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CONFERENCE PAPERS
- Garg Sambhav (2011): "Business Ethics" Paper presented at the Annual International Conference for the All India Management Association, New Delhi, India, 19–22 June.

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- Kumar S. (2011): "Customer Value: A Comparative Study of Rural and Urban Customers," Thesis, Kurukshetra University, Kurukshetra.

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- Garg, Bhavet (2011): Towards a New Natural Gas Policy, Economic and Political Weekly, Viewed on July 05, 2011 http://epw.in/user/viewabstract.jsp

COMPARATIVE STUDY OF PERAMETRIC AND NON-PARAMETRIC VALUE AT RISK (VaR) METHODS

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ABSTRACT
Investment nowadays is become a very hectic task. Most of the time people think about how much they can lose on their investment. Value at Risk is a way to give answer of these questions, at least within a reasonable bound. However, in this paper, I am going to calculate VaR of an equity portfolio using parametric as well as non-parametric approaches and going to do the comparison between these VaR methods. In this study, I will examine the inputs to VaR: market data and find out, using this data how we can calculate the VaR using different VaR methods. In this paper I am taking return data and applying Variance-Covariance, Historical Simulation and Monte Carlo Simulation method on that data. For comparing all these VaR method I am using Back-Testing method. Based on the result of back testing method we can find out which method is most suitable for the perticular situation.

KEYWORDS
Investment, Risk, VaR.

INTRODUCTION
Value at Risk (VaR) has been an important component of financial risk management. It has become commoditized, such that VaR systems solutions can be bought 'off the shelf'. It has become enshrined within the financial regulations of the world's banks. In this thesis, I am going to calculate VaR of an equity portfolio using parametric as well as non-parametric approaches. Risk management is defined as the process of monitoring the risks that a financial institution is exposed to, and taking action to maintain this exposure within levels set by the board's risk appetite.
VaR is defined as the portfolio loss that will not be exceeded with a given level of confidence, over a given trading horizon. This is not an absolute limit on loss and must not be read as such. In this study, we will examine the inputs to VaR: market data and using this data how we can calculate VaR. The report also considers the problems that can occur when putting this data together. We describe different approaches of calculating VaR, using the common classifications of variance-covariance, historic simulation and Monte Carlo. The text assesses the differences in the way they process data, the different data requirements and the qualitative requirement for computational power. Also, the description highlights circumstances that lead to favoring one approach over another, the type of market (normal or non-normal), and the type of instrument (linear or non-linear).
This study also looks at the outputs of VaR, when using each of the approaches described above. Some approaches will offer a consolidated number only, but others offer more insight into the sources of risk. We outline how financial institutions can use the back testing approach to validate their VaR process, which consists of data, models and procedures.

MOTIVATION AND REAEARCH OBJECTIVE
Value at Risk has been a developing science for more than a decade. The regulators around the world apply pressure to financial institutions, large or small, to provide Value at Risk measures as part of their regulatory returns. The cost of developing an internal methodology is high. Many smaller financial institutions find that the cost of compliance with the regulatory regime is similar to larger institutions with deeper pockets. For this reason, they may turn to off the shelf methodologies built in to software packages. Such institutions must be wary of implementing an external methodology that is inappropriate for the types of risk. These risks may include exposure to options, financial instruments that present multiple dimensions of risk and headaches for the risk manager. There are plenty of methods available for calculating VaR At the very basic level we can classify these methods into two groups-parametric and non-parametric approaches. We take the most popular methodologies, variance-covariance, historical simulation and Monte-Carlo simulation to calculate VaR, and assess suitability of these methods for risk measurement of equity portfolio. In particular, we examine these methodologies, and ask whether these approaches will provide risk measures consistent with the other more complicated approaches. The framework used to produce result can in fact be used more generally, for any portfolio for which a variance-covariance matrix can be derived. These methods have dominated the Value at Risk literature, as a central reference point for academic interest. Much of the research published on the methodology has focused on the techniques used to collect the data, assessing the data and calculating the final value of VaR. Other things which have been taken care of are distribution of return data, assumption of normality and simulation techniques to generate data set.

LITERATURE REVIEW
As Value at Risk has long been a central focus of risk measurement and management, there has been a huge array of literature. We have referred a few major studies with its appropriateness with our present study. Amongst earlier studies, Crnkovic and Drachman (1995) developed a metric and compared relative performance comparison between standard variance-covariance method and historical simulation approach. Studies by Schinassi(1999) dwell on dependency of VaR models on historical relationships between price movements in different markets and their trend to break down during times of stress and turbulence in event of structural breaks in relationships across markets.

In the Indian context, some remarkable researches have been carried out on VaR. Srinivasan, Shah, Ganti and Shah (2000) pointed that the computational cost involved as one of the drawbacks of the method and proposed the computational geometry techniques. Sarma, Thomas and Shah (2000) evaluated performance of a few alternative VaR models, using India's Nifty stock market index as a case study and adopted a bi-direction approach i.e., statistical model selection and model selection based on a loss function.

Dharba (1999) presented a new method for computing the VaR for a set of fixed- income securities based on extreme value theory that models the tail probabilities directly without making any assumption about the distribution of entire return process.

Nath & Reddy (2003) worked on foreign exchange market in India and studied various VaR methods using the Rupee-Dollar exchange rate data to understand which method is best suited for Indian system.

Varma (1999) empirically tested of different risk management models in the Value at Risk (VaR) framework in the Indian stock market with special emphasis on EWMA model and GARCH-GED specification. Samanta & Nath (2003) studied three categories of VaR methods, viz., Variance- Covariance (Normal) methods including Risk-Metric, Historical Simulation (HS) and Tail-Index Based approach.

