Value at Risk (VaR): A new technique using Multilevel Monte Carlo Simulation for a derivative portfolio

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This paper will try to look into the two important methods for the calculation of Value at Risk (VaR) for non linear portfolio using Monte Carlo Simulation method. The two techniques - Closed form VaR and Multilevel Monte Carlo VaR for valuing the derivative portfolio are explained in details. In case of multilevel Monte Carlo simulation, it has been found that with decrease in the number of inner Monte Carlo simulation, VaR values changes only little. The two methods viz. closed form method and the Multilevel Monte Carlo method is compared with the result of the closed form VaR (taken as reference VaR). It has been concluded that when closed form formula is not available for the valuation of a derivative, then multilevel method VaR can be preferred over the closed form method VaR, the former being more efficient in terms of accuracy and computational time.

1. Introduction

A firm needs to have an idea of the losses it may face under sudden and extreme developments. Some of the events which may lead to these types of cases are - sudden breakdown of normality such as the defaulting on loans by a large country, a war leading to a breakdown in the supply of essential commodities, or a natural calamity. In other cases, the normal relationships continue to hold but chance leading to a clustering of adverse events still exists. The continuously growing level of sophistication of financial engineering has challenged risk systems - this is one of the causes of the sub-prime crisis - which can be demonstrated by the frequent rogue trading cases, the recent one at UBS (2011, loss of US$ 2mn) and at Morgan Stanley (2008, loss of 9mn US$). In order to guarantee the appropriate management of activities, risk managers need to remain independent from the daily conduct of the business, possess the highest degree of integrity and empowerment within the organisation, and rely on robust and validated risk systems. JP Morgan, Investment and analytics consulting article (March 2009) says a robust risk management framework is based on five essential components: a) a strong corporate governance that diffuses a positive risk culture from the top to the bottom of the organisation, b) a coherent and exhaustive set of policies and procedures, c) the technological capability to extract data about the organization’s Performance and the risk of its uncertain environment, d) know-how in measuring

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this uncertainty, e) ability to monitor risk on an ongoing basis in order to optimise the risk taking process.

Risk management teams have historically calculated various risk measures, such as the size of open positions, the degree of maturity mismatch in the net position, the exposures of every single asset, the volatilities of those assets, and so on. These measures are very diverse and seem difficult not only to implement since the market is constantly evolving, but also to enforce within a multi-layered and multi-location organisation.

2. Literature Review

Value at Risk or VaR, as a tool, has been globally accepted as the risk measure for internal risk management. Basel II accord of 2004 provided a framework based on VaR to regulate how much capital a bank should set aside for use on a bad day. Technically, VaR of a portfolio which is stated as “n-day P percent VaR is V” means that the loss over the next n days will be less than or equal to V with probability of P percent. For more than 18 years, a risk statistic called Value-at-Risk has arisen as a powerful tool to capture with a single estimate the complexity of an organization’s portfolio because of its ease to use and to implement across the board (though this apparent simplicity can be misleading at times since VaR is only valid within the set of assumptions that has surrounded its computation). We have greeks which give local description of risk arising from various fluctuations, VaR attempts to give (or estimate) global summary by measuring the possible loss under extreme circumstances. It has to be noted that VaR does not cover the most extreme circumstances. For that, Expected shortfall (Conditional VaR) and other measures are to be used.

Value-at-Risk (or VaR) calculates the worst expected loss over a given horizon at a given confidence level under normal market conditions. It provides a single number summarising the organization’s exposure to market risk and the likelihood of an unfavorable move. VaR provides a predictive tool to prevent portfolio managers from exceeding risk tolerances that have been developed in the portfolio policies. It can be measured at the portfolio, sector, asset class, and security level. Multiple VaR methodologies are available and each has its own benefits and drawbacks. The three main methodologies for measuring VaR are Parametric (also called Analytical), Historical Simulations, and Monte Carlo Simulations.

