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Predicting and Evaluating Value at Risk Estimate Using Volatility Forecasting Models

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***AB*STRACT**

Value-at-Risk (VaR) is a statistical measure that determines the probability of a portfolio of assets losing a certain amount in a given time period due to adverse market conditions with a particular level of confidence. The study examined value-at-risk estimates performance in predicting agricultural market risk, the monthly data on some selected crops price was used to assess the Value at Risk (VaR) methods with respect to their efficiency and consistency in some selected commodities (Beans, Maize, and Imported Rice). The market risk of each crop was estimated using Exponential Weighted Moving Averages (EWMA), Historical simulation method and Extreme Value Theory (EVT) methods. The predictive performance of each method was assessed using the Failure Ratio and the Kupiec PoF test statistic. The results revealed that different commodities have different degrees of market risk. The time plots show the existence of volatility clustering occurred due to the frequent changes of market price. The figure also shows that there is persistence in the magnitude of the price changes. The high and low volatilities were observed for a significant period of time, which is a symptom of correlation with the previous values. In relation to volatility, the maize price is the most volatile (0.2733), followed by the rice price (0.1152) while the beans price has the least volatility (0.0805). The result shows that the Rice and Beans have the lowest level of market risk while Maize has the highest level of market risk. The study also found that the extreme value theory (EVT) has the least number of violations and rejections while the EWMA model shows the highest number of violations and rejection.

Key words: Value at Risk, Violation, Volatility, EVT, Kupiec PoF

1. Introduction

Each situation in life bring together many types of risks. Risk is defined as the general uncertainty of future outcomes, instability due to unexpected results. Thus, the estimation of value at risk (VaR) is essential for efficient decision making in the agricultural sector. For instance, farm financial sectors want to know the level of market risk faced by borrowers; farm and agribusiness managers want to estimate market risk before investing and borrowing money and policy makers need an accurate market risk measure to design farm income policies. Despite the risky nature of agricultural businesses, the use of VaR to measure market risk is limited. Relatively few studies have applied VaR in agriculture.

Over the past few years, modeling and forecasting Value-at-Risk (VaR) has become a popular area of research and has gained a great deal of attention from academicians, researchers and others, this is because Value-at-Risk (VaR) is considered as an important concept for many economic and financial applications, like risk management, portfolio optimization and asset pricing (Virdi, 2011). Value-at-Risk (VaR) is an important risk measurement tool for practitioners because of its wide implications on business' losses and regulatory capital requirement. VaR measures the lower tail of the distribution and maximum portfolio loss that could occur for a given holding period with a given confidence level (Virdi, 2011). The risk means any uncertain situation in the business and the probability of loss as a result of uncertain events in the business. The most famous type of risk that is related to the securities is market risk, which relates to the uncertainty regarding the change in the price of securities. Three important components of VaR are confidence level, period and potential loss in value. Confidence level refers to probability of the expected minimum loss. Period refers to the reference period and the holding period, where Reference period captures the extent of information captured in VaR measure i.e. length of historical data used. As in the financial sector, agricultural financial returns are inherently risky due to production and demand uncertainty, particularly following trade liberalization and other reforms (Virdi, 2011). Many studies have been conducted on the proper and correct estimation of financial risk, especially after the financial crisis of 2008 (Jorion 2002).

The key input to VaR models is volatility, therefore the characterization of asset or portfolio volatility is of great importance when implementing and testing VaR models. The correct choice of volatility model is one of the most important factors in determining the effectiveness of VaR.

The first ideas for assessing portfolio risk came from Markowitz, who measured the risk using mean variance behaviour. Two measures of risk later emerged: VaR (Value at Risk) and CVaR (Conditional Value at Risk). VaR is much easier to calculate than most measures for risk and therefore takes an important position in practice. During 1996, 99 % VaR is accepted by the Basel Accord as the main measure of risk for determination of possible loss.

The importance of VaR as a technique for risk measurement raised the necessity of evaluating the accuracy of VaR (Blanco & Oks, 2004). Hence, to address these concerns Backtesting is a popular tool among researchers and professionals. Backtesting is a process to evaluate the accuracy of VaR. One needs to evaluate the model and preferably compare its performance to other models. Since one model might fit well to certain time-series, but fail when it is applied to a different set of time- series.

The aim of this study was to evaluate value-at-risk estimates in predicting agricultural market risk on the basis of the Extreme Value Theory (EVT), the Historical simulation method and Exponential Weighted Moving Averages (EWMA) models.

