Measuring Financial Risk in Stock Returns: A Case of Nairobi Stock Exchange

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Abstract: ***Value-at-Risk is an important concept in financial management, financial reporting and risk management. In this study, we have used this tool to assess risk in stocks listed in the Nairobi Stock Exchange. It is commonly used because it summarizes risk into a single value which is easily understood. Daily average share prices from January 2003 to December 2013 of Kakuzi and BAT stocks were analyzed. This is a sample of the NSE-20 index stocks which are among Kenya's top stock over 2008-2012 period. In estimating VaR, we need to estimate the volatility of the returns, specify the holding period and the confidence interval.. We modeled the volatility of the two selected stocks using a GARCH model. We selected the appropriate order of GARCH for each of the stocks using AIC instead of using the most commonly used GARCH (1, 1). GARCH (4, 2) best fitted Kakuzi data and GARCH (5, 4) BAT data. From the residual analysis the models performs well and we therefore used them in estimating VaR of each of the stocks. Backtesting a VaR model is important as it helps determine whether the model is able to capture risk well. This study reveals after backtesting the VaR model of the two stocks, that the model does not capture risk well since the actual number of exceedances exceeds the number of exceedances proposed by 95% confidence interval.***

Keywords: Risk, GARCH, VaR, Volatility, Stock

1. Introduction

Risk is the negative deviation of actual outcome from the expected outcome. This arises from uncertainty that exists in the market due to changes in market activities. There are various types of financial risk. Definition of some of these financial risk include: credit risk-risk due to uncertainty in a counter party's ability to perform on an obligation, Liquidity risk-risk due to the uncertainty in the ability to unwind a position especially because the market cannot fully absorb it, Market risk-risk arising from uncertainty in the market value of the portfolio due to changes in market condition the possibility of an investor to experience losses due to factors that affect the overall performance of the financial markets. It cannot be eliminated though diversification, though it can be hedged against. In this study we consider market risk.

In the recent past, vulnerability of investors to market risk has significantly increased, since some of the sources of this risk include recessions, political turmoil, changes in interest rates and terrorist attacks. There are various methods that researchers have come up with, which address this type of risk. One of the methods that has been used in quantifying market risk is Value-at-Risk. The use of the model was triggered by the stock market crash in 1987. Basel committee gave a capital requirement for all financial institutions to cover for market risk. VaR model has been used in calculating this capital.

Value-at-Risk measures the worst expected loss over a given horizon under normal market conditions at a given level of confidence Jorion(2001). It consists of three items which are, holding period or time, quantile and loss. The Value-at-Risk model summarizes risk into a single value which is easily understood, making it easy to understand the level of exposure of portfolio to market risk. Risk models are only useful if they measure risk accurately thus it is important to back-test the Value-at-Risk model. In this study we will consider Kupiec POF (1995) (proportion of failure) which is under unconditional coverage test.

2. Previous Research

Value-at-Risk concept has been used by many researchers and can be traced back to the 1922 capital requirement of New York Stock Exchange which was imposed on the member firms (Glyn.A. 2002). Several authors came up with Value-at-Risk measure for use mainly in their firms.

Markowitz (1952) developed a means of selecting portfolios that would optimize reward for a given level of risk. The author used variance of simple return metric. The Value-at-Risk measure proposed by the author incorporated covariance between risk factors in order to reflect hedging and diversification effect. The covariance matrix of risk factors was to be constructed using Bayesian technique. This VaR measure was for practical portfolio optimization work.

However the VaR concept was not known or used by most companies until it was launched by JP Morgan in October 1994. During the 1980's, the companies developed internal firm wide Value-at-Risk systems. Several hundred key factors were modeled. Various VaR metrics were employed using the assumption that portfolio values are normally distributed. In their model, the authors used delta to approximate portfolio function by weighting the residuals in computing variances. Thus the name delta-weighted normal model was used. The VaR model developed is also known as the RiskMetric. Since the launch, the VaR model has been adapted for use in asset management and for the estimation of market risk in the long term horizon (culp et al 1998).

