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Estimating the Value at Risk Using Monte Carlo Simulation

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Abstract:
In this paper, for calculating the VaR, we have employed the Monte Carlo simulation approach, which is a semi-parametric method. Using Microsoft Excel and R, we estimated VaR estimates for several assets Over three years Jan 2019 to Dec 2021. The asset data is downloaded from yahoo finance. we have estimated one-day VaR for these assets and back-tested it. The duration involves before covid-19 and after the covid-19 situation in the Indian market. The percentage of failure is done by the Binary Proportion of Failures for this strategy.

***Key Words**: Value at Risk (VaR), Monte Carlo simulation,COVID, Back-testing.*

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I. Introduction

Nowadays, the most widely use market risk measure is a value at risk (VaR). Value at risk calculates the expected possible loss on a particular investment for a certain time horizon with a given probability. To compute VaR, there are three primary methods: parametric, non-parametric, and semi-parametric.

Our results show how the Monte-Carlo simulation model failed in the covid period where there was a sudden market crash in India due to a total lockdown in March 2020. We conclude that Monte-Carlo simulation with normal distribution assumption can predict good estimates of VaR when the market is in normal condition, but as market never stays in normal conditions and fluctuations are there, simple Monte-Carlo with normal distribution assumption is not sufficient. In our sample period of pre-COVID & post-COVID periods, where total lockdown was declared by the government VaR estimates were under-estimated by this model. Although for some sectors this was less affected.

Risk measurements tools such as value-at-risk (VaR) commonly used in the financial industry for risk management. Monte Carlo simulation has long been recognized as a reliable method for estimating VaR. Basel I, usually known as the Basel Accord, is a banking regulation agreement reached in 1988 in Basel (Switzerland) by the Basel Committee on Bank Supervision (BCBS). It includes recommendations on credit, market, and operational risks. Its goal is to make sure financial organizations have sufficient capital on hand to meet their obligations and absorb uncertain losses.

II. Literature Review

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.

Pankaj Yawalkar and Prasad Rao (2004) tested various methods for estimating value at risk. 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 indicates 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.

Value at Risk (VaR) is a statistic that quantifies the extent of possible financial losses within a firm with portfolio, or position over a specific time frame. This metric is most used by investment and commercial banks to determine the extent and probabilities of potential losses in their institutional portfolios.

We want to calculate the Value at Risk (VaR), which is defined as the most likely loss, or the most "negative" price change, whose probability falls within a pre-specified confidence interval over a pre-specified time horizon (investment period). As an illustration, consider the following: If an Asset has a VaR of Rs. 25 over a one-day investing period with a confidence level of 95%, that implies the Asset has a 5% chance of losing Rs. 25 or more during that period. In other words, there is a 95% chance that the losses over one day will not exceed Rs. 25 if the indicated Asset is used.

The goal of this research is to use Monte Carlo computer simulations to calculate VaR for various investment periods, prior period lengths, and confidence intervals. With a historical window of three years, our results reveal that the Monte Carlo technique performs good in calculating VaR at 95%, 99%, and 99.9%. We also see a relationship between the VaR and the estimation window length and historical time. A 95% N-day VaR score of "V%" indicates that we are 95% confident that we will not lose more than V% in the next N days. In this paper, we have calculated one-day VaR for various assets of the Indian stock market, with 95%, 99%, and 99.9% confidence intervals. The paper is structured as follows. In the next section, brief introduction of the Monte Carlo method to calculate VaRis done in next section Data Analysis and Back-testing are done and at last results and Conclusions are there with a bibliography.

III. Data And Method

3.1 Data

For calculation of VaR 95%, 99% and 99.9% we have used sample of 50 assets from NSE India. Historical data of these assets are downloaded from yahoo finance. We have used data of assets Over three years from Jan 2019 to Dec 2021 which involves pre-COVID and post-COVID situations in Indian stock market. It also includes the Lockdown announcement period of March 2020. Total 742 trading days historical data is used. And 100 days historical data is used to predict 101^{st} days VaR Estimate.

3.2 Monte-Carlo Simulation approach

The Monte Carlo simulation methodology has several similarities to historical simulation. The main difference is that rather than carrying out the simulation using the observed changes in the market factors over the last N periods to generate N hypothetical stock profits or losses, one chooses a statistical distribution that is believed to adequately capture or approximate the Possible changes in the market factors. Then, a pseudo-random number generator is used to generate thousands or perhaps tens of thousands of hypothetical changes in the market factors. These are then used to construct thousands of hypothetical stock profits and losses on the current portfolio, and the distribution of possible stock profit or loss. Finally, the value at risk is then determined from this distribution of simulated returns as,

$$r_t = \mu + \sigma * Z_t$$

$Where, Z_t =$ Random number, μ= mean, σ = St. Deviation.