Analytical VaR is the simplest methodology to compute VaR and is rather easy to implement for a fund. The input data is rather limited, and since there are no simulations involved, the computation time is minimal. Its simplicity is also its main drawback. First, Analytical VaR assumes not only that the historical returns follow a normal distribution, but also that the changes in price of the assets included in the portfolio follow a normal distribution. And this very rarely survives the test of reality. Second, Analytical VaR does not cope very well with securities that have a non-linear payoff distribution like options or mortgage-backed securities. Finally, if our historical series exhibits heavy tails, then computing Analytical VaR using a normal distribution will underestimate VaR at high confidence levels and overestimate VaR at low confidence levels.
Here I will be considering the third main methodology to calculate VaR i.e. using Monte Carlo Simulation method. Their advantage is they are capable of producing very accurate estimates of value-at-risk, however, these methods are not analytically tractable, and they are very time and computer intensive.

3. Methods of measuring Value at Risk: Monte Carlo simulation Method

Value at Risk prominence has grown because of its simplicity. It helps the firm to measure the risk of an individual instrument, or the risk of an entire portfolio. Value at risk measures is also potentially useful for the short-term management of the firm’s risk. For example, if VAR figures are available on a timely basis, then a firm can increase its risk if VAR is too low, or decrease its risk if VAR is too high. As already discussed above, there are different ways to measure VaR but all them has their own pros and cons.

Given the advantage of Monte Carlo simulation method of giving accurate estimates of VaR especially in the case of non linear portfolio, this method will be explored. It is the most complex methodology to compute VaR of a portfolio of financial instruments employing Monte Carlo simulations. Monte Carlo Simulations corresponds to generating random numbers which are used to compute a formula that does not have a closed (or analytical) form. Drawing random numbers over a large number of times (a few hundred to even millions depending on the problem in question) will give a good indication of the formula.

Monte Carlo simulation generates different scenarios for the possible portfolio value at some later time t. The number of possible scenarios depends upon the number of financial assets and instruments in the portfolio. As described earlier, n-day P percent VaR means that with P percent probability, one can say that the loss on the portfolio will not be more than the VaR amount over the next n-day. Similarly, the possible scenarios generated using simulation can be compared with the initial value of the portfolio. The worst (1-P)th percent scenario’s positive difference with the initial portfolio will give the VaR for the next n-day. Generating higher number of scenarios will give more accurate result. The methodology of measuring VaR of a portfolio containing correlated stocks only (linear portfolio i.e. having no options) is described below.

3.1 Methodology

The important thing to get VaR using Monte Carlo simulation is to get large number of portfolio value scenarios for the day on which we want to measure VaR. In this case, only stocks are considered in the portfolio. Stock prices are supposed to follow the standard stock price model, Geometric Brownian motion (GBM) which will be used to generate the simulated values. GBM equation is given by

\[ dS_t = \mu S_t dt + \sigma S_t dz \]

Where \( S_t \) is the stock price on t-th day and \( S_{t+1} \) is the stock price next day. \( \mu \) is the drift term and \( \sigma \) is the volatility term. \( \varepsilon \) is the random term generated which is in \( dz \) (\( = \varepsilon \sqrt{dt} \)).

Length of the analysis horizon, say T, is decided and it is divided into a large
number N of small time increments \( t \) where \( t = T/N \). Then random number is generated which is used as in the above GBM equation. Given drift and volatility, we can find the \( S_{t+1} \) term for \( t=0 \) where \( S_t \) is called the spot price of the stock. Generating random number as many number of times as much the number of simulations is intended and updating the current price, \( S_0 \), by the last \( S_{t+1} \), will give us the simulated stock values.

For correlated assets in the portfolio, correlated random numbers has to be generated. The variance-covariance matrix showing the covariances between any two stocks has to be calculated. It will be used to get the cholesky decomposition matrix, say \( R \). Applying this to a vector of uncorrelated samples, a vector is produced with the covariance properties as the same that is to be modelled. When \( R \) goes matrix multiplication with the normal random number generated, then we get the correlated random number, say \( \text{corrand} \). Now, this \( \text{corrand} \) matrix can be used in getting the simulated stock prices described above using GBM equation. Thus, we can get as many numbers of simulated stock prices for the N steps or the time interval. N should be as large so that the continuity assumption in the GBM can be satisfied. The above process will result in getting the simulated stock prices for the N steps. Nth step is \( dt \) time after \( (N-1) \)th step. The final matrix contains the stock prices at different steps for the number of simulations run. Given the simulated stock prices at different point of time, the scenarios corresponding to a particular step for which \( \text{VaR} \) has to be calculated need to be selected.