Raina & Mukhopadhyay (2004) found out optimal allocation of a unit capital between the portfolio elements so as to maximize VaR. The algorithm has been validated using a three-asset portfolio example.

Samanta G.P. and Thakur, S.K. (2006) assess the accuracy of VaR estimates obtained through the application of tail-index. The database consists of daily observations on two stock price indices. BSE Sensex and BSE 100 from 1999 to 2005. Results show that tail index based methods provide relatively more conservative VaR estimates and have greater chances of passing through the regulatory backtesting. Among .a plethora of studies only broad conto urs of related literature are presented here.

In a survey of VaR disclosure by major international banks between 1996 and 2005,

Perignon and Smith (2007) find that 73% of the banks which disclosed their VaR methodology use HS. They offer two reasons for the popularity of this method. First, as noted above, banks want to avoid model or estimation risk. For large and complex portfolios driven by thousands of risk factors, they prefer not to depend on estimates of time varying volatilities and correlations. So, they choose a nonparametric and flexible method of VaR estimation, viz. HS. Second, banks and regulators want their capital charge estimates to be smooth over time and not to be widely different from day to day. Since HS uses the same unconditional distribution of returns over one or two years, internal capital estimates remain stable.

As noted in Basu (2006), an unintended consequence of using a nonparametric method is that very large losses, caused by sudden shocks, might lie way beyond 99% HSVaR. Even if the market suddenly becomes more volatile, since historical losses are much lower, HSVaR might not be able to respond to an increase in market risk (Pritsker 2006). While preserving the estimation benefits of the nonparametric technique, we want the VaR forecast to reflect (at least in part) higher current volatility.

This brings us to Volatility-weighted Historical Simulation (VWHS, Hull and White 1998). Since this also uses the empirical distribution of returns, it can accommodate fat tails if they are present in the data. Moreover, historical returns are adjusted or updated, in this method, as per the most recent market volatility. Since the adjusted returns are assumed to be repeated in future as well, the idea is that most recent volatility would continue for the chosen horizon. The level of capital would then be in line with the latest, rather than historical, market volatility. Therefore, the effect of any stress event, which leads to a temporary spike in volatility, will be felt on both VaR (capital) and Expected Shortfall (beyond VaR). This method is suitable for estimating the level of capital during an abnormal period, like the meltdown in Sensex as described at the outset, when volatility is not only supposed to be high but also clustered.

Simple historical simulation also puts equal weights on all past returns. As a result, periods of high and low volatility are bunched. Equal weighing overestimates risk during low-volatility phases and underestimate it during high-volatility phases. Secondly, event risk might not be captured. For instance, a one-time currency market crash might not be captured even at 99% VaR. Thirdly, ghost effects might occur if a few extreme events, from the past, are in the dataset. The VaR might be unduly high. It will fall drastically once such losses move out of the sample.

This brings us to BRW Historical simulation (Boudoukh et. al. 1998, Allen et. al. 2004). This method is a combination of simple HS and EWMA. So, it is also known as the hybrid method. In this method, older returns get lesser weights than more recent ones.

RESEARCH METHODOLOGY

In this study I have chosen the requisite confidence level, forecast horizon and historical observation period, which are enumerated below.

CONFIDANCE LEVEL

The confidence level is p = (1- a), which defines the probability of the expected maximum loss. The market risk surface can be analyzed by varying the level of confidence. The most common confidence levels are between 95 % and 99 %, although they can vary between 90 % and 99.9% (Hendricks, 1996). The Basel Committee requires the use of 99 % confidence level in official reporting (Basel Committee, 2006), as it must be high enough for capital requirement calculations, but a lower level of confidence (e.g. 95 %) can be used for internal reporting. In my study, I have selected 95% and 99% level of confidence both in order to find out VaR for internal purpose and reporting purpose.

FORECAST HORIZON

The length of the period, for which the expected maximum loss is forecasted, is known as forecast horizon or holding period. Large deviations in the portfolio value are more probable over a long period than a short one, and VaR is usually greater for a holding period of one month than for a day, for instance. The portfolio composition is assumed to remain static for VaR over the holding period. The adequate length of the holding period depends on whether the risk is measured from a private or a regulatory perspective (Christoffersen et al., 1998). Trading activity and the liquidity of the assets (i.e. the time and ability to convert a position to cash) has also an impact on the adequate length of the holding period (Khindanova and Rachev, 2000). In practice, the holding period can vary from one trading day to some years, but the Basel Committee requires the use of 10-day holding period for official reporting. They still permit the use of a shorter holding period and scaling of VaR to correspond 10-day holding period1 (Basel Committee15, 2006). As such I have taken 10- days horizon for computing VaR i.e. the reference data remains static for 10- day period.

HISTORICAL OBSERVATION PERIOD

The length of the data sample in VaR calculation is known as the historical observation period. This observation period connects VaR to the history of the market risk factors, as the volatility of the risk factors is determined based on the length of the historical observation period. In practice the observation. The regulatory standard sets a minimum length of one year for the historical observation period (Basel Committee, 2005), while the period may vary from a month to several years in practice. A one-period VaR can be scaled to a long horizon VaR by multiplying by the square root of the length of the horizon. For instance, a one-day VaR may be scaled to ten-day VaR by multiplying it by 10.

Hendricks22's (1996) results highlight the Basel Committee requirement for a minimum historical observation period of 250 days, as he finds shorter periods to produce inaccurate VaR measures. I have taken considerable long period from 2nd January 2007 to 30th Nov 2009 having 716 data points.