3.3 Program Algorithm

The basic features of the algorithm that calculates the VaR for Indian equities using Monte Carlo simulations are presented below. We have used R programming for this.We have used asset price data downloaded from yahoo finance.

- ➢ The data of particular asset is downloaded from yahoo finance in R as a timeseries data for time-period 1^{st} Jan 2019 to 31^{st} Dec 2021.
- ➢ For analysis daily closing price is used for particular assetand null values are removed from the data.
- ➢ Next, we calculate daily log return using these daily close prices.
- ➢ Then,we use the first 100-day daily returns to calculate Mean (μ), Standard Deviation(σ) as normal distribution parameters for these 100 days sample period.
- ➢ Next, we use Mean and Standard Deviation to generate 100000 Hypothetical returns scenarios.
- ➢ And then, we choose the 5^{th}quantile, 1^{st} quantile and 0.1^{st} quantile observation for 95%, 99% and 99.9% confidence interval respectively and predictVaR value of 101^{st} Day.
- ➢ As we already have original return data of 101^{st} day, we compare it with the predicted VaR value and count the failure and non-failure for the day.
- ➢ To predictVaR of 102^{nd} DaySame process of taking historical 100 days return data i.e., day-2 to day-101 is used and calculation of VaR 95%, 99% and 99.9% is repeated.

- This process is done for 642 days over our historical sample period of data.
- Here original returnsare back tested with predictedVaR, and probability of Return values is less than VaR values is calculated.

IV. Data Analysis and results

Using the algorithm described in previous section we predicted VaR values for 95%, 99% and 99.9% confidence interval. Predicted VaR values are plotted with original returns data. We have calculated the total failure rates(probability) for all three confidence intervals for these assets. It is listed in Table-1. Some of the assets are discussed as below.

Figure-1 showsTata Motors original log return data is plotted with predictedVaR 95% , 99% and 99.9% confidence interval using R-Programming for period from 01st January 2019 to 31st December 2021(3 years). Similarly figure-2 to figure-7 represents the timeseries plot of original asset returns with predicted 95% , 99% and 99.9% VaR, for assets Adani Power, Infosys, HDFC bank, Indian Oil, Tata steel and Bajaj finance respectively.

