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Risk Modelling in Healthcare Markets: a Comparative Analysis of three Risk Measurement Approaches

Henry Asante ANTWI[1]
Zhou LULIN[2]
Ethel YIRANBON[3]
James Onuche AYEGBA[4]
Mary-Ann YEBAOH[5]
Emmanuel Osei BONSU[6]

[1,2,3,4]School of Management, Jiangsu University, 301 Xuefu Road, Zhenjiang 212013, Jiangsu, P.R. China, [2]E-mail: ZLL62@126.com (Corresponding author)
[5]Department of Computer Science, Faculty of Applied Science, Kumasi Polytechnic, P.O. Box 854, Kumasi, Ghana
[6]School of Business, Ghana Institute of Public Administration, Accra, Ghana

Abstract *Health care, due to its high upfront costs and centrality to humankind, is often considered 'different' and best left outside the domain of markets. But such blanket opposition ignores valid reasons for not dismissing the value markets could bring. Since its inception in 1948 the NHS in England has gradually evolved (and devolved) into a very different being. No longer is it – in the words of health policy analyst Rudolf Klein the 'secular church', maintained and presided over by disciples of its founder, Aneurin Bevan. In its current state, the NHS functions on the basis of what has been variously called a 'quasi', 'mimic' or 'internal' market with its own risk levels for investors. For risk managers, at the centre of strong risk management is suitable risk metrics that are constructed using complex mathematical models. This study looks at the three approaches and how they apply in computing VaR. For the three techniques, VaR is defined and the main methodologies. Thereafter, the methods are applied, separately, to the data so as to compute VaR. The results is presented and analysed respectively. Next, we discuss the advantages and disadvantages associated with the three approaches. Furthermore, we will discuss the critical yet complex issues involved with the model accuracies and mapping up of positions related to risk factors and model volatility. The report concludes with a brief summary on the issues pertinent to VaR analysis.*

Key words Risk Modelling, Healthcare Markets, Analytical Method, Monte Carlo Simulation, Historical Simulation

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1. Introduction

Health care, due to its high upfront costs and centrality to humankind, is often considered 'different' and best left outside the domain of markets. But such blanket opposition ignores valid reasons for not dismissing the value markets could bring. Since its inception in 1948 the NHS in England has gradually evolved (and devolved) into a very different being. No longer is it – in the words of health policy analyst Rudolf Klein – the 'secular church', maintained and presided over by disciples of its founder, Aneurin Bevan (Barnes, 2013).

In its current state, the NHS functions on the basis of what has been variously called a 'quasi', 'mimic' or 'internal' market with its own risk levels for investors. For risk managers, at the centre of strong risk management is suitable risk metrics that are constructed using complex mathematical models. However, even quantitative approach to risk alone is not enough in defining the nature of risk. One cannot wholly put faith in quantitative risk management. Some of the methods used rely heavily on complicated models that do not add value to risk measurement; some techniques can only be understood and utilised only to the level of expertise of risk managers (Markovich, 2007).

In fact, the so called complex and efficient models did nothing at all to foresee the recent sub-prime crisis that brought the global economy to their knees. Therefore, risk managers who exclusively rely on models expose their companies to the events that shook the whole world. On another perspective, the models may actually be meaningful but there is some level of human error and operational risk in any given organisation. Forecasting and risk models are important metrics but they are a mere representation of financial risk management (Taleb, 1997).

In this study we analyse share prices and returns of UDG Healthcare PLC and Worldwide Healthcare Trust PLC using descriptive statistics, analytic VAR, Monte Carlo VAR and historical analysis/Bootstrap VAR. The report looks at the behaviours of the individual stocks over a period of 5220 days to construct analytic VAR for 260-day. This report aims at analysing, applying and discussing the most widespread models that are used in modern risk management across the industry, Value-at-Risk (VaR). Under normal market conditions, Value at risk is the worst possible loss over a given investment horizon based on a given level of confidence (Einhorn, 2008). VaR can be computed for different types of risks such operational risk, market risk and credit risk among others. Our study mainly focuses on market risk because it is based on stock market prices. Market risk occurs when asset prices are mismatched against each other (or within a portfolio). These assets are usually marked to market based on stochastic price movements and other market parameters. With the complexities in the market, VaR is a single digit that summarises how investors are exposed to market risk and the probability of an unfavourable price movement. Generally, there are three designated approaches to estimation of VaR; parametric (aka analytical method), Monte Carlo simulations and Historical simulations. This study will look at the three approaches and how they apply in computing VaR. For the three techniques, VaR is defined and the main methodologies. Thereafter, the methods are applied, separately, to the data so as to compute VaR. The results will be presented and analysed respectively. Next, we will discuss the advantages and disadvantages associated with the three approaches. Furthermore, we will discuss the critical yet complex issues involved with the model accuracies and mapping up of positions related to risk factors and model volatility. The report will conclude with a brief summary on the issues pertinent to VaR analysis.