DATA SOURCE

The data set used is S& P CNX Nifty as available from National Stock Exchange website for the period from 2nd January 2007 to 30th Nov 2009 as for Historical Simulation Value at risk, time horizon should be 2 years at least.

METHODOLOGY

Through this project we can analyze various VAR methods. what are the various parametric and non parametric value at risk measures, how we can apply each of them to calculate value a risk of particular dataset and selecting the most appropriate measure based on performance evaluation and back-testing of each of the measure.

I am going to take return data of any leading stock or simply return data of any leading index (for ex. NIFTY) and calculate Value at Risk for single return data.

METHODOLOGY CONSIST OF FOLLOWING STEPS:

I. Calculating the Value at Risk using Variance-Covariance Method.
   - Calculate mean and Std. Dev. Using some Volatility measure (for ex. **GARCH** or **E-GARCH**).
   - Find out the distribution for these values.
   - Calculate VAR for these inputs.

II. Calculating the Value at Risk using Historical Simulation.
   - Collect the return data for period of 1 year.
   - Apply HS Method for calculating VAR

III. Calculating the Value at Risk using Monte Carlo Simulation.
   - Generate random return for given mean and Std. Dev.
   - Calculate VAR for this return data

IV. Applying the Back-Testing on the each of the above methods.
   - Select the appropriate back-testing method (for ex. COV and regression analysis).
   - Compare the given value at risk methods based on the out put of back-testing.
   - Select the most appropriate Value at Risk method.

A. Variance-Covariance Method-

Calculating VaR using this method includes following steps-

1. Define current portfolio value=1000000
2. Confidence level- 95% for internal purpose And 99% for credit rating and reporting purpose
3. Forecast horizon-10 days so we will calculate 10 day- VaR

10 Days-VaR= SQRT (10)*Daily VaR

4. Historical Observation Period-I am taking S&P CNX Nifty data from 1 Jan 2007 to 30 Nov 2009.
5. Define the return distribution as the normal distribution for the index return data.
6. Calculate the value of Mean and Std Dev for this index return data series.

1- Portfolio Mean Return,

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{1}{n}(x_1 + \cdots + x_n)$$

Where x1, x2, x3 …xi are P/L Return data.

2- Portfolio Std. Dev.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2},$$

7. Using the distribution, ,Mean and Std Dev values calculate the 95 percentile and 99 percentile values by taking z-values .05 and .01 respectively.

   95 percentile value at risk,

   VAR=$|\mu_P + z\sigma|$ V

   Where, $\mu_{P= \text{expected return}}$, $V = \text{portfolio}$ value , σ = volatility

8. Using these percentile value calculate the 95 percentile and 99 percentile VaR of the index portfolio and than 10 Days-VaR for the same.

B. Advanced Variance-Covariance method using GARCH Volatility Estimate-

Here initial 6 steps are same as variance-covariance method. In 7th step while calculating Std Dev of return instead of using normal variance formula we will take use of GARCH Volatility Estimate.

Variance equation of GARCH model is

$$\sigma_t^2 = \omega + \alpha(\epsilon_{t-1} - \theta\,\sigma_{t-1})^2 + \beta\,\sigma_{t-1}^2$$
$$\alpha,\ \beta \ge 0;\ \omega > 0$$

For index returns, parameter θ is usually estimated to be positive; in this case, it reflects the leverage effect, signifying that negative returns increase future volatility by a larger amount than positive returns of the same magnitude.

GARCH (1,1) ESTIMATION OF 0.414509010801167

Method: ML - BFGS with analytical gradient				
date: 03-28-10				
time: 17:04				
Included observations: 715				
Convergence achieved after 32 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
omega	1.470504	0.263769	5.574972	2.48E-08
alpha_1	0.352033	0.065858	5.345341	9.02E-08
beta_1	0.470891	0.055599	8.469351	0
Log Likelihood	-1566.36			
Jarque Bera	888.8842		Prob	0
Ljung-Box	2.053679		Prob	0.151839

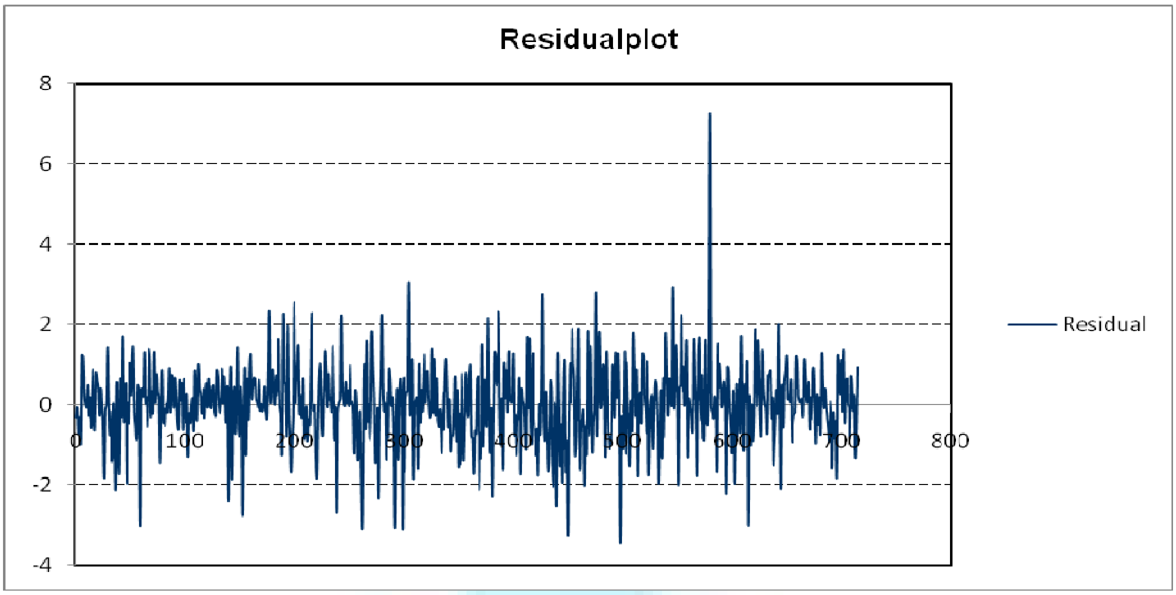
Using the distribution, ,Mean and Std Dev values calculate the 95 percentile and 99 percentile values by taking z-values .05 and .01 respectively.

