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FORECASTING VOLATILITY IN SUB-SAHARAN AFRICA'S COMMODITY MARKETS

Matthew Kofi Ocran[*], Nicholas Biekpe[**]

Abstract

Using spot prices from eighteen commodities traded by most Sub-Saharan African countries, this paper evaluates the out-of-sample volatility forecasting efficiency of seven models. The models evaluated included random walk, simple regression and five models from the ARCH family of models. Standard loss functions are used to examine the relative performance of the competiting models. The non-ARCH family of models consistently outperformed the ARCH family of models on all the evaluation criteria. Of the two non-ARCH family of models, the autoregressive model was superior. The results of the study suggest that government agencies in Sub-Saharan Africa that manage inflows from commodity markets can use autoregressive models in predicting volatility of inflows. Again, risk management strategies will be best served with autoregressive models.

Key words: Sub-Saharan Africa, volatility forecast, model evaluation, commodity spot prices.
JEL Classification: G12, G15.

1. Introduction

Commodity prices have been one of the most volatile international asset prices. Kroner *et al.* (1993) argue that failed attempts at forecasting commodity prices can be attributed in part to their relatively high volatility. However, most commodity price forecasts have not dealt with the issue of volatility adequately. In order to address price forecast failures, forecasts have sometimes been generated within given confidence intervals. Confidence intervals are then described with their associated probabilities to reduce ex-post forecast errors. As discussed in Kroner *et al.* (1993), these confidence intervals are estimated on the assumption that volatility does not change over time. However, there are papers that show the existence of volatility changes in commodity prices. For instance, Ocran and Biekpe (2005) indicate nine out of eighteen commodities of importance to Sub-Saharan African economies experienced significant changes in volatility over the past four decades. Given the crucial role that commodities play in the economies of Sub-Saharan Africa, understanding volatility forecasting can be very helpful in economic decision-making. Poon and Granger (2003) discuss in detail why forecasting volatility is critical in various spheres of influence of international asset prices as well as in monetary policy.

The purpose of this paper therefore is to examine forecasting accuracy of seven volatility forecasting models using weekly prices in eighteen commodity markets. Earlier studies examined volatility forecasting using market expectations (Taylor, 1986; Kroner *et al*., 1995; Fleming *et al*., 2000; Martiens and Zein, 2002; Szakmary *et al*., 2002). Thus far no empirical work has examined the efficiency of volatility forecasting models for commodity markets considering a wide range of time-series models, though such work has been done for stock.

Forecasting models evaluated include both linear and non-linear models and competing models are evaluated with the aid of standard (symmetric) loss functions. The range[1] of commodities selected makes it possible to answer the question as to whether volatility forecasting models show a similar or different forecasting ability. The study also addresses the concerns raised in Leamer (1983) and Mackinlay (1990) that investigating alternate data samples (i.e. across markets or time) provides reliable out-of-sample robustness check.

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[1] Commodities studied include agricultural raw materials, industrial and precious metals as well as food commodities.

To the extent that most SSA countries depend on commodities for the greater part of their export earnings, an improved understanding of future volatility outcomes can be useful in managing risk associated with export earnings. Again, results of the study would prove valuable to risk managers who rely on measures of volatility for assessing commodity price risk in order to develop risk-management strategies. The rest of the paper is structured as follows: section 2 briefly reviews selected studies on volatility forecasting and section 3 discusses data issues. The methodology is outlined in section 4, whilst empirical results and forecast evaluations are given in section 5. The conclusions of the study are presented in section 6.

2. Literature Review

In a comprehensive review by Poon and Granger (2003) they examine ninety-three published and unpublished papers that evaluate volatility forecasting models of financial market assets. The questions that Poon and Granger (2003) address are whether volatility forecasting as a procedure was implementable. The other research question addressed is determination of the relative efficiency of the range of volatility forecasting models in the literature. The paper identified four main types of models for volatility forecasting. These were historical[1], the ARCH family of models, implied volatility[2] and stochastic volatility forecasts (see Poon and Granger (2003) for detailed descriptions of the various model types). The range of assets covered in the volatility forecasting literature was mostly stocks, bonds and foreign exchange. Futures options underlying market indices and returns of various asset markets have also attracted a lot of research attention. However, commodity spot and futures option volatility forecasting do not appear to have attracted much attention. Of the ninety-three studies reviewed by Poon and Granger (2003), only five consider commodities.

Empirical work on volatility forecasting can also be grouped based on the nature of the information used. One of these uses market expectations derived from option pricing models, whereas the other uses time-series modelling. In addition to the two main methods, there is also a strand of literature that uses a parametric approach. However, researchers have argued that parametric methods perform poorly (Pagan and Schwert, 1990; Kenneth, West and Dongchul, 1995), hence they are left out of the present review. Following mainstream literature on financial markets, neural network-based models, genetic programming and time change and duration approaches are also ignored (cf. e.g. Engle and Russel, 1998; Kroner *et al*., 1993).

