1)$.

Assume that $\{a_t\}$ follows the stochastic process:

$$a_t = \mu + \varepsilon_t \qquad \ldots (1.1)$$

$$here\ \varepsilon_t = z_t\, \sigma_t \quad where\ zt \sim iid(0, 1)$$

where $\sigma_t^2 = E(z_t^2\, | I_{t-1})$ and $z_t$ has the conditional distribution function G(z),

$$G(z) = Pr(z_t < z | I_{t-1}) \qquad \ldots (1.2)$$

Let VaR with a given probability $\alpha \in (0, 1)$, denoted by $VaR_\alpha$ and is defined as the quantile of the probability distribution of financial returns:

$$F(VaR_\alpha) = Pr(a_t < VaR_\alpha) = \alpha\ or\ VaR_\alpha = \inf\{v \mid \Pr(a_t \leq v) = \alpha\}$$

This quantile can be estimated by two different ways: (1) inverting the distribution function of financial returns, $F(a)$, and (2) inverting the distribution function of innovations, with regard to $G(z)$ the latter, it is also necessary to estimate $\sigma_t^2$.

$$VaR_\alpha = F^{-1}(\alpha) = \mu + \sigma_t\, G^{-1}(\alpha) \qquad \ldots (1.3)$$

Hence, a VaR model involves the specifications of $F(a)\ or\ G(z)$. The estimation of these functions can be carried out using the following methods:

(1) non-parametric methods: The non-parametric methods involve, Historical Simulation, and non-parametric density estimation methods.

(2) parametric methods: The parametric methods involves different volatility models like EGARCH(1,1), GJR-GARCH(1,1), TGARCH, TS-GARCH(1,1), PGARCH(1,1), APGARCH(1,1), AGARCH(1,1), SQR-GARCH, QGARCH, VGARCH, NGARCH, NAGARCH(1,1), MS-GARCH(1,1), RS-APARCH, EWMA method etc., different Density functions, and Higher-order conditional time-varying moments.

(3) semi-parametric methods: Semi-parametric methods involve combination of parametric and non-parametric approach. Volatility-weight historical simulation, Filtered Historical Simulation, CAViaR model, Extreme Value Theory, and Monte Carlo Simulation.

Conditional Value at Risk (CVaR) quantifies the expected losses that occur beyond the VaR breakpoint. CVaR also known as ES is simply defined as

$$CVaR_\alpha = E\{VaR_\alpha > a_t : a_t \in I_{t-1}\} \qquad \ldots (1.4)$$

The next question that arises is, by which model we can have an accurate estimation of the VaR value. VaR models are only useful if they accurately predict future risks. In order to verify that the results obtained from different VaR models calculations are reliable and consistent, the models should be back-tested with appropriate statistical methods. In back-testing procedure actual profits and losses are compared to predicted VaR estimates.

## III. Monte Carlo Simulation

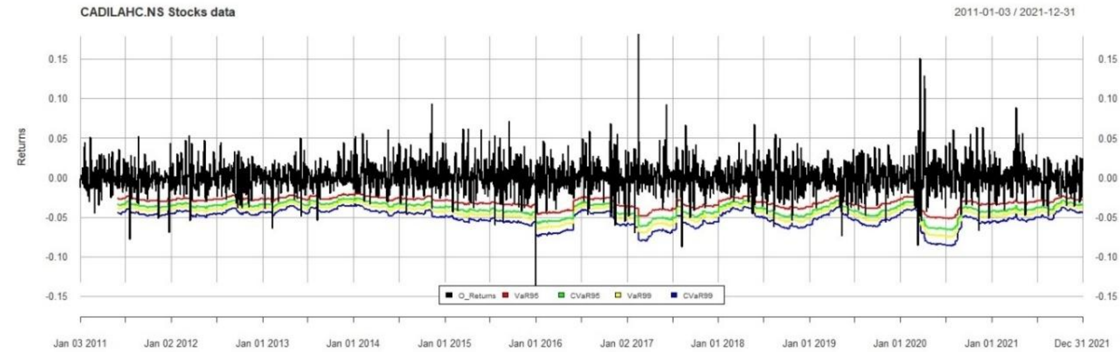
This approach is most comprehensive for calculating Value at risk, and conditional value at risk. Using simulation, we produce huge number of scenarios for the next day (in this paper we have done 100000). For each of these scenarios, the asset return is determined. These are then used to compute VaR. This method is so robust because of the large number of scenarios produced for the next day. As the number of scenarios produced grows, they cover nearly all the potential values that the asset might have. This allows us to cover most of the possibilities that can arise. The generation of random numbers is the most important aspect here, and the random number generator chosen has an impact on the range of possibilities covered. Quasi random number generators are stronger than pseudo random number generators at generating a wide variety of potential values. This approach also consists of determining the volatility. For the volatility estimation there are several techniques; here we will follow unconditional volatility and exponentially weighted moving average.