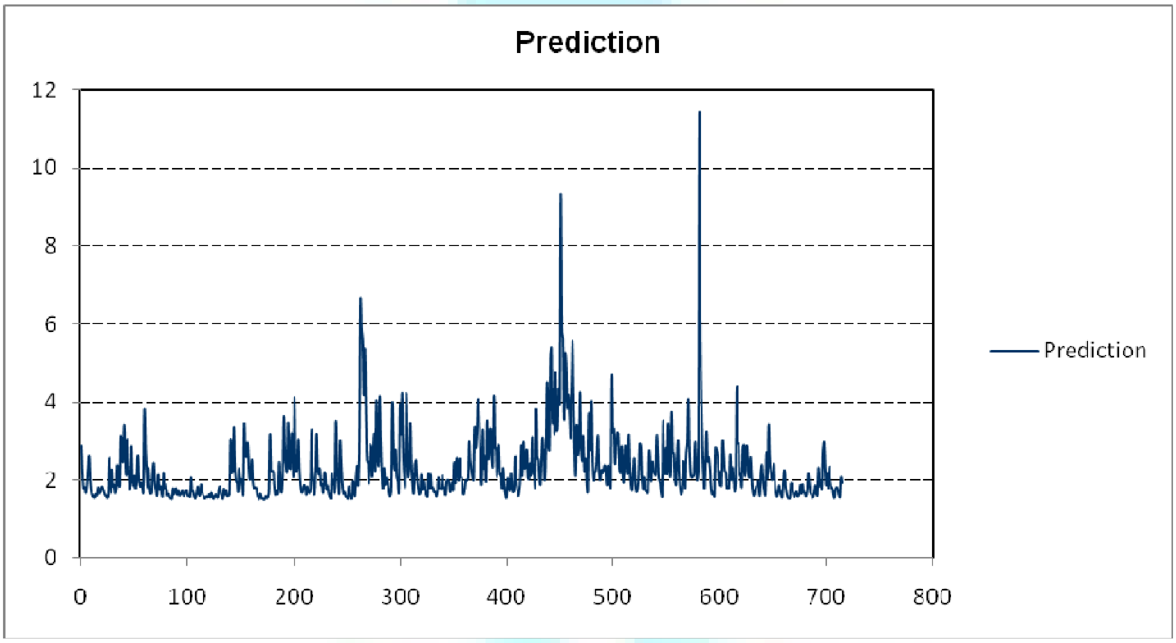
95 percentile value at risk, where Z(0.05) = -1.64485 , For 99 percentile VaR Z(0.01) = -2.32635

VAR=$|\mu_P - z\sigma|$ V

Using these percentile value calculate the 95 percentile and 99 percentile VaR of the index portfolio and than 10 Days-VaR for the same 10 Days-VaR= SQRT

(10)*Daily VaR



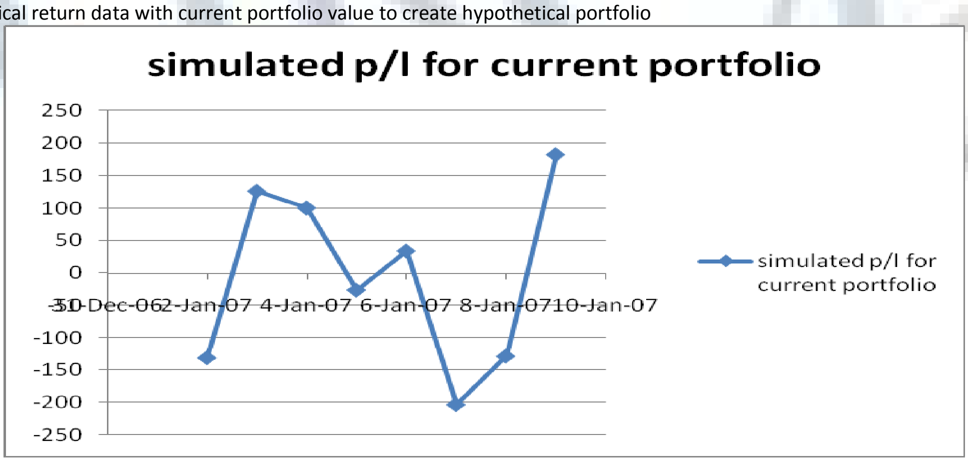


C- Historical simulation VaR Method-

1. Historical simulation method includes following Steps-
2. Define current portfolio value=1000000
3. Confidence level- 95% for internal purpose And 99% for credit rating and reporting purpose
4. Forecast horizon is 10 days so we will calculate 10 day- VaR

10 Days-VaR= SQRT (10)*Daily VaR

5. Historical Observation Period-I am taking S&P CNX Nifty data from 1 Jan 2007 to 30 Nov 2009
6. Calculating daily return data
7. Multiply this historical return data with current portfolio value to create hypothetical portfolio

