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Efficiency and Consistency Assessment of Value at Risk Methods for Selected Banks Data

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Authors' contributions

This work was carried out in collaboration among all authors. Authors YM, SUG and IEE designed the study, managed the literature searches, wrote the protocol and performed the statistical analysis. All authors read and approved the final manuscript.

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Abstract

The study assesses Value at Risk (VaR) methods with respect to their efficiency and consistency in selected banks of the Nigeria Stock Market. The daily data on share prices of each bank was used from 2006 to 2018. The Value at Risk of each bank was estimated and the predictive performance of each method was assessed using the Failure Ratio and the Confidence Interval. The quality of each method was assessed based on the efficiency and consistency of the estimates. The VaR of each bank was estimated using Historical Simulation, Kernel Estimator, Empirical Estimator and Weighted Mean methods. The weighted mean method had the least estimates while Kernel estimator method had the highest estimates. The Failure Ratio and Confidence Interval show that Historical and Empirical methods had the least number of rejections at both confidence levels. The efficiency and consistency of the various methods shows the Historical Simulation and Weighted mean method had the minimum mean square errors (MSE). The Banks A, D and E gives an efficient and consistent result with Historical Simulation while B and C, is more efficient and consistent with weighted mean method.

Keywords: VaR; weighted mean; stock market; Nigeria.

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1 Introduction

A commercial bank is an institution that provides financial services, including issuing money in various forms, receiving deposits of money, lending money and processing transactions and the creating of credit [1]. Over different periods, there has been a lot of crises that affects both banks and other financial markets such as; the stock market crash (1987), the financial crisis (1997-1998), Global financial crisis (2007-2008), Venezuelan banking crisis (2009-2010) and Irish banking crisis (2008-2011). These issues of market crash, financial crisis and bank crisis has lead to bank runs, banking panics and systemic banking crises. A lot of bank failures were attributed to the inappropriate use of derivatives and lack of sufficient internal controls. Banks were weakened and some regulations were put in place so that they have sufficient capital reserve based on the risk structure. The need for improved risk management, especially for financial organizations, became clear at that time.

Value at Risk is risk measures which calculate the total capital a firm needs to cater for risk. Banks and financial organizations need to keep certain amount of money in order to cater for risk in their organizations. Not just keeping of capital, but adequate capital to meet the adverse movements of the market.

It is a matter of concern in practice whether the reported VaR is truly in line with the actual level of risks, estimated by the banks. Moreover, research shows that different techniques of calculating Value at Risk (VaR) have the tendency of providing varying results. The study by Dargiri [2], described and assessed the accuracy of predicted Value at Risk by applying parametric and nonparametric approaches using Malaysia industries. The nature of any Economy depends on the activities of that country, since VaR measures and quantifies level of financial risk within a firm.

VaR has gained rapid acceptance as a valuable approach to address and measure market risk because of its ability to quantify risk in a single number. Authors, among others (Jadhav and Ramanathan [3]; Rodrigues [4]; Guhary [5]; Cerovic [6]; Vladimir [7] and Ringqvist [8]) have estimate risk using parametric methods and nonparametric methods, in parametric a specified distribution is fitted to the observed returns by calibrating the parameters. This method is, of course, very sensitive to the assumption of distribution.

According to Jadhav and Ramanathan [3], which stated that, the correct estimation of VaR is essential for any financial institution, in order to arrive at the accurate capital requirements and to meet the adverse movements of the market. They gave a brief review of some of the existing parametric and non-parametric methods of estimating VaR. Comparison between the estimators were made using in-sample and out-of-sample back-testing techniques of Kupiec likelihood test. The extreme value theory and observation closest to $[n\alpha]$ was seen to perform well compared with all other methods.

The study by Ringqvist [8], investigates several models that estimate the financial risk measure with the objective to find the best model for the Swedish stock market. Using 1-day forecasted VaR at 95% and 99% level the following VaR models were compared: Basic Historical Simulation (HS), age weighted HS (AWHS), volatility weighted HS (VWHS) using a GARCH model, Normal VaR and t-distributed VaR. The study was performed on the Swedish stock exchange data OMXS and on the single stock series Boliden for the years 2005-2013. Running a backtest of the models it was found that the VWHS, where the volatility is modeled with a GARCH(1:1) model, estimates 1-day 95% and 99% VaR most accurately on the Swedish stock market and is therefore preferred to the other models.