The next step is to find the portfolio value for that step which can be calculated by multiplying the vector with the number of shares of each of the stock. Getting the different possible portfolio values for the assets following GBM is the main task to calculate \( \text{VaR} \) using Monte Carlo Simulation.

Sorting (in ascending order) the portfolio values \( (V_t) \) for that particular time will assemble the worst possible values in the top that the portfolio can take. Initial portfolio value \( (V_0) \) need to be calculated to get the idea of loss that the portfolio can make over the next T days. The difference between the initial portfolio value and the portfolio values generated through various scenarios is used to get the idea that how much the portfolio can make a loss. It gives pre-event notion that the portfolio value can decrease by some value over the next T day. If the 5th percent of the sorted portfolio value is lesser than the initial portfolio value \( (V>0) \), then the decrease is termed as the T day \( \text{VaR} \) with 95 (100-5) percent confidence interval.

**Advantages**

If the number of stocks in the portfolio increases then, the Monte Carlo simulation technique can be very time consuming. The benefit of this technique is that they can model instruments with non-linear and path dependent payoff functions, especially complex derivatives. The sorted values that we got give the idea of worst possible values i.e. information on extreme events. Also, any possible distribution can be used to get the \( \text{VaR} \) as far as we can take care of the fact that assumed distribution is indeed applicable.
Disadvantages

The first and foremost disadvantage of the Monte Carlo VaR calculation is the time it takes to give the final result and hence, the computer power it requires to run the various simulations. Let's say if we have a portfolio of 500 assets and want to run 10,000 simulations (which still is a poor choice) then, we need to run 5 million simulations which is very time consuming and require huge computer power. This drawback intensify when derivatives comes into picture in the portfolio. Also, the large number of simulations can lead to increase in the model risk.

But the VaR calculation using Monte Carlo simulation has become popular in the industry owing to the accurate estimate of the losses that it gives. The advantages overcome the disadvantages and now the remaining.

4. Closed Form Method VAR

Now, let's consider option too in the portfolio which makes the valuation of the portfolio little complex. The sole aim when VaR is to be calculated is to find the simulated portfolio value for that day for which we want the VaR. Since, derivatives have been added now so, the valuation of the non-linear part of the portfolio will be of main concern. Valuation of the linear part (the part containing stocks only) will be the same as described in the previous section. The important thing that needs to be taken care is that all the underlying assets of the options need to be arranged in the top of the matrix containing the spot prices. Here, valuation of the non-linear part of the portfolio will be discussed through closed form VaR i.e. pricing options through Black Scholes model given by

\[ C = S_0 N(d_1) - K \exp(-rT) N(d_2) \]

Where, \( S_0 \) is the spot price, \( r \) is the risk free rate, \( \sigma \) is the volatility, \( K \) is the exercise price and \( T \) is the time to maturity. \( N \) is the cumulative distribution function of normal distribution. \( C \) and \( P \) are the call and put option price respectively.

The closedForm OptionPricing gives the way to value European options using Black Scholes formula. The first idea is to get the underlying asset of each of the derivatives to know the exact correlated paths. The co-variance matrix to be used in getting the stock paths has to incorporate all the underlying assets of the options in the portfolio. For example, if stock A is not in the portfolio but options written on stock A is in the portfolio then the corresponding stock must be considered in getting the correlated stock paths because any movement in stock prices of A will affect the other stocks and hence, the entire portfolio. Since the underlying asset is not actually in portfolio hence, its weight should be given zero when calculating the portfolio value. Thus, linear part of the portfolio can be valued by this way.

For the non-linear part (containing options), consider the spot prices of all the options \( S_0 \) matrix), the risk free rate of interest \( r \), volatilities \( \sigma \) and time to maturity \( T \). These are the values that is required as input in the closed form formula. The spot prices to be considered for the option pricing should be the same as the correlated stock paths suggested by the Monte Carlo simulation. The reason behind this is that portfolio value to be known should be on the day over
which VaR has to be measured. Hence, the spot prices of the underlying asset should be of that day only. For example, if t-day VaR has to be calculated then option prices to be known are of that day only. The closed form formula to value option on tth day requires stock price of that day, which will be used as the spot price in the closed form formula and given other parameters, options can be valued.