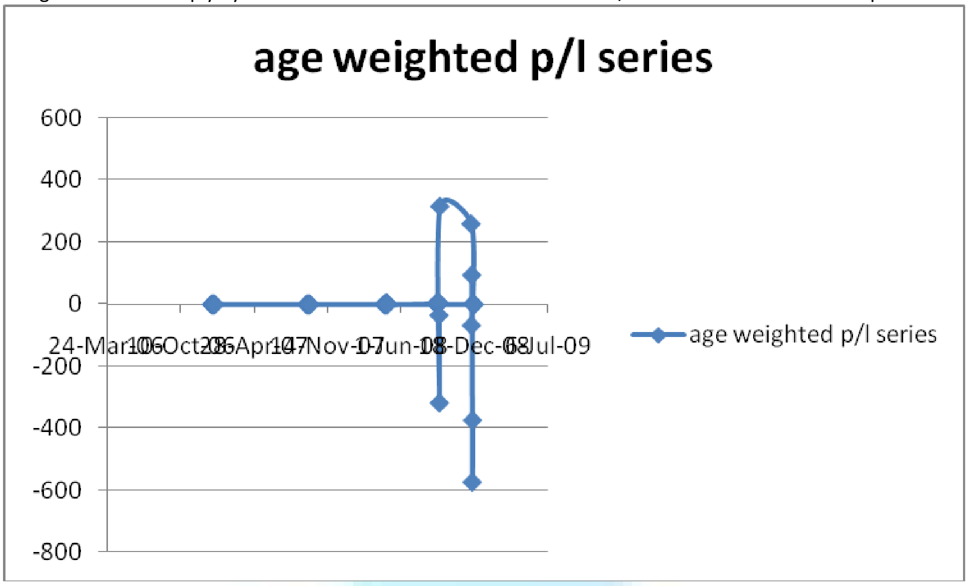


8. Arrange this in descending order and plotting histogram of this data
9. Calculate 95th and 99th percentile values using hypothetical return data.

D- Age-Weighted (BRW) Historical Simulation -

This method, also referred to as hybrid Historical simulation, is a combination of simple HS and EWMA. The steps for computing BRW HS VaR are as follows:

1. Give least weight to the oldest return and increase weights for more recent ones. Value taken for weight factor is 0.97.
2. Sort returns in ascending order and multiply by current market value to obtain simulated P/L for all return data and the portfolio.



3. The simulated loss corresponding to a cumulative weight of *x%* is the *(100-x) %* VaR. Linear interpolation might be used to find this number.
4. All other steps are like Historical Simulation Method.

E- Monte Carlo Simulation Method-

Computing VaR with Monte Carlo Simulations follows a similar algorithm to the one we used for Historical Simulations in our previous issue. The main difference lies in the first step of the algorithm – instead of picking up a return (or a price) in the historical series of the asset and assuming that this return (or price) can re-occur in the next time interval, we generate a random number that will be used to estimate the return (or price) of the asset at the end of the analysis horizon.

Monte Carlo Simulation incorporated following steps-

Step 1 - Take the length T of the analysis horizon 3 year and divide it equally into a large number N of small time increments Δt (i.e. Δt = T/N) as I am calculating 1 day VaR so Δt is 1 day.

For illustration, I am computing a daily VaR consisting of one trading day. Therefore N = 1 days and Δt = 1 day. The main guideline here is to ensure that Δt is large enough to approximate the continuous pricing we find in the financial markets. This process is called discretization, whereby we approximate a continuous phenomenon by a large number of discrete intervals.

Step 2 – Drawing a random number from a random number generator and updating the index value at the end of the first time increment.

It is possible to generate random returns or prices. In most cases, the generator of random numbers will follow a specific theoretical distribution. This may be a weakness of the Monte Carlo Simulations compared to Historical Simulations, which uses the empirical distribution. When simulating random numbers, we generally use the normal distribution.

In this study, I use the standard stock price model to simulate the path of an index return as defined by:

$$R_i = (S_{i+1} - S_i) / S_i = \mu\, \delta t + \sigma\, \phi\, \delta t^{1/2} \quad (1)$$

Where

- R_i is the return of the index on the ith day
- S_i is the index value on the ith day
- S_{i+1} is the index value on the i+1th day
- μ is the sample mean of the index number
- δt is the timestamp
- σ is the sample volatility (standard deviation) of the stock index
- ϕ is a random number generated from a normal distribution

At the end of this step/day (δt = 1 day), we have drawn a random number and determined S_{i+1} by applying (1) since all other parameters can be determined or estimated.

Step 3 – Repeat Step 2 until reaching the end of the analysis horizon T (3 years) by walking along the N time intervals.

At the next step/day (δt = 2), we draw another random number and apply (1) to determine S_{i+2} from S_{i+1}. We repeat this procedure until we reach T and can determine S_{i+T}. In this case, S_{i+n} represent the estimated (terminal) index value in three year of the sample.

Step 4 – Calculate the terminal index return for all the simulated paths.

Now as I have the daily index values for the given time period, we can calculate the index return by using continuous return formula as following.

Index return, **Ri = ln (Si/Si-1)**

Step 5 – Repeat Steps 2,3 and 4 for a large number M(1000) of times to generate 1000 different paths for the index over T.