Literature on volatility forecasting of financial market assets usually examines whether implied[3] volatility predicts realised volatility underlying futures better and, if so, whether this is done efficiently (see Latane and Rendlemen, 1976). Studies on implied volatility and realised volatility are not decisive about the relative importance of implied volatility as against realised volatility. The strand of literature that disagrees with the use of implied volatility claims that implied volatility has no correlation with realised volatility (see Canina and Figlewski, 1993; Day and Lewis, 1992; and Lamoureux and Lastrapes, 1993). For instance, Canina and Figlewski (1993) assert that options markets do not necessarily process market information efficiently; consequently volatility forecasts using option price were flawed. Christensen and Prabhala (1998) conclude with a set of results that is opposed to the conclusions of Canina and Figlewski (1993). Other papers, such as that by Jorion (1995), suggest that implied volatility is efficient in predicting return volatility of foreign exchange futures; however, the author concedes that estimated implied volatility forecasts are biased.

Day and Lewis (1993) evaluated volatility forecasting models of crude oil futures and options. The models in order of merit ranking based on efficiency were: implied historical, GARCH-M and EGARCH. The study used daily data covering November to March 1991. Using exponential weighted variance-covariance matrix, Fleming *et al.* (2000) forecasted volatility of the Standard and Poor's 500 Index Futures (S&P 500), T-bond and gold futures. Among the conclusions of the authors was that an equally weighted bill portfolio was effective in forecasting volatility and

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[1] This class of models included random walk and historical averages of squared returns. Also included in the historical volatility models are time-series models that use moving averages, exponential weights and autoregression models.
[2] These are related to models that estimate volatility using the Black-Scholes (1973) model and other assumptions. The approach uses implied standard deviations of option prices.
[3] Thus the volatility component of the Black-Scholes (1973) option pricing formula.

risk premia of assets of varying maturities. In another study on commodities (Kroner *et al.*, 1995), the authors examined the futures options on cotton, corn, cocoa, wheat, sugar, silver and gold. The paper compares the volatility forecasting abilities of seven models. Three of these were tested using derived volatilities, two using historical volatility, whilst the last model combined both derived volatility and realised volatility in the forecasting exercise. Kroner *et al.* (1993) suggest that when different forecasting models were combined they tend to predict commodity price volatility better than the various individual forecasting models. Martiens and Zien (2002) evaluated the efficiency of implied volatility, log ARFIMA and GARCH models in forecasting volatility in Standard and Poor's 500 Index Futures (S&P 500), the yen/dollar exchange rate futures and crude oil futures. Like most studies that attempt to forecast volatility using futures options, the authors identified implied volatility models as the most efficient. Using data from futures options from various exchanges, Szarkmary *et al.* (2003) compared implied volatility models based on option prices. The authors studied financial asset prices across various financial asset markets. These included commodities, interest rates, foreign exchange and futures options on S&P 500. Szarkmary *et al.* (2003) concluded that generally implied volatility outperforms models based on realised volatility.

Thus far the paper by Kroner *et al.* (1995) is the only one to have examined volatility forecasting models within the framework of time-series analysis; however, the authors did not explore a broader range of time-series models as they considered only GARCH and historical forecast models. However, the authors came to a conclusion that suggests that combined volatility forecasting models are superior to either the time-series or GARCH model evaluated. Poon and Granger (2003) contradict this result by arguing that combinations of forecasts rather suggest mixed results.

One contribution of this paper is that a broader spectrum of time-series models from the existing literature on volatility forecasting is examined.

3. Data Issues

Monthly spot prices for eighteen commodities traded by most Sub-Saharan African countries covering the period 1980 (1) and 2006 (5) were used. The commodities examined are: gold, aluminium, copper, iron, crude oil, rubber, cotton and timber. The rest were cocoa, coffee, tea, sugar, groundnut, groundnut oil, palm oil, sisal and tobacco. All data series were obtained from IMF (2005). See Appendix Table for description of the individual series.

According to the literature on volatility forecasting, volatility may be defined as standard deviation of returns over a given forecast horizon (Kroner *et al.*, 1993). Following the literature, the series used in the present work were obtained by estimating the square root of average monthly returns over the forecast horizon. The estimated volatility series are termed as 'actual' as they are used to represent actual volatility over the period under consideration. Thus the actual monthly volatility is defined as the within-month standard deviation of commodity spot market prices.

4. Methodology

This section of the paper summarises seven models identified for volatility forecasting. Since all the forecasting models are standard in the literature, they are discussed only briefly. Models used for the forecasts are: random walk, simple regression (i.e. autoregression model), ARCH, GARCH, GJR-GARCH, E-GARCH and PGARCH.

The approach adopted for forecasting involves first obtaining parameters of selected models using first half of the data and then applying the estimates to the second half of the data for out-of-sample forecasts.