### *3.1. Data analysis*

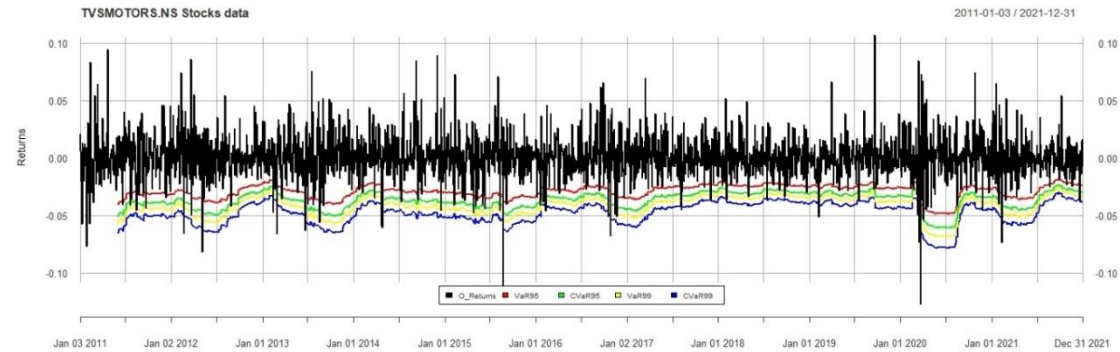
For the estimation of value at risk using Monte Carlo simulation we have selected sample of 49 stocks from the National stock exchange of India (NSE) for the maximum period of 11 years starting from 1-1-2011 or from the date that asset stocks are listed after that and ending date 31-12-2021. Data is downloaded from Yahoo finance. The whole work is done with R computer program.

The libraries used for reading the data, fitting the data, simulating the prices, plotting the results were quantmod. For simulation we have used 100 days historical return data mean and variance and predicted next day returns. This process is done for period 1-1-2011 to 31-12-2021.

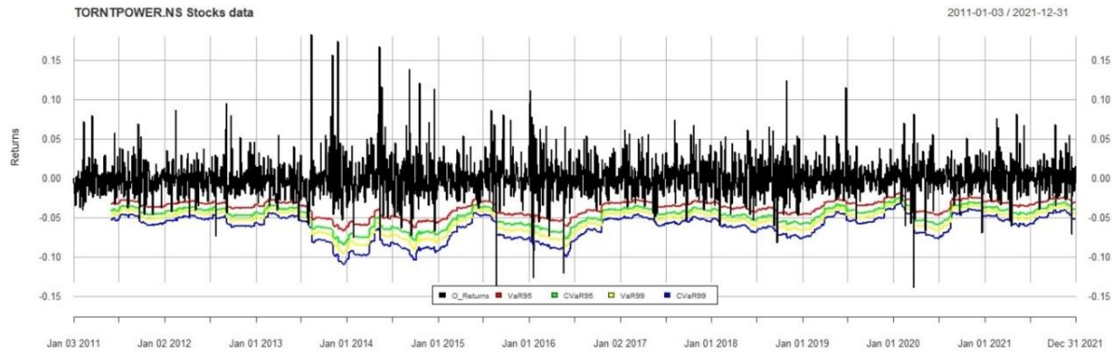
For few of the assets the results of calculated VaR and CVaR with 95% and 99% are given in the figures below.