Initially, I have generated one path for this index (from i to i+n). Running Monte Carlo Simulations means that we build a large number M of paths to take account of a broader universe of possible ways the index value can take over a period of three year from its current value (S_i) to an estimated terminal price S_{i+T}. Indeed, there is no unique way for the index to go from S_i to S_{i+T}. Moreover, S_{i+T} is only one possible terminal value for the index amongst an infinity. Indeed, for a index value being defined on $\Re+$ (a set of positive numbers), there is an infinity of possible paths from S_i to S_{i+T}.

It is an industry standard to run at least 10,000 simulations even if 1,000 simulations provide an efficient estimator of the terminal price of most assets. In this study, I ran 1,000 simulations for illustration purposes.

Step 6 – Rank the M terminal index return from the smallest to the largest, read the simulated value in this series that corresponds to the desired (1-α)% confidence level (95% or 99% in our case) and deduce the relevant VaR, which is the difference between S_i and the αth lowest terminal stock price.

As we want the VaR with a 95% and 99% confidence interval. In order to obtain it, I will need first to rank the M terminal stock prices from the lowest to the highest. Then we read the 1% and 5% lowest percentile in this series. This estimated terminal price, $S_{i+T}^{1\%}$ means that there is a 1% chance that the current stock price Si could fall to $S_{i+T}^{1\%}$ or less over the period in consideration and under normal market conditions. If $S_{i+T}^{1\%}$ is smaller than S_i (which is the case most of the time), then S_i - $S_{i+T}^{1\%}$ will corresponds to a loss. This loss represents the VaR with a 99% confidence interval.

F- Back Testing Method-Regression Analysis

For conducting back testing of VaR methods we are using regression analysis on each VaR method by taking CV (coefficient of variation) as the independent variable and VaR measure as the dependent variable.

Back testing is consist of following steps-

In order to conduct regression analysis between VaR and CV we need series of value for these two variables. As we have 720 return data of index. We will divide this data series into 48 overlapping return data series of 250 return data.

Now we will calculate the Coefficient of variation and Value at Risk for each of the data series. First we calculate Analytical VaR, Monte Carlo VaR, and Historical VaR for each data set by applying techniques discussed above.

As now we have VaR data for each of the method, now we will calculate CV (coefficient of variation) for each dataset using following formula.

$$\text{Coefficient of Variation} = \frac{\text{Standard Deviation}}{\text{Expected Return}}$$

Now we will apply the regression analysis on the given 48 data series which will consist of following steps-

Step 1 – Applying Regression Analysis on VaR calculated by each of the method.

1.1 – Regression Analysis of 99 percentile VaR calculated by Variance-Covariance Method-

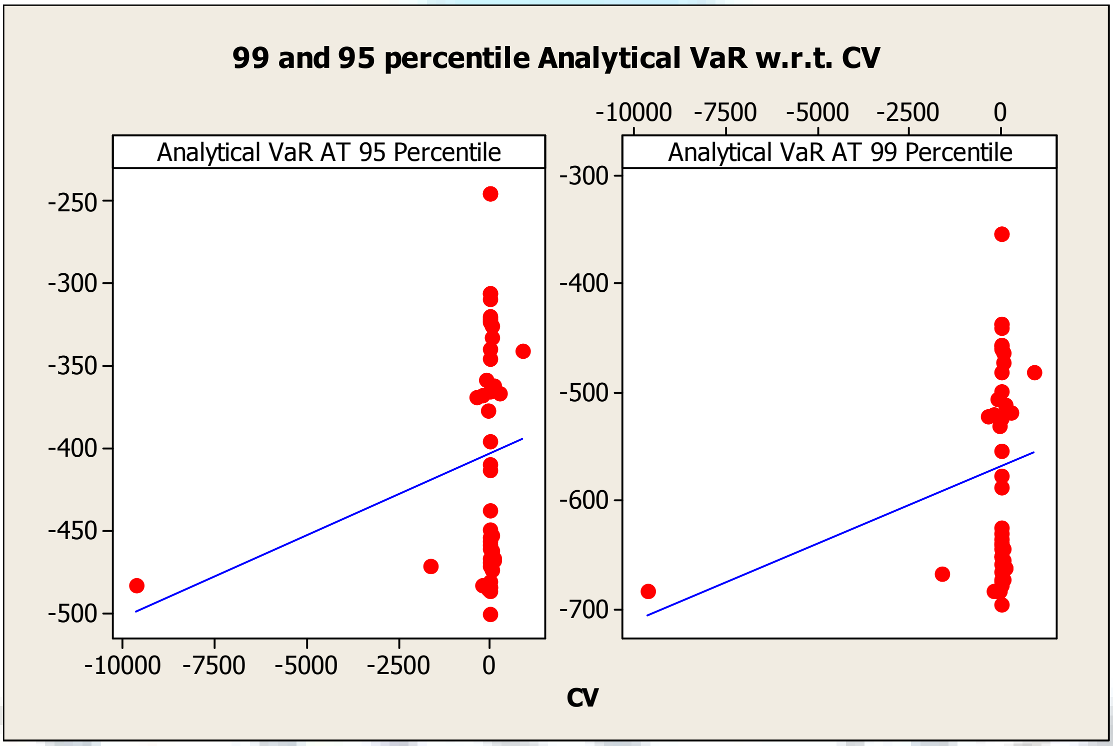
The regression equation is

Analytical VaR AT 99 Percentile = - 569 + 0.0142 CV

REGRESSION ANALYSIS OF ANALYTICAL VAR AT 99% CONFIDENCE LEVEL

Predictor	regression Coefficient	SE Coefficient	T value	P value
Constant	-569.01	14.36	-39.62	0.000
CV	0.06424	0.01010	1.41	0.0165

S = 98.2846 R-Sq = 40.1%



1.2 – Regression Analysis of 95 percentile VaR calculated by Analytical VaR Method-