Random Walk (RW) Model

The thrust of this model is that the best forecast of this month's volatility is volatility observed in previous month. The model is formally written as:

$$\hat{\sigma}_{F,m}(RW) = \hat{\sigma}_{m-1}, \tag{1}$$

where $\hat{\sigma}^2_{F,m}$ is monthly volatility forecast for month *m* and $\hat{\sigma}_{m-1}$ is actual volatility for previous month.

Simple Regression (SREG)

A simple autoregression procedure is used as a forecasting tool following Brailsford and Faff (1996), and Balaban *et al.* (2003). Monthly volatility is regressed on its lagged values over the sample period: *m = 1………124*. The model is represented as:

$$\sigma_{\alpha,m} = \kappa + \beta\sigma_{\alpha,m-1} + \delta_{m-1}. \tag{2}$$

With the aid of the estimated regression parameters, the forecast for the first month of forecast period is constructed (*m*=124):

$$\sigma_{f,m} = \gamma + \beta\sigma_{a,m-1}. \tag{3}$$

The regression is updated monthly with a rolling sample of 125 observations. Thus for each commodity the estimation involves 125 regressions in order to obtain out-of-sample forecasts of monthly volatility.

ARCH Model

Changes in variance in price behaviour of financial assets are very important in predicting prices on financial markets, including commodity markets. However, unlike the ARCH family of models, other volatility models tend to assume constant variance, hence a range of ARCH type of models are examined to assess their usefulness in forecasting volatility in commodity prices. The simplest form, standard ARCH (1), in which conditional mean function is considered as first-order autoregression (Engle, 1982) and is given as:

$$R_t = c + \rho R_{t-1} + \varepsilon_t \tag{4}$$

whilst the conditional variance is defined as:

$$h_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1}. \tag{5}$$

The monthly forecast errors (ε_t) are assumed to be conditionally normally distributed with mean zero and variance h_t, with information set γ at t-1. Like the simple regression model, SREG, the ARCH model is routinely updated using monthly returns in the mean and variance functions.

GARCH Model

The GARCH model's attractiveness for forecasting financial time series is well documented in the literature (Harris and Solis, 2003). The model estimates conditional mean and conditional variance jointly. Studies have suggested that adequacy of GARCH (1, 1) as against higher-order GARCH (p,q) models, hence the focus on GARCH (1,1) (see Akjiray, 1989; Lamourex and Lastrapes, 1990). The essence of the model is that volatility in time t depends on volatility in time t-1 and the squared forecast error of time t-1:

$$h_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta h_{t-1}. \tag{6}$$

GJR-GARCH

Glosten, Jagannathan and Runkle (1993) modify the GARCH model to address asymmetric problem[1] in conditional volatility due to the leverage effect. Another reason for the perceived asymmetry in volatility is due to the relationship between information arrival and volatility (see Campell and Hentschel, 1992). The Glosten modification of GARCH (GJR-GARCH) introduces a dummy variable, *D*, which takes on the value of one if $\varepsilon_{t-1} \prec 0$ and zero if $\varepsilon_{t-1} \succ 0$. The model is given as:

[1] One stylised fact about financial market returns suggests a negative correlation between past returns and future volatility (see Bouchard and Porters, 2001); this is termed the leverage effect.

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 D_{t-1} + \beta h_{t-1}. \quad (7)$$

EGARCH

Another variation of the standard GARCH aimed at addressing problem of asymmetry in financial asset price behaviour is the exponential GARCH by Nelson (1991). Unlike GJR-GARCH, EGARCH does not require restrictions on the coefficients of the residual terms. Since the model is about the natural log of h_t; variance of h_t can only be positive no matter the sign of the other coefficients in the model. Following Balaban *et al.* (2003), the simplest form of the model, EGARCH (1, 1) is used:

$$\ell n h_t = \alpha_0 + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \lambda\left(\left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}}\right) - \sqrt{\tfrac{2}{\pi}} \right) + \beta \ell n h_{t-1}. \quad (8)$$

P-GARCH

The standard deviation of the GARCH model – known as Power GARCH (PGARCH) – was introduced by Taylor (1986) and Schwert (1989). In PGARCH the standard deviation is rather modelled as against modelling of variance in most of the ARCH-family of models. Din *et al.* (1993) generalised the Power GARCH specification. In Power GARCH an optional parameter γ can be added to account for asymmetry in modelling up to order r. The model also affords one the opportunity to estimate the power parameter δ instead of imposing it on the model. PGARCH can be represented as follows:

$$\sigma_t^\delta = w + \sum_{i=1}^{p} \alpha_i \left(\left|\varepsilon_{t-i}\right| - \gamma \varepsilon_{t-i}\right)^\delta, \quad (9)$$

where, $\delta \succ 0$, $|\gamma_i| \le 1$ for all $i,.........r$

$\gamma_i = 0$ for all $i \succ r$, and $r \succ p$.