2. Materials and Methods

2.1. Data Sample

Prices

This section presents and describes a table of summary statistics for each of the shares individually (UDG Healthcare PLC and Worldwide Healthcare Trust PLC) as well as the returns for the two assets. Thus, we will look at key descriptive statistics such as mean, standard deviation, kurtosis, and skewness to describe the normality or non-normality of the data over the defined period. Computations are performed in excel and the results are presented in table 1.1.

Table 1.1. Descriptive statistics, Prices

	UDG	WHT
Mean	363.62	575.98
Standard Deviation	167.73	205.24
Kurtosis	-0.94	-0.78
Skewness	0.17	-0.62
Range	718.16	818.28
Minimum	51.20	133.33
Maximum	769.36	951.61
Confidence Level (95.0%)	4.55	5.57

Looking at table 1.1 above, the daily mean share price for UDG Healthcare PLC is 363.62, with a standard deviation of 167.73. Thus, on average, UDG Healthcare PLC traded at 363.62 in the period under study. The minimum share price was 51.2p, while the highest price was 769.36p. This shows a great deal of variability in the share price and it is important to look at the shape of the distribution. The distribution for UDG Healthcare PLC stock prices is positively skewed (Skewness = 0.17), given that skewness is between −0.5 and +0.5, the distribution of share prices is approximately symmetric. Kurtosis is -0.94, the distribution's peak is lower and broader than a normal distribution, and the tails are shorter and thinner too. In summary, UDG Healthcare PLC's stock price is not normally distributed for the period under study. This can be visualised in the fig. 1. below. Comparing, UDG Healthcare PLC and Worldwide Healthcare Trust PLC, the later has a higher mean stock price and has a higher standard deviation in daily price. This implies that the Worldwide Healthcare Trust PLC appears to be riskier than UDG Healthcare PLC, in terms of price volatility.

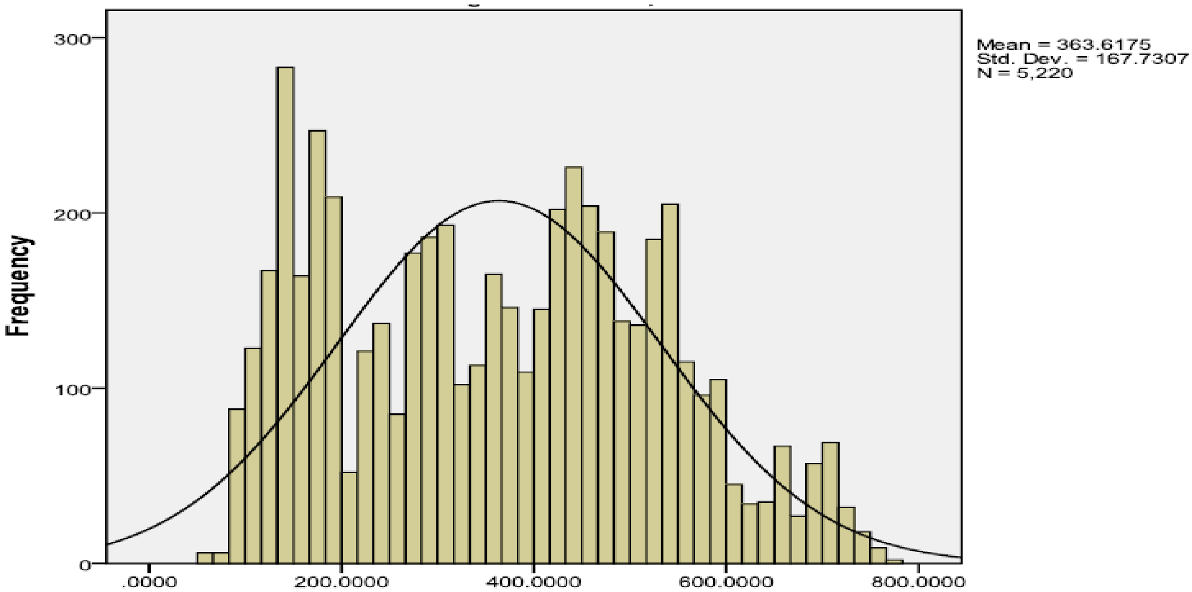

Figure 1. UDG Healthcare PLC Stock Prices

As for Worldwide Healthcare Trust PLC stock prices, mean daily stock price is 575.98p, with a standard deviation of 205.24. The minimum stock price during the analysed period is 133.33, while the maximum stock price is 951.61, giving a range of 818.28. This shows a great variability between the minimum stock price and the maximum. The distribution has a kurtosis of -0.78, implying that the distribution's central peak is lower and broader compared to a normal distribution and its tails are shorter and thinner. The distribution is negatively skewed (skewness =-0.62); the left tail is longer. The data is moderately skewed given that the skewness is between -1 and +1. The distribution of Worldwide Healthcare Trust PLC stock prices is shown in fig. 2 below.