Etuk et al. [9] estimated Value at Risk and Expected Shortfall in the presence of fat tails in returns using historical data of five selected banks in Nigeria First Bank, Zenith Bank, UBA, Guaranty Trust Bank and Access bank, using the following methods; GARCH(1,1) dynamics with Extreme Value Theory, Cauchy and Burr XII distributions. The authors evaluate Value at Risk and Expected Shortfall forecasting performance using various backtesting approaches. It was shown that models with Extreme Value Theorem and Cauchy Distribution give better fit than Burr. This implies that GARCH-Cauchy can calculate the minimum required capital to cover the market risks of the banks.

Etuk et al. [10] estimated Value at Risk and Expected Shortfall in Nigerian banks using Normal, Lognormal, Weibull and Extreme Value Theorem to assess the efficiency of the various methods. It was discovered that First, Access bank gives more efficient estimate with EVT while Zenith, UBA and Gtb is efficient with Weibull distribution.

This work will assess the performance of some nonparametric Value at Risk techniques based on their efficiency and consistency properties, using information from five (5) major banks in Nigeria.

2 Materials and Methods

This section briefly discusses the some nonparametric methods for the estimation of Value at Risk: Historical Simulation, Kernel Estimator, Empirical Estimator and Weighted Mean.

2.1 Data used for the study

The study used share price of five major banks listed in the Nigerian Stock Market (First Bank, UBA, GT Bank, Zenith Bank and Access Bank). The closing price at each trading day will be used covering the period, 3rd January 2006 to 31st December 2018.

2.2 Value at risk

Value-at-risk is defined as the maximum potential loss in the value of a portfolio of financial instruments with a given probability over a certain horizon. VaR is the $100(1-\alpha)$th quantile of the loss function, where p is the upper tail probability. It is the possible maximum loss over a given holding period within a fixed confidence level. Mathematically, VaR confidence level α is given by the smallest number 1 such that the probability of loss L to exceed 1 is not greater than 1 – α, as follows:

$$VaR_{\alpha} = \inf\left\{l \in R : P(L > l) \le 1 - \alpha\right\} \quad (1)$$

$$VaR_{\alpha} = \inf\left\{l \in R : F_L(l) \ge \alpha\right\} \quad (2)$$

The lowest value of the portfolio return at the chosen time horizon "t" with a certain probability "α" is determined from the distribution of return.

$$1 - \alpha = P(x < R_{\alpha}) = \int_{-\infty}^{R_{\alpha}} f(x)dx \quad (3)$$

2.3 Historical simulation method

Let $X_{(1)} \le X_{(2)} \le X_{(3)} \le \cdots \le X_{(n)}$ denote the order statistics in ascending order corresponding to the original financial returns $X_1, X_2, \cdots X_n$. The historical method suggests to value at risk estimate by

$$VaR_p(X) = X_{|np|} \quad (4)$$

where p is the upper tail probability.

2.4 Kernel estimator

The kernel estimator of a density f, based on a sample $X_1, ..., X_n$, is given by

$$\hat{f}(x) = \frac{1}{nh}\sum_{j=1}^{n} K\left(\frac{x - X_j}{h}\right) \tag{5}$$

where X_j is the j^{th} observed return, K is a kernel function, h is a bandwidth and n is the size of sample. The kernel function K is defined to be a symmetric and continuous probability density function, and the bandwidth h controls the smoothness of the estimated density, and so it affects the bias of the estimated density. Equation above shows that the kernel density estimator is an equally weighted linear combination of the kernel function K evaluated at each observation, with weight i/n at each kernel function or observation. Accordingly, a kernel estimator of F(x) is:

$$\hat{F}_{n,h}(x) = \frac{1}{n}\sum_{j=1}^{n} G\left(\frac{x - X_j}{h}\right) \tag{6}$$

where $G(x) = \int_{-\infty}^{x} K(u)du$. Where $u = \frac{(x-x_i)}{h}$, the kernel function used is normal..An estimator of the VaR can be obtained by solving the following equation:

$$\frac{1}{n}\sum_{j=1}^{n} G\left(\frac{VaR_{\propto,h}(x) - X_j}{h}\right) = \propto \tag{7}$$

for a given value of $\alpha = 0.05$, [11].