In symmetric PGARCH $\gamma_i = 0$ for all *i*. It is also interesting to note that PGARCH model becomes standard GARCH when $\delta = 2$ and $\gamma_i = 0$ for all *i*.

5. Empirical Results and Forecast Evaluation

Out-of-sample forecast results

Following the literature on volatility forecasting, the popular loss functions or error statistics are used in measuring the performance of the various models examined (see Pindyck and Rubbenfield, 1991; Brailsford and Faff, 1991; and Balaban *et al*., 2004). The error statistics used are: Root Mean Squared Error, RMSE; Mean Absolute Error, MAE; Mean Absolute Percentage Error, MAPE and the Theil Inequality Coefficient, TIC. The statistics are defined as:

$$RMSE = \tfrac{1}{12} \sum_{m=125}^{249} \sigma_{f,m} - \sigma_{a,m}, \quad (10)$$

$$MAE = \tfrac{1}{124} \sum_{m=125}^{249} \left|\sigma_{f,m} - \sigma_{a,m}\right|, \quad (11)$$

$$MAPE = 100 \times \tfrac{1}{124} \sum_{m=125}^{249} \left|\sigma_{f,m}^2 - \sigma_{a,m}^2\right| / \sigma_{a,m}, \quad (12)$$

$$TIC = \sqrt{\sum_{m=125}^{249} (\sigma_{f,m} - \sigma_{a,m})} \Big/ \sqrt{\sum_{m=125}^{249} \sigma_{f,m}^2} + \sqrt{\sum_{m=125}^{249} \sigma_{a,m}^2}. \quad (13)$$

In the equations above, $\sigma_{f,m}$ denotes volatility forecast for month m, whilst $\sigma_{a,m}$ signifies actual volatility in month m. Forecast errors represented by equations (10) and (11) are determined largely by the scale of the dependent variable; they are therefore useful as relative measures for comparing forecasts for the same series across different models. Smaller forecasting error statistics indicate superior forecasting ability of a given model. MAPE and TIC, on the other hand, are scale invariant. Theil inequality coefficient lies between zero and one, with zero denoting perfect fit.

For each of the error statistics a standardized (relative) error statistic is also computed following Balaban *et al*. (2004). The worst performing model for each commodity volatility forecast is used as benchmark. The advantage of benchmarking is that it makes error statistics readily interpretable. Tables 1, 2, 3 and 4 show actual and relative volatility forecast error statistics across the four volatility forecast error measures. Discussion of the findings of the study would therefore be conducted along individual error statistics after which conclusions shall be drawn regarding the efficacy of individual models based on their ranking.

Root Mean Squared Error, RMSE

Considering the RMSE statistics, it is found that the autoregressive model of order two, AR (2) and the random walk models were virtually at par. They both outperform the whole range of models evaluated on nine out of the eighteen commodities examined. Among the ARCH-type of models ARCH (1) and EGARCH (1, 1) perform better than the others. The worse performer was, however, GARCH (1, 1) (See Table 1).