2. Research Background

Empirically, evidences from literature reviewed show that nonparametric kernel estimator and the normal density estimator models have been applied more extensively in estimation and forecasting agricultural market VaR than other methods. Han (2008) used the Zhengzhou Commodity Exchange hard wheat future prices. By constructing hard wheat futures, he estimated the VaR value through contracts yielded continuous time series data. From his findings, he projected a method of marginal levels and combining VaR curve to apply a sole early warning indicator of the products futures market risk. Kourouma et al. (2011) investigated the VaR and predictable deficit for S&P 500, CAC 40, Crude Oil and Wheat indexes during 2008 economic crisis and showed an underestimation of the risk for the categorical Value at Risk models as compared to conditional models. The study conclude that the underestimation is stronger using the historical VaR approach than when using extreme values theory VaR model. Tarasov (2011) examined the VaR and expected shortfall approach throughout entire distribution of outcomes within the climatic regions of Ukraine. The Monte Carlo standard deviation, autocorrelation and simulation results show the best risk modeling. Wang et al. (2010) analyzed the fruit market (strawberry, watermelon, grape, pear, banana, orange and Fuji apple). The study utilized the Value at Risk model and exposed that various fruits have various degrees of price risk. Pears, apples and bananas have lower levels of risk. The watermelons and Strawberries have comparatively higher levels of risk, while oranges and grapes have average levels of risk. The results further explained that fruits have similar characteristics fit to the similar market risk level. Tesfalidet et al. (2014) examined the skewness and leptokurtic VaR model that combine the Cornish Fisher and EWMA methods using weekly returns data of Maple Leaf Foods stock and Canadian feedlot cattle feeding margin data. The study exposed that EWMA method of VaR assessment produce the most suitable results particularly for returns with positive skewness, meanwhile the Cornish-Fisher method of VaR provide a better experimental returns as compared to other methods. Musa, Iniabasi and Gulumbe (2019) examined and estimated the performance of Gaussian Density, Weighted estimator and Extreme Value Theory models in measuring Value at Risk (VaR) using data of some selected banks in Nigeria. The results of the weighted estimator of VaR estimate for in-sample predictions, shows that the p-value of 0.07141 of Guaranty Trust Bank was able to estimate VaR correctly. The out-of-sample predictions indicate the extreme value estimates with the p-values greater than α have specifies VaR correctly. The study expose that VaR prediction with extreme value theory method outperforms other methods in forecasting VaR. Musa et al (2019) used the daily data on share price to assess Value at Risk (VaR) methods with respect to their efficiency and consistency in selected banks of the Nigeria Stock Market. 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 VaR of each bank was estimated using Historical Simulation, Kernel Estimator, Empirical Estimator and Weighted Mean methods. The study found that 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. Rehman et al. (2018) analyzed the sizes and degrees of China major crops market risk using normal density estimator. The practical consequences indicated that the normal distribution model is not appropriate used in evaluating the major crops market risk due to various degrees of market risk in various crops such as the cotton and soybean crops with higher levels of market risk.

It was observed that the normal density estimator models have been applied more extensively in estimation and forecasting agricultural market VaR, however, the parametric method has some shortcomings. The most important one is that it assumes that the behavior of agricultural market returns follows normal distribution pattern, which is often not the case. Another drawback of this approach is that it assumes that the volatility is constant over time and that it assigns equal weights to each return.

3. Research Data

The purpose of this study was to present and test the estimation of VaR based on the econometric approach, with empirical results of measuring VaR in a sample of four selected crops (Rice, Maize, Beans and Onion Bulb). The nature of the data is secondary. The data on the selected crops price (in monetary unit) was used to measure the relative performance of different VaR models in the estimation of agricultural market risk. The data for the study was adopted from National bureau of statistics (NBS) Statistical Bulletin.

4. Research Methodology

4.1 The Value at Risk (VaR) of Portfolio

Value at Risk (VaR) seeks to estimate the market risks in terms of asset price volatility. VaR, as defined by Jorion (2001), synthesizes the biggest (or worst) loss expected from a portfolio, within determined time periods and confidence intervals.

Formally, VaR is defined for a long position in an asset S over a time horizon *j*, with

Probability p (0<p<1):

$$p = P(\_P_j \leq VaR) = F_j(VaR) \quad 1$$

where $\_P_j$ represents the gain or loss of position P, given by $P_j = P_{t+j} - P_t$.

