Exchange rate forecasting in the West African Monetary Zone: a comparison of forecast performance of time series models

Haruna, Issahaku and Abdulai, Hamdeeya and Kriesie, Maryiam and Harvey, Simon K.

University for Development Studies, Ghana, University for Professional Studies, Ghana, University of Ghana, Legon, Bank of Ghana

18 February 2015

Exchange rate forecasting in the West African Monetary Zone (WAMZ): a comparison of forecast performance of time series models

Abstract

It has become an undisputable fact in economics and finance that conventional exchange rate determination models cannot outperform the random walk model in out-of-sample forecasting. We evaluate the empirical veracity of this well-known fact in the West African Monetary Zone (WAMZ). We compare the out-of-sample forecast accuracy of the random walk hypothesis *vis-a-vis* the Autoregressive Moving Average (ARIMA) model, Generalised Autoregressive Conditional Heteroskedastic (GARCH) based models, and Vector Autoregressive (VAR) model. The root mean square error (RMSE) is used as the measure of forecast accuracy. We find evidence to refute the body of economic literature that supports the view that forecasts from the RWM are unbeatable. We show that if a non-linear RWM is estimated, and the RMSE is used as the measure of forecast performance, the VAR model, the ARIMA model, and the GARCH(-M) model generally outperform the RWM. However, when the assumption of linearity is sustained, the RWM convincingly outperforms all other models. We show that the type of model to use to achieve forecast accuracy depends on the time horizon, and the country for which the forecast is to be made.

Keywords: forecasting, exchange rate, West African Monetary Zone (WAMZ), time series models, Root Mean Square Error (RMSE), forecast evaluation

JEL Codes: B23, C22, C53, E17

1. Introduction

Six West African states (Gambia, Ghana, Guinea, Liberia, Nigeria and Sierra Leone) signed the 'Accra Declaration' in April 20, 2000 to set up a second monetary zone to be called the West African Monetary Zone (WAMZ), by the year 2003. But, the establishment of the common currency zone has been postponed three times (January 1, 2003; July 1, 2005; December 1, 2009) due to the inability of member states to achieve convergence criteria on a consistent basis. The new date proposed for the launch is 2015. But the facts on the ground point to another postponement. Key to the establishment of a monetary zone is the exchange rate, since the nature of the prior stability of the exchange rate of member countries will determine the stability of the common currency when it eventually comes into force. The questions that continue to vex researchers and policymakers are: (1) how best can the exchange rate of each country be forecast and over what horizon? (2) Will the famous Random Walk Model (RWM) produce better forecast than other time series models? This paper aims to find answers to these questions.

Increased globalization in recent times has resulted in increasing integration of trade, finance, people and ideas in one global market place with international trade and cross border flows being the main elements of the integration. A key determinant of whether countries benefit from this integration is their exchange rate. An exchange rate generally refers to the rate at which one currency is exchanged for another. Where exchange rate is volatile it may be an obstacle to economic growth, described by Jhingan (2005) as 'foreign exchange constraint'. The exchange rate is an important part of the transmission mechanism in many of the policy evaluation models. The exchange rate usually enters as part of an arbitrage equation relating the interest rate in one country to the interest rates in other countries through the expected rate of appreciation of the exchange rate. The exchange rate also affects the terms of trade and thus the flow of exports and imports. Furthermore, the exchange rate can affect real output volatility (Ono, 2013). Changes in the exchange rate affect the price of foreign goods sold in another country and is then passed through to domestic prices. A stable exchange rate is therefore preferred. Disturbances in trade balance are said to be the main drivers of exchange rate fluctuations in non-CFA Sub-Saharan African countries (Sissoko and Dibooglu, 2006).

WAMZ countries consider exchange rate as a key macroeconomic policy instrument that could significantly impact member countries' competitiveness as well as export promotion and economic growth. The Central Banks of the WAMZ countries have consequently pursued exchange rate policies aimed at providing an environment that promotes exchange rate stability, with a view to maintaining price stability and promoting sustainable output growth. However, sharp currency depreciation in most of the countries causes increases in the general price levels and a reduction in output growth. One of the key reasons for this is the existence of large external debt denominated in foreign currencies that increases in value relative to the domestic currency as a result of depreciation, reducing the economy's net wealth.