2.5 Empirical estimator

Let $X_1, X_2, ..., X_n$ be a random sample from a return distribution F(.), with $X_{(1)} \leq \cdot\ \cdot\ \cdot \leq X_{(n)}$ as the corresponding order statistics. For given α, define $j = [n\alpha]$ and $g = n\alpha - j$

By standard result on empirical distribution ([12]), the pth quantile can be estimated by

$$VaR_p(X) = F^{-1}(1-p) = X_{(i)}, \quad 1 - p \in \left[\frac{i-1}{n}, \frac{i}{n}\right) \tag{8}$$

2.6 Weighted estimator of value at risk

In this section, we proposed a new VaR model known as the weighted estimator. Let $x_1, x_2, x_3, \ldots, x_n$ be a set of random variables with the weighted mean given by

$$\mu^* = \frac{\sum_{i=1}^{n} w_i^* x_i}{\sum_{i=1}^{n} w_i^*} \tag{9}$$

For the normalized weight

$$\sum_{i=1}^{n} w_i = 1$$

The weighted variance given by

$$\hat{\sigma}^2_{weighted} = \frac{\sum_1^n w_i^* (x_i - \mu^*)^2}{\sum_{i=1}^{n} w_i^*} \tag{10}$$

$$V\hat{a}R_{(\alpha)} = \mu^* + z_\alpha \hat{\sigma}_{weighted}$$

2.7 Predictive performance procedure

In-sample VaR computation and backtesting allow us to examine only the past performance of the VaR models. The real contribution of VaR computation is its forecasting ability, which provides investors or financial institutions with the information about the largest loss they may incur. The rolling window length (the observation period) used to estimate the model parameters is also an important factor. The rolling window of 25, 50, 100, 200, 250 and 500 are tested to estimate of VaR based on all the methods.

Forecasting quality of the estimated methods was estimated using the Violation Ratio, where the number of the Observed Violation is compared to the number of predicted violations, [13].

$$\text{Violation Ratio} = \frac{\text{Number of observed violations}}{\text{Number of predicted violations}} \tag{11}$$

Thus, the confidence interval by Alexander (2009) is adopted due to sampling error;

$$n\alpha + Z_\theta\sqrt{n\alpha(1-\alpha)}, \qquad n\alpha - Z_\theta\sqrt{n\alpha(1-\alpha)}$$

The Null hypothesis is accepted if the cumulative number of violations falls within confidence interval.

2.8 Comparison of estimators

The Mean Squared Error for Value at Risk (VaR) by [14] is given;

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[\hat{F}(x_i) - VaR\right]^2 \tag{12}$$

where $\hat{F}(x_i)$is the share price of returns for each day, while VaR is the computed estimate for each methods. The method with the minimum mean squared error (MSE) becomes the best method for the estimation of VaR.

3 Results and Discussion

The results were obtained from the use of Historical Simulation, Kernel density, Empirical Quantile and Weighted mean estimator. The share price was divided into two sections; the in-sample which was the share price from 2006 – 2018 and the out-of-sample represent the rolling window of 2/3 of the original sample [3]. The variables are represented by letters A, B, C, D and E (the identity of each bank is hide).

Table 1. Estimation of value at risk with in-sample, α = 0.05 and 0.01

Variable	Historical simulation		Kernel estimator		Empirical estimator		Weighted estimator	
	α=0.05	**α=0.01**	**α=0.05**	**α=0.01**	**α=0.05**	**α=0.01**	**α=0.05**	**α=0.01**
A	45.1	56.0206	52.1840	62.4428	45.13	56.81	41.4830	50.7455
B	48.5	63.05	54.9925	64.7207	48.66	63.22	39.2721	47.2291
C	50.9	55.44	54.3871	58.6393	50.9	55.50	37.4011	47.1462
D	33.83	36.91	35.7106	37.6883	33.84	36.95	32.2775	36.8580
E	19.32	24.00	22.3453	24.7097	19.32	24.01	16.7644	20.0796

Table 1 shows the estimate of the various in sample VaR estimate using the various methods at α = 0.05 and α = 0.01 significance levels. Historical Simulation estimates at averages at 39.53 and 47.08412, Kernel method at 43.9239 and 49.64016, Empirical Method had 39.57 and 47.298 while Weighted Mean had

33.43962 and 40.41168. The overall averages shows that Weighted Mean had the least VaR estimate at α = 0.05 while Kernel had the highest VaR estimate. At α = 0.01, Historical Simulation had the least VaR estimate while Kernel had the highest.