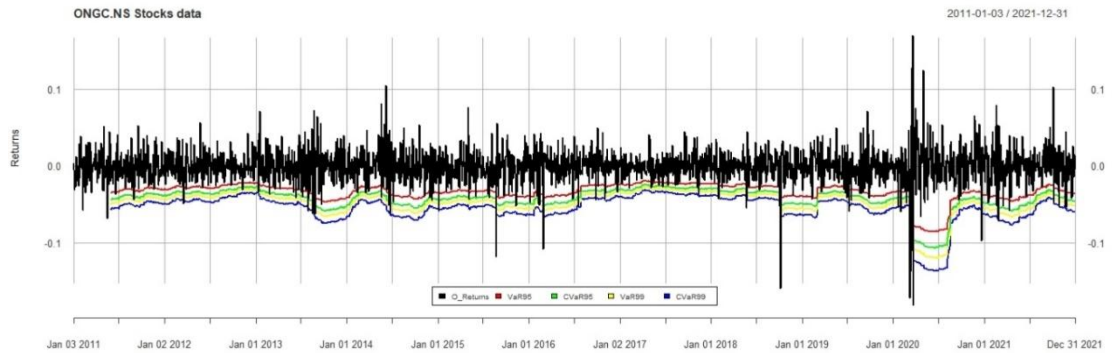

**(Figure 1)**



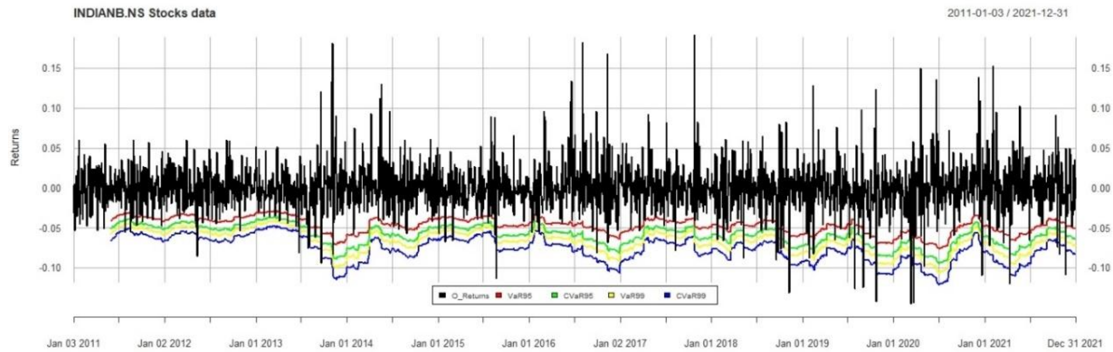

**(Figure 2)**



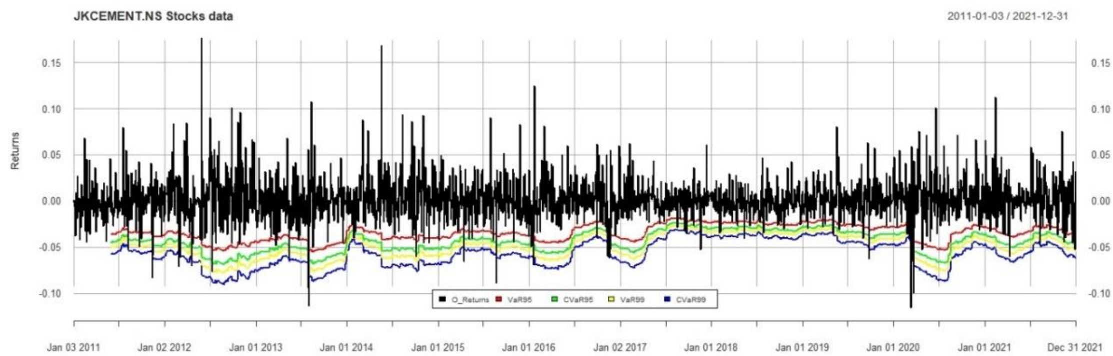

**(Figure 3)**




**(Figure 4)**




**(Figure 5)**

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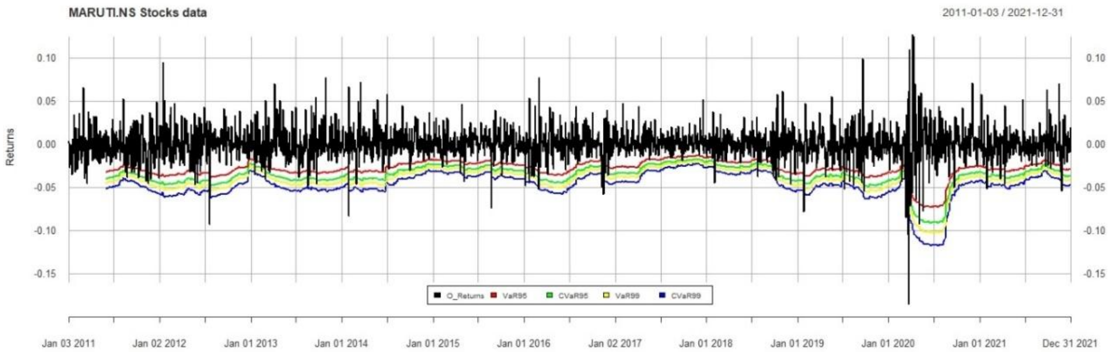



**(Figure 7)**

Predicted VaR and CVaR data is compared with original returns over 2611 days or possible available days as given in the table-1 and average failure rate is calculated using binary Back test.
Binary function value of any day is defined as

$$f(n) = \begin{cases} 1 & if\, r_n < VaR_\alpha(n) \\ 0 & if\, r_n \geq VaR_\alpha(n) \end{cases}$$

and in this way we get binary sequence of ones and zeros and calculating mean of this we get failure rate.
i.e. for sequence (1,1,1,0,0, 1,….) where 1 indicates failure and 0 indicate non-failure day

$$failure\ rate = \frac{total\ failure\ days}{total\ no.of\ days}$$

For each asset in our sample, we have calculated failure rate for 95% VaR and 99% VaR, also the same calculation is done for CVaR.