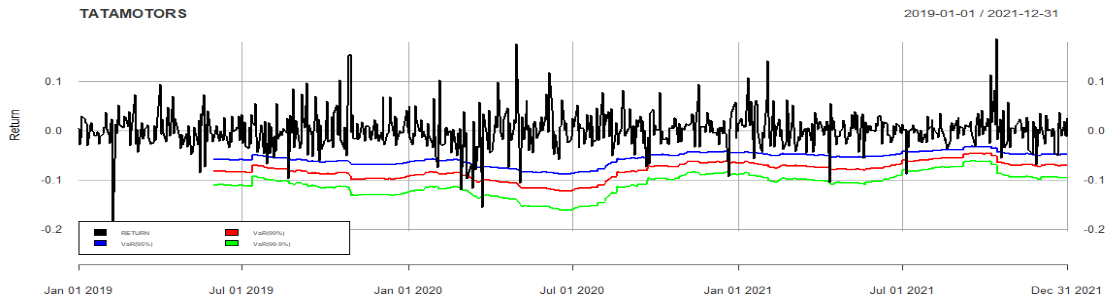


Figure 1

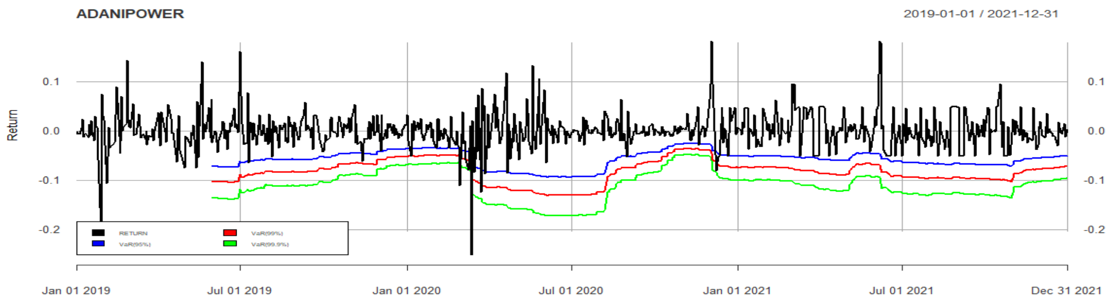
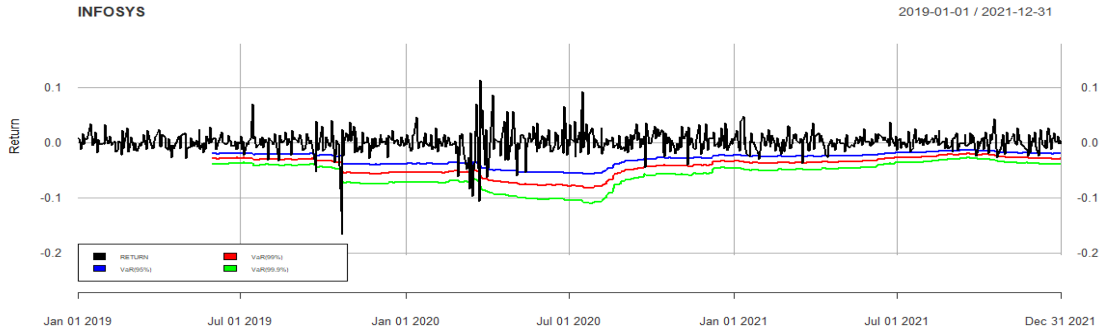


Figure 2



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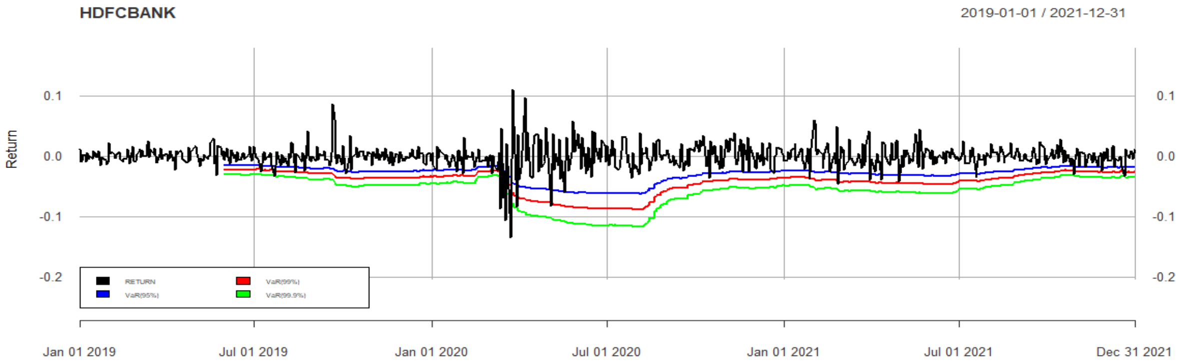

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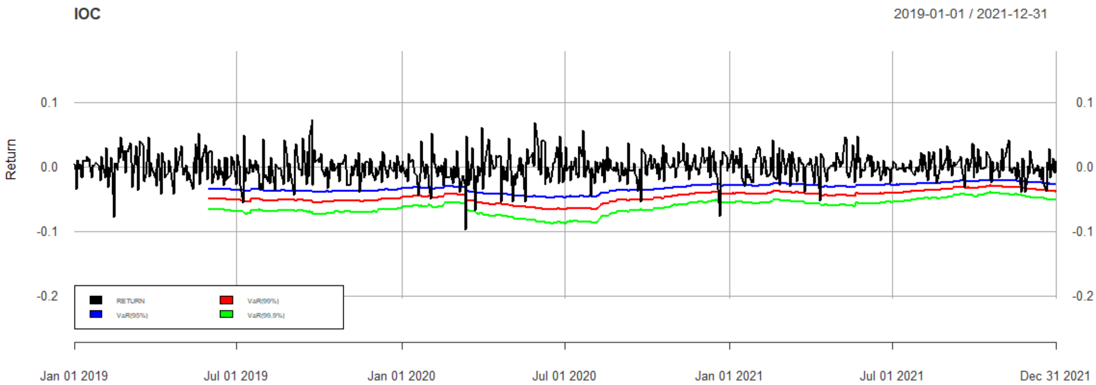