In this way, the non-linear part of the portfolio can be valued by valuing all options using the closed form and using the correlated stock prices generated from Monte Carlo simulation. For each number of simulation run, there will be different stock price of that asset to be used as spot in the Black Scholes formula, and hence it will be a vector with numsim (number of simulation) values for option price for each asset. The non-linear portfolio value can be computed given the number of each option in the portfolio.

Adding the linear and the non-linear part of the portfolio calculated above, we can get portfolio value on any day within the time horizon considered. This will give large no. of simulated portfolio values (equal to the number of simulation run) which need to be sorted so that the possible scenarios can be known i.e. on tth day, the worst to the best values that the portfolio can take. Higher the number of simulation i.e. of the order of 10^5, better will be the result. The next task in line is to calculate the initial portfolio value because this will indicate that the possible value the portfolio is indeed a loss or not. If the worst value of the portfolio on the concerned day is higher than the initial portfolio, then there is no worry for the risk manager and VaR on that day for any confidence interval is 0. If the loss is a positive value, it means that in the extreme events, portfolio value can decrease from its initial value and the difference is the VaR for the tth day. To know the t-day VaR with 95 percent confidence interval, the 5th percent of the sorted value is taken and if this value has decreased from the initial value, then the decrease is the loss and is the 95 percent t-day VaR. This is the loss that the rm can face over the next t days and hence, risk manager should keep aside this much amount. This is the way how closed form VaR can be calculated. In short, Non-linear part of portfolio.
5. Multilevel Monte Carlo VaR

In this technique, the linear part of the portfolio is to be valued as in the same way as in the previous cases. One thing that has to be taken care is that all the underlying stocks (of the options in the portfolio) has to be included in getting the stock paths whether stock is in the portfolio or not. This takes care of the possible correlation effect in the stock prices and will give the correct prices to be used as spot in valuing the options. The term "multilevel" Monte Carlo here signifies the different level of simulation used. The first level Monte Carlo simulation (also called outer Monte Carlo simulation) is used to get the simulated stock prices for the different point of time in the time horizon and the second level Monte Carlo simulation (also called inner Monte) is used to get the option prices.

The correlated stock prices found through simulation in the previous section is essentially the outer Monte Carlo simulation which gives the different simulated values of the linear part of the portfolio. Here, the inner Monte Carlo simulation leading to the valuation of derivatives in the portfolio will be covered. As already discussed that if t-day VaR of a portfolio has to be calculated using Monte Carlo simulation method, then different scenarios of the portfolio value on the t\textsuperscript{th} day is required. Inner Monte Carlo is used to value the non-linear part of the portfolio on t\textsuperscript{th} day. It means the options in the portfolio will be priced on t\textsuperscript{th} day using Monte Carlo simulation method.

The disadvantage that this method has is the long time it takes to give the result. Increasing the number of inner Monte Carlo simulation as well as the number of outer Monte Carlo simulation increases the time and for 3 stocks and 2 options, and for the number of inner and outer simulation being 10,000 and 20,000 takes around 8 hours to give the VaR result.

4.1 Inner Monte Carlo Simulation

The correlated stock prices generated through outer Monte Carlo simulation has to be stored and t\textsuperscript{th} time prices (equal to number of simulation run) of the corresponding underlying stocks need to be considered as the spot price for the options. The other parameters requiring attention are the remaining time to maturity (which will be equal to the original time to maturity, minus the current day i.e. t-day here), the number of times stock prices are generated for a particular simulation (equal to the original number of times minus the time passed). Rest of the parameters will remain the same throughout the life of the options. File n shows that how an option can be valued using Monte Carlo simulation method.
6. A Numerical Example

Here, numerical examples are discussed on the various methods described above. The coding for the different methods was written in MATLAB of which the name and their description can be found in the appendix. These examples will clarify clearly on the various steps that have been described above. Examples are taken in which rest subsection deals with Monte Carlo simulation method VaR will be calculated where portfolio is purely linear i.e. no derivatives in it. In the second subsection, a complex portfolio will be taken and the two techniques described above will be used to solve the VaR calculation.

