VALUE AT RISK: HISTORICAL SIMULATION OR MONTE CARLO SIMULATION

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ABSTRACT

Risk measurement provides fundamental support to decision making within the industry. The market risk of a portfolio refers to the chance of financial loss due to the joint movement of systematic economic variables such as interest and exchange rates. Measuring market risk is essential to regulators in evaluating solvency and to risk managers in apportioning limited capital. Value at Risk (VaR) is standard risk measures and reporting tool in current risk management practice. It measures the possible loss on a portfolio for a stated level of confidence if adverse movements in market prices were to occur. The VaR methodologies Historical Simulation and Monte Carlo Simulation are discussed. After analyzing ten stocks on the Ghana Stock Exchange, the Monte Carlo Simulation provides a better VaR estimate than the Historical Simulation.

Keywords: Value at Risk, Historical Simlation, Monte Carlo Simulation, Ghana Stock Exchange

I. INTRODUCTION

Risk, in the financial world is the cost of doing business, the uncertainty of any transaction or activity usually measured in a monetary value [16] or is a measure of the volatility of a portfolio's future value [6]. Banks and other institutions face financial risks during their period of operation. In risk management, risk is categorized into three namely operational risk, credit risk and market risk. Risk management has become a crucial topic for financial institutions, non - financial corporations, regulators and asset managers. It deals with how risk is controlled and balances the chance of gains. Banks and financial institutions utilize a number of highly sophisticated mathematical and statistical techniques to manage market risk. Value at Risk (VaR) developed in 1993 is now a standard and widely accepted measure in managing market risk. The rules of using VaR are well recognized and acknowledged in the short-term risk management practice. VaR is a measure for estimating market risks of a given portfolio. From a financial perspective, VaR is an estimate of how much can be lost from a portfolio over a set time horizon with a specified degree of confidence. The portfolio can be either a single trader's portfolio or the portfolio of the whole bank. VaR is used most often by commercial and investment banks even though it can be used by any entity to measure its risk exposure, to capture the potential loss in value of their traded portfolios from adverse market movements over a specified period. This is then compared to their available capital and cash reserves to ensure that the losses can be covered without putting the firms at risk

The Basel Accords issued by the Basel Committee on Banking Supervision (BCBS), is a set of recommendations or guidelines for regulations in the banking industry. It has recommended the need for banks and financial institutions to manage market risk using the VaR under the Basel II accord. The Basel II accord is based on three main pillars which are Minimal regulatory capital requirements, Supervisory review of capital adequacy and Market discipline and Disclosure. The objective of the Basel II accord is to stimulate the improvement of risk management. The recommendations of the Basel Committee is limited in its enforcement because compliance varies across jurisdiction as each central bank determines the method of implementation and associated requirements but extends to all banks. VaR analysis is used both by the international supervisor (Basel Committee) as a check on a banks solvency and internal management of firms as a tool to give limits to their traders. The Basel Committee has authorized institutions to use internal VaR models to check whether their reserves is enough to cover for any loss incurred.

This paper seeks to which of the VaR models (Historical Simulation and Monte Carlo Simulation) provides a better result using ten stocks traded on the Ghana Stock Exchange

II. VALUE AT RISK

Linsmeier and Pearson [18] described VaR as follows: "VaR is a single, summary, statistical measure of possible portfolio losses". VaR measures the worst expected loss over a given horizon under normal market conditions at a given level of confidence [16]. In statistical terms the VaR can be thought of as a quantile of the returns distribution [8].