In a study that examined the effect of exchange rate policy on the bi-lateral intra-WAMZ and global inter-WAMZ export trade, Balogun (2007) finds that the coefficient estimates of bilateral exchange rate was not significant in explaining the changes in the bilateral intra-WAMZ exports, but not the case with the world inter-WAMZ regression results in which one of the partner's exchange rate is significant and positively influenced their collective exports to the rest of the world. In a similar study, Adjasi, Biekpe and Osei (2011) argue that movements in the exchange rate tend to have an effect on the operational costs of firms and this in turn has implications for the share price movements of such firms on the stock market. Rapid movements in the exchange rate would therefore influence share prices of listed African firms and in turn also influence returns of the stock market. Exchange rate fluctuations could thus have serious and long-lasting effects on stock prices. In order to test this hypothesis they use data of monthly frequencies for seven African countries. Their findings confirm the strand of literature which proposes that exchange rate increases reduce the demand for local stocks and thereby drive down stock prices.

Hence, the management of exchange rate has become a great concern to policy makers and academicians alike. In the academic circles, Engle (1982) and Bollersley (1986) and others have craved various sophisticated approaches such as the Autoregressive Conditional Heteroscedastic (ARCH) model and the generalized ARCH (GARCH) and some of its likes to identify and tackle the various forms and manifestation of volatility in financial time series such as the exchange rate. Notwithstanding the rapid evolution of time series models for forecasting financial time series, it remains unsettled as to which particular time series model produces the most accurate forecasts. In the particular case of the exchange rate, the debate is centred on whether or not the random walk model is beatable in terms of forecast performance. Ever since the publication of the highly-cited paper of Meese and Rogoff (1983), endorsing the unbeatability of the naïve random walk model (RWM) forecasts, some researchers have held the view that exchange rate forecast from the naïve RWM is the best. For instance, in a study, Abhyankar *et al.* (2005) call the inability of models grounded on monetary fundamentals to outperform the random walk as a ‘‘major puzzle in international finance’’. Evans and Lyons (2005) also confirm the Meese–Rogoff finding by describing it as haven proven to be robust over several decades. Meese and Rogoff (1983) attribute the inability of exchange rate models to outperform the RWM to simultaneous equations bias, sampling errors, stochastic movements in the true underlying parameters, misspecification and nonlinearities.

Another group of researchers (for example, Mark, 1995; MacDonald, 1999; Mark and Sul, 2000; Kim, 2012; Moosa and Burns, 2014) hold the view that, contrary to the position of Meese and Rogoff, the RWM can be outperformed. Kim (2012) argues that, the inability to outperform the RWM is down to the omission of a wide range of macroeconomic variables from conventional models. Kim (2012) proves this point by showing that a nonlinear factor model outperforms the RWM. Similarly, in a paper published recently, Moosa and Burns (2014) show that conventional monetary models of exchange rates can beat the random walk in out-of-sample forecasting if forecasting power is measured by direction accuracy and profitability.

Thus, the evidence regarding the “best” time series model for forecasting exchange rate series remains inconclusive. We add to this body of knowledge by examining the forecasting power of four different time series models within WAMZ countries. We explore the following questions: (1) is there a failure to outperform exchange rate forecast from the RWM in the WAMZ? If not, which is the best time series model for forecasting exchange rate for each country in the WAMZ? Specifically, the study compares the forecast performance of an ARCH type RWM to the forecasts from Autoregressive Integrated Moving Average Model (ARIMA), an ordinary GARCH model, and a GARCH in the mean (GARCH-M) model, and the Vector Autoregressive (VAR) model.

The study is different from previous studies in a number of ways. First, unlike previous studies which employ a linear RWM (these previous studies are not based on WAMZ data), ours is non-linear. We compare the forecast over four different forecast horizons while in the extant literature most comparisons have often been done from between 1 to 3 forecast horizons. Also, previous studies arbitrarily chose the type of time series model, say a GARCH(1,1). Our study is unique in the sense that we do not impose a model of the same nature for all countries. This is important because, it allows us to perform forecast using the best model that fits the specific time series model for each country. In addition, most previous studies compare at most 3 time series models while we compare four. Lastly, to the best of our knowledge, this is the first attempt at comparing the forecast performance of time series models for all WAMZ countries in a single study. We find that, there is no single time series forecasting model that fits all WAMZ countries exchange rate data. The type of forecasting model appropriate for a given country depends on the time period under consideration.

The rest of the paper is organized as follows. In section 2, we explore some literature on the topic. Section 3 gives details of the research methodology employed. Results and discussion of the forecast performance of the various time series models are presented in section 4. Section 5 concludes the paper.

2. Literature review

Vilasuso (2002) finds that a number of exchange rate volatility ‘stylized facts’ have been documented since the abandonment of the Bretton Woods system of fixed parities decades ago. This section of the paper thus reviews some of these ‘stylized facts’ and the extant literature. Empirically, most studies have forecasted exchange rate volatility by collecting and using data with intraday, daily, weekly and monthly frequency. Balaban (2004) investigates out-of-sample forecasting accuracy of the symmetric and asymmetric conditional variance models for the US dollar-Deutsche mark exchange rate volatility by collecting daily continuously compounded exchange rate returns, over a 24-year period. The forecast performance is then evaluated using statistics such as symmetric and asymmetric statistical error. The mean error (ME), the MAE (mean absolute error), the MSE (mean squared error), the mean absolute percentage error (MAPE) are the symmetric measures. Balaban (2004) finds that the symmetric criteria consistently choose the EGARCH and GJR-GARCH models respectively as the best and the worst.