Table 2. Estimation of value at risk with 500 out-sample, α = 0.05 and 0.01

Variable	Historical simulation		Kernel estimator		Empirical estimator		Weighted estimator	
	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01
A	19.9923	21.4019	20.8476	21.9907	20.0216	21.5734	20.8334	24.2410
B	24.9575	25.9492	26.1663	27.7985	24.9982	27.1951	23.9636	26.7089
C	14.6553	16.8918	16.0253	17.9638	14.6989	17.1865	13.5699	16.0720
D	29.2438	30.1612	29.7916	30.3883	29.2671	30.2431	29.5524	33.3039
E	11.0024	11.3188	11.1914	11.3936	11.0106	11.3462	11.1731	12.6037

Table 2 shows the estimate of the various 500 out sample VaR estimate using the various methods at α = 0.05 and α = 0.01 significance levels. Historical Simulation estimates at averages at 19.97026 and 21.14458, Kernel method at 20.80444 and 21.90698, Empirical Method had 19.99928 and 21.50886 while Weighted Mean had 19.81848 and 22.5859. The overall averages shows that Weighted Mean had the least VaR estimate at α = 0.05 while Kernel had the highest VaR estimate. At α = 0.01, Weighted Mean had the least VaR estimate while Kernel had the highest.

Table 3. Estimation of value at risk with 250 out-sample, α = 0.05 and 0.01

Variable	Historical simulation		Kernel estimator		Empirical estimator		Weighted estimator	
	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01
A	19.7355	20.9503	20.5802	21.5705	19.7573	21.4019	20.4768	23.8626
B	24.6001	26.3052	25.7891	27.1937	24.6313	26.9492	20.2061	21.4772
C	14.2770	16.1421	15.5969	17.2092	14.3089	16.8918	13.0966	15.4869
D	29.0317	29.9141	29.6176	30.2140	29.0502	30.1612	29.1018	32.7513
E	10.9276	11.2350	11.1311	11.3357	10.9342	11.3188	11.0055	12.3982

Table 3 shows the estimate of the various 250 out sample VaR estimate using the various methods at α = 0.05 and α = 0.01 significance levels. Historical Simulation estimates at averages at 19.71438 and 20.90934, Kernel method at 20.54298 and 21.50462, Empirical Method had 19.73638 and 21.34458 while Weighted Mean had 18.77736 and 21.19524. The overall averages shows that Weighted Mean had the least VaR estimate at α = 0.05 while Kernel had the highest VaR estimate. At α = 0.01, Weighted Mean had the least VaR estimate while Kernel had the highest.

Table 4. Estimation of value at risk with 200 out-sample, α = 0.05 and 0.01

Variable	Historical simulation		Kernel estimator		Empirical estimator		Weighted estimator	
	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01
A	19.5718	20.9503	20.3337	21.3184	19.7355	21.4019	20.3770	23.6187
B	24.3752	26.3052	25.4411	26.8306	24.6011	26.9492	3.4835	26.0830
C	14.0400	16.1421	15.4411	16.7573	14.2770	16.8918	13.0402	15.3862
D	28.8896	29.9141	29.4578	30.1106	29.0317	30.1612	29.1613	32.7899
E	10.8773	11.2350	11.0759	11.3015	10.9276	11.3188	11.0295	12.4146

Table 4 shows the estimate of the various 200 out sample VaR estimate using the various methods at α = 0.05 and α = 0.01 significance levels. The following results were obtained with the respective α. Historical

Simulation estimates at averages at 19.55078 and 20.90934, Kernel method at 20.34992 and 21.26368, Empirical Method had 19.71458 and 21.34458 while Weighted Mean had 15.4183 and 22.05848. The overall averages shows that Weighted Mean had the least VaR estimate at α = 0.05 while Kernel had the highest VaR estimate. At α = 0.01, Weighted Mean had the least VaR estimate while Kernel had the highest.

Table 5. Estimation of value at risk with 100 out-sample, α = 0.05 and 0.01

Variable	Historical simulation		Kernel estimator		Empirical estimator		Weighted estimator	
	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01
A	19.1464	19.8892	19.9580	20.6456	19.7355	21.4019	20.2251	23.4819
B	23.7932	24.8142	24.9172	25.8817	24.6011	26.9492	23.6033	26.2923
C	13.4384	14.5025	14.6359	15.6971	14.2770	16.8918	12.7712	15.0745
D	28.4962	29.1603	29.1667	29.6607	29.0317	30.1612	29.1059	32.7399
E	10.7371	10.9730	10.9738	11.1459	10.9276	11.3188	11.0221	12.4126

Table 5 shows the estimate of the various 100 out sample VaR estimate using the various methods at α = 0.05 and α = 0.01 significance levels. The following results were obtained with the respective α. Historical Simulation estimates at averages at 19.12226 and 19.86784, Kernel method at 19.93032 and 20.6062, Empirical Method had 19.71458 and 21.34458 while Weighted Mean had 19.34552 and 22.00024. The overall averages shows that Weighted Mean had the least VaR estimate at α = 0.05 while Kernel had the highest VaR estimate. At α = 0.01, Weighted Mean had the least VaR estimate while Kernel had the highest.