It takes spot price values generated from the outer Monte Carlo and other required parameters already defined in the geometric Brownian motion equation. So, for all the simulated spot prices \(S_t\), the option prices can be calculated and stored in a matrix form. In other words, non-linear part of the portfolio is valued by using Monte Carlo simulation technique. Now, the same thing as described in the earlier section can be done to get the total portfolio value by adding the linear part to the corresponding non-linear part of the portfolio to get the large number of scenarios (or the portfolio values). Sorting will give the worst values that the portfolio can take over the next \(t\) days. Initial portfolio value need to be known so that loss (if any) can be found. With the given confidence interval, VaR can be calculated for the non-linear portfolio.
Monte Carlo Simulation VaR of portfolio containing Correlated Stocks only

File corstock deals with the calculation of VaR of the portfolio which contains (correlated) stocks only. This section corresponds to the methodology described in the section 2 of the report.

Let’s take a portfolio containing 2 correlated stocks, A and B, with a correlation coefficient of 0.4. Stock A and B have spot price of Rs. 100 and Rs. 110 respectively. The volatilities of stock A and B are 0.6 and 0.8 respectively with drift of 5 percent for both the stocks. The number of shares of stock A in the portfolio is 50 and for the stock B it is 100. The problem is to calculate the 1-day VaR with 95 percent confidence interval using Monte Carlo Simulation method.

VaR calculation using Monte Carlo Simulation requires large number of simulated portfolio values on the given day on which VaR has to be calculated. Here, large number of simulated portfolio values is required on next day (1 day VaR). For portfolio values we need simulated stock prices next day and its product value with the number of shares gives us the portfolio value. Now, for the correlated assets in the portfolio, simulation requires use of correlated random to be used in the formula of geometric Brownian motion (GBM) equation. So, for this purpose cholesky decomposition matrix will be used on the variance-covariance matrix. The matrix when multiplied with the uncorrelated random numbers captures the correlation effect of the two stocks and it can be used as the term in the equation. Generating random numbers as high as the number of simulation say 100000 simulations, then 2 by 252 no. of correlated random number is required for 100000 times. Using GBM equation where all other parameter values are provided, stock prices can then be simulated and can be stored in a matrix. The rest column of the matrix gives the measure of the simulated price on 1st day, the value of interest. The rest row corresponds to stock A and second row gives the stepwise simulated stock price for B. Choose the first column (i.e. day 1 prices) for all the 100000 simulations and multiply this matrix with the number of share matrix, W, [50 100]. This will give us the 100000 portfolio values on day 1.

Sorting this portfolio values from ascending to descending order gives the worst values that the portfolio can take. Now, since VaR is the loss that the portfolio can make, initial portfolio need to be found which is equal to the spot price of the stocks producted with the no. of shares.

Now, the simulated portfolio values need to be subtracted from the initial portfolio that has been calculated above to see if the portfolio will make a loss or not on the next day. If the worst value of the sorted vector containing the simulated portfolio value is greater than the initial portfolio value then, it means that portfolio is not going to make a loss and VaR is equal to 0. The VaR can be looked with confidence interval, so here 95 percent confidence interval means the 5-th percent worst simulated portfolio value need to be selected and the difference of it with the initial portfolio value gives the VaR. Intuitively, it suggests that current portfolio value can decrease by the VaR amount calculated over the next 1 day and hence,
risk manager need to keep this much amount to avoid these type of extreme events. 894.9 is the 1-day VaR value for the portfolio with 95 % confidence interval.

6.2 VaR of Non-linear portfolio using the two methods described above

Here, an example is taken of a complex portfolio containing 3 stocks, A, B and C, and 2 call options 1 and 2. The underlying asset of option 1 is stock A and the underlying asset of option 2 is some other stock, say stock D. Stock D is not in the portfolio. But the catch here is that stock D must be included in valuing the linear part of the portfolio because the movement in stock prices of D will affect the movement of stock price of other assets since there is correlation among the assets.

Spot price of stocks A, B and C are 100, 110 and 200 respectively. The spot price of stock D is Rs. 80 only. The risk free rate of interest is 5% in the risk neutral world. The volatilities of stock A, B, C and D are 0.8, 0.6, 0.5 and 0.7 respectively. The no. of shares of stock A, B and C are 100, 150 and 200 respectively. The no. of options of 1 and 2 are 300 and 350 respectively. Let's calculate 1-day VaR with 95% confidence interval for the portfolio given that the exercise price of the options 1 and 2 are 104 and 83 with expiration time of 1 year.