Tenti (1996) finds that for years, two unresolved opposing views have existed between the trading and academic communities about the statistical properties of exchange rate. While traders considered exchange rates to have persistent trends that permitted mechanical trading systems, researchers on the other hand, presented evidence supporting the random walk hypothesis. The presence of random walk in currency markets however is a sufficient but not a necessary condition for the existence of a weak form of the efficient market hypothesis -that past movements in the exchange rate could not be used to foretell future movements.

Madura, Martin and Wiley (1999) compare the forecast performance of random walk; implied forward rate (FR); and ARIMA models using twelve (12) emerging market currencies. In order to test for forecast accuracy they use the mean absolute percentage forecast error. They show that the RWM outperforms the FR and ARIMA models despite the inclusion of expectation components. They further find the forecast of Latin American currencies to be more error prone.

West and Cho (1995) set out to compare the out-of-sample forecast performance of univariate homoscedastic, GARCH, AR, and nonparametric models based on bilateral weekly data collected over a 12 year sample period. The data they collect are on exchange rates which are measured as dollars per unit of foreign currency, between the US and Canada, France, Germany, Japan, and the United Kingdom. Unlike previous studies such as Balaban (2004), their study focuses on the mean squared prediction error (MSPE). West and Cho (1995) then take logarithmic differences of the series, and then multiply it by 100. They focus on RMSPE because mathematical expectations have minimum RMSPE, so a good statistical model for the expected value of exchange rate squares will tend to have forecast errors whose average squared value is small. Their results confirm earlier studies which find the GARCH models outperforming the other models over the short horizon (one-week).

Faust, Rogers and Wright (2001) find that a random walk forecast of the exchange rate generally outperforms alternative models drawn from economic theory. A number of authors have also found models whose out-of-sample forecasting performance improves upon a random walk. Kilian and Taylor (2003) however find that the goal of exploiting economic models of exchange rate determination to beat naïve random walk forecasts remains as elusive as ever. They establish findings that corroborate the evidence presented in Taylor *et al.* (2001) that there is strong- albeit nonlinear – mean reversion in monthly dollar real exchange rates.

Simpson and Grossmann (2011) compare the out of sample forecast of relative purchasing power parity (PPP) based models to that of a RWM over short horizons. The PPP models are based on the consumer price index (CPI), producer price index (PPI) and a proxy for traded goods indexes. For all the currencies considered, they find the PPP model to show appreciable gains over the RWM.

Employing monthly exchange rate data for six industrialized countries from, Moosa and Burns (2014), assess the ability of other models to beat the RWM. They find that it is difficult, though not impossible, for conventional macroeconomic models to outperform the random walk model in terms of the root mean square error and similar quantitative measures of forecasting accuracy that depend entirely on the absolute forecasting error. They further find that, the VAR model outperforms the RWM in terms of the RMSE. They argue that the VAR model outperforms the RWM because, by introducing a lagged dependent variable, the VAR can be described as an augmented random walk. Thus, it amounts to using a random walk model to beat another random walk model. Some studies however, do not find the VAR as superior to the RWM.

For example, Fullerton *et al.* (2001) use a set of error correction models to represent the behaviour of the exchange rate between the Mexican peso and the U.S. dollar. Their findings led them to conclude that although dynamic simulation properties of the equations are acceptable, in no case do they generate levels of accuracy that exceed that associated with a simple random walk. This implies that, whether or not a model beats the RWM is not necessarily dependent on its dynamic nature as Moosa and Burns make us believe. Thus, the debate about the best time series model for forecast remains unresolved.

From the extant literature, most of the studies use samples of an average of five countries. However, none of these studies has yet been conducted on a sub-regionally African integrated body such as the West African Monetary Zone (WAMZ). A study of this nature could therefore help countries within WAMZ in their effort to establish a common currency for trade in the near future. Like the Euro of the European Union, the opportunities thereof will be enormous. Furthermore, the study's findings will be useful to West African businesses and indeed other international businesses that are spread over different countries who raise long and short term funds from international markets. The study will also help firms that confine their entire business to the domestic market only because a change in foreign exchange rate can change the business and competition scenario for the firms.

Also, unlike previous studies that use a linear RWM, this study specifies and estimates a nonlinear RWM for the forecast comparison over four different horizons. This study contributes to the body of knowledge in the subject matter by filling theoretical and empirical gaps identified. We provide further evidence to show that, even linear time series models like the ARIMA, can in some situations outperform the random walk model.