4.2. Extreme Value Theory

One method of extracting extremes from a sample of observations is to take the exceedances over a predetermined, high threshold u. POT method models the distribution of exceedances over a certain threshold. The models assume that returns are exactly from extreme value distribution, thus they assess distribution parameters – scale, shape and tail index. The model key assumption is that extreme returns are independent and identically distributed.

Let $X_1, X_2, \ldots, X_n$ be a sequence of independent and identically distributed random variables with the distribution function *F*. An exceedance over threshold *u* occurs when for any *t=1,…,n* and let the excess over threshold be defined by *Yi*. It follows that the behavior of extreme events is given by the conditional probability function *Fu* of excess values over threshold *Yi* which is:

$$V\hat{a}R_{(\alpha)}(X) = u + \frac{\hat{\beta}(u)}{\hat{\xi}}\left(\left(\frac{n(1-\alpha)}{N_u}\right)^{-\hat{\xi}} - 1\right) \qquad 2$$

WhereN_u is the number of observations above the threshold level (u), McNeil (1997).

The Expected Shortfall of Extreme Value Theorem is given as;

$$ES_{(\alpha)}(X) = \frac{1}{1-\xi}\left\{u + \frac{\hat{\beta}}{\xi}\left(\left(\frac{n(1-\alpha)}{N_u}\right)^{-\hat{\xi}} - 1\right)\right\} + \frac{\beta-\xi u}{1-\xi} \qquad 3$$

Where u = location parameter which is the threshold value, β = scale parameter and ξ = shape parameter

4.3. Riskmetrics (Exponential Weighted Moving Average)

As with all models previously discussed, the Riskmetrics model measures volatility of the sample data. There is one added feature; it does not give equal weights to all the observations within the sample period like the Variance Covariance model. It uses Exponentially Weighted Moving Average (EWMA). Which adds a decay factor to the model, it determines how the different weights are distributed among the sample observations. JP Morgan set a value for the decay factor, being 0.94 for daily and 0.99 for monthly holding periods. The Riskmetrics model is represented by the following equation:

$$\sigma_t^2 = \gamma_{t-1}^2 (1-\lambda) + \lambda\sigma_{t-1}^2 \qquad 5$$

Where lambda represents the decay factor.

Moreover, we used the following VaR equation for volatility modeled with EWMA under the assumption of normal distribution:

$$VaR_{t,\alpha} = z_{1-\alpha}\sigma_t \qquad 6$$

Where $z_{1-\alpha}$ is the lower α percentile of standard normal distribution.

4.4 Backtests

Backtesting is an important part of the Value-at-Risk model evaluation process. It takes the values that have been calculated by the selected model and tests if the model has been accurate enough to justify its use on a given portfolio. A violation is when the actual return exceeds the Value-at-Risk number for that date. If the exceptions are within statistical limits, model is accepted otherwise rejected.

4.5. The Kupiec Test

Let *N* be the observed number of exceedances in the sample, over a *T* period of time when the portfolio loss over a fixed interval $r_{t,t+1}$ was larger than the VaR estimate, where (Campbell, 2005):

$$I_{t+1} = \begin{cases} 1, & if \;\; r_{t,t+1} \geq -VaR_t \\ 0, & if \;\; r_{t,t+1} < -VaR_t \end{cases}$$

The failure number follows a binomial distribution where the expected exception frequency is *p* = *N*/*T*. The ratio of failures, *N*, to trials, *T*, under the Null hypothesis should be p. The appropriate likelihood ratio statistic is:

$$LR_c = 2\,ln\left[\left(1-\frac{N}{T}\right)^{T-N}\left(\frac{N}{T}\right)^{N}\right] - 2\,ln[(1-p)^{T-N}p^N] \qquad 7$$

The Kupiec test has a chi-square distribution, asymptotically, with one degree of freedom. This test can reject a model for both high and low failures, but, as stated by Kupiec (Kupiec, 1995), its power is generally poor, so conditional coverage tests, such as the Christoffersen test, can be used for the further examination of VaR model reliability.