There is wide literature on the application of VaR model in different financial sectors. Basel committee gave a requirement for all banks to use the model is estimating the capital requirement for covering against market risk. This was as a result of market crashes such as 1987 stock market crash. Some of this literature includes the following;

Duffie (1997), give a fairly broad and accessible overview of VaR. Authors discuss some of the econometric modeling required to estimate VaR. Author suggest that for one to measure VaR, one has to consider a number things which include; a model for computing the sensitivity of returns of the underlying instrument, a model for price risk in the underlying market and many others. Authors discuss models for price risk in the underlying market highlighting key issues such as fat tails, behavior and estimation of volatility and correlation. The discussed models include; basic model of returns, risk-neutral versus actual value at risk, jump-diffusion stochastic volatility and many more. They also consider the accuracy of shortcut VaR approximation methods based on multiplication of an analytically estimated portfolio standard deviation by some scaling factor, for example, 2.33 when using 99% confidence intervals under normality assumption.

Danielsson and de vries (2000) propose a semi-parametric method for VaR evaluation. The largest risks are modeled parametrically, while smaller risks are captured by non-parametric empirical distribution function. The semi-parametric extreme value (EV) method falls between the two known categories of VaR methodologies i.e. parametric method of conditional volatilities, and non-parametric method of unconditional volatilities. Authors combine non-parametric historical simulations with parametric estimation of the tails return distribution. They use two methods of extreme value estimator which are pre-sampling, and post sampling methods and show that they are good at tracking the expected value of exceedances. Authors also carry out a study of implications of adding an index option to the portfolio. They show that addition of the option index results in lower VaR estimate than if it is left out.

Andrey R. (2002) explains the use of VaR concept in portfolio management considering the Swiss banking system as an example. The author discusses the economic importance of VaR in portfolio management. The author also describes the dynamic Value-at-Risk and estimate advantages and disadvantages of using it in portfolio management. He states that dynamic Value-at-Risk addresses the question of how one can define the general trading rules and build a single adaptation scheme for risk estimation. In the thesis, the author address the problem of daily market movement and portfolio adaptation according to determined limits and rules which are crucial factors in the dynamic Value-at-Risk appreciation. Historical and Monte-Carlo simulation methods are used in the analysis.

As stated earlier, there is need to backtest the VaR model. Nieppola. O. (2009) carried out a research on backtesting VaR model used by Finnish Institutional investors. The results of the study revealed that there were problems with the system brought a severe underestimation of risk. Another factor that contribute to the under performance of the model as potrayed by the study is the turbulent market environment.

3. Material and Methods

In this study, we have considered two of the Kenya's top stock over the period 2008-2012 period as sample of the stocks traded in NSE. These are Kakuzi ltd and British American Tobacco (BAT) which are listed in the Nairobi Stock Exchange. The data is from a period of ten years, which is from January 2003 to December 2013.We have defined returns as follows;

$$R_t = -ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where; P_t is today's share price;
P_{t-1} is yesterday's share prices,
R_t is the daily return

We assume returns are normally distributed.

That is $R_t \sim N(0, \sigma_t^2)$, $t = 1,2,\ldots$

Where

$$\sigma_t = \sqrt{\omega + \beta R_{t-1}^2 + \alpha\sigma_{t-1}^2}$$

Which is a GARCH (1,1) process.
ω, β, α are the parameters of the GARCH process which satisfy
$\omega > 0$, $\beta \geq 0$, $0 < \alpha < 1$
σ_{t-1}^2 is yesterday's variance in returns
σ_t is today's standard deviation or volatility

Therefore returns can be written as;

$$R_t = \sigma_t e_t, \quad e_t \sim N(0,1)$$

Using returns, the theoretical VaR model is given by

$$VaR_\theta = \sigma_t e_\theta$$

Where, e_θ is the θ quantile of e_t.

We therefore, estimate the VaR at θ by estimating the volatility σ_t.