Dowd [14] presented a detailed guide to VaR and how is applied in risk management in his book "Beyond Value-at-Risk: The New Science of Risk Management" which addressed the use of VaR in many fields of risk management in a company, while analysing the usefulness of the measure. Pritsker [23] examined the accuracy of VaR estimates for derivatives using Monte Carlo Simulation methods. The study stresses the significance of the trade-off between accuracy and computation time, as well as the relevance of defining the distribution of returns of the assets. Artzner [3] pioneered the term "coherent risk measures" by specifying some criteria's which such risk measures must follow. They conclude that VaR in general is not a coherent risk measure, because it fails the sub-additive condition for all returns distributions. Cotter and Dowd [9] analyzed the accuracy of quantile-based risk measures. Monte Carlo Simulation was proposed as the best method for calculating the accuracy of such measures. The conclusion was that excess kurtosis which is one of the characteristics of the distributions under consideration, have great effect on the accuracy of estimates. Daníelsson [11] examines the modern risk models and their limitation for both regulators and management. In particular, the accuracy of the models was studied at different confidence levels and was concluded that the RiskMetrics models are the best at 95% level in terms of accuracy, but their performance diminishes at 99%. And that the Basel accord capital requirements based on VaR are criticized as arbitrary and ineffective. Danielsson and Zigrand [12] addressed the issue of scaling of VaR for different time horizons and distributions and concluded that the square-root of time regulation underrates the risk. The bias is large and increases for longer horizons but is relatively insignificant for the 10-day period which agrees with the requirements of BCBS. Dowd [14], Jorion [17] and Daníelsson [13] suggested that in order to incorporate risk changes quickly and precisely into VaR forecasts, more complex models with time-dependent volatility should be used to forecast standard deviation needed for use in VaR calculation. There is also a trade-off between the size of the estimation window (the total number of returns used to forecast VaR) and the speed at which the forecasts will adjust to new information [13]. Linsmeier and Pearson gave a detailed overview of the most common and practiced approaches: Historical Simulation, parametric VaR, and Monte Carlo simulation. Marrison [20] and Zambrano [25] address the same methods, and, after describing them, they highlight the drawbacks of each method. [2] asserted that total capital required by a regulator in the bank is the summation of credit, market and operational risk capital obligation. The bank has the freedom to choose its own internal model for measuring market risk. The bank can therefore choose its own VaR model for estimating and calculating the market risk capital obligation. Glasserman [15] researched on modifying the Monte Carlo Method for VaR and found out that the calculation of VaR offered a trade-off between speed and accuracy for large portfolios and also the Monte Carlo method was frequently slower.

HISTORICAL SIMULATION

Historical Simulation (HS) is a non-parametric VaR method which assumes that past returns are a good guide for forecasting future returns. HS represents the easiest way of calculating VaR for many portfolios. The approach makes no assumptions about the statistical distribution of these returns because it uses past data on daily returns to arrive at a VaR number and the risk factors are deduced from historical observations [1]. HS has some enviable advantages due to its simplicity. It does not require estimation of statistical entities like volatilities and correlations and most importantly does not make any assumptions about the probability distributions therefore fat tails of the return distributions are accounted for [5]. The method can also be applied practically to any type of financial portfolio and uses full valuations [16]. However, HS has some disadvantages such as, enough data is not available. This problem arises when new financial instruments which were just introduced to the market or have shorter market data are introduced to the portfolio. Since HS mainly relies on historical data, it is the most difficult when dealing with new assets for a clear reason: there is no historic data available to calculate the Value at Risk even though this could be a disadvantage to any of the approaches for estimating VaR [10].

The steps taken to calculate VaR using Historical Simulation are as follows:

- First returns of assets are drawn directly from the historical prices
- Using the desired confidence level, VaR is calculated by taking a percentile of the returns and multiplying it by the notional value and square root of the holding period

- **MONTE CARLO SIMULATION**

Monte Carlo Simulation (MC) is the most well-known methodology when there is a requirement to develop a sophisticated and powerful VaR framework, however it is additionally by a wide margin very difficult to execute [14]. The Monte Carlo method is based on creating a substantial huge number of possible future prices using a simulation algorithm. The subsequent variations in the portfolio's worth are then examined to reach at a single VaR number [7]. The upside of Monte Carlo Simulation is that the Monte Carlo Simulation methodology can be changed in accordance with economic forecasts [21] and the disadvantage is its computationally intensive and also the manager must input particular hypothetical probability distribution to create samples from. The most vital issue with Monte Carlo methodology is its computational time because it needs a lot of resources, particularly with huge portfolios. As a result, the implementation may turn out to be expensive [16]. A prospective limitation is also model risk, which arises because of wrong assumptions about the estimating models and vital stochastic procedures. If these parameters are not specified properly, VaR estimates will be misleading [16].

The steps taken to calculate VaR using Monte Carlo Simulation are as follows:

- First the preferred probability distribution is selected
- The appropriate parameters are entered
- A series of random numbers are generated from the probability distribution and random numbers generated. 10,000 samples are generated 100 times to make 1,000,000 samples which represent returns of the assets
- Using the chosen confidence level, VaR is calculated by taking a percentile of the returns and multiplying the percentile value by the notional value and square root of the holding period