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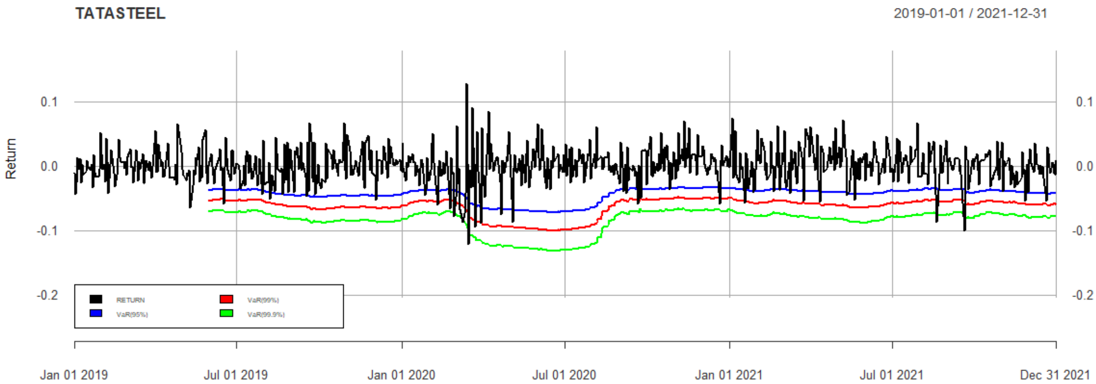

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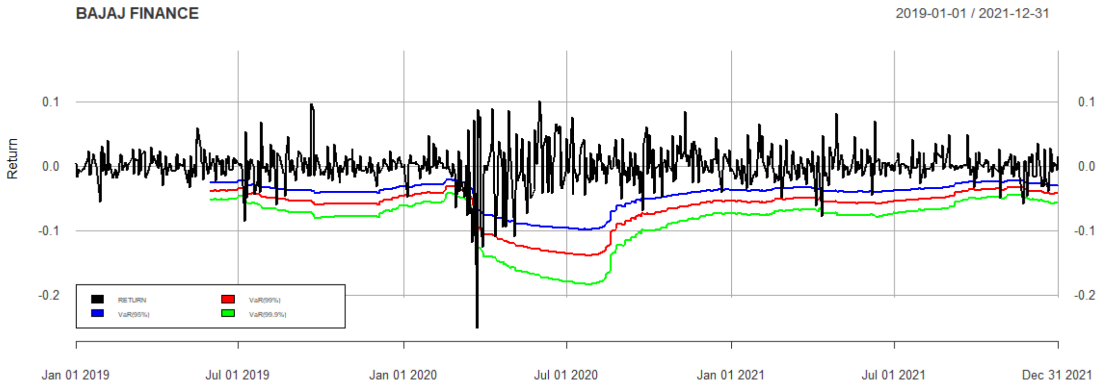

Figure 7

4.1Back-Test

For Back testing we have compared daily returns withPredicted VaR values. We calculate the failureas Expected value that VaR value is greater than original daily returns. $i.e. E(r < VaR)$. To calculate it we used binary function as follows.

If predicted VaR value is greater than the daily return,I(t) value is 1.And the PredictedVaR value is less than the Daily return to get$I$(t) value is 0.

$$I(t)= \begin{cases} 1 \;\; if \;\; R_t < VaR(t) \\ 0 \;\; if \;\; R_t \geq VaR(t) \end{cases}$$

Where, R_t = Daily Return, $VaR(t)$ = Predicted VaR

And calculate all probability of getting 1 on 642 Days. The probability of getting 1 is greater than 5% at a 95% confidence level is called underestimateVaR. The probability of getting 1 is less than 5% at a 95% confidence level is called Overestimate VaR. as well as the same process for 99% and 99.9% confidence intervals and gets the failure rates.