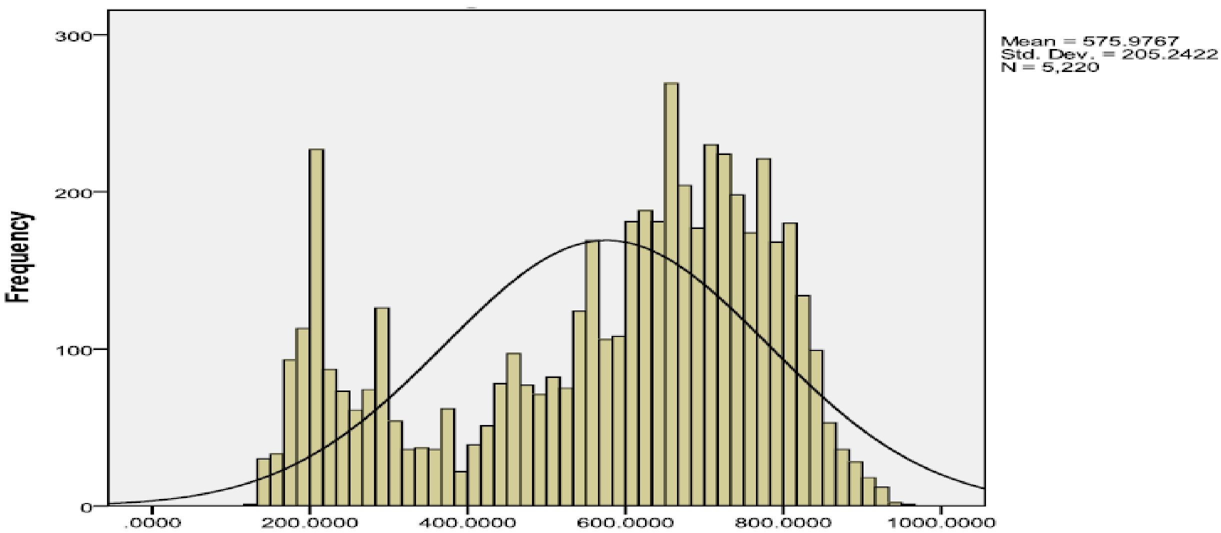

Figure 2. Worldwide Healthcare Trust PLC Stock Prices

Returns

The data shows that the mean daily return on UDG Healthcare PLC's stock is 0.02%, with a standard deviation. Minimum daily return plunged to -28.56%, while a maximum daily return was 54.95%, with a range of 83.52%. Returns are not normally distributed given that the distribution is highly peaked with a kurtosis of 40.45; the distribution is also highly skewed with a skewness of 1.21. Cumulative return for the period under study is 100.43%. The histogram showing the distribution for UDG Healthcare PLC's stock returns is shown in fig. 3 below.

