



## RISK AT VALUE: PARAMETRIC AND MONTE CARLO SIMULATION

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**ABSTRACT** The three main Value at Risk methodologies are historical, parametric and Monte Carlo Simulation. Cheung & Powell using a step-by-step teaching study, showed how a nonparametric historical VaR model could be constructed using Excel, thus benefitting teachers and researchers by providing them with a readily useable teaching study and an inexpensive and flexible VaR modelling option. This article extends that work by demonstrating how parametric and Monte Carlo Simulation VaR models can also be constructed in Excel, thus providing a total Excel modelling package encompassing all three VaR methods.

**KEYWORDS :** Value At Risk, Parametric Value At Risk, Monte Carlo Simulation, Finance.

## INTRODUCTION

The major attraction of using a nonparametric approach, as argued by Cheung and Powell is avoiding the misspecification of probability density functions of risk factors in an era of frequent financial disturbance. If trading conditions are deemed to be normal then the VaR calculation can be simplified considerably if the distributions of the risk factors can be assumed to belong to certain parametric families, such as normal or gamma distribution. This leads to the use of the parametric method. Some researchers, especially those with a statistical background, may find the use of the parametric method to derive VaR rather restrictive and over-simplified, preferring instead that the probability distributions of the risk factors are derived empirically. This can be done by Monte Carlo simulation if the mechanisms of changes in the risk factors are known. In this paper, we assume that a stochastic process can model the mechanism of changes in asset returns, thus the asset returns are presented as a probability distribution rather than values. Moreover, we incorporate a self-contained pseudo-random number generator into our Monte Carlo simulation method, which as far as we know is a first in financial modeling using an Excel 2007 spreadsheet.

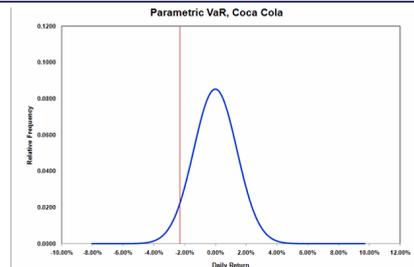
## PARAMETRIC METHOD: SINGLE ASSET

Using the parametric method, the researcher specifies a probability distribution that characterises the likely values of a risk factor. Bachelier used the central limit theorem to derive a normal distribution for share price movements in the Paris Stock Exchange, and discovered that successive changes in share prices are approximately normal. This normality assumption for asset returns has been in place since then. However, in the Black-Scholes model, share prices are assumed log-normally distributed, consistent with continuous compounding.

The crucial step in the parametric method is to obtain the mean and standard deviation of the normal distribution from the historical data series. Once these values are obtained, we can proceed to calculate the 5% VaR return by entering 5% in the first argument of the Excel function *NORMINV* (probability, mean, standard deviation). The 5% VaR value is then calculated by multiplying the exposure by (1 – the absolute value of the 5% VaR return). To plot the parametric VaR diagram, we construct a table with 80 bins for the calculation of the relative frequencies of the normal distribution. In Excel, the probability density function of a normal distribution is calculated by *NORMDIST* (*x*, mean, standard deviation, cumulative) where *x* is the *x*-coordinates showing the daily returns, mean and standard deviation are the parameters of the normal distribution, and cumulative = FALSE for the probability density function. The execution of this procedure is presented as a screenshot

Figure 1 Parametric One-day 5% VaR, Coca Cola

This shows the histogram of Coca Cola returns and the corresponding 5% VaR line using the parametric method. Data is contained in Cell F25:H84 of Table 1 where the *x*-coordinates representing the returns are listed in Cells F23:F83, the absolute frequencies in Cells G23:G83, and the resulting relative frequencies in Cells H23:H83. The insertion of the 5% VaR return line is thoroughly discussed in Cheung and Powell and will not be repeated here.



## MONTE CARLO SIMULATION METHOD: SINGLE ASSET

Monte Carlo simulation relies heavily on probability theory to drive the simulation process. It involves conducting repeated trials of the values of the uncertain input(s) based on some known probability distribution(s) and some known process to produce a probability distribution for the output. That is, each uncertain input or parameter in the problem of interest is assumed to be a random variable with a known probability distribution. The output of the model, after a large number of trials or iterations, is also a probability distribution rather than a numerical value. In the context of VaR, the uncertain input is the one-step-ahead asset returns and the uncertain outputs are the 5% VaR return and value. The process linking the inputs with the output is the geometric Brownian motion process.

## PARAMETRIC METHOD: MULTIPLE ASSET PORTFOLIO

Assume our investor increases their portfolio holdings by purchasing \$1.5 million shares in Bank of America (BoA). The investor now has a portfolio of \$2.5m with \$1m (40%) Coca Cola and \$1.5 million (60%) BoA. When additional assets are introduced into the portfolio, we need to account for correlation and covariance between the assets before calculating the VaR. We use the variance-covariance matrix, which is the approach used by RiskMetrics (J.P. Morgan & Reuters 1996), who introduced VaR. We start with a two asset portfolio. The steps involved are shown in Table 5, and further reading on this approach can be obtained in 2004.

## CONCLUSION

The study, together with the prior work shows how a complete range of VaR models, encompassing all three main VaR methods, can be constructed in Excel. The step-by-step teaching study approach allows teachers, students and researchers to build inexpensive VaR models. These range from simplistic parametric methods suitable for normal trading conditions through to more complex historical and (most complex) Monte Carlo models not dependent on a normal distribution assumption and more suited in times of frequent financial disturbance. The Excel models are highly flexible and easy to change as well as offering a range of modelling techniques such as the real or pseudo random number generators.

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