CRITICISM OF VALUE AT RISK

VaR is mostly criticized for not being a coherent risk measure i.e. VaR fails for the four axioms of a coherent risk measure as proposed by Artzner et al [3] i.e. Sub-additivity, Positive homogeneity, Monotonicity and Transition property. The sub-additivity of VaR is one of the most discussed and criticized properties, since in some cases portfolio VaR will be higher than the sum of individual positions VaRs, which discourages diversification [3]. In addition, since VaR highly depends on historical returns and/or the Gaussian assumption, there exists a significant possibility of prediction errors that will affect the quality of VaR estimation. Beder [4] pointed out that VaR is extremely sensitive to parameter choice. Artzner et al [3] also pointed out that VaR disregards any loss beyond the VaR level because it measures only quantiles of losses. As a consequence, a risk manager might be tempted to increase losses beyond the VaR level and avoid loss within confidence level since the risk manager solely depends on VaR

III. METHODOLOGY

VAR FORMULA

In monetary terms, a general VaR formula [24], is given by

$$VaR_{\alpha} = -F^{-1}(R^{k})_{(\alpha)} \times N \times \sqrt{h} \quad (1)$$

where:

F^{-1} = distribution of returns,
α = confidence level,
R^{k} = k-day return values
N = Amount to be invested or Notional value,
h = holding period,

PARAMETERS OF VAR FORMULA

- Amount Invested(Notional): The notional (N) is the total value of portfolio. N is used to convert VaR into monetary form.
- Holding Period(h): Holding Period has been defined as how long the portfolio composition is held constant but it is also can be viewed as the

time needed to completely liquidate shares without affecting the market

- Confidence Level: The confidence level is the quantile measured for VaR and the confidence interval is how certain the VaR model is.
- Time Period: The Basel Committee requires at least, data of one year for the calculation of market risk. The time period is the window size used to represent the portfolio risk

All parameters are decided by the financial manager but are heavily swayed by suggestions made in the Basel Accords

- **DATA**

The sample under consideration consists of ten (10) stocks traded on the Ghana Stock Exchange namely AngloGold Ashanti Limited(AADS), Ayrton Drugs Manufacturing Company LTD (AYRTN), Benso Oil Palm Plantation Limited (BOPP), Fan Milk Ltd(FML), Ghana Commercial Bank Ltd.(GCB), Ghana Oil Company Limited(GOIL), HFC Bank Ltd(HFC), SIC Insurance Company Limited(SIC), Societe Generale Ghana(SOGEGH) and Total Petroleum Ghana Ltd(T OTAL)

The period under consideration starts from June 25, 2007, to October 31, 2014. The series of returns is defined as

$$R_t = \frac{N_t - N_{t-1}}{N_{t-1}} \qquad (2)$$

where

R_t, the return
N_t the Stock Price in day t.

IV. DISCUSSION

The VaR was calculated for one (1) day at a 95% confidence level to cater for traders on the stock exchange where trading is done frequently and at a 99% confidence level at ten (10) days for the banks using it as a basis for their minimum capital requirement as stated by the Basel II accord. In the estimation, the notional value or amount invested was assumed to be one (1).

The three parameter loglogistic distribution is used in the Monte Carlo Simulation since it was the best probability distribution when tested by [22]

The last column of Figure 1 to Figure 10 shows the actual loss or gain which was added for back testing and comparison of respective companies