Table-1: Back-testing results in failure rates

STOCK	Days	VaR at 95%	VaR at 99%	VaR at 99.9%
SAIL	642	6.23%	2.18%	1.09%
ASHOK LEYLAND	642	9.19%	3.89%	2.18%
MARUTI SUZUKI	642	5.91%	3.42%	1.40%
TATA MOTORS	642	5.14%	2.18%	1.09%
TVSMOTORS	642	7.47%	2.65%	0.77%
BANK OF BARODA	642	7.63%	2.34%	0.62%
HDFCBANK	642	11.21%	4.83%	2.65%
ICICI BANK	642	8.57%	4.47%	2.34%
INDIAN BANK	642	4.67%	1.87%	1.40%
SBI BANK	642	10.75%	5.67%	2.80%
AMBUJA CEMENT	642	6.07%	3.12%	1.09%
JK CEMENT	642	2.49%	0.93%	0.31%
RAMCO CEMENT	642	6.39%	2.65%	1.09%
AB CAPITAL	642	5.30%	2.65%	1.09%
BAJAJ FINANCE	642	8.88%	5.76%	3.12%
INFOSYS	642	7.32%	3.43%	2.18%
TCS	642	7.32%	3.11%	1.87%
IOC	642	6.54%	2.80%	1.40%
ONGC	642	6.23%	2.80%	1.09%
CADILA HEALTHCARE	642	6.07%	2.18%	0.62%
SUN PHARMA	642	7.47%	3.27%	0.93%
ADANI POWER	642	7.00%	1.24%	0.47%
TATA POWER	642	2.96%	1.09%	0.62%
HIND ALU. CO.	642	4.98%	2.34%	1.09%
TATA STEEL	642	5.14%	2.02%	1.25%
APOLLO TYRE	642	8.10%	3.27%	2.02%
MRF TYRE	642	6.07%	2.80%	1.09%
JKTYRE	642	3.42%	1.25%	0.78%
CEAT TYRE	642	4.82%	2.34%	1.25%
BALKRISHNA IND	642	4.98%	2.49%	1.25%
SAIL	642	6.23%	2.18%	1.09%
JSW STEEL	642	4.98%	2.65%	1.40%
JINDAL STEEL	642	8.26%	4.20%	2.65%
TORENT POWER	642	2.49%	1.56%	0.77%
POWER GRID	642	4.98%	1.56%	0.46%
JSW ENERGY	642	3.42%	0.93%	0.15%
DR REDDY LAB	642	8.10%	3.89%	1.56%
DIVIS LAB	642	2.80%	1.56%	0.93%
CIPLA	642	5.14%	2.02%	0.47%
OIL	642	3.27%	1.56%	0.93%
HINDUSTAN PETROLEUM	642	6.70%	2.18%	0.93%
BHARAT PETROLEUM	642	7.32%	3.74%	2.02%
WIPRO	642	7.16%	2.96%	0.93%
MPHASIS	642	4.05%	1.71%	0.62%
HCL TECHNOLOGY	642	6.23%	2.95%	1.25%

LIC HOUSING FIN.	642	8.88%	4.98%	2.18%
ICICI PRUDENT	642	7.63%	3.89%	1.56%
HDFC LIFE	642	7.94%	4.36%	2.34%
ULTRATECH CEMENT	642	8.41%	3.43%	1.87%
SHREE CEMENT	642	6.23%	3.12%	1.87%

V. Conclusion& Discussion

In this work, for a sample of 50 assets, we have calculated Value at Risk for different confidence intervals using the Monte Carlo Simulation for 95%, 99%, and 99.9% confidence intervals. Here the sample period is of 742 Trading Days (3-Year) which involves data Before Covid-19 and after the Covid-19 effect in India.

The Monte Carlo simulation method works well in regular market condition but in a turbulent market condition where sudden market fall is there model do not work adequately. For such market conditions we can involve other volatility models and other distributions too.

This analysis shows, which Sectors had a major, minor and no effect on volatility, of covid-19 and lockdown. Table-1 show the corresponding failure rates for 95%, 99% and 99.9% VaR. The failure rates for 95%, 99% and 99.9% VaR should be near to 5%, 1% and 0.1% respectively. As from the Table-1, we can see that failure rates for most of the assets of our sample is higher than required. Here most of the failures occurred in the month of march due to announcement of total lockdown in India. we can conclude that some sectors which are highly affected by covid-19 and lockdown for example Banking sectors, automobile sectors, real estate etc. also, their associated industries were affected for example, due to lockdown real estate sector was affected and due to that cement companies have sudden drop in stock price. We can observe that due to lockdown most of transportation industry were closed and due to that automobile companies like Ashok Leyland Pvt. Ltd. had sudden drop in stock price.

