VALUE AT RISK MEASUREMENT FOR SOME SELECTED FINANCIAL RETURNS IN NIGERIA STOCKS

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Abstract : Value at risk technique (a measure of market risk) is the potential loss which can occur with α % confidence over a holding period of D days. This paper measures the value at risk (VaR) of some selected financial returns in Nigeria stock market from the banking sector, oil sector and food & beverages. They are Zenith Bank, First Bank of Nigeria, Total, Oando, Nestle and Flourmill. VaR was computed for three different confidence levels, 95%, 97.5% and 99% for the six stocks considered under a period of 1356 trading days between 04/01/2007 – 26/06/2012. For each stock returns, the obtained VaRs differ and increase respectively for the α -confidence levels. Significantly, the 1-Day VaR result showed that the Nestle stock has a high probability of making profit at the 99% confidence level while the Oando stock has the highest VaR and volatility. Numerical results are tabulated for investors' guide to know which stock promises higher expected yields, the most risky, less risky and volatile in all. The result also shows a reflection of the global economic meltdown.

Keywords: Portfolio, Returns, Value-at-Risk (VaR) and Volatility.

Introduction : In financial market risk measurement, value at risk technique has proved to be a very useful and popular tool. Faced with volatile financial market, both banks and non-financial companies are investing considerable resources in risk management systems. Such types of risks faced include business risks, market risks, operational risks, legal risks and liquidity risks. But in this paper, focus is only on measuring market risk (also called price risk) which is the type that is most easily quantifiable from a mathematical point of view.

The concept and use of value at risk shortened as VaR is a late 20th century discovery and is still recently in use. VaR was first used by major financial firms in the late 1980's to measure the risks of their trading portfolios. Since that time, the use of VaR has exploded. Currently, VaR is used by most major financial derivative dealers to measure and manage risks. The introduction of value at risk VaR as an accepted methodology for quantifying market risk is a part of the evolution of risk management. The application of VaR has been extended from its initial use in security houses to commercial banks and corporates, and from market risk to credit risk, following its introduction in October 1994 when JP Morgan launched risk metrics. By definition, VaR is a measure of the worst expected loss that a firm may suffer over a period of time that has been specified by the user, under normal market conditions and a specified level of confidence. This measure may be obtained in a number of ways, using a statistical model or by computer simulation.

Researches in the field of financial economics have long recognised the importance of measuring the risk of a portfolio of financial assets or securities. Indeed, concerns go back at least four decades when appropriate definition and measurement of risk were explored by Markowitz (1952). But, in recent years, the growth of trading activities and instances of financial market instability has prompted new studies underscoring the need for market participants to develop reliable risk measurement techniques. Darryll (1996) worked on evaluation of value-at-risk models using historical data and recognition of these models by the financial and regulatory communities is evidence of their growing use. For example, the Basel committee on banking supervision endorsed the use of such models in 1996 having spelt out the the risk management guidelines for derivatives in 1994, the same year in which the Bank for International Settlements Fisher Report urged financial intermediaries to disclose measures of value-at-risk publicly which led to the introduction of Risk Metrics database for use with third party value-at-risk software by financial and non-financial firms, Morgan (1995).

Consequently, this has interested many researchers such as Lopez (1996), Jorion (1997), Dowd (1998), Best (1998), Prause (1999), Pensal and Bensal (2001), Moix (2001) and other renown researchers who either worked on value-at-risk, regulatory valuation of value-at-risk, measurement of market risk and implementing value-at-risk. But notably, Eberlein, Kristen and Kallsen (2003) worked on the paper "Risk management Based on stochastic Volatility" which became the founding ideas for Mattias and Olsbo (2003), in their thesis, to jointly work on value-at-risk using stochastic volatility models thereby giving an extension to the work of Eberlein, Kristen and Kallsen (2003) by investigating other stochastic volatility models other than in Mattias and Olsbo (2003). Up to date, researchers in the field of computational mathematics and mathematics of finance are still working on VaR related issues to encourage its growing use.

Hence, this paper measures the value at risk VaR of some selected financial returns in Nigeria stock market from the banking sector, oil sector and food & beverages. They are Zenith Bank, First Bank of Nigeria, Total, Oando, Nestle and Flourmill. VaR will be computed for three different confidence levels, 95%, 97.5% and 99% for the six stocks considered under a period of 1356 trading days between 04/01/2007 – 26/06/2012.