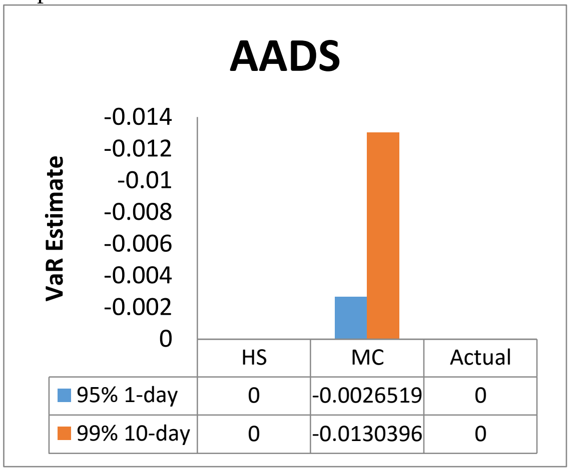


Figure 1: VaR Estimate For AADS

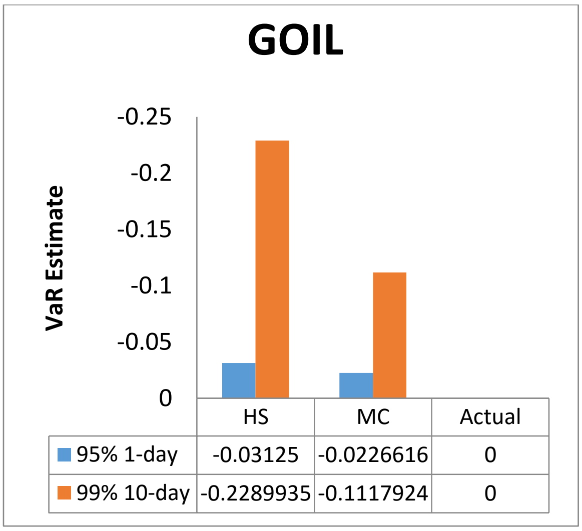


Figure 2: VaR Estimate For GCB

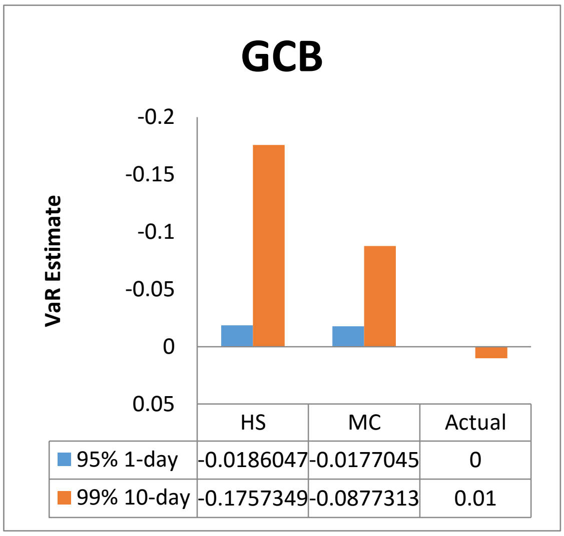
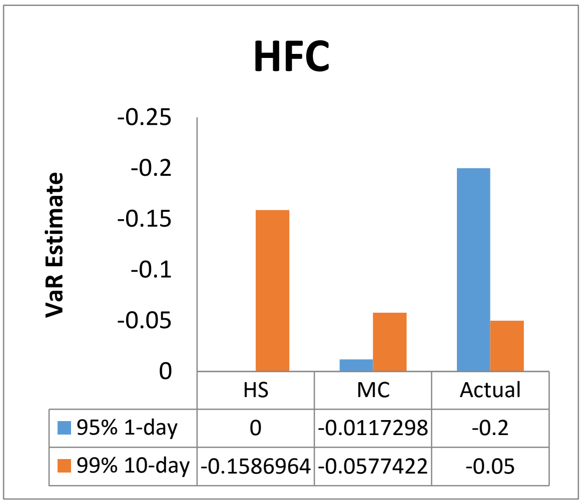