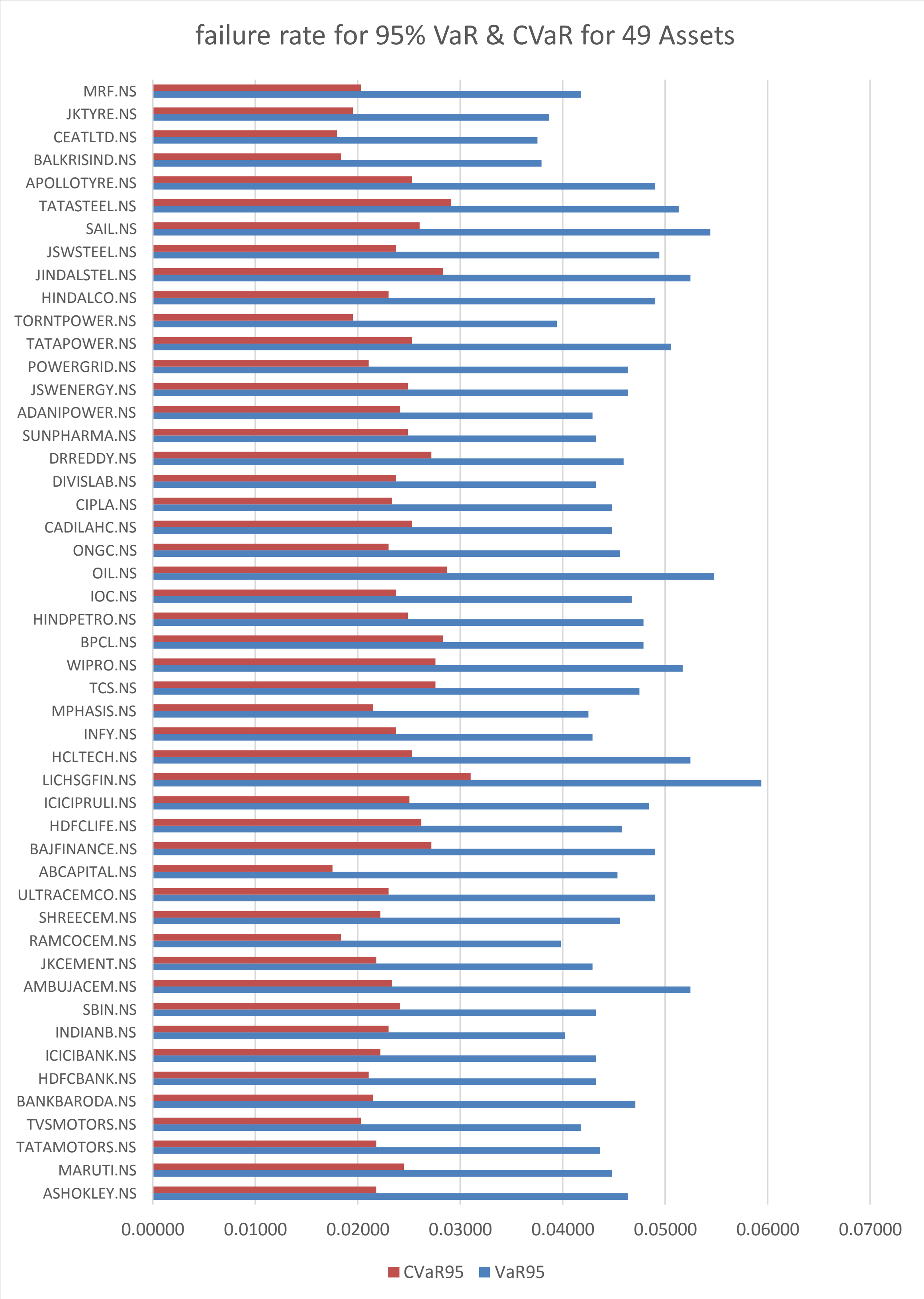
## IV. Results

In this paper we have calculated one day value at risk and conditional value at risk for 49 stocks from Yahoo finance using Monte Carlo simulation in R. The VaR for 49 stocks computed at 95% and 99% confidence interval over 11-year time period. Assets ABCAPITAL.NS, HDFCLIFE.NS and ICICIPRULI.NS were not listed in 2011 for those assets' calculation is done for available maximum data. For the volatility estimation we have used 100 days historical volatility. After the estimation of VaR and CVaR we have compared both predicted and real return values. For the simulation rounds, 100000 simulations have been taken in this approach. Result of failure rate are given in table.