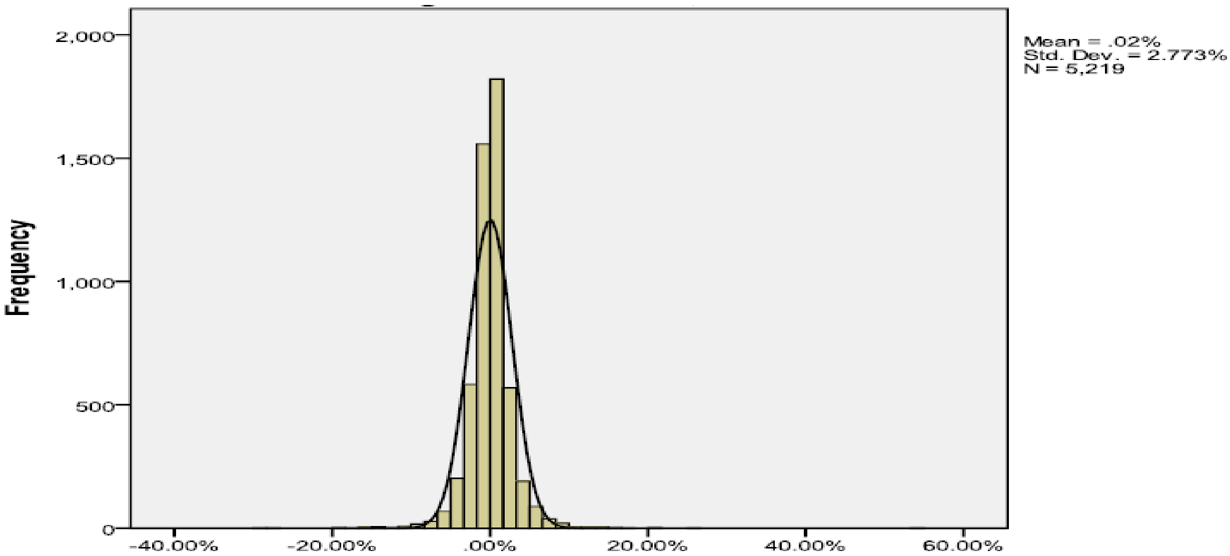

Figure 3. UDG Healthcare PLC's Stock Returns

Table 2. Descriptive statistics, Returns

	UDG Healthcare	*WHT*
Mean	0.02%	0.03%
Standard Deviation	2.77%	1.86%
Kurtosis	40.4470	8.6755
Skewness	1.2160	-0.2228
Range	83.52%	35.22%
Minimum	-28.56%	-20.80%
Maximum	54.95%	14.42%
Sum	100.43%	131.90%

Mean daily return for Worldwide Healthcare Trust PLC's stock is 0.03%, with a standard deviation of 1.86%. At ceteris paribus, we can say that Worldwide Healthcare Trust PLC's stock had a higher return than that of UDG Healthcare PLC and carried lower risk; comparing the standard deviations. The distribution is also excessively peaked, though not as that of UDG Healthcare PLC; kurtosis is 8.68. The distribution is negatively but moderately skewed, skewness = -0.22. Stock returns for Worldwide Healthcare Trust PLC is lower than that of UDG Healthcare PLC, given that the minimum daily stocks return are -20.80%, while the maximum daily stock return is 14.42%, with a range of 35.22%. The cumulative daily stock return is 131.90%, this is higher than that of UDG Healthcare PLC, 100.43%. The above distribution can be visualised in fig-4, a histogram plotted to see the behaviour of the data. The daily mean return on asset is 0.01%, with a standard deviation of 2.35%. The asset does not follow a normal distribution given that the mean data is excessively peaked with a kurtosis of 48.51 and is positively skewed with skewness of 1.49. The minimum daily return on the asset is - 50.12%, while the maximum daily return is 26.39%, with a range of 76.52%. The assets yield a positive return, with slightly lower volatility than that of UDG Healthcare PLC but higher than that of Worldwide Healthcare Trust PLC. The descriptive statistics are summarised in table-3 below, while the distribution can be visualised in fig. 4 below:

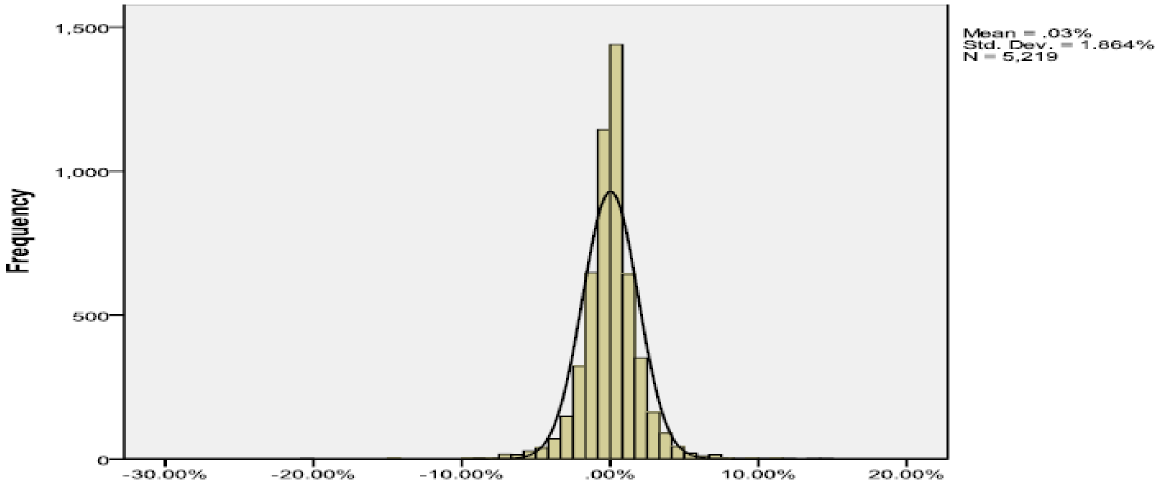

Figure 4. Worldwide Healthcare Trust PLC stock returns

Table 3. Descriptive Statistics, return on Asset

	Asset Return
Mean	0.01%
Standard Deviation	2.35%
Kurtosis	48.51
Skewness	-1.49
Range	76.52%
Minimum	-50.12%
Maximum	26.39%
Sum	31.47%