Table 1

Root Mean Squared Error statistic

	Tea		Cocoa		Coffee		Sugar		Groundnut		Groundnut oil	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.11072	0.30277	0.12008	0.25282	0.07922	0.09757	0.03035	0.22846	0.71143	1.00000	0.07999	0.18296
AR (2)	0.11286	0.30861	0.12015	0.25298	0.07122	0.08773	0.02956	0.22250	0.06429	0.09037	0.07998	0.18295
ARCH (1)	0.28336	0.77483	0.46381	0.97653	0.78805	0.97070	0.12595	0.94802	0.20901	0.29379	0.42517	0.97251
GARCH (1,1)	0.26579	0.72680	0.46837	0.98613	0.78499	0.96692	0.13285	1.00000	0.21090	0.29644	0.42506	0.97227
EGARCH (1,1)	0.26005	0.71109	0.47326	0.99643	0.63747	0.78521	0.12290	0.92507	0.27828	0.39116	0.42560	0.97350
GJR-GARCH (1,1)	0.26538	0.72567	0.47496	1.00000	0.78131	0.96239	0.13021	0.98012	0.23461	0.32978	0.41102	0.94014
PGARCH (1,1)	0.36570	1.00000	0.47182	0.99339	0.81184	1.00000	0.12636	0.95110	0.21546	0.30285	0.43719	1.00000
	Cotton		Sisal		Palm oil		Rubber		Shrimp		Tobacco	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.04933	0.20402	0.06111	0.09165	0.01149	0.01845	0.04954	0.14708	0.04385	0.37740	0.03468	0.08638
AR (2)	0.04431	0.18326	0.06279	0.09416	0.11231	0.18031	0.05777	0.17151	0.04353	0.37471	0.03781	0.09417
ARCH (1)	0.22692	0.93847	0.65575	0.98347	0.57085	0.91647	0.33530	0.99544	0.11576	0.99643	0.37379	0.93100
GARCH (1,1)	0.23444	0.96959	0.66578	0.99852	0.57739	0.92697	0.33663	0.99940	0.11533	0.99275	0.40149	1.00000
EGARCH (1,1)	0.24179	1.00000	0.60540	0.90796	0.58199	0.93435	0.33350	0.99011	0.11663	1.00386	0.31204	0.77721
GJR-GARCH (1,1)	0.23696	0.98001	0.66677	1.00000	0.57609	0.92488	0.33683	1.00000	0.11570	0.99591	0.30996	0.77201
PGARCH (1,1)	0.23738	0.98176	0.62842	0.94248	0.62288	1.00000	0.33566	0.99653	0.11618	1.00000	0.36765	0.91570
	Crude oil		Timber		Aluminum		Iron ore		Copper		Gold	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.07259	0.19848	0.05782	0.18793	0.07370	0.14112	0.04986	0.19201	0.10830	0.16382	0.05034	0.15205
AR (2)	0.07998	0.21871	0.05045	0.16397	0.07326	0.14028	0.04985	0.19199	0.10349	0.15654	0.05046	0.15241
ARCH (1)	0.36136	0.98812	0.28318	0.92035	0.52221	0.99995	0.25950	0.99944	0.65928	0.99726	0.33109	1.00000
GARCH (1,1)	0.36471	0.99728	0.29037	0.94370	0.52087	0.99738	0.25965	1.00000	0.65467	0.99028	0.32958	0.99545
EGARCH (1,1)	0.36533	0.99899	0.28743	0.93416	0.39331	0.75313	0.25880	0.99674	0.65715	0.99404	0.33322	1.00646
GJR-GARCH (1,1)	0.27901	0.76293	0.29124	0.94652	0.52223	1.00000	0.25618	0.98663	0.66110	1.00000	0.32393	0.97837
PGARCH (1,1)	0.36570	1.00000	0.30769	1.00000	0.38987	0.74654	0.22970	0.88464	0.62695	0.94836	0.32504	0.98173

Mean Absolute Error, MAE

The autoregressive model, AR (2), clearly dominates as the best when the models' performances are evaluated using the mean absolute error statistic. The model occupies top rank for twelve commodities, whilst random walk takes first position for the remaining six commodities. The AR (2) outperforms all the other models predicting price volatilities in metal (aluminium, iron, copper and gold) as well as price volatility for food commodities. However, for the random walk model no clear pattern regarding particular commodity groups could be established. See Table 2.

Table 2

Mean Absolute Error statistic

	Tea		Cocoa		Coffee		Sugar		Groundnut		Groundnut oil	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.08465	0.38173	0.09135	0.22280	0.05526	0.07893	0.02445	0.21248	0.05110	0.21773	0.04803	0.13211
AR (2)	0.08761	0.39508	0.09003	0.21957	0.05625	0.08034	0.02410	0.20939	0.04726	0.20135	0.04320	0.11884
ARCH (1)	0.22176	1.00000	0.39255	0.95739	0.67576	0.96520	0.10768	0.93561	0.16555	0.70536	0.35746	0.98328
GARCH (1,1)	0.20567	0.92746	0.39745	0.96933	0.67114	0.95859	0.11509	1.00000	0.16805	0.71601	0.35739	0.98308
EGARCH (1,1)	0.20068	0.90494	0.40694	0.99248	0.52031	0.74317	0.10683	0.92828	0.23470	1.00000	0.35499	0.97648
GJR-GARCH (1,1)	0.20530	0.92581	0.41002	1.00000	0.66718	0.95294	0.11258	0.97819	0.19083	0.81306	0.34727	0.95525
PGARCH (1,1)	0.20894	0.94222	0.40418	0.98575	0.70013	1.00000	0.10968	0.95304	0.17205	0.73306	0.36354	1.00000
	Cotton		Sisal		Palm oil		Rubber		Shrimp		Tobacco	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.03828	0.18525	0.03534	0.05640	0.09125	0.17121	0.03548	0.12251	0.03561	0.34826	0.02831	0.07926
AR (2)	0.03398	0.16444	0.03622	0.05781	0.08924	0.16744	0.04419	0.15258	0.03527	0.34492	0.02977	0.08336
ARCH (1)	0.19034	0.92105	0.61485	0.98126	0.48647	0.91274	0.28907	0.99818	0.10165	0.99405	0.32023	0.89657
GARCH (1,1)	0.20006	0.96810	0.62554	0.99832	0.49201	0.92314	0.28951	0.99970	0.10134	0.99101	0.35717	1.00000
EGARCH (1,1)	0.20665	1.00000	0.56084	0.89507	0.49770	0.93383	0.28869	0.99684	0.10225	1.00000	0.25714	0.71993
GJR-GARCH (1,1)	0.20244	0.97961	0.62659	1.00000	0.49091	0.92107	0.28960	1.00000	0.10161	0.99365	0.25517	0.71441
PGARCH (1,1)	0.20282	0.98147	0.58561	0.93460	0.53297	1.00000	0.28919	0.99860	0.10192	0.99677	0.31333	0.87724
	Crude oil		Timber		Aluminum		Iron ore		Copper		Gold	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.05830	0.21018	0.04258	0.11710	0.06027	0.12855	0.01039	0.06247	0.08515	0.14171	0.03941	0.05653
AR (2)	0.06147	0.22159	0.03971	0.10920	0.05986	0.12767	0.01034	0.06217	0.07937	0.13208	0.03902	0.05597
ARCH (1)	0.27354	0.98614	0.22822	0.62765	0.46882	0.99994	0.16611	0.99864	0.59941	0.99754	0.2737	0.39258
GARCH (1,1)	0.27651	0.99683	0.23550	0.64767	0.46737	0.99685	0.16634	1.00000	0.59556	0.99113	0.28951	0.41522
EGARCH (1,1)	0.27706	0.99881	0.23255	0.63956	0.32691	0.69725	0.16501	0.99203	0.59764	0.99461	0.27495	0.39433
GJR-GARCH (1,1)	0.19028	0.68596	0.36361	1.00000	0.46885	1.00000	0.16347	0.98276	0.60088	1.00000	0.69725	1.00000
PGARCH (1,1)	0.27739	1.00000	0.24595	0.67641	0.32308	0.68910	0.11821	0.71064	0.56926	0.94737	0.27034	0.38772