That is,

$$\hat{\sigma}_t = \sqrt{\hat{\omega} + \hat{\beta} R_{t-1}^2 + \hat{\alpha}\hat{\sigma}_{t-1}^2}$$

Therefore, the estimated VaR becomes

$$\widehat{VaR}_\theta = \hat{\sigma}_t e_\theta$$

Which is the same as:

$$\widehat{VaR}_\theta = \sqrt{\hat{\omega} + \hat{\beta} R_{t-1}^2 + \hat{\alpha}\hat{\sigma}_{t-1}^2} * e_\theta$$

We only need to estimate the volatility using the data to get the Value-at-Risk (VaR). In this study we also wish to forecast value-at-risk. We have used square root of time rule to forecast 5 and 10-days VaR.

$$VaR^t = \sqrt{T} * \widehat{VaR}_\theta$$

It is important to back test the VaR model and in this study we used Kupeic's proportion of failure to backtest the model.

4. Results

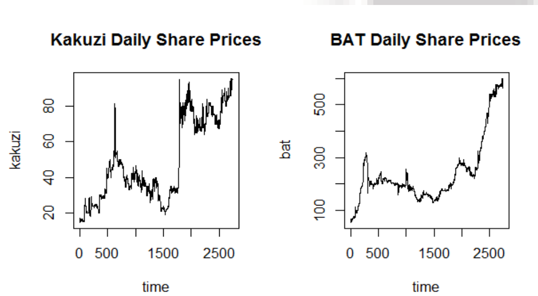

Figure 1: Dataset plots

It is clear from the above plot that stock prices have irregular variations. There are various causes of change in prices of stock. These include political stability, perception and participation of investors, gross earnings of the company, company image and general market sentiments.

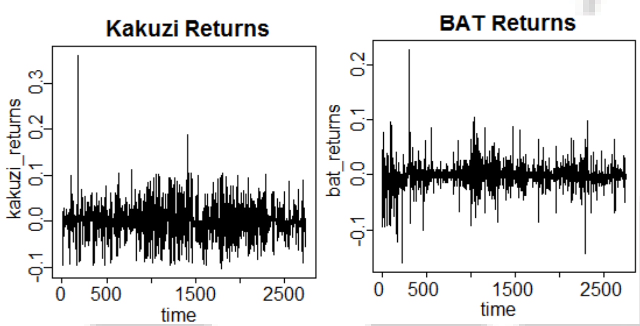

Figure 2: Stock returns

The appropriate order of GARCH was determined by use of AIC. The GARCH model parameters were estimated using Quasi-maximum likelihood estimation method. GARCH (4, 2) is appropriate for Kakuzi and GARCH (5, 4) for BAT. These are the models that have the minimum AIC. We used these GARCH models to estimate the volatility of these stocks.

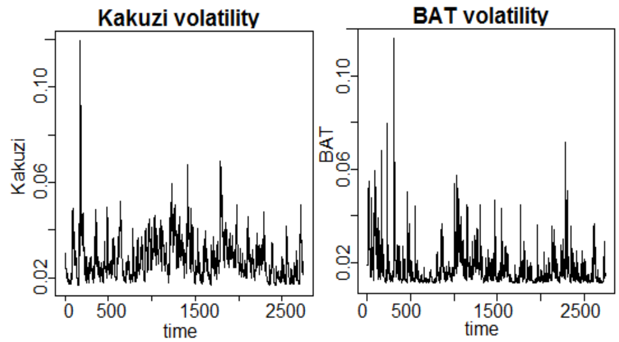

Figure 3: Volatility

From the above plot, there is evidence of volatility clustering, that is high fluctuation are followed by high ones and low functions by low ones. We can now estimate the historical VaR.