3. Research methodology

3.1 Data

Monthly data on the exchange rate of the six WAMZ countries to the US dollar was obtained from the World Bank financial statistics database. The data span from June 1994 to May 2014. The exchange rate variables are expressed in terms of units of the local currency per one unit of the US dollar. The sample is split at January 2013 into an estimation period and a forecasting period. We use observations from June 1994 to January 2013 to estimate the model and then perform an out-of sample forecasts over the period February 2013 to May 2014. Four forecast horizons are used: 1-step ahead (one month), 3-steps ahead (three months), 6-steps ahead (six months), and 12-steps ahead (one year). The RMSE is used as the basis for judging forecast accuracy while the Mean Absolute Error (MAE) is used a robustness checks.

3.2 Model specification

ARIMA model specification

The ARIMA model consists of an Autoregressive (AR) part where the series depends on its past values, and a Moving Average (MA) component where the series depends on its past errors. The general version of the ARMA (p, q) model is given by:

$$S_t = \gamma_o + \sum_{i=1}^{p} \gamma_i S_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \varphi_i \varepsilon_{t-i} \qquad (1)$$

Where S_t is exchange rate, ε_t is a white noise series, p and q are non-negative integers, γ_i and $\varphi_i$are coefficients of the AR and MA terms respectively, S_{t-i} is the lag of exchange rate, ε_{t-i} is the lag of the error which describes innovations in exchange rate. The ARIMA model implies that the series, in this case exchange rate, depends on its past values and the past values of white noise series.

An ARIMA process shows a combination of the characteristics of the AR and MA processes. An AR process has a geometrically declining ACF (autocorrelation function) and a number of non-zero points of PACFs (partial auto correlation functions) while an MA process has a number of non-zero points of ACFs and geometrically declining PACFs. ARIMA process will be having both geometrically declining ACF and PACF. An essential condition for time series analysis is that, the underlying series must be stationary. So for the stationary conversion of the series, one more letter ("I") is added in the ARMA process, which shows the number of times the underlying series must be differenced to make it stationary. On account of this transformation, the ARMA process is also referred as ARIMA process.

The multi-step ahead forecast (ℓ-step) is presented as:

$$\hat{S}_h(\ell) = E(S_{h+\ell}|F_h) = \gamma_o + \sum_{i=1}^{p} \gamma_i \hat{S}_h(\ell - i) - \sum_{i=1}^{q} \varphi_i \varepsilon_h(l - i) \qquad (2)$$

Where *h* is the forecast origin and F_h the information available at the forecast origin *h*.

Specification of the ARCH-Type RWM

This study employs a non-linear RWM which is of the ARCH-type. It is specified as follows:

$$S_t = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_t \qquad (3a)$$
$$h_t = \beta_0 + \sum_{i=1}^{p} \beta_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-1} \qquad (3b)$$

Equation 3a is the conditional mean equation. The second equation (equation 3b) describes the conditional variance of the monthly exchange rate series h_t, modelled as a function of its own lagged q conditional variances and the lagged p squared residuals. Due to the widely held notion by Meese and Rogoff (1983) and other researchers following them, that the RWM is unbeatable, we use the RWM as the benchmark model.

GARCH family

There are a number of models used in estimating univariate volatility of financial time series under the Generalised Autoregressive Conditional Heteroscedastic framework. Some of these include autoregressive conditional heteroscedastic (ARCH) model, generalised autoregressive conditional heteroscedastic (GARCH) model, a GARCH in the mean (GARCH-M) model, the exponential GARCH (EGARCH) model, the conditional autoregressive moving average (CHARMA) model, and the random coefficient autoregressive (RCA) model. As an illustrative example, we employ the GARCH model to describe the methodology under this section.

Developed independently by Bollerslev (1986) and Taylor (1986), the GARCH model allows the conditional variance to be dependent upon its own past lags. The GARCH model was developed due to the fact that its predecessor ARCH model required too many parameters to describe the volatility of asset return (Tsay, 2005). The simplest representation of the model - GARCH (1, 1) is given by:

$$\varepsilon_t = \sigma_t \epsilon_t \qquad \sigma_i^2 = \alpha_0 + \alpha_i \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (4)$$

Where $\{\epsilon_t\}$ represents a sequence of error terms. The model states that the current fitted variance (σ_i^2) is a weighted function of a long-term average value (dependent on α_0), information about volatility during the previous period ($\alpha_i \varepsilon_{t-1}^2$) and the fitted variance from the model during the previous period ($\beta \sigma_{t-1}^2$).