1.1 A Typical Nigerian Financial System

A typical Nigeria financial system houses the federal ministry of finance and this consequently gives directives to Central Bank of Nigeria (CBN), Nigeria Deposit Insurance Corporation (NDIC), Securities and Exchange Commission (SEC), National Insurance Commission (NIC) and Federal Mortgage Bank of Nigeria (FMBN), all of which serve as regulatory authorities to other financial institutions. The CBN is directly in charge of money market, specialized banks (e.g. Bank of Industry, Agric. Bank), commercial banks, financial companies. The NDIC regulates money market in which all discount houses. Bureau de change and insurance companies manage. More importantly, SEC supervises the capital market which the Nigerian Stock Exchange, NSE (from where this research obtained the stocks data) readily controls with the teaming work of the registrars, Stock brokers and issuing houses. All primary mortgage institutions and insurance companies are favourably disposed in the Nigerian financial system. For example, the NIC regulates the insurance companies.

Value at Risk (VaR **) :** VaR is a measure of market risk. It is the maximum loss which can occur with α % confidence over a holding period of D days. This simply means using a probability of α percent and holding period of D days, as entity's VaR is the loss that is expected to be exceeded with only a probability of α % during the next D-day holding period. VaR is the expected loss of a portfolio over a specified time period for a set level of probability. For example, if a daily VaR is stated as ₦100000 to a 95% level of confidence, this means that during the day there is only a 5% chance that the loss the next day will be greater than ₦100000.

VaR is calculated within a given confidence interval, typically 95%, 97.5% and 99%; it seeks to measure possible losses from a position or portfolio under "normal" circumstances. The definition of normality is critical and is essentially a statistical concept that varies by firm and by risk management system. Put simply however, the most commonly used VaR models assume that the prices of assets in the financial markets follow a normal distribution. To implement VaR , all of a firm's positions data must be gathered into one centralized database. Once this is completely done, the overall risk has to be calculated by aggregating the risks from individual instruments across the entire portfolio. The potential move in each instrument (that is, each risk factor) has to be inferred from past daily price movements over a given observation period. For regulatory purposes, this period market is at least one year. Hence, the data on which VaR estimates are based should capture all relevant daily market moves over the previous year.

There is no one VaR number for a single portfolio, because different methodologies used for calculating VaR produce different results. The VaR number captures only those risks that can be measured in quantitative terms: it does not capture risk exposures such as operational risk, liquidity risk, regulatory risk or sovereign risk.

Financial theory assumes that returns (not prices or price change are the compensation for risks. There are two standard definitions of return; percentage R_t^p and Logarithmic log-returns (or geometric) R_t^l. Expected return is the difference between potential benefits and potential costs, while risk is the degree of uncertainty associated with the expected returns.

Definition 1: Let P_t denote the price at time t, then percentage returns and log-returns are defined as

$$R_t^p = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{P_t}{P_{t-1}} - 1,\; R_t^l = \log(\frac{P_t}{P_{t-1}}) \quad (1)$$

R_t^l May take value on the real line and for R_t^p to have property, it would imply negative prices.

Remark 1: Although R_t^p only takes values in $[-1, \infty)$, they are commonly modeled as random variables taking values on the whole real line (e.g. Gaussian).

Standard result from interest rate theory, applied on returns, lead us to the following relationship between continually compounded returns. R_t^c and 1-period R_t^p.

$$R_t^c = \log(1 + R_t^p) \approx R_t^p + o(R_t^P) \quad (2)$$

Hence, log-return is therefore sometimes called continuously compounded returns.

Remark 2: Since log-returns are usually small, we can use a first order Taylor expansion of R_i^l. This gives

$$R_t^l = \log(1 + R_t^l) = \log(\frac{p_t}{p_{t-1}}) = R_t^l \quad (3)$$

$\Rightarrow$ The difference between R_t^l and R_t^p usually is relatively small. If we assume the price process, P_t, to be of exponential type, i.e.

$$p_t = \ell^{X_t} \quad (4)$$

Log-returns will coincide with increments of the process X_t.

Remark 3: Throughout this paper, we will use log-returns R_t^l.

Definition 2:

$$VaR_{\alpha,D} = -\inf\left\{x \in R : P(R_{t,D} \le x) \ge \alpha\right\} \quad (5)$$

Where α is the probability value of finding lower return, D is the number of days of observation and $R_{t,D}$ is the return at time t on D-day.

Remark 4: The minus sign is there to present VaR as positive value.

Calculations are often performed for $D = 1$ (with 1-day VaR simply denoted by VaR_α) and to obtain the D-day VaR, the following approximation is often used. Thus, $VaR_{\alpha,D} \approx \sqrt{D} \times VaR_{\alpha,1}$ (6)

These formulas hold with equality only when the returns are additive, independent and identically distributed (i. i. d) Gaussian with zero mean.