Again, like the RMSE measure, the non-ARCH type of models performed better than the ARCH-types as a group. Among the ARCH-type the best performing model was EGARCH (1,1) followed by ARCH (1), with GARCH (1,1) as the poorest performer.

Mean Absolute Percentage Error, MAPE

Again using mean absolute percentage error as model evaluation criterion, AR (2) performed better than all the other models. Following AR (2) was the Random Walk (RW) model. Among the ARCH-family of models volatility forecasts error associated with E-GARCH was the lowest for six commodities, the lowest in five commodities for the ARCH model, three for P-GARCH and GJR-ARCH respectively. The simple GARCH model recorded the highest forecast errors.

Table 3

Mean Absolute Percentage Error statistic

	Tea		Cocoa		Coffee		Sugar		Groundnut		Groundnut oil	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	2.17767	0.39098	1.29727	0.22097	2.52914	0.06940	2.71777	0.20815	0.86018	0.22136	0.77271	0.13031
AR (2)	2.25517	0.40490	1.28150	0.21829	2.58760	0.07100	2.68587	0.20571	0.79536	0.20468	0.69733	0.11760
ARCH (1)	5.56974	1.00000	5.63914	0.96056	35.01615	0.96085	12.63211	0.96748	2.75886	0.70998	5.92981	1.00000
GARCH (1,1)	5.12995	0.92104	5.71218	0.97300	35.04374	0.96160	13.05678	1.00000	2.80065	0.72074	5.92837	0.99976
EGARCH (1,1)	5.09813	0.91533	5.83161	0.99334	27.51979	0.75514	12.01000	0.91983	3.88581	1.00000	5.65212	0.95317
GJR-GARCH (1,1)	5.21010	0.93543	5.87069	1.00000	34.85199	0.95634	12.88419	0.98678	3.16707	0.81503	5.71651	0.96403
PGARCH (1,1)	5.30015	0.95160	5.79668	0.98739	36.44306	1.00000	12.45665	0.95404	2.86398	0.73704	5.76324	0.97191
	Cotton		Sisal		Palm oil		Rubber		Shrimp		Tobacco	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	1.64567	0.18113	0.61002	0.05760	1.95691	0.18068	1.76043	0.12625	3.06468	3.49305	0.32634	0.08025
AR (2)	1.46066	0.16077	0.62337	0.05886	1.91136	0.17648	2.24104	0.16072	3.03281	3.45673	0.34676	0.08527
ARCH (1)	8.13715	0.89561	10.38982	0.98099	9.96648	0.92021	13.90204	0.99701	8.75846	9.98270	3.64729	0.89692
GARCH (1,1)	8.72599	0.96042	10.57311	0.99830	10.06662	0.92946	13.91262	0.99777	8.75455	9.97824	4.06644	1.00000
EGARCH (1,1)	9.08559	1.00000	9.46364	0.89354	10.16168	0.93823	13.94378	1.00000	0.87736	1.00000	2.92408	0.71908
GJR-GARCH (1,1)	8.85742	0.97489	10.59114	1.00000	10.04667	0.92761	13.91146	0.99768	8.75789	9.98205	2.90158	0.71354
PGARCH (1,1)	8.87843	0.97720	9.88357	0.93319	10.83065	1.00000	13.91826	0.99817	8.76339	9.98832	3.56771	0.87735
	Crude oil		Timber		Aluminum		Iron ore		Copper		Gold	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	3.64830	0.22416	1.14428	0.17955	0.83845	0.13020	0.50363	0.05962	1.08972	0.13870	0.88733	0.06378
AR (2)	3.81446	0.23437	1.07230	0.16825	0.69733	0.10829	0.50130	0.05935	1.01648	0.12938	0.87876	0.06316
ARCH (1)	16.07778	0.98786	5.96522	0.93601	6.43917	0.99994	0.16611	0.01967	7.83392	0.99714	6.30875	0.45345
GARCH (1,1)	16.23006	0.99722	6.14937	0.96490	6.41902	0.99681	8.44708	1.00000	7.77528	0.98967	13.91262	1.00000
EGARCH (1,1)	16.25823	0.99895	6.07476	0.95319	4.66450	0.72435	8.37185	0.99109	7.80707	0.99372	6.33918	0.45564
GJR-GARCH (1,1)	11.89028	0.73057	6.17112	0.96831	6.43956	1.00000	8.32057	0.98502	7.85642	1.00000	6.20862	0.44626
PGARCH (1,1)	16.27538	1.00000	6.37306	1.00000	4.41346	0.68537	5.73240	0.67863	7.37277	0.93844	6.22408	0.44737