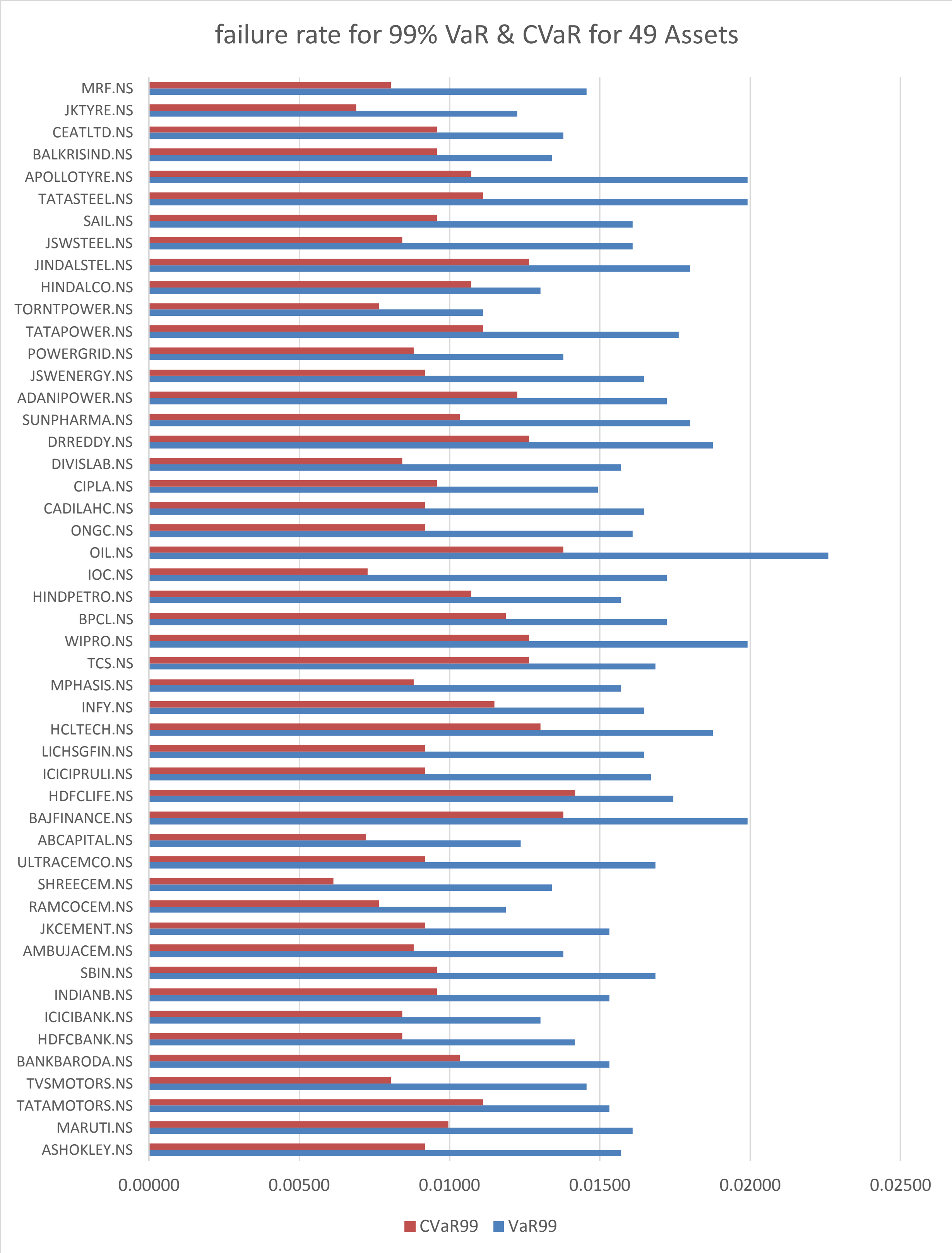
*(**Table 1**: Calculated failure rate for VaR and CVaR using binary back-test methods for 95% and 99% confidence level)*