The volatility equation above has an accompanying mean equation which usually follows an ARMA process. In this study we determine for each country whether a GARCH model or a GARCH-M is more appropriate model for forecasting each exchange rate. The GARCH-M is considered because in finance, the return on an asset depends on its volatility. In a GARCH-M model, we add the volatility term to the equation to symbolise the fact that the returns on the exchange rate series depend on the volatility. The associated mean equation which follows an AR(1) process and contains a GARCH term is:

$$S_t = \phi_0 + \phi_1 S_{t-1} + c\sigma_i^2 + \varepsilon_t \qquad (5)$$

Where the current exchange rate S_t depends on its previous value (S_{t-1}). As usual $\{\varepsilon_t\}$ is the error term. The coefficient *c* is a measure of risk premium.

The GARCH (1, 1) can be extended to a GARCH (p, q) formulation, where the current conditional variance is specified to depend upon *q* lags of the squared error and *p* lags of the conditional variance as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \sigma_{t-2}^2 + \cdots + \alpha_q \sigma_{t-q}^2 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-2}^2 + \cdots + \beta_p \varepsilon_{t-p}^2 \qquad (6)$$

or

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

After estimating the above model we can then forecast the model over a time horizon. Using the GARCH (1, 1) as an example and given *h* as the forecast origin, we can generate the1-step forecast as follows:

$$\sigma_{h+1}^2 = \alpha_0 + \alpha_1 \varepsilon_h^2 + \beta \sigma_h^2$$

Where ε_h and σ_h^2 are known at time *h*. Based on this, the 1-step ahead forecast is:

$$\sigma_h^2(1) = \alpha_0 + \alpha_1 \varepsilon_h^2 + \beta \sigma_h^2$$

To generate the multi-step forecast, we make use of the fact that $\varepsilon_t = \sigma_t \epsilon_t$ and rewrite the GARCH (1, 1) volatility equation as:

$$\sigma_{t+1}^2 = \alpha_0 + (\alpha_1 + \beta_1)\sigma_t^2 + \alpha_1 \sigma_t^2 (\epsilon_t^2 - 1)$$

Given $t = h + 1$, we can rewrite the above equation as:

$$\sigma_{h+2}^2 = \alpha_0 + (\alpha_1 + \beta_1)\sigma_{h+1}^2 + \alpha_1 \sigma_{h+1}^2 (\epsilon_{h+1}^2 - 1)$$

Based on the fact that $E(\epsilon_{h+1}|F_h) = 0$, we can write the 2-steps ahead forecast at the forecast origin *h* as:

$$\sigma_h^2(2) = \alpha_0 + (\alpha_1 + \beta_1)\sigma_h^2(1)$$

Thus, we can write the multi-step ahead forecast generally as:

$$\sigma_h^2(\ell) = \alpha_0 + (\alpha_1 + \beta_1)\sigma_h^2(l-1), \quad \ell > 1$$

$$\hat{S}_h(\ell) = E(S_{h+\ell}|F_h) = \gamma_o + \textstyle\sum_{i=1}^{p} \gamma_i\, \hat{S}_h(\ell - i) - \sum_{i=1}^{q} \varphi_i\, \varepsilon_h(l - i) \qquad (7)$$

Specification of the VAR Model

The vector autoregressive (VAR) model is a multivariate time series model. It was made popular in econometric time series by Sims (1980). A VAR is a systems regression model and can be viewed as a hybrid between univariate time series and simultaneous equations models. Thus, a VAR model contains more than one dependent variable. The VAR helps to overcome endogeneity problem which is often common in most time series models. The general form of the VAR (VAR(p) model) is presented as:

$$S_t = \phi_0 + \varpi_1 S_{t-1} + \cdots + \varpi_p S_{t-p} + \varepsilon_{1t} \qquad (8)$$

Where S_t is a vector of endogenous variables, ϕ_0 is a k-dimensional vector, ϖ is a $k \times k$ vector and $\{\varepsilon_t\}$ is a sequence of serially uncorrelated random vectors with zero mean and a positive definite covariance matrix $\sum$.

In this study we employ a multivariate VAR which models the exchange rate series of each country as a function of the lagged values of other countries exchange rates. Thus, S_t is a vector of endogenous variables defined as:

$$S_t = [GB\_US, GH\_US, GU\_US, LI\_US, NG\_US, SI\_US]$$

Where GB_US is the exchange rate of the Gambian Dalasi to the US Dollar, GH_US is the exchange rate of the Ghana Cedi to the US Dollar, GU_US is the exchange rate of the Guinean Franc to the US Dollar, LI_US is the exchange rate of the Liberian Dollar to the US Dollar, NG_US is the exchange rate of the Nigerian Naira to the US Dollar, and SI_US the exchange of the Sierra Leonean Leone to the US Dollar.