Methods For Estimating Value At Risk : There are different methods for estimating VaR, but the most popular three methods are; historical simulation, Monte Carlo Simulation (MCS) and Model Building Approach (MBA). Details of these methods are provided in Mattias and Viktor (2003) and Linsmeier and Pearson (1996), but for the purpose of this work, the MBA will be used.

The MBA is sometimes referred to as variance-covariance approach and it has two features. The two features can be explicitly put as:

i. Equally weighted moving average approach whereby the calculation of portfolio standard deviation is given by

$$\sigma_t = \sqrt{\frac{1}{(k-1)}\sum_{s=t-k}^{t-1}(X_s-\mu)^2} \quad (7)$$

Where σ_t is the estimated standard deviation of the portfolio at the beginning of day t. Parameter k is the number included in the moving average (the "observation period"). X_s is the change in portfolio value on day s while μ is the mean change in portfolio value. μ is always assumed to be zero.Exponentially weighted moving average approach whose formula for the portfolio standard deviation σ_t is given by

$$\sigma_t = \sqrt{\frac{1}{(1-\lambda)}\sum_{s=t-k}^{t-1}\lambda^{t-s-1}(X_s-\mu)^2} \quad (8)$$

The parameter λ referred to as the "decay factors" which determines the rate at which the weights on past observations decay as they become more distant. VaR is then calculated as

$$1-\alpha = \int_{-\infty}^{-VaR_\alpha} f_{R_t}(s)ds = F_{R_t}(-VaR_\alpha) \quad (9)$$

Where f_{R_1} and F_{R_1} as the assumed (continues) density function and distribution function respectively for the returns. In other words

$$VaR_\alpha = -F_{R_t}^{-1}(1-\alpha) \quad (10)$$

And in most cases, the distribution function has to be inverted numerically. It is well known that, though uncorrelated, returns exhibit dependence, we will model the returns in two ways, each incorporating dependence, and one approach is to model the price process as an exponential semi-martingale, i.e. $s_t = S_0 e^{M_t}$ for a semi-martingale M_t which has a decomposition $M_t = \alpha_t + m_t$ where α_t has locally bounded variation and m_t is a local martingale such that $\alpha_t = m_t = 0$ and the stochastic volatility as a Gaussian Ornstein-Uhlenbeck process, i.e.

$$e^{\beta_t}s_t = e^{\beta_0}s_o + \sigma\int_o^t e^{\beta_s}dB \quad (11)$$

where B_s is a Brownian motion. The second part to assume that returns have the representation

$$R_t = \mu + \sigma_t X_t \quad (12)$$

Where X_t is a Levy process? The devitalized innovation, X_t are assumed independent.

$\Rightarrow$Assuming $\sigma > 0,\ X_t = \dfrac{R_t-\mu}{\sigma_t}$ form an i. d. d. sequence.

Now, denoting the $\alpha-$level VaR for R_t and X_t, $VaR_\alpha^{R_t}$ and $VaR_\alpha^{X_t}$ respectively work under the assumption that $VaR_\alpha^{R_t} = \mu + \sigma_t V$ (13)

Remark 5: The term used to denote combination of assets (underlying assets or basic assets) in financial mathematics is called a portfolio. Stocks, currencies, derivative securities (these themselves are assets), commodities and stock indices are examples of assets which may feature as underlying. While volatility, in financial market context, is a measurement of the change in price process over a given period of time.

It should be noted that a single asset or stock can form a portfolio and combination of many assets or stocks can be a portfolio whose VaR can be respectively measured or computed. If we take the simplest example, a portfolio containing just two assets, equation (14) below gives the volatility of the portfolio based on the volatility of each instrument in the portfolio (X and Y say) and their correlation with one another.

$$V_{port} = \sqrt{x^2 + y^2 + 2xy.\rho(xy)} \qquad (14)$$

Where x is the volatility of asset X, y is the volatility of asset Y, ρ is the correlation between assets X and Y. The correlation coefficient between two assets uses the covariance between the assets in its calculation. The standard formula for covariance is shown as (15)

$$Cov = \frac{\sum_{t=i}^{n}(x_i - \bar{x})(y_i - \bar{y})}{n-1} \qquad (15)$$

The covariance calculation enables us to calculate the correlation coefficient, shown as

$$\rho = \frac{Cov(x, y)}{\sigma_x \sigma_y} \qquad (16)$$

Where $\sigma_x \sigma_y$ is the standard deviation of each asset.