| No. | Asset name | No. of days | Failure rate VaR95 | Failure rate CVaR95 | Failure rate VaR99 | Failure rate CVaR99 |
|---|---|---|---|---|---|---|
| 1 | ASHOKLEY.NS | 2611 | 0.04634 | 0.02183 | 0.01570 | 0.00919 |
| 2 | MARUTI.NS | 2611 | 0.04481 | 0.02451 | 0.01609 | 0.00996 |
| 3 | TATAMOTORS.NS | 2611 | 0.04366 | 0.02183 | 0.01532 | 0.01111 |
| 4 | TVSMOTORS.NS | 2611 | 0.04174 | 0.02029 | 0.01455 | 0.00804 |
| 5 | BANKBARODA.NS | 2611 | 0.04711 | 0.02145 | 0.01532 | 0.01034 |
| 6 | HDFCBANK.NS | 2611 | 0.04328 | 0.02106 | 0.01417 | 0.00843 |
| 7 | ICICIBANK.NS | 2611 | 0.04328 | 0.02221 | 0.01302 | 0.00843 |
| 8 | INDIANB.NS | 2611 | 0.04021 | 0.02298 | 0.01532 | 0.00957 |
| 9 | SBIN.NS | 2611 | 0.04328 | 0.02413 | 0.01685 | 0.00957 |
| 10 | AMBUJACEM.NS | 2611 | 0.05247 | 0.02336 | 0.01379 | 0.00881 |
| 11 | JKCEMENT.NS | 2611 | 0.04290 | 0.02183 | 0.01532 | 0.00919 |
| 12 | RAMCOCEM.NS | 2611 | 0.03983 | 0.01838 | 0.01187 | 0.00766 |
| 13 | SHREECEM.NS | 2611 | 0.04558 | 0.02221 | 0.01340 | 0.00613 |
| 14 | ULTRACEMCO.NS | 2611 | 0.04902 | 0.02298 | 0.01685 | 0.00919 |
| 15 | ABCAPITAL.NS | 970 | 0.04536 | 0.01753 | 0.01237 | 0.00722 |
| 16 | BAJFINANCE.NS | 2611 | 0.04902 | 0.02719 | 0.01992 | 0.01379 |
| 17 | HDFCLIFE.NS | 917 | 0.04580 | 0.02617 | 0.01745 | 0.01418 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 18 | ICICIPRULI.NS | 1198 | 0.04841 | 0.02504 | 0.01669 | 0.00918 |
| 19 | LICHSGFIN.NS | 2611 | 0.05936 | 0.03102 | 0.01647 | 0.00919 |
| 20 | HCLTECH.NS | 2611 | 0.05247 | 0.02528 | 0.01877 | 0.01302 |
| 21 | INFY.NS | 2611 | 0.04290 | 0.02375 | 0.01647 | 0.01149 |
| 22 | MPHASIS.NS | 2611 | 0.04251 | 0.02145 | 0.01570 | 0.00881 |
| 23 | TCS.NS | 2611 | 0.04749 | 0.02758 | 0.01685 | 0.01264 |
| 24 | WIPRO.NS | 2611 | 0.05170 | 0.02758 | 0.01992 | 0.01264 |
| 25 | BPCL.NS | 2611 | 0.04787 | 0.02834 | 0.01723 | 0.01187 |
| 26 | HINDPETRO.NS | 2611 | 0.04787 | 0.02489 | 0.01570 | 0.01072 |
| 27 | IOC.NS | 2611 | 0.04673 | 0.02375 | 0.01723 | 0.00728 |
| 28 | OIL.NS | 2611 | 0.05477 | 0.02872 | 0.02260 | 0.01379 |
| 29 | ONGC.NS | 2611 | 0.04558 | 0.02298 | 0.01609 | 0.00919 |
| 30 | CADILAHC.NS | 2611 | 0.04481 | 0.02528 | 0.01647 | 0.00919 |
| 31 | CIPLA.NS | 2611 | 0.04481 | 0.02336 | 0.01494 | 0.00957 |
| 32 | DIVISLAB.NS | 2611 | 0.04328 | 0.02375 | 0.01570 | 0.00843 |
| 33 | DRREDDY.NS | 2611 | 0.04596 | 0.02719 | 0.01877 | 0.01264 |
| 34 | SUNPHARMA.NS | 2611 | 0.04328 | 0.02489 | 0.01800 | 0.01034 |
| 35 | ADANIPOWER.NS | 2611 | 0.04290 | 0.02413 | 0.01723 | 0.01226 |
| 36 | JSWENERGY.NS | 2611 | 0.04634 | 0.02489 | 0.01647 | 0.00919 |
| 37 | POWERGRID.NS | 2611 | 0.04634 | 0.02106 | 0.01379 | 0.00881 |
| 38 | TATAPOWER.NS | 2611 | 0.05056 | 0.02528 | 0.01762 | 0.01111 |
| 39 | TORNTPOWER.NS | 2611 | 0.03945 | 0.01953 | 0.01111 | 0.00766 |
| 40 | HINDALCO.NS | 2611 | 0.04902 | 0.02298 | 0.01302 | 0.01072 |
| 41 | JINDALSTEL.NS | 2611 | 0.05247 | 0.02834 | 0.01800 | 0.01264 |
| 42 | JSWSTEEL.NS | 2611 | 0.04941 | 0.02375 | 0.01609 | 0.00843 |
| 43 | SAIL.NS | 2611 | 0.05439 | 0.02604 | 0.01609 | 0.00957 |
| 44 | TATASTEEL.NS | 2611 | 0.05132 | 0.02911 | 0.01992 | 0.01111 |
| 45 | APOLLOTYRE.NS | 2611 | 0.04902 | 0.02528 | 0.01992 | 0.01072 |
| 46 | BALKRISIND.NS | 2611 | 0.03792 | 0.01838 | 0.01340 | 0.00957 |
| 47 | CEATLTD.NS | 2611 | 0.03753 | 0.01800 | 0.01379 | 0.00957 |
| 48 | JKTYRE.NS | 2611 | 0.03868 | 0.01953 | 0.01226 | 0.00689 |
| 49 | MRF.NS | 2611 | 0.04175 | 0.02030 | 0.01455 | 0.00804 |