Based on the VAR(p) model, we can perform 1-step ahead, 2-step ahead and multi-step ahead forecast as follows:

1-step ahead forecast:

$$S_h(1) = \phi_0 + \sum_{i=1}^{p} \varpi_i \, S_{h+1-i}$$

The 2-step ahead forecast is:

$$S_h(2) = \phi_0 + \varpi_1 S_h(1) + \sum_{i=2}^{p} \varpi_i \, S_{h+2-i}$$

If weak stationary pertains, the ℓ −step ahead forecast $S_h(\ell)$ converges to its mean vector as the forecast horizon increases.

In the study, the Schwarz Information Criteria is used as the model selection criterion.

3.4 Forecast evaluation

Generally, there are two main approaches to forecasting, viz: econometric (structural) forecasting and time series forecasting. Econometric forecasting relates one dependent variable to a series of independent variables while time series forecasting entails predicting the future values of a series given its previous values and/or previous values of an error term. The approach used in this study is time series forecasting. Forecasting of financial time series can be performed in-sample or out-of-sample. The same set of data used in estimating the model is used for forecasting in-sample. Due to the fact that we will generally expect forecast models to perform well in-sample, it is usually imperative to estimate the model by setting aside some of the observations as a hold out sample. In this case, the model is estimated using some of the data, and then forecasts are done using the hold out sample. This is known as out-of-sample forecasting. This paper employs the out-of sample forecast approach. We compare the forecasts performance of the time series models over four (4) forecasts horizons: one month, three months, six months and twelve months. We use the Root Mean Square Error (RMSE) as the measure of forecast accuracy. The RMSE is simply the standard deviation of the forecast errors. Therefore, the smaller the value of the RMSE the better the forecast. It is given by the formula:

$$RMSE = \sqrt{\frac{1}{F}\sum_{t=1}^{F} \vartheta_t} \qquad (9)$$

where $\vartheta_t = S_{t+h} - \hat{S}_{t+h}$, S_{t+h} are the actual series, and $\hat{S}_{t+h}$ are the forecast series.

4. Results and discussion

4.1 Descriptive statistics

Table 1 contains the descriptive statistics of the exchange rate series for each of the WAMZ countries. For each of the series, the volatility is smaller than the average. Given the volatility values, there is quite some amount of volatility in the exchange rate series. GB_US is the exchange rate of the Gambian Dalasi to the US Dollar, GH_US is the exchange rate of the Ghana Cedi to the US Dollar, GU_US is the exchange rate of the Guinean Franc to the US Dollar, LI_US is the exchange rate of the Liberian Dollar to the US Dollar, NG_US is the exchange rate of the Nigerian Naira to the US Dollar, and SI_US the exchange of the Sierra Leonean Leone to the US Dollar. Thus, each exchange rate is in units of the local currency per unit of the US Dollar.

Table 1. Descriptive statistics

	GB_US	GH_US	GU_US	NG_US	LI_US	SI_US
Mean	21.51168	0.907384	-6325.725	107.6379	49.05591	2532.028
Median	24.76302	0.896362	2013.466	128.1516	56.81000	2621.295
Maximum	39.60000	2.830000	7460.083	164.7198	83.57000	4331.236
Minimum	9.305682	0.092007	-1249115.	21.89000	1.000000	570.0351
Std. Dev.	8.772546	0.618115	106958.3	49.92167	25.13187	1154.646
Skewness	-	0.639124	-10.88984	-0.890942	-0.995187	0.024679

	0.120633					
Kurtosis	1.609289	2.936302	120.2185	2.267398	2.725569	1.979368
Jarque-Bera	19.92287	16.37978	142145.4	37.11818	39.86443	10.44127
Probability	0.000047	0.000277	0.000000	0.000000	0.000000	0.005404
Sum	5162.803	217.7722	-1518174.	25833.09	11626.25	607686.6
Sum Sq. Dev.	18392.86	91.31373	2.73E+12	595629.4	149060.1	3.19E+08
Observations	240	240	240	240	237	240

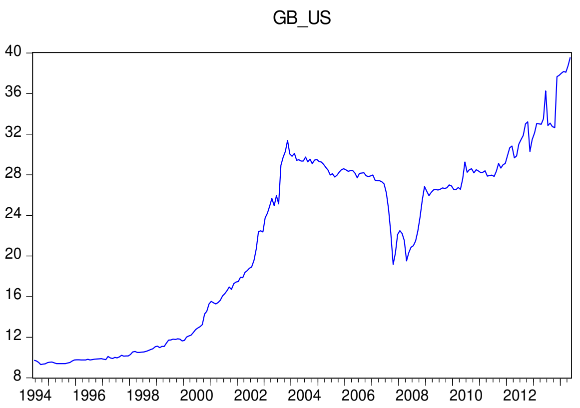
Apart from the series for Ghana and Sierra Leon which are positively skewed, the rest of the series are negatively skewed. The skewed nature of the data is confirmed by the Jarque-Berra statistics which show that all the exchange rate series are non-normally distributed.