2.2. Analysis of Data

Analytical VAR

VaR is an ex-ante tool that is used to ensure that risk tolerances on individual assets and portfolios are not exceeded. Analytical VaR (aka Parametric VaR) is based on the assumption that returns follow a normal or lognormal distribution; these are parametric distributions. Analytical VaR is expressed as equation (1) as follows:

$$VAR_{1-\alpha} = -X_\alpha * P \quad (1)$$

Where; VaR11-α is the expected value at risk at the given level of confidence. Xα is the percentile of the left-tail of a normal distribution. This is described using the expected return on the asset/portfolio. Confidence levels of 95% or 99% are normally used to make sense of the estimated VaR. P is the value of the asset or portfolio that is marked-to-market. Using the central limit theorem, equation (1) can be re-written as follows:

(2)

$$VAR_{1-\alpha} = -(\mu + z_\alpha * \sigma) * P \quad (2)$$

Where; VaR11-α is the expected value at risk at the given level of confidence, µ is the expected return on the security or asset, z is the value of the normal distribution, is the expected volatility and P is the holding period. The results of the two stocks (Worldwide Healthcare Trust PLC and UDG Healthcare PLC) are presented below.

Table 4. Analytical VAR

Expected Return on Asset	0.01%
Expected Volatility	2.35%
Holding period	260
Initial value (Mean difference between UDG and Worldwide Healthcare Trust PLC	£3.36
VAR at 95% Confidence Level	£2.10
VAR at 99% Confidence Level	£2.97
Actual Price after 260 days	£3.66

The results show that, if market conditions remain normal, there is a 5% chance that this asset may lose at least £2.10 at the end of the next 260 trading days. Also, under normal market conditions, there is 1% chance that the asset will lose £2.97 at the end of the next 260 trading days.

2.3. Advantages and Disadvantages of Analytical VaR

Analytical VaR is the easiest and most straightforward methodology to compute VaR and simple to implement even to portfolio. The data required for model input is somewhat limited, and given that we do not need to carryout simulations, computation time is significantly reduced. However, it is this simplicity that is the main drawback for this approach. One of the main disadvantages of analytical VaR is that it assumes that historical returns are normally distributed; however, as seen above the returns of the asset are not normally distributed. In addition, the method assumes that the changes in price of the assets used in the computation follow a normal distribution. In the trading world, this is very unlikely to pass the test of reality (Brown, 2007). Another limitation of analytical VAR is that the approach cannot be effectively applied on securities that exhibit a non-linear distribution of payoff, particularly derivatives such as options (Haug, 2007). Finally, given that the returns above have heavy tails; the distribution has a kurtosis that is greater than 3, then the estimated Analytical VaR that is based on the normal distribution undervalues VaR at the higher confidence level (99%) and overestimates VaR at the lower confidence level of 95%.

2.4. Monte Carlo VAR

This section describes the computation for the 260-day Monte Carlo VAR for the returns to the asset, based on the given data. VAR's for 95% and 99% confidence levels are computed. Estimating VAR using Monte Carlo Simulations is closely related to the algorithm used in computing VAR using historical simulations. However, Monte Carlos is different in terms of the first step– instead of using an expected historical price or return, Monte Carlo generates a random number that will is used to estimate the assets price or return at the end of the analysis period (Glasserman, 2004). The following are the main steps involved in Monte Carlo simulation:

Step 1: Setting the analysis horizon, T and dividing T equally into a large number of small time increments Δt (i.e. Δt = T/N).

In this analysis, we compute a 260-day Monte Carlo VaR. Hence, for this particular case N = 260 days and Δt = 1 day. In order to compute daily VaR, we will divide each day per the number of trading hours in one day, the larger the better. The guiding principle is to ensure that Δt is large enough to estimate the continuous pricing that takes place in the trading world. In finance, the process is referred to as discretisation; where a continuous event is approximated using a large number of discrete periods.

Step 2: This step involves generating a random number using excel so as to update the asset price at the first increment.