failure rate for 95% VaR & CVaR for 49 Assets
MRF.NS
JKTYRE.NS
CEATLTD.NS
BALKRISIND.NS
APOLLOTYRE.NS
TATASTEEL.NS
SAIL.NS
JSWSTEEL.NS
JINDALSTEL.NS
HINDALCO.NS
TORNTPOWER.NS
TATAPOWER.NS
POWERGRID.NS
JSWENERGY.NS
ADANIPOWER.NS
SUNPHARMA.NS
DRREDDY.NS
DIVISLAB.NS
CIPLA.NS
CADILAHC.NS
ONGC.NS
OIL.NS
IOC.NS
HINDPETRO.NS
BPCL.NS
WIPRO.NS
TCS.NS
MPHASIS.NS
INFY.NS
HCLTECH.NS
LICHSGFIN.NS
ICICIPRULI.NS
HDFCLIFE.NS
BAJFINANCE.NS
ABCAPITAL.NS
ULTRACEMCO.NS
SHREECEM.NS
RAMCOCEM.NS
JKCEMENT.NS
AMBUJACEM.NS
SBIN.NS
INDIANB.NS
ICICIBANK.NS
HDFCBANK.NS
BANKBARODA.NS
TVSMOTORS.NS
TATAMOTORS.NS
MARUTI.NS
ASHOKLEY.NS
0.00000
0.01000
0.02000
0.03000
0.04000
0.05000
0.06000
0.07000
CVaR95
VaR95

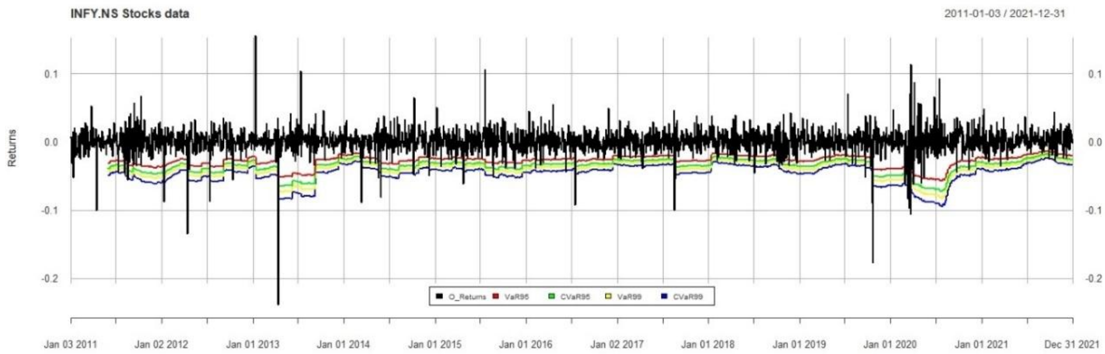
(Figure 8)




(Figure 9)