4.2 Time series characteristics of the models

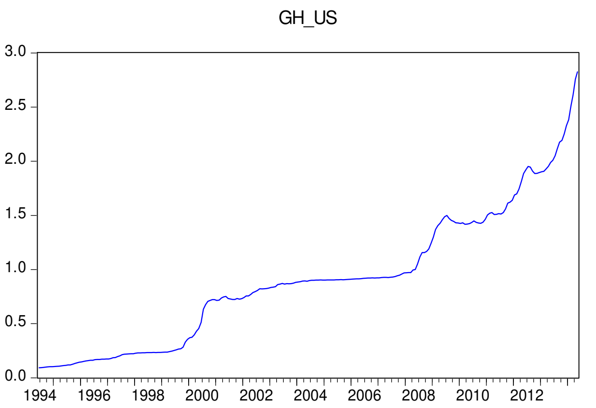
In time series analysis, it is imperative to examine the characteristics of the series in terms of stationarity and the order of integration. From the graphs of the levels in Figure 1, there is an upward trend in each of the series suggesting that the series are all probably non-stationary. But, because of the ambiguity in judging stationarity from the graphs of the series we employ the ADF to test for unit root. The results are shown in Table 2.

Figure 1. Graphs of the levels of the series in the dataset

(a) Gambia

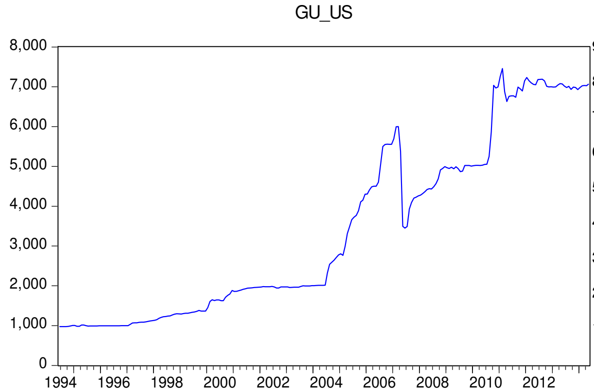


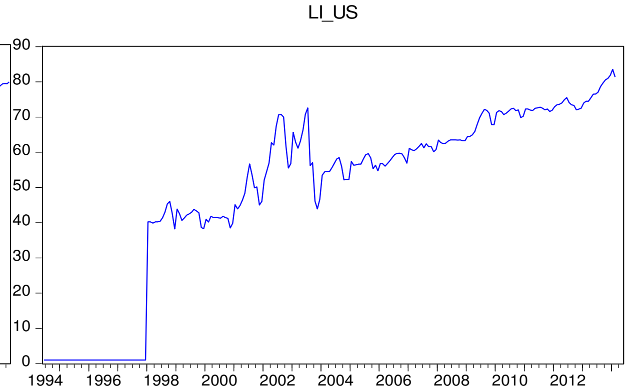
(b) *Ghana*



(c) Guinea

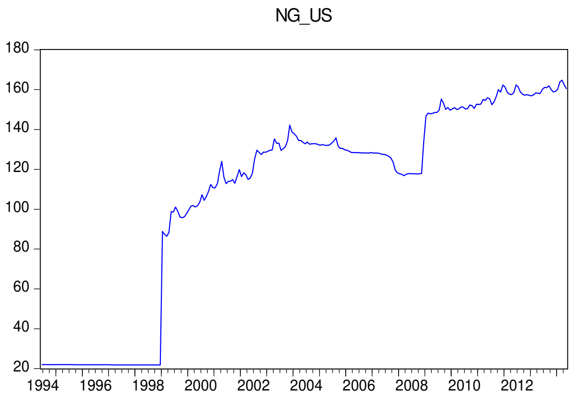
(d) *Liberia*

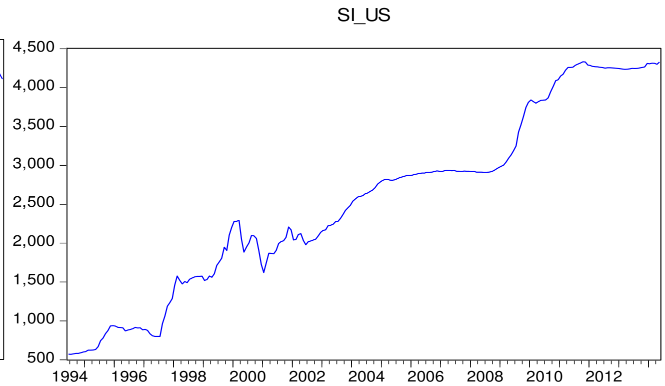




(e) Nigeria

(f) Sierra Leone





At levels, all the exchange rate series in the WAMZ are non-stationary at 5% since all the p-values are greater than 0.05. However, the series are all stationary at first difference. Thus, all the series are integrated of order I(1). The implication is that all the series enter the model at first difference.