Spreadsheets such as excel can allow us to generate random prices or returns on an asset or portfolio. The generated random numbers follow a particular distribution; usually, they are normally distributed. This is what may present a weakness of the Monte Carlo methodology as compared to other approaches, particularly historical simulations that make use of empirical distribution. This report simulates the path of the asset price using a standard price model from the *i*th defined as follows:

$$R_i = \frac{P_{i+1} - P_i}{P_i} = \mu \delta t + \sigma \varphi \delta t^{1/2} \quad (3)$$

Where; Ri is the return on the asset on the ith day, Pi+1 is the price of the asset on the i+1th day, Pi is the pric of the asset on the ith day, μ is the expected stock price, δt is the time-step, σ is the standard deviation of the stock price, and ϕ is a generated random number that follows a normal distribution. After completing this step for each day (where δt = 1 day), we will have generated a random number and computed Pi+1 using equation (3) because the other parameters can be estimated.

Step3: In this step, we replicate Step 2 up to the end of the analysis horizon T by moving along N intervals

This involves drawing up of draw another random number and applying equation (3) to estimate Si+2 from Si+1, note that δt = 2. The procedure is repeated until we reach the end of the horizon, T where we will determine Si+T, in this report we will reach Si+260; the terminal stock price.

Step 4: Here we repeat steps 2 and 3 as many times as possible to generate M different paths for the stock over the given time horizon T.

Monte Carlo Simulations involves many iterations to build a large number M of paths that take into consideration of a broader set of possible outcomes of the asset price over the 260 day period from the current value (Pi) to the forecasted terminal price Pi+260. Practically, there is no any exceptional way for the asset to change from Pi to Pi + 260. Furthermore, Pi+260 is practically only one likely terminal among a set if infinite possibilities of the terminal asset price. Without a doubt, defining the asset price using a set of positive numbers yields an infinite family of possible paths spanning Pi to Si+T. This is the main reason why equation (3) is based on the standard asset price model to prevent Monte Carlo Simulations from suffering problems of excessive information loss. In essence, longer analysis horizon and larger number of iterations provide more accurate estimates of the forecasted stock prices. However, longer simulations come at the expense of time taken to run them. In the modelling industry, the norm is to run at least 10,000 simulations so as to provide an efficient estimator of the terminal price of assets.

Step 5: In this step, M terminal asset prices are ranked in the order of magnitude; from the smallest to the largest. The corresponding simulated value to the 95% or 99% is picked and used to determine the appropriate VAR; this is simply the difference between the initial price Pi and the lowest terminal stock price at the given α level.

Results

Assumptions	
Initial asset price (S0)	£3.36
Expected return (m), annual	2.2%
Volatility (s), annual	45%
Each interval in days (t)	1
Value-at-Risk (VAR) @ 95th %	£1.37
Value-at-Risk (VAR) @ 99th %	£1.77
Actual Price After 260 days	£3.66

Therefore, there is a 5% chance that the asset value will fall to £1.09 or below. If this takes place, we will experience a loss of about £1.99 (£3.36-1.37). This loss is the daily VAR estimate at monthly 95%

confidence level. In addition, there is a 1% chance that the value of the asset will fall to £1.77 or below, generating a loss of £1.59.

2.5. Advantages of Monte Carlo Simulation

Monte Carlo Simulations has some advantage over Historical and Analytical Simulations approached to computing VAR. Even though Monte Carlo maybe time consuming, the approach can be applied on assets and securities that do follow a liner path such as exotic derivatives. In addition, Monte Carlo VAR does not suffer problems related to extreme events like historical VAR; hence, the approach provides a comprehensive analysis of these events that are likely to occur beyond VAR (Novak, 2011). Last but not least, Monte Carlo simulation can use any statistical distribution to simulate asset prices or returns based on the analyst's discretion as long as it is justified by underlying assumptions (Nicholas, 2007).

Drawbacks of Monte Carlo Simulations VAR

According to Chiu *et al.,* (2010), the main demerit of Monte Carlo VAR is the time required to run all the simulations, as well as the ability of the computer to run the simulations. Assuming a scenario where we have more about 1,000 assets and, as per the industry, we want to run 10,000 simulations on each asset. This will mean that we will have about 10 million simulations, without considering the eventual simulations that may be necessary to price complex assets such as options and mortgage backed securities. The high numbers of simulations increase model risk. Thus, it would be very costly to develop an engine that effectively runs thousands of Monte Carlo Simulations. Asset managers can overcome this problem by purchasing a commercial solution or outsourcing the project to experienced third parties. The latter solution may be even better given that it enhances independence of the simulations; hence, it may be more reliance and accurate (Choudhry, 2004).

Historical Simulations VAR

The underlying assumption of historical methodology is that past performance of a stock or portfolio is important in predicting the future. In other words, historical VAR assumes that the recent past will repeat itself in the immediate future. It is this assumption that weakens the methodology because the assumption may not apply in volatile markets or during times of financial difficulties; for example, the recent global financial crisis. The algorithm below demonstrates how this method is applied. The method is rather straightforward and easy. Prices of an asset or portfolio are adjusted after every run. This significantly differs from local valuation where one only uses initial asset or portfolio price and how this is exposed to different scenarios to estimate VAR. Historical simulation VAR is described as follows:

Step 1: The first step is to compute asset returns between each time interval

This involves setting up the time interval and computing returns between these intervals. In this report, we compute daily price returns. Given that we have more than 5000 daily returns, we can be confident that the data will provide a meaningful VAR.