The regression equation is Analytical VaR AT 95 Percentile = - 403 + 0.0100 CV

REGRESSION ANALYSIS OF ANALYTICAL VAR AT 95% CONFIDENCE LEVEL

Predictor	regression Coefficient	SE Coefficient	T value	P value
Constant	-403.17	10.59	-38.06	0.000
CV	0.010013	0.007447	1.34	0.0185

S = 72.4981 R-Sq = 30.8%

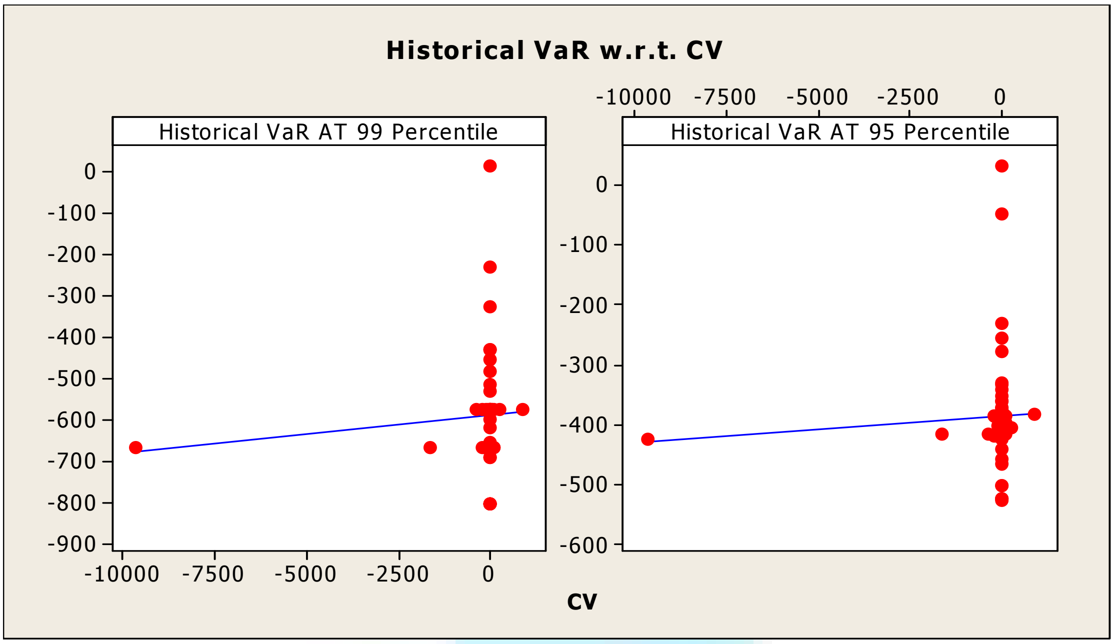
1.3 – Regression Analysis of 99 percentile VaR calculated by Historical Simulation Method-

The regression equation is Historical VaR AT 99 Percentile = - 590 + 0.0090 CV

REGRESSION ANALYSIS OF HISTORICAL VAR AT 99% CONFIDENCE LEVEL

Predictor	regression Coefficient	SE Coefficient	T value	P value
Constant	-590.22	20.92	-28.22	0.000
CV	0.0895	0.01470	0.61	0.0546

S = 143.133 R-Sq = 28%



1.4 – Regression Analysis of 95 percentile VaR calculated by Historical Simulation Method-
The regression equation is Historical VaR AT 95 Percentile = - 385 + 0.0046 CV

REGRESSION ANALYSIS OF HISTORICAL VAR AT 95% CONFIDENCE LEVEL

Predictor	regression Coefficient	SE Coefficient	T value	P value
Constant	-385.18	14.99	-25.69	0.000
CV	0.0456	0.01054	0.43	0.0667

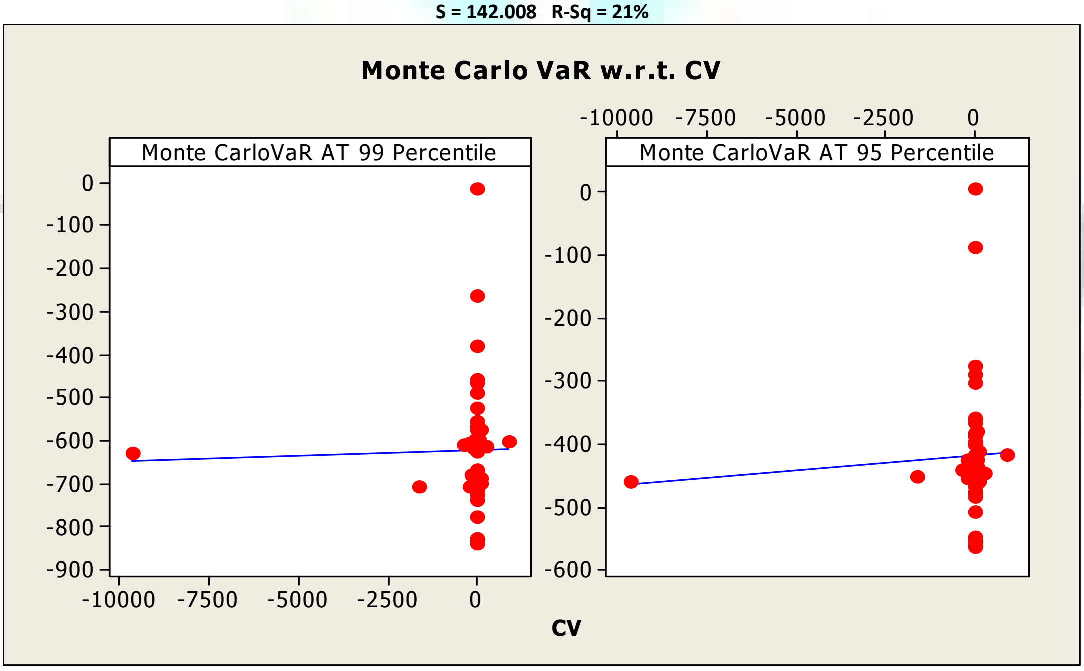
S = 102.593 R-Sq = 16%

1.5 – Regression Analysis of 99 percentile VaR calculated by Monte-Carlo Simulation Method-
The regression equation is Monte Carlo VaR AT 99 Percentile = - 622 + 0.0025 CV