Theil Inequality Coefficient, TIC

Theil inequality coefficient statistics also indicate superiority of the AR (2) model in forecasting commodity price volatility among the commodities examined. In thirteen of the commodities AR (2) produced the least forecast errors for eleven commodities, whilst random walk was the preferred model for five commodities. However, in cases where the random walk proved superior, the difference in forecast error as compared with AR (2) was quite marginal. Considering the relative performances of the ARCH family of models, GJR-GARCH and ARCH were at par. E-GARCH and P-GARCH were also of equal strength, with GARCH as the worst model. See Table 4 below.

Table 4

Theil Inequality Coefficient statistic

	Tea		Cocoa		Coffee		Sugar		Groundnut		Groundnut oil	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.01459	0.38556	0.00852	0.25140	0.01538	0.02956	0.01619	0.02389	0.05110	1.00000	0.00647	0.01864
AR (2)	0.01488	0.39328	0.00852	0.25152	0.01561	0.03000	0.01572	0.02319	0.00540	0.10567	0.00614	0.01767
ARCH (1)	0.03783	1.00000	0.03315	0.97854	0.15171	0.29157	0.06651	0.09813	0.01770	0.34629	0.03405	0.09806
GARCH (1,1)	0.03557	0.94005	0.03348	0.98816	0.15235	0.29280	0.06885	0.10158	0.01783	0.34882	0.03405	0.09804
EGARCH (1,1)	0.03475	0.91848	0.03388	1.00000	0.52031	1.00000	0.06470	0.09546	0.02378	0.46543	0.03485	0.10034
GJR-GARCH (1,1)	0.03551	0.93849	0.03402	1.00404	0.15176	0.29168	0.67776	1.00000	0.01994	0.39019	0.34727	1.00000
PGARCH (1,1)	0.03610	0.95419	0.03376	0.99652	0.15658	0.30093	0.06612	0.09756	0.01825	0.35721	0.03589	0.10335
	Cotton		Sisal		Palm oil		Rubber		Shrimp		Tobacco	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.01035	0.09189	0.00052	0.00868	0.01203	0.17641	0.01219	0.14266	0.01878	0.37235	0.00200	0.00927
AR (2)	0.00930	0.08261	0.00538	0.08918	0.01176	0.17251	0.01410	0.16504	0.01865	0.36971	0.00121	0.00561
ARCH (1)	0.04775	0.42416	0.05924	0.98242	0.06193	0.90823	0.08494	0.99422	0.04997	0.99051	0.02197	0.10171
GARCH (1,1)	0.04879	0.43342	0.06020	0.99842	0.06272	0.91974	0.06885	0.80587	0.04972	0.98553	0.02358	0.10917
EGARCH (1,1)	0.05007	0.44476	0.05442	0.90260	0.06313	0.92572	0.08436	0.98739	0.05045	1.00000	0.01826	0.08453
GJR-GARCH (1,1)	0.11258	1.00000	0.06030	1.00000	0.06256	0.91745	0.08544	1.00000	0.04993	0.98979	0.01813	0.08396
PGARCH (1,1)	0.04930	0.43789	0.05662	0.93898	0.06819	1.00000	0.08506	0.99560	0.05020	0.99510	0.21597	1.00000
	Crude oil		Timber		Aluminum		Iron ore		Copper		Gold	
Model	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Random walk	0.05830	0.46565	0.00676	0.02860	0.00513	0.13646	0.01396	0.18300	0.00693	0.16647	0.005578	0.06534
AR (2)	0.02558	0.20434	0.00676	0.02860	0.00510	0.13566	0.01396	0.18299	0.00662	0.15910	0.00559	0.06549
ARCH (1)	0.12340	0.98563	0.03887	0.16444	0.03761	0.99995	0.07623	0.99937	0.04153	0.99753	0.03592	0.42075
GARCH (1,1)	0.12479	0.99670	0.03992	0.16889	0.03751	0.99729	0.07628	1.00000	0.04127	0.99126	0.08537	1.00000
EGARCH (1,1)	0.12505	0.99877	0.03949	0.16707	0.02803	0.74508	0.07600	0.99634	0.04141	0.99462	0.03614	0.42332
GJR-GARCH (1,1)	0.09912	0.79171	0.23636	1.00000	0.03762	1.00000	0.07536	0.98790	0.04164	1.00000	0.03519	0.41217
PGARCH (1,1)	0.12520	1.00000	0.04220	0.17854	0.02777	0.73833	0.06646	0.87126	0.03972	0.95403	0.03530	0.41350