Figure 3: VaR Estimate For GCB



,Figure 4: VaR Estimate For HFC

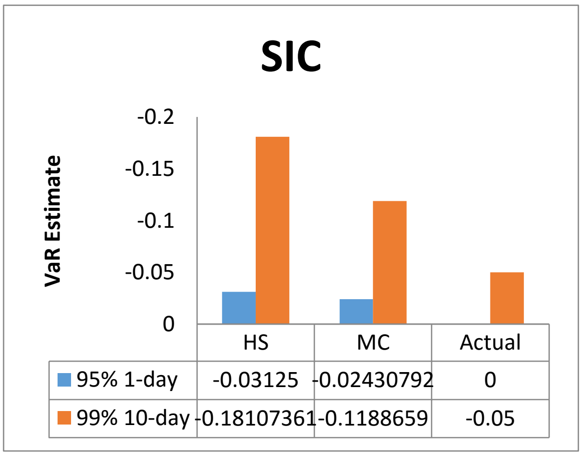


Figure 5: VaR Estimate For SIC

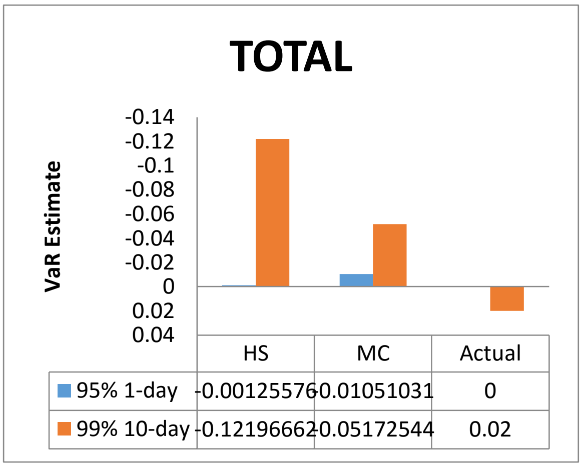


Figure 6: VaR Estimate For TOTAL

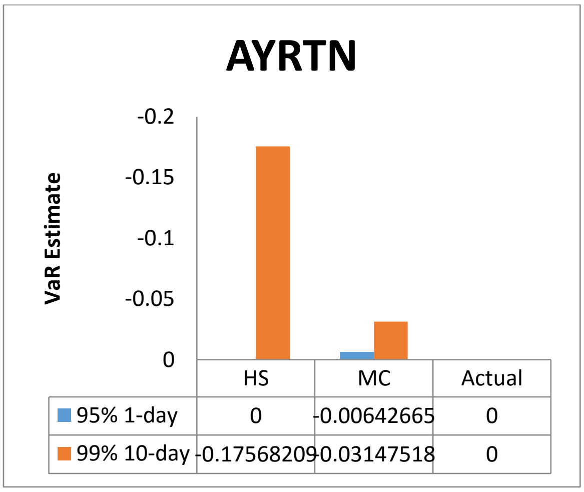


Figure 7: VaR Estimate For AYRTN

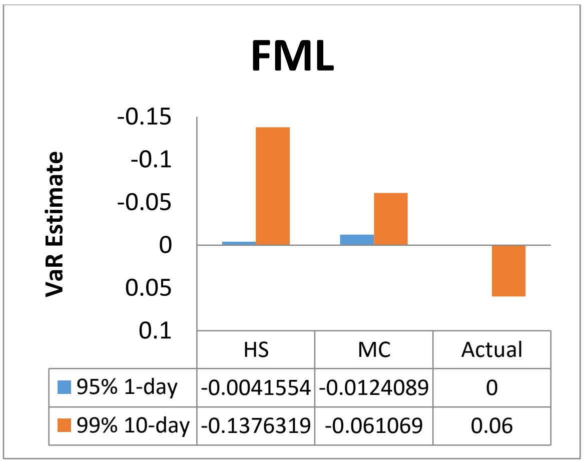


Figure 8: VaR Estimate For FML

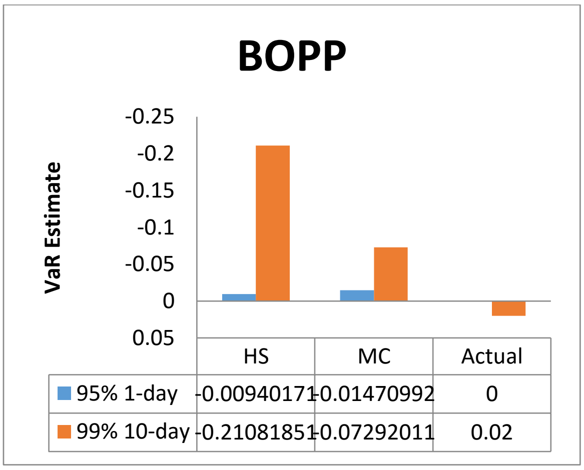


Figure 9: VaR Estimate For BOPP

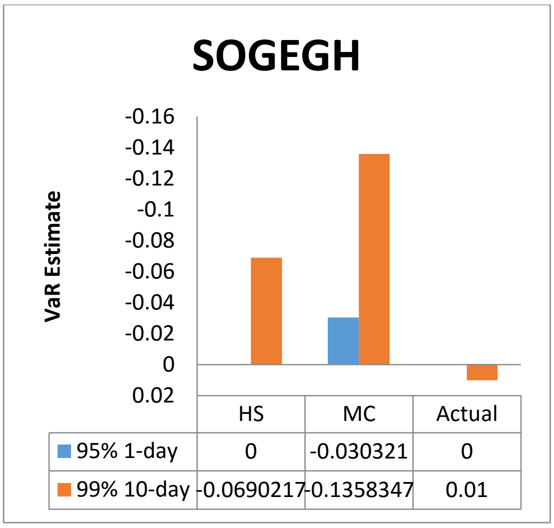


Figure 10: VaR Estimate For SOGEGH

V. CONCLUSION/ FURTHER STUDIES

From the VaR analysis in Figure 1 to Figure 10 The Monte Carlo Simulation provides a better result than the Historical Simulation. As much as the research was geared toward predicting the likely estimate using Value at Risk method, a VaR figure should never be considered to be completely dependable, which was the error most banks have made in the past [16] but as long as the limitations and significance of VaR are realized it can be used as a very strong risk management tool. This was evident in HFC were actual loss were higher than the VaR estimates.

Future studies should be conducted on the following

- The tail decay of the return distributions of Ghanaian financial data.
- Expected Shortfall which is also a risk measure to accompany VaR results, which quantify maximum potential losses.

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