5. Result and Discussion

Table 1. Summary Statistics

	Beans	Maize	Onion	Rice
Minimum	341.0	199.1	209.9	410.4
Quartile1	384.1	253.6	279.3	503.2
Median	405.3	282.5	342.7	405.3
Mean	406.7	296.3	346.5	558.4
Quartile3	415.6	307.7	378.9	659.6
Maximum	497.6	488.3	656.7	788.7
Std.Dev.	34.0233	88.0595	100.0894	97.1247
Skewness	0.8566	1.1080	1.3380	0.5960
Kurtosis	1.063325	0.6973	1.879151	0.6813

Table 1, shows that the minimum, maximum, mean and median price of Beans, maize, Onion Bulb and Rice from January 2017 to May 2021. In this result the Onion Bulb has the highest standard deviation and Beans has the least standard deviation which indicates greater spread in the Onion Bulb price. It is also observed that the Beans, Maize, Onion Bulb and Rice have skewed positively to the right which indicate that the price inclined to the right side of the distribution, the kurtosis values also indicates that the distributions produce fewer and less extreme outliers than normal distribution.

Table 2. Summary Statistics of the Monthly Returns

	Beans	Maize	Onion	Rice
Minimum	-0.26054	-0.2210	-0.5351	-0.1486
Quartile1	-0.04111	-0.0338	-0.0842	-0.0799
Median	-0.00396	0.0021	0.0216	-0.0344
Mean	0.00086	0.0196	0.0034	-0.0030
Quartile3	0.04700	0.0676	0.1413	0.1180
Maximum	0.29449	0.3738	0.5220	0.1712
Std.Dev.	0.0805	0.1048	0.1863	0.1152
Skewness	0.3402	0.4951	0.2652	0.2720
Kurtosis	3.4670	1.7771	0.8327	1.3762

Table 2 shows the minimum, mean and median of monthly returns of Beans, Maize, Onion Bulb and Rice from January 2017 to May 2021 with the estimated volatility represented by the standard deviations which will be used to measure the market risk, called Value at Risk (VaR). In relation to volatility, represented by the standard deviations of the returns, the Onion Bulb price is the most volatile (0.1863), followed by the rice price (0.1152), then Maize price(0.1048) while the beans price has the least volatility (0.0805)

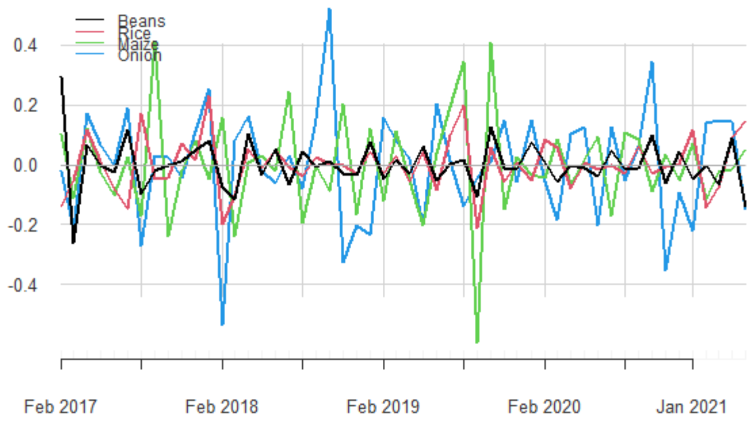
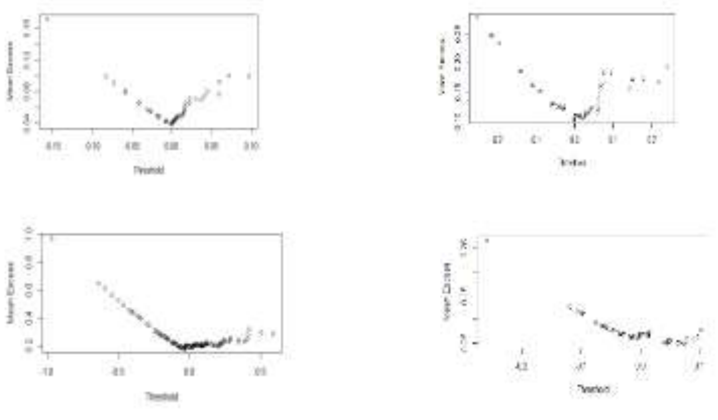


Fig.1: Continuous Compounded Monthly Returns of Beans, Rice, Maize and Onion Bulb

Figure 1, shows the existence of volatility clustering emerged due to the frequent changes of price. The figure also shows that there is persistence in the magnitude of the price changes. The high and low volatilities could be observed for a significant period of time, which is indication of correlation with the past values. We can also see from the graph that the data is now reasonably close to stationary.