REGRESSION ANALYSIS OF MONTE CARLO VAR AT 99 % CONFIDENCE LEVEL

Predictor	regression Coefficient	SE Coefficient	T value	P value
Constant	-622.40	20.75	-29.99	0.000
CV	0.0255	0.01459	0.17	0.0862

S = 142.008 R-Sq = 21%



1.6 – Regression Analysis of 95 percentile VaR calculated by Monte-Carlo Simulation Method-

The regression equation is Monte Carlo VaR AT 95 Percentile = - 418 + 0.0049 CV

REGRESSION ANALYSIS OF MONTE CARLO VAR AT 95 % CONFIDENCE LEVEL

Predictor	regression Coefficient	SE Coefficient	T value	P value
Constant	-418.48	15.26	-27.42	0.000
CV	0.0489	0.01073	0.46	0.0651

S = 104.442 R-Sq = 14%

RESULT AND ANALYSIS

We begin the analysis with VaR Calculation. First, we compute VaR using variance-Covariance method. Next, we apply Historical simulation and Monte Carlo method and estimate the VaR once again. The results are summarized in the following tables.

VALUE AT RISK BY DIFFERENT METHODS

Variance-Covariance method		
Confidence Interval	VaR at given percentile	10 Days VaR
95%	-370.0422	-1170.176
99%	-524.871	-1659.79

Advanced Variance-Covariance method using GARCH Volatility Estimate		
Confidence Interval	VaR at given percentile	10 Days VaR
95%	-372.8808	-1179.153
99%	-528.8863	-1672.485

Historical Simulation method		
Confidence Interval	VaR at given percentile	10 Days VaR
95%	-363.296	-1148.84
99%	-602.237	-1904.44

Age-Weighted Historical Simulation method		
Confidence Interval	VaR at given percentile	10 Days VaR
95%	-366.8529	-1184.9163
99%	-677.63	-1961.715

Monte Carlo Simulation method		
Confidence Interval	VaR at given percentile	10 Days VaR
95%	-370.583	-1190.356
99%	-682.9273	-1994.745

After calculating VaR by these three methods next we performed Back Testing. In this we applied regression analysis on these VaR with CV (coefficient of variation). In doing so first we make 48 subsets of data and calculated CV and VaR for these datasets. After that we apply regression analysis on this data.

REGRESSION ANALYSIS OUTPUT

	Historical VaR AT 99 Percentile	Historical VaR AT 95 Percentile	Analytical VaR AT 99 Percentile	Analytical VaR AT 95 Percentile	Monte Carlo VaR AT 99 Percentile	Monte Carlo VaR AT 95 Percentile
regression Coefficient	0.0895	0.0456	0.06424	0.010013	0.0255	0.0489
R-square	28 %	16%	40.1 %	30.8 %	21 %	14 %

COMPARING THE RESULT OF REGRESSION ANALYSIS OF DIFFERENT VAR METHOD

As now we have regression coefficient and R-square of coefficient of variation and VaR calculated by each of the method. The closer its R squared value is to one, the greater the ability of that model to predict a trend. We will compare these values and find out which is the most accurate, most efficient and most suitable method for calculating the VaR of given Index. Values of R^2 outside the range 0 to 1 can occur where it is used to measure the agreement between observed and modeled values and where the "modeled" values are not obtained by linear regression.

As we can see from the table, R-square values are given; R-square for variance covariance VaR is higher than other which indicates that Variance Covariance VaR is the best predictor of risk. R^2 is often interpreted as the proportion of response variation "explained" by the repressors in the model. Thus, $R^2 = 1$ indicates that the fitted model explains all variability in *y*, while $R^2 = 0$ indicates no 'linear' relationship Higher R-square indicates higher sensitivity of that parameter w.r.t. independent variable which in this case is CV (coefficient of variation). R-square for Variance Covariance VaR is more close to one which means it is best among all VaR measures. Monte Carlo is least, which signify that Monte Carlo is not appropriate for calculating VaR of the given equity index.

CONCLUSION

The outcome of this study shows that Variance Covariance VaR method is best suitable method for given equity index. Result generated by this method is in line with Coefficient of variation in comparison to other method.

In this study I have taken Equity index portfolio which consists of linear components so this is basically a linear portfolio. So we can conclude that Variance Covariance is the best fit method for linear portfolios.

Historical simulation failed to generate the desired result because of its dependency on past data. By seeing our result we can say that in Index portfolio dependency on past data is very poor and risk is independent of past data up to an extend.

Monte Carlo is very complex method. It consists of so much simulation part and is very much calculation oriented and very much complex. In this study this method has derived least significant result which indicates that Monte Carlo is not suitable for linear portfolio like equity index. It is well suited for non-linear complex portfolios.

So finally we can say that Analytical VaR method is the best method for calculating VaR of an equity index.

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