Step 2: Applying the computed returns to the current value of the assets

We calculate the daily returns on the asset for the period under study and we assume that the returns will occur in the same way in future. In this report we assume a 260 trading days. It is assumed that these returns will occur in the future with the same likelihood. Thus, we begin by looking at the asset's historical returns and then we apply these returns to the current value of the asset. This yields a new value for the asset. Next, we look back in time based on by an extra interval (two days). The calculated returns are assumed to occur tomorrow at the same probability as historical returns. The asset is re-valued with the new prices iteratively until we reach the beginning of the period. For this report, we will have had 259 simulations.

Step 3: Sorting data of the simulated returns in an ascending order

After applying these changes to the given asset 259 times, this yields 259 simulations for the portfolio prices. Given that the VAR looks at the worst possible loss that can occur over an investment horizon, we sort the prices in an ascending order so as to focus on the on the tail of the distribution.

Step 4: Looking-up for the simulated value for the confidence level

The final step is to set the confidence levels; her we have 95% and 99%. This is the corresponding values in the series of the sorted forecasts of the asset at the given confidence level; finding the VAR at 95% and at 99% confidence levels.

Results

Historical Simulations VaR	
Number of Observations	5219
Initial Value	£ 3.36
VAR @95%	£ 1.55
VAR @99%	-£ 0.13
Actual Price after 260 days	£ 3.66

Historical simulations show that, there is a 5% chance that the value of the asset will fall to £1.55 or below; thereby generating a loss of £1.81(£3.36-£1.55). Also, there is a 1% chance that the value of the asset will increase to 0.13 or above; thereby generating a profit of £3.49 (£3.36+£0.13).

Merits of Historical VAR

Estimating VAR using historical simulation has various merits. One of the advantages is that it does not formulation of any assumption regarding the distribution of returns of an asset or portfolio. Secondly, specifically for portfolios, the method does not need one to compute the standard deviations and correlations between assets in the portfolio. As we have seen in the exercise above, the volatilities are implicitly reflected in the daily asset prices. Thirdly, as long as extreme events and fat tails of the distribution are contained in the time series data, they are captured are captured in the model. Lastly, the use of market wide aggregation is relatively uncomplicated (Allen & Powell, 2009).

Shortfalls of Historical VAR Analysis

The methodology is very intuitive and easy to understand and implement. However, it still has some disadvantages. Firstly, the approach heavily relies on a given historical dataset that carries its own idiosyncrasies. The problem with the market is that it will always have idiosyncrasies; which vary depending on a myriad of factors. For example, if we perform a historical analysis in the bear market, VAR is likely to be overestimated. In the same way, if we perform the analysis in a bull market, the increasing returns may underestimate VAR. Secondly; historical simulation does not take into consideration the changes that take place in the market such as changes in structure, legislation and asset weights in a portfolio, among other factors. A practical example is in the EU market, where historical returns will not factor in the introduction of the Euro in 1999. Thirdly, historical methodology may not be easy to compute when a portfolio is constructed using complex securities or an extremely large number of assets. This problem can be minimised by mapping the assets to the underlying risk factors; this preserves the behaviour of the portfolio. Fourthly, it is not easy to perform sensitivity analysis using the methodology. Lastly, the methodology requires a minimum number of observations to make the VAR reliable.

Bali *et al.,* (2007) argue that using a long estimation period is required because shorter periods may lead to biased results. A rule of the thumb is that data should be of at least four years so as to run 1,000 historical simulations. Furthermore, the assumption that historical simulation captures extreme events becomes irrelevant in the ever changing financial markets. Security prices move with economic cycles; for instance, the markets were highly volatility and prices plunged during the recent global financial crisis. Even the most of sophisticated financial pundits did not see it coming. Therefore, financial analysts must have an economist approach to risk so as to factor in the idiosyncrasies that accompany assets and the market as a whole. Also, it is important to bear in mind the VAR estimates rely on a series of assumptions that make the model stable and consistent over a period of time; the assumptions can be adjusted based on the market situation. Therefore, in order to enhance the accuracy of the historical VAR, it is important to weight on the recent data as well as historical data given that there may be major differences in the prices.