Table 6. Estimation of value at risk with 50 out-sample, α = 0.05 and 0.01

Variable	Historical simulation		Kernel estimator		Empirical estimator		Weighted estimator	
	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01
A	19.7573	19.8892	20.2165	20.6456	19.8174	21.4019	20.4119	23.6745
B	24.6313	24.8142	25.2773	25.8817	24.7145	26.9492	23.2977	25.8294
C	14.3089	14.5025	15.0250	15.6971	14.3968	16.8918	12.8949	15.1891
D	29.0502	29.1603	29.3681	29.6607	29.1008	30.1612	29.2042	32.8396
E	10.9342	10.9730	11.0445	11.1459	10.9520	11.3188	10.9804	12.3451

Table 6 shows the estimate of the various 50 out sample VaR estimate using the various methods at α = 0.05 and α = 0.01 significance levels. The following results were obtained with the respective α. Historical Simulation estimates at averages at 19.73638 and 19.86784, Kernel method at 20.18628 and 20.6062, Empirical Method had 19.7963 and 21.34458 while Weighted Mean had 19.35782 and 21.97554. The overall averages shows that Weighted Mean had the least VaR estimate at α = 0.05 while Kernel had the highest VaR estimate. At α = 0.01, Weighted Mean had the least VaR estimate while Kernel had the highest.

Table 7. Estimation of value at risk with 25 out-sample, α = 0.05 and 0.01

Variable	Historical simulation		Kernel estimator		Empirical estimator		Weighted estimator	
	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01	α=0.05	α=0.01
A	19.7573	19.8174	19.8213	19.8533	19.8174	19.8892	22.0120	25.1715
B	24.6313	24.7145	24.7200	24.7643	24.7145	24.8142	25.0455	27.5900
C	14.3089	14.3968	14.4027	14.4496	14.3968	14.5025	14.4470	16.7502
D	29.0502	29.1008	29.1305	29.1603	29.1008	29.1603	31.2178	34.7085
E	10.9342	10.9520	10.9531	10.9625	10.9520	10.9730	11.8085	13.1393

Table 7 shows the estimate of the various 25 out sample VaR estimate using the various methods at α = 0.05 and α = 0.01 significance levels. The following results were obtained with the respective α. Historical

Simulation estimates at averages at 19.73638 and 19.7963, Kernel method at 19.80552 and 19.838, Empirical Method had 19.7963 and 19.86784 while Weighted Mean had 20.90616 and 23.4719. The overall averages shows that Weighted Mean had the least VaR estimate at α = 0.05 while Kernel had the highest VaR estimate. At α = 0.01, Weighted Mean had the least VaR estimate while Kernel had the highest.

3.1 Comparative of the predictive performance of the VaR methods

The predictive performance was carried out using the Violation Ratio by [13].

Table 8. Summary of Backtesting with α = 0.05

Method	Sample size							
	In Sam	**500**	**250**	**200**	**100**	**50**	**25**	**Total**
Historical	1	0	0	0	0	0	0	1
Kernel	5	5	3	1	0	0	0	14
Empirical	1	0	0	0	0	0	0	1
Weighted	5	4	1	0	0	0	0	10

Table 8 present the number of rejections on the different methods with the different rolling windows. The method with the least number of rejections gives a better fit. Historical Simulation and Empirical Estimator have the minimum number of rejections at α = 0.05.

Table 9. Summary of backtesting with α = 0.01

Method	Sample size							
	In Sam	**500**	**250**	**200**	**100**	**50**	**25**	**Total**
Historical	0	1	0	0	0	0	2	3
Kernel	3	0	0	0	0	0	0	3
Empirical	0	0	0	0	0	0	0	0
Weighted	4	0	1	0	0	0	0	5

Table 9 present the number of rejections on the different methods with the different rolling windows. The method with the least number of rejections gives a better fit. Historical Simulation and Empirical Estimator have the minimum number of rejections at α = 0.01.