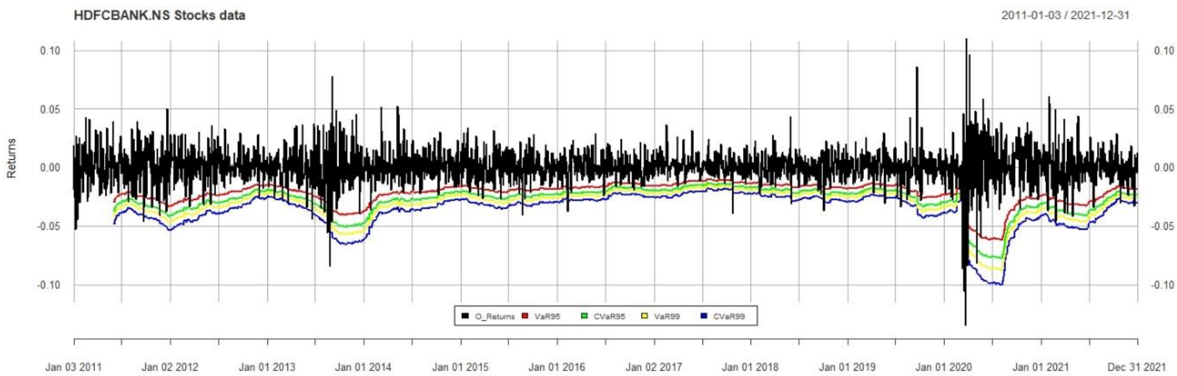
## V. Conclusion

In conclusion after applying the model to real data available on yahoo finance it is observed that in both cases 95% and 99% VaR failure rates are near to 5% and 1% respectively. In Monte Carlo simulation random numbers are generated using Normal distribution. Also, volatility plays an important role in this simulation, various volatility modeling approaches are available for use. As we can see the failure rate in Table-1 for 95% VaR we are getting failure rate near to 5%. When we go for 99% VaR the risk is bit under-estimated, and we can see the failure rate in Table-1 is almost more than 1.5%. Also, here we have considered total failure days out of 2611 days, and as the return data will not always behave normally and they accommodate fat tail, change of distribution is required for some assets. The empirical distributions can accommodate the fat tails and so for that we do not have to face the problems of underestimating VaR value and that is done by Normal distribution. From the following figure we can also see that VaR violations occurs in some clusters because volatility also occurs in cluster.

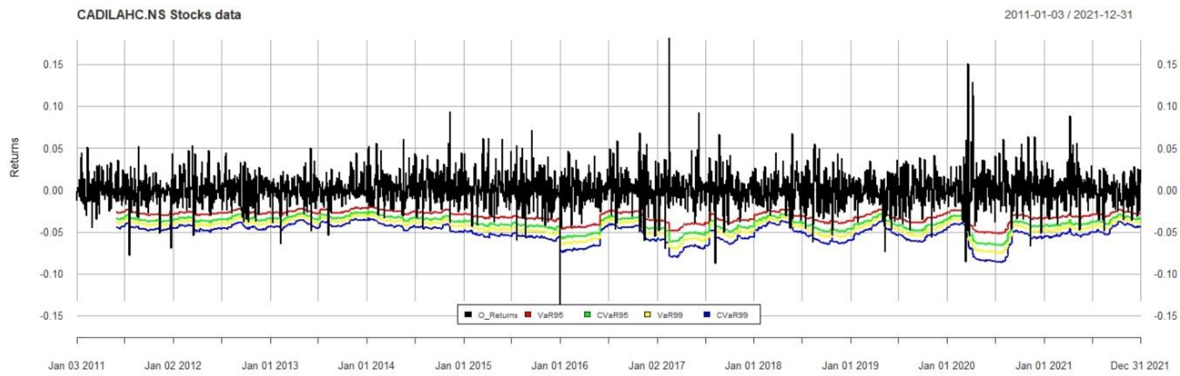



**(Figure 10)**

So failure rate is not uniformly working on the data period. To check that we can also go for other back testing approaches like Kupiec POF-test that involves cumulative VaR failure rate. For Monte Carlo Simulation, to find good approximation, it is required to have large number of simulation scenarios. For modification we can use different volatility models. In this method we can use the short historical data of 100 days and predict the VaR value, if we use more data and even a filtered data to have mean and standard deviation, we can get better result which will be good for normal market conditions. Although it works well in normal smooth market condition only, in turbulent market situations, our use of historical data can lead to underestimation or overestimation of risk. Although for CVaR we should have failure rate near to half of 5% and 1%, but because of volatility clustering and abnormal market events, the failure rate can also increase. We conclude that, it is good to use 100 days historical data and simulate future scenarios for measuring VaR and CVaR. It gives equivalent failure rate in 95% VaR and CVaR. We have used different sectors assets in our sample of 49 assets. We can also conclude that for some sectors stock simulation works well. Also as in India lockdown due to covid was announced in march 2020 due to COVID pandemic




**(Figure 11)**




**(Figure 12)**

almost all stocks are having high volatility crashes during that period other than some pharma companies.

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