(c) (d)

Fig.2: Mean excess plot for Rice, Onion bulb, Maize and Beans.

From fig.4.5, a suitable threshold for EVT model was selected for determining the optimum threshold using a mean excess plot which plots thresholds against the mean exceedances.

Table 3: Maximum Likelihood Estimates (MLE) of the estimated parameters of GEV

	location parameter(u)	β = scale parameter	ξ = shape parameter
Maize	-0.03970544	0.17046023	-0.15877884
Beans	-0.01399056	0.04651308	-0.13070190
Rice	-0.01616029	0.05867307	-0.11399472
Onion	-0.04168187	0.11975968	-0.05380050

Table 4: Value-at-Risk (VaR) based on Extreme Value Theory (EVT)

	95% confidence level $V\hat{a}R$	99% confidence level $V\hat{a}R$
Maize	0.1891	0.3738
Beans	0.0884	0.1949
Rice	0.1333	0.2432
Onion	0.3174	0.5671

Table 4. Gives the estimated VaR using extreme value theory (EVT) which revealed that the maize and Onion have the highest market risk as compared to Beans and Rice. The result gives the estimated value at risk of 0.0883951 and 0.0883951 for Beans at 95% and 99% confidence levels respective. The result also shows that the Maize has the average level of market risk at both 95% and 99% confidence levels with estimated VaR of -0.1891 and -0.3738, while the Onion bulb displayed high level of market risk with estimated VaR of -0.3174 and -0.5671 at 95% and 99% confidence levels respectively.

Table 5: Value-at-Risk (VaR) estimates based on Exponential Weighted Moving Averages

	95% confidence level $V\hat{a}R$	99% confidence level $V\hat{a}R$
Maize	-0.0593	- 0.2148
Beans	-0.0622	-0.1211
Rice	-0.0029	-0.0130
Onion	-0.1807	-0.2007

Table 7, gives the estimated VaR based on EWMA model which also exposed different market risk level for different commodities. The result shows that the Rice has the lowest level of price risk while Onion bulb has the highest level of market risk at 95% confidence level, with estimated VaR of -0.0029 for Rice and -0.1807 for Onion bulb. The result also shows that the Maize has the highest level of market risk at 99% confidence level with estimated value at risk of - 0.2148.

4.3 Models Backtesting

The predictive performance of the above methods of estimating Value at Risk was assessed using the Failure Ratio and the Kupiec PoF test statistic.

Table 6: Kupiec's POF Test

		95% confidence level		99% confidence level	
	Model	violations	Test statistic	violations	Test statistic
Maize	Historical	3	2.1988	1	1.0000
	EWMA	18	4.2161	7	5.0891
	EVT	4	2.2376	1	3.0748
Beans	Historical	0	1.0000	0	1.0000
	EWMA	3	2.1988	0	1.0000
	EVT	2	1.7151	0	1.0000
Rice	Historical	2	1.7151	1	3.0748
	EWMA	24	4.5161	19	4.0043
	EVT	3	2.1988	0	1.0000
	Historical	0	1.0000	0	1.0000
Onion	EWMA	4	2.2376	3	3.4240
	EVT	0	1.0000	0	1.0000

Table 8, gives the back test result of violation ratio and Kupiec proportion of failure test which shows that for 95% confidence level, the number of exception, N for extreme value theory (EVT) is small compared to that of EWMA which exhibit higher number of violations. The result shows that the value at risk (VaR) estimation with extreme value theory (EVT) method perform better than other methods (EWMA and Historical Simulation) in forecasting agricultural market risk. Furthermore the forecast VaR for 95% and 99% confidence levels based on extreme value theory (EVT) gave good results, that is calculated likelihood ratio at 95 % confidence level is less than the critical value ($X^2(1) = 3.84$), where the test statistic reject the assumptions of good models at both 95% and 99% confidence level estimated VaR for maize and Rice based on EWMA models.

6. Conclusion

From the results obtained from the analysis, it can be concluded that different agricultural commodities have different degrees of price risk. Beans and Rice have lowest levels of market risk. The maize and Onion bulb have the highest level of market risk. It can also conclude that the extreme value theory (EVT) method of VaR forecasting produce the most suitable results at both confidence levels (95% and 99%). The Failure Ratio and Confidence Interval show that the extreme value theory (EVT) had the least number of rejections at both confidence levels (95% and 99%).

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