3. Discussions

In this report, we assume the initial value of asset is £3.36, the difference between Worldwide Healthcare Trust PLC stock price and UDG Healthcare PLC's stock price on 22/02/2012. This value is chosen because the last value of the data is £3.66, on 08/11/2012—creating a 260 days difference. The value is chose to compare how the models predict the VAR and the actual stock performance; this is some kind of back testing to see which model is more pessimistic among the three. VaR is a predictive tool that risk managers use to know the risk tolerances of assets, sectors, security and portfolios. As we have seen above, there are multiple methods for estimating VAR, and each approach has its own advantage and disadvantage. From the results, under normal market conditions, analytical approach shows that there is a 5% chance that the asset will lose at least £2.10 at the end of the next 260 trading days, generating a loss of £1.26. Also, there is 1% chance that the asset will lose £2.97 at the end of the next 260 trading days, generating a loss of £0.39. Based on Monte Carlo approach, there is a 5% chance that the asset will fall to £1.09 or below, this can lead to losses of £1.99. In addition, there is a 1% chance that the value of the asset will fall to £1.77 or below, generating a loss of £1.59. The historical method approximates an expected loss of £1.81 at 95% confidence level. However, the asset is likely to be profitable given that is likely to make a profit of £3.49. Comparing the three methods, the Monte Carlo simulation gives the most pessimistic view of losses, while the analytical VaR seems to provide the most pessimistic view of risk among the three methods.

	Expected loss in 260 days	
Method	@ 95 % confidence level	@ 95 % confidence level
Analytical Method	£1.26	£0.39
Monte Carlo Simulation	£1.99	£1.59
Historical Simulation	£1.81	(£3.49)

VaR is an estimate and not a uniquely defined value. In addition, the analysis is based on a 260 trading day period. Moreover, this approach does not take into consideration the possible losses in extreme occasions when losses surpass VaR. using VaR we should bear in mind this limitations. The merits of using VaR are also its weaknesses. VaR methodology is only valid when it is interpreted based on the specified assumptions. These assumptions include the confidence level and the holding period—as in our case, 95% and 99% confidence level and 260 day period. The use of confidence level ensures good interpretation of results because it expresses the accuracy of results. As the confidence level increases, we expect that the VaR estimate to approach the actual value (Bank for International Settlements, 2006).

Furthermore, among the approaches to VaR computation, the most complex approach is Monte Carlo Simulations. The method utilizes a complex algorithm that generates random numbers. Thus, Monte Carlo simulation is not analytical, it is based on some trial and error in picking up occurrences, leading to multiple solutions when excel re-calculates. Thus, the VaR methodology has been rather controversial since its popularity that dates back to 1994. The role of VaR has also come under scrutiny lately, some arguing that it works perfectly when the market is normal but fails adversely in a turbulent market (Einhorn, 2008). The author further argues that VaR focuses on risk management at the center of the distribution, while neglecting the tails, creating an incentive to absorb excess risks that are not likely to occur. Looking back at the recent global financial crisis, VaR was only good to risk professionals, but worsened the crisis by using historical information to suggest that the impending risk was manageable. Indeed, the methodology is often misinterpreted and hazardous when misinterpreted. Another common argument against VaR is that the method is sub-additive (Dowd, 2005). Thus, combining VaR in a portfolio can lead to a higher VaR than the VaR of individual assets.

4. Conclusions

The problem of risk measurement dates back into the old days. The management of risk is a great concern of regulators and financial managers. The study demonstrates that three approaches to VaR calculations can be generated in excel spreadsheets. The modelling package handles a significantly large quantity of observations and output numbers. In conclusion, analytical VAR is straightforward to implement given that it requires simple steps to compute. In the financial industry, Monte Carlo VAR is often used to forecast prices of portfolios, it is the industry norm. The advantages of the approach surpass its weakness by far. Notwithstanding the time and effort spend on estimating VAR for assets and portfolios, the undertaking merely represents a portion of the time that risk manages should invest on VAR. As a matter of fact, risk managers should also invest time on verifying the models used to estimate VAR; particularly their reliability, credibility and relevancy through back testing. Moreover, managers should simulate how the asset or portfolio of assets reacts to extreme events that may occur in the investment horizon-this is what is known as stress testing.

Amid the disadvantages of the historical simulations methodology, a large number of financial institutions use this approach in their analysis. The rationale is that working with empirical returns is the real deal that can get accurate VAR. Nonetheless, the accuracy of any VAR approach depends on back testing and stress testing. VAR is a number that needs to be backed by assumptions and sound methodology and rigorous computations. Hence, VAR can only be beneficial if it properly captures the risk profile of a complex assets and portfolios. VAR is a critical tool that must be continuously reconciled with adequate back testing. This will be important in gaining important insights into the future insights of assets and portfolio and how the model would behave if the asset changes adversely or assets in a portfolio.

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