Value At Risk Implementation, Analysis And Discussion : The raw data (daily prices) of the stocks were obtained from www.cashcraft.com and also available in Nigerian Stock Exchange database. The data collected are for 1356 trading days between January 2007 and June 2012 whose returns were computed using the log-return, from equation (2). The results are only shown here, for brevity sake since the data is very voluminous (a 31-page collected data). Here, ZB is Zenith Bank Plc., FBN is First Bank of Nigeria Plc., TOT is Total Plc., OND is Oando Plc., NST is Nestle Nigeria Plc. and FLN is Flourmill Nigeria Plc. The process involved in computing the VaR is as follows:

The D-day stock (portfolio) unit value P_t at time t is noted from the obtained stock data.

The mean value $\bar{R}_t^l$ and standard deviations σ_t of the log-returns are calculated.

The confidence level α is chosen.

After the determination of the 3 steps above which are the required parameters, the minimum return is obtained using the NORM.INV function in excel since the returns distribution is taken to be normally distributed.

This is followed by finding the stock (portfolio unit value in Nigerian naira, ₦, currency) with respect to the foregoing steps.

Finally, the stock VaR (in Nigerian naira, ₦, currency) is determined by subtracting the calculated stock value from the D-day stock value at time, t.

Remark 6: The Microsoft excel (also with application of the Hoadley add-in for excel) is a veritable tool in the computation.

The table below shows the result analysis for the VaR of the stocks financial returns for the three α - confidence levels; 0.95, 0.975 and 0.99.

Stock	Mean Return, $\bar{R}_t^l$	Standard Dev., σ_t	Confidence Level, α	Min. Return	Stock Value (₦)	VaR (₦)	Volatility, σ_t^2	Stock Price P_t
ZB	-0.184835	0.24375	0.95	-0.58577	10.17354	14.38646	0.059414	24.56
ZB	-0.184835	0.24375	0.975	-0.66258	8.28713	16.272872	0.059414	24.56
ZB	-0.184835	0.24375	0.99	-0.75188	6.093773	18.46623	0.059414	24.56
FBN	-0.252102	0.23737	0.95	-0.64254	11.54577	20.75423	0.056346	32.30
FBN	-0.252102	0.23737	0.975	-0.71735	9.1297689	23.170231	0.056346	32.30
FBN	-0.252102	0.23737	0.99	-0.80431	6.320648	25.97935	0.056346	32.30
TOT	-0.191729	0.08897	0.95	-0.33807	124.4438	63.55616	0.007915	188.0
TOT	-0.191729	0.08897	0.975	-0.36610	119.1734	68.82657	0.007915	188.0
TOT	-0.191729	0.08897	0.99	-0.39869	113.0454	74.95455	0.007915	188.0
OND	-0.711371	0.27869	0.95	-1.16978	-11.6297	80.12965	0.077668	68.50
OND	-0.711371	0.27869	0.975	-1.25759	-17.64519	86.14519	0.077668	68.50
OND	-0.711371	0.27869	0.99	-1.35970	-24.63957	93.13957	0.077668	68.50
NST	0.186669	0.14628	0.95	-0.05394	222.3245	12.67547	0.021397	235.0
NST	0.186669	0.14628	0.975	-0.10003	211.49245	23.5075486	0.021397	235.0
NST	0.186669	0.14628	0.99	0.153626	271.1022	-36.10218	0.021397	235.0
FLN	0.002272	0.21679	0.95	-0.35431	41.64691	22.85309	0.046997	64.50
FLN	0.002272	0.21679	0.975	-0.42262	37.24079	27.25921	0.046997	64.50
FLN	0.002272	0.21679	0.99	-0.50205	32.117722	32.382278	0.046997	64.50

From the table, Oando has the highest VaR and volatility calculated with Nestle having the least VaR at 0.95 confidence level, while Total has the lowest volatility. By implication, a stock with high volatility is more risky but could promise better or higher returns while the one with low volatility is less risky to invest in but necessitates lower returns or yields. One readily sees that with Oando 1-Day VaR, a potential loss of over what is invested is obtained which makes it risky for investors to invest in. Nestle with the least VaR is worth investing in and this is evidence from the fact that the closing unit price P_t at the 1356th trading day data is ₦245 compared to the January 4, 2007 price of ₦235.

Similarly, Oando still has the highest VaR and volatility calculated with Zenith Bank having the least VaR at 0.975 confidence level while Total equally has the lowest volatility. On a remarkable note, Nestle has a negative $VaR_{0.99}$ which is an indication of a promising future yield. Oando still maintains its records at all the $\alpha-$level $VaRs$. This is a reflection of the global economic meltdown era when the stock market crashed.

Conclusion : The concept of value at risk is an important risk measurement in portfolio selection and the market. From the foregoing, this enables investors to understudy the market and make choices of investment. The above results can be presented graphically and the VaRs can be extended to stochastic volatility models, but essentially out of the scope of this paper.

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