Table 10. Summary of MSE of VaR , α = 0.05 and 0.01

Bank	α = 0.05							α = 0.01						
	IS	**500**	**250**	**200**	**100**	**50**	**25**	**IS**	**500**	**250**	**200**	**100**	**50**	**25**
A	W	H	H	H	H	H	H	W	H	H	H	H	H	H
B	W	H	W	W	W	W	H	W	H	W	W	H	H	K
C	W	W	W	W	W	W	H	W	W	W	W	H	H	H
D	W	H	H	H	H	H	H	W	H	H	H	H	H	H
E	W	H	H	H	H	H	H	W	H	H	H	H	H	H

Table 10 is the summary of the mean square error of VaR with different methods at α = 0.05 and 0.01 with the different rolling windows. The method with the highest numbers of Mean Square error gives an efficient result compare to other ones. Where H(Historical), K(Kernel), E(Empirical Estimator) and W(Weighted Mean). The result shows that Weighted Mean and Historical Simulation have the highest numbers of MSE.

The result of Table 11 shows the summary of the frequency of occurrence of different methods of estimation of Value at Risk at both confidence levels. The results show that Historical and Weighted Mean had the highest number of Mean Square error.

Table 11. Summary of MSE of VaR , α = 0.05 and 0.01

Method	**VaR**	
	0.05	**0.01**
Historical	21	20
Kernel	0	0
Empirical	0	0
Weighted	14	10

3.2 Discussion

The study assesses the efficiency and consistency of Value at Risk (VaR) techniques in some 5 banks of the Nigeria Stock market.

The results shows the in-sample estimation of VaR and the out of sample estimation with different banks and with an average of 2678 sample size on each banks and 500, 250, 200, 100, 50 and 25 for the out of sample. The weighted mean had the least VaR estimate across all the sample sizes while Kernel had the highest VaR estimate across all rolling windows.

The work combines the Violation Ratio and the Confidence Interval measure to test for the predictive performance of VaR. It is expected that if the estimator is well specified that the violation ratio should be as close to one or a bit above one, the exception must fall within the specified confidence interval. Values above the confidence interval, underestimate risk while below the confidence interval means overestimation of risk. The predictive performance of Historical Simulation at various sample size shows that number of rejections of 1 at 95% confidence level, while the number of rejections of 3, it underestimate at B bank (500, 25), E bank at 25 sample point at 99% confidence level. For Kernel Estimator at various sample sizes, the number of rejections of 14 at 95% confidence level whiles the number of rejections of 3, at 99% confidence level. The Empirical Estimator at various sample size show the number of rejections of 1 and underestimate at E bank(in sample) at 95% confidence level, while the numbers of rejections was 0 at 99% confidence level. It was shown that the various sample size of Weighted Estimator show that the number of rejections of 10 with overestimations at A bank and E bank (500) and at B bank (250) at 95% confidence level. while the number of rejections of 5 at 99% confidence level.

The efficiency of the various methods of VaR estimation were asses using the Mean Squared Error(MSE). The mean squares error which measure the average squared difference between the estimated values and the actual value and the result that is close to zero, give the best result. The most efficient point estimator is the one with the smallest mean square error. The methods with representation H(Historical), K(Kernel), E(Empirical Estimator) and W(Weighted Mean) shows that Weighted Mean and Historical Simulation have the highest numbers of MSE.

The consistent assessment of Value at Risk with the different methods assessed the different sample sizes using the mean square error. The results show that the consistent estimator requires a large sample size for it to be more consistent and accurate. Weighted mean distribution gives a more consistent results compare to their counterpart in the estimation of Value at Risk.

4 Conclusion

The assessment of Value at Risk methodologies, with respect to their efficiency and consistency in selected banks of the Nigeria Stock Market shows that A bank , D bank and E bank gives an efficient and consistent result with Historical Simulation while B bank and C bank, is efficient and consistent in Estimating Value at Risk with Weighted mean. This useful information can facilitate Bank risk manager to measure firm-level market risk and Bank Executives to set limits of risk and Regulators to determine capital requirements.

5 Implication of the Findings

(a) Historical Simulation method gives the best fit method in the estimation of the minimum capital requirement of A, D, and E banks.
(b) Weighted Mean give the best fit in the estimation of the minimum capital requirement of B and C banks.
(c) The market volatilities are not properly captured by Kernel methods.
(d) It was also found that when the sample size is large, Historical Simulation and Empirical methods give an efficient and consistent result.

Competing Interests

Authors have declared that no competing interests exist.

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