6.2.1 Closed form VaR

The simulated stock prices next day i.e. on day 1 for stock D and A are available with us with all other parameters required in Black Scholes model for pricing call options. The stock prices of D and A on day 1 (contained in a vector of 20000-by-1 matrix) will be used as spot because non-portfolio value is required on day 1 and hence, the spot price to be used as of that day stock price. File Vectorform OptionPricing is used to get the call option price after 1 day. The change that is required is that on the next day the remaining time to maturity will be (1-1/252) year. Hence, the call option values on day 1 is calculated using black scholes formula and it is multiplied with the number of options in the portfolio to get the non-linear portfolio value. This will be a 20000-by-1 matrix which when added to the linear portfolio value computed earlier will give us the total portfolio value which will be used further to calculate the 1-day VaR with 95% confidence interval. The 1 day VaR is found to be 3720.

6.2.2 Multilevel Monte Carlo VaR

In this case, the simulated stock prices on day 1 for both the underlying stocks (from the outer Monte Carlo paths), A and D, are stored in a 20000-by-2 matrix. Now, for stock A i.e. fixing the column of the matrix and for all rows, the options 1 will be priced using Monte Carlo simulation method. Stock paths (GBM) will be generated using the spot price being the stock price on day 1 for the stock A for all the 20000 cases. The other parameters will change too to make algorithm more efficient like now the number of intervals for which prices are required is 251 times (252-1) because the day 1 price has to be considered as spot and hence, 251 days(1-1/252 year) are left for maturity. Options are valued on day 1 by calculating the present value of the expected payoff that the options can give. Subtracting the last column of the inner Monte Carlo paths generated by exercise price for stock A will give the expected payoff and when discounted by the $e^{\frac{\sigma^2(\Delta t)}{2}}$ term will give the
present value. This will be done for options 2 only where the stock paths for stock D will be simulated again on day 1. The matrix now consist of different possible option prices for the two options 1 and 2. This when multiplied with the no. of options of 1 and 2 gives the non-linear portfolio value which will be 20000 element vectors. This matrix will be added to the linear portfolio value computed earlier will give us the total portfolio which will be used further to calculate the 1-day VaR with 95% confidence interval.

7. Conclusion

In this report, VaR calculation techniques have been discussed for the linear as well as the non-linear portfolio using Monte Carlo simulation method. Monte Carlo simulation is a useful technique for measuring VaR in case when the closed form formula for valuation of the financial instrument is not known. Then, it generates possible values and for a large number of simulation run, a correct estimate of VaR can be known. For a linear portfolio, the main task was to generate the correlated asset paths for a large number of times and then, VaR can be measured in an easy manner.

For a non-linear portfolio which carried options in the portfolio, two methods have been discussed to calculate the VaR. The valuation of linear part of the portfolio was done as described for stocks only portfolio but the two techniques actually pertain to the valuation of options using closed form formula and multilevel Monte Carlo simulation method. The first method closed form VaR has been used as the reference VaR because this method gives the actual valuation of the European options which is indeed in the portfolio taken here. The other two methods have been compared that which one of them can be used when a closed form formula is not available for valuing a derivative.

Multilevel Monte Carlo VaR uses simulation run at two different stages namely, outer Monte Carlo and inner Monte. Outer Monte Carlo simulation’s sole purpose was to generate the correlated asset paths which can be used to value the linear part (stocks only) of the portfolio. The inner Monte Carlo simulation run was used to value the derivatives where the spot price was taken as same as that of what generated in the outer Monte Carlo simulation. Options were valued using the inner simulation run at the desired point of time (the day on which VaR has to be calculated) and then, VaR was measured given the confidence interval. The interesting thing that has been found here is that decreasing the number of inner Monte Carlo simulation run, ceteris paribus, does not affect the VaR value that much, not more than 1% for no. of inner simulation run even lesser than 40!
8. References

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Appendix: Results

1. Positive Correlated Stocks movement: MATLAB output

2. Percentage Error in VaR calculation with respect to closed form VAR
Multilevel 1-day VaR value for 10 different scenarios for the given portfolio

All the MATLAB codes will be shown during the presentation.