In summary, the two non-ARCH-based models, namely autoregressive (2) and random walk, consistently outperform the ARCH-family of models. This outcome is largely in conformity with the findings of studies that dwelt on returns on other financial assets other than commodities (see Tse, 1991; Tse and Tung, 1992; McMilan, Speight and Gwilym 2000; Balan *et al*., 2004). The second notable outcome of the work is that within the ARCH family of models no clear pattern of superiority could be established with respect to model complexity and forecast ability. Nonetheless, the E-GARCH model had a slight advantage over the standard ARCH model. The GARCH model consistently generated the highest forecast errors and was thus clearly the worst performing model. Results concerning the ACH-family of models are also consistent with mixed results in the literature concerning identification of the most superior model in the sub-group of the ARCH family of models.

6. Conclusions

Though volatility forecasting appears to be a widely researched area in the finance literature, commodity markets have not attracted much attention thus far. Performances of a wide range of volatility forecasting models have been investigated with mix results. This paper sought to add to the literature by using a single unifying framework evaluating a large number of volatility forecasting models across 18 commodity markets. The analysis covered the 20-year period 1985-2005. The commodities considered were: gold, iron, aluminum, copper, crude oil, rubber, timber, cotton, cocoa, tea, coffee, sugar, tobacco, sisal, groundnut, groundnut oil, shrimp and palm oil.

Seven forecasting models used in the analysis were random walk, the autoregressive model of order two, ARCH, GARCH, E-GARCH, GJR-GARCH and P-GARCH. The forecast models were then compared using the traditional symmetric evaluation statistics root mean squared error, mean absolute error, mean absolute percentage error and the Theil inequality coefficient statistic.

The main finding of the study is that the autoregressive regression model of order two, AR (2), forecasts commodity price volatility better than the other six models evaluated. The results of the study suggest that government agencies in Sub-Saharan Africa which manage inflows from commodity markets can use autoregressive models in predicting volatility of inflows. Again, risk-management strategies involving the use of commodity market volatility will be best served with autoregressive models in forecasting commodity volatility.

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Appendix

Table 1

Commodity Data Description

Commodity	Description
Crude Oil	Simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh, US$ per barrel
Tea	Mombasa, Kenya, Auction Price, US cents per kilogram
Sugar	Sugar, Free Market, Coffee Sugar and Cocoa Exchange (CSCE) contract no.11 nearest future position, US cents per pound
Tobacco	US Dollars per Metric Ton, US
Cocoa beans	Cocoa, International Cocoa Organization cash price, CIF US and European ports, US$ per metric tonne
Coffee	Coffee, Other Mild Arabicas, International Coffee Organization New York cash price, ex-dock New York, US cents per pound
Cotton,	Cotton Outlook 'A Index', Middling 1-3/32 inch staple, CIF Liverpool, US cents per pound
Groundnuts (peanuts)	Groundnuts (peanuts), 40/50 (40 to 50 count per ounce), cif Argentina, US$ per metric tonne
Groundnut oil	US Dollars per Metric Ton, Nigeria
Sisal	US Dollars per Metric Ton, East Africa
Timber	Hard Logs, Best quality Malaysian meranti, import price Japan, US$ per cubic meter
Palm oil	Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, US$ per metric tonne
Rubber	No.1 Rubber Smoked Sheet, FOB Malaysian/Singapore, US cents per pound
Shrimp	Frozen shell-on headless, block 16/20 count, Indian origin, C&F Japan, US$ per kilogram
Gold	United Kingdom, average price US$/oz
Copper	Copper, grade A cathode, LME spot price, CIF European ports, US$ per metric tonne
Iron Ore	Iron Ore, 67.55% iron content, fine, contract price to Europe, FOB Ponta da Madeira, US cents per dry metric tonne unit
Aluminum	Aluminum, 99.5% minimum purity, LME spot price, CIF UK ports, US$ per metric tonne