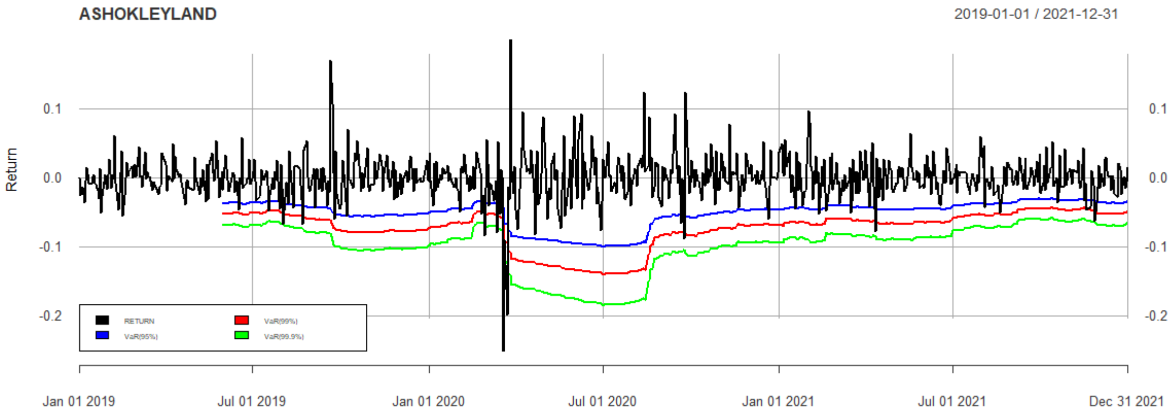

Figure 8

Figure 9 indicates HDFC Banks data, it shows the covid-19& total lockdowneffect as highlighted with circle.From the graph we can see thatVaR is underestimated in beginning of lockdown and Market crash period, and then after VaR is overestimated with 95%, 99%, and 99.9% confidence respectively. Which indicates failure of our model for this asset.

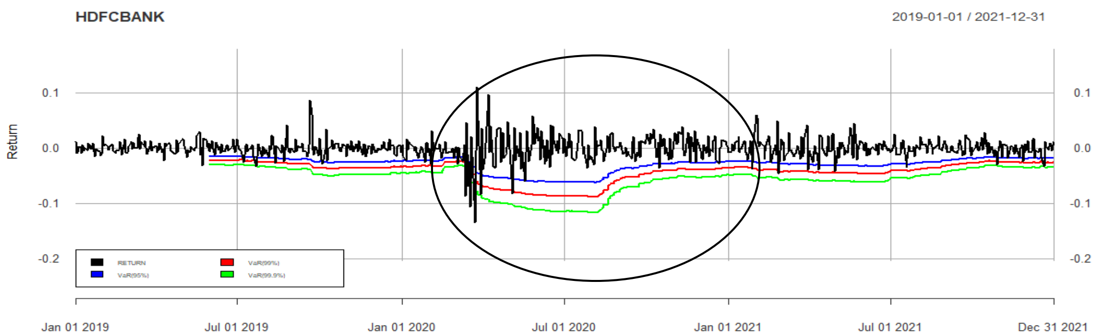

Figure 9

We also came across one observation and analysis that indicates pandemic& total lockdown had less effect on volatility of Power and Tyers sectorsassets.

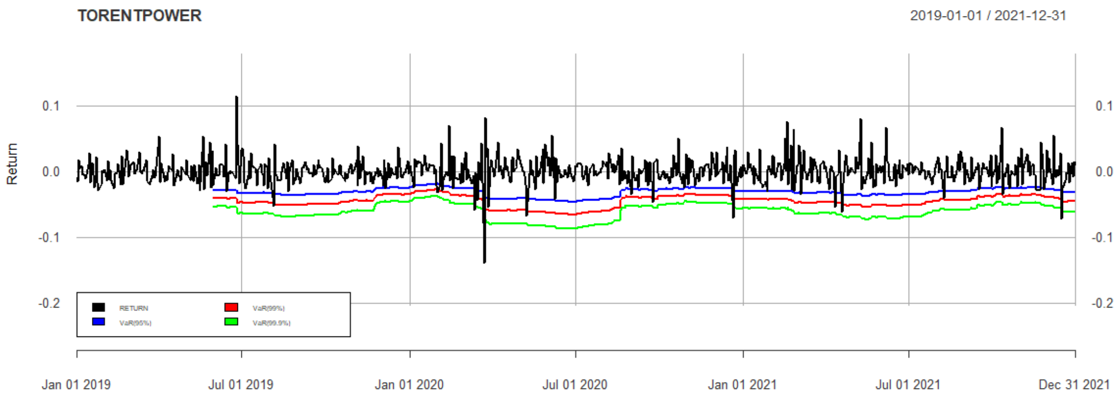

Figure 9

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