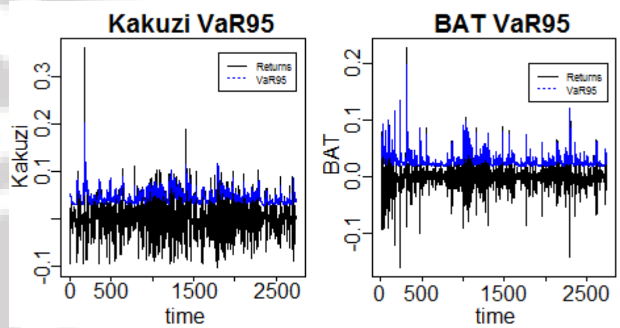

Figure 4: VaR at 95% CI

These are the plots of VaR (95% confidence interval). The returns are plotted and the VaR superimposed since we wish to study how well the model performs in capturing risk in these stocks. The VaR has been superimposed on the upper side of the graph because defined negative returns in equation [eq:returns]. This is because our interest is on the negative returns of the stocks. It can be seen that two extreme ruturns in Kakuzi exceed the VaR level. The VaR does not cover most of the big fluctuation in kakuzi stock prices. The VaR model is able to capture risk well in BAT stock. Value-at-Risk summarizes risk into a single number which is easily understood. Therefore we can estimate the VaR of 2014's first trading day which is 0.03862051for Kakuzi and 0.03032805 for BAT. Therefore to get the 5-day VaR forecast, we use the square root of time rule given by equation and 10-day VaR using the square root of time rule. These forecasts are shown in table

Table 1: VaR forecast

Horizon	*Kakuzi*	*BAT*
5-days	0.005461764	0.004289034
10-days	0.007693389	0.00606561

We have backtested the VaR model using the Kupeic's unconditional coverage test. In this study we use a package in R known as 'rugarch' to carry out the test. This package carries out both conditional and unconditional tests on the data and reports whether the null hypothesis should be rejected or we fail to reject it.

Table 2: VaR backtest

	Kakuzi	*BAT*
Expected exceedances	137	137
Actual exceedances	2610	2692

From the above table, we reject the null hypothesis and conclude that the observed failure rate is significantly different from the failure rate suggested by the confidence level used to calculate VaR.

5. Conclusion and Recommendation

Using the AIC, the analysis found GARCH (4,2) to fit Kakuzi stock data well and GARCH(5,4) fits BAT data. The Value-at-Risk estimate over one-day holding period is 0.0386 for Kakuzi and 0.0303 for BAT. We have also managed to forecast the 5 and 10-day VaR. In backtesting number of exceedances in the data exceeds the number of exceedances suggested by the confidence interval. These means that the VaR model does capture risk well for the two stocks.

The VaR model has some limitations such as the fact that it only captures 95% of the risk. The unreported 5% of the risk can cause a company to liquidate. Another limitation of the VaR model is that it does not report the worst-case loss. Due to these limitations, the VaR model should not be used in isolation in risk management. The model shows that it does not capture risks well since the further research can be done using non-parametric methods such as historical simulation method to overcome the limitations of the parametric variance-covariance method. Extreme value theory may be applied in order to capture risk under the irregular market conditions.

References

[1] Bollerslev T. (2002),'Generalized Autoregressive Conditional Heteroskadasticity", Journal of Econometrics (p.307-327).
[2] Danielsson J. and de Vries G (2000):"Value-at-Risk and Extreme Returns," second edition.
[3] Duffie D. and Pan J. (1997): "An overview of Value at Risk", Preliminary Draft.
[4] Engle, R (1982): "Autoregressive conditional Heteroskedasticity with estimates of the Variance of United Kingdom inflation".
[5] Engle R. and Patton J. (2001):"What Good is a Volatility Model.
[6] Jorion, P. (2001), Value at Risk, The: EW Benchmark for Managing Financial Risk, 2nd Edition, McGraw-Hill, United States.
[7] Garbade K. (1986): "Assessing Risk and Capital Adequacy for Treasury Securities", Topics in money and securities Market.
[8] Glyn A. (2002): "History of Value-at-Risk: 1922-1998", Working papers.
[9] J.P. Morgan, (1994): "Risk Metrics", second edition
[10] Lumsdaine R. (1996): "Consistency and Asymptotic Normality of Quasi-Maximum Likelihood Estimator in IGARCH (1, 1) and covariance Stationary GARCH(1,1) Models", Econometrica, Vol 64 pp575-596.
[11] Lumsdaine R. (1995): "Finite-Sample Properties of Maximum Likelihood Estimator in GARCH (1, 1) and IGARCH (1, 1) model: A Monte Carlo Investigation", Journals of Business and Economic Statistics, vol 13 no 1.
[12] Kupiec, P. (1995), Techniques for Verifying the Accuracy of Risk Management Models, Journal of Derivatives 3:73-84.

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