Table 2. Augmented Dickey-Fuller (ADF) tests for WAMZ countries

	ADF-Unit Root Test (t-statics)		**ADF-Unit Root Test (p-value)**	
Variable	Level	First Difference	Level	First Difference
GB_US	0.244114	-14.46089	0.9748	0.0000
GH_US	2.535463	-5.383662	1.0000	0.0000
GU_US	-0.283918	-10.26707	0.9239	0.0000
LI_US	-1.531529	-14.69232	0.5160	0.0000
NG_US	-1.365544	-14.95857	0.5989	0.0000
SI_US	-0.785649	-9.523119	0.8209	0.0000

Cointegration test

We conduct a Johansen cointegration test to determine whether to estimate a restricted VAR or an unrestricted VAR (Vector Error Correction Model). We exclude the Gambia sample from the VAR tests because when it is included the sample size of the entire series cuts off at 2011. Both the Trace and the Maximum Eigenvalue cointegration rank test in Table 3a and Table 3b indicate that there is no cointegration at the 5% level. This is despite the fact that the series are integrated at order 1(1).

Table 3a. Unrestricted cointegration rank test (trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.*
None	0.103725	60.43617	69.81889	0.2222
At most 1	0.083884	35.03025	47.85613	0.4464
At most 2	0.029552	14.70420	29.79707	0.7989
At most 3	0.019226	7.744809	15.49471	0.4931
At most 4	0.013872	3.240862	3.841466	0.0718

**Trace test indicates no cointegration at the 0.05 level*

Table 3b. Unrestricted cointegration rank test (maximum eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.*
None	0.103725	25.40592	33.87687	0.3581
At most 1	0.083884	20.32606	27.58434	0.3190
At most 2	0.029552	6.959387	21.13162	0.9555
At most 3	0.019226	4.503948	14.26460	0.8027
At most 4	0.013872	3.240862	3.841466	0.0718

** Maximum Eigenvalue test indicates no cointegration at the 0.05 level*

This implies that we can proceed to estimate an unrestricted VAR model and perform the forecast.

4.3 Evidence of nonlinearity in the residuals of the linear Random Walk Model (RWM)

One of the claims of this study is that a linear random walk model will not fit the exchange rate series in the WAMZ. This is verified by testing whether the residuals retrieved from the naïve random walk models indicate model misspecification. We employ the BDS test developed by Brock, Dechert and Scheinkman (1987). The BDS test is arguably the most popular test for nonlinearity. It was originally designed to test whether data follows an IID (Independently and Identically Distributed) process with the view to detecting the presence of non-random chaos. Subsequently, the BDS test has been used to test for model misspecification. When applied to the residuals of a fitted linear model, the BDS is able to identify remaining linear dependence and the existence of any omitted nonlinear structure. Failure to reject the null hypothesis implies that we cannot reject the linear model. A rejection of the null however means that the original linear model has been misspecified, calling for the need to use a nonlinear model.

Table 4 indicates that, with the exception of the model for Guinea, the models for all other countries show a significance of the BDS test even at 1% (all the p-values are zero). Thus, we reject the null hypothesis of linearity. This means that, the exchange series for Gambia, Ghana, Liberia, Nigerian and Sierra Leon do not follow a linear random walk process. Alagidede (2011) explains that, nonlinearity could be indicative of market inefficiency, variations in investors' response to price information, or lags in response to information.

In the case of Guinea, we fail to reject the null hypothesis of linearity. This means that the exchange rate series for guinea follows a linear random walk process. On the basis of the above results, we proceed to estimate a linear random walk for Guinea and nonlinear random walk for the other countries.

Table 4. BDS Test for Residuals

Exchange Rate Variable	Dimension	BDS Test Statistic	Standard Error	Z-statistic	P-value
GB_US	2	0.066713	0.008284	8.053641	0.0000
	3	0.119232	0.013260	8.991618	0.0000
	4	0.162350	0.015917	10.19993	0.0000
	5	0.196001	0.016728	11.71674	0.0000
	6	0.216079	0.016271	13.27991	0.0000
GH_US	2	0.091915	0.007750	11.85970	0.0000
	3	0.151275	0.012379	12.22016	0.0000
	4	0.194018	0.014824	13.08788	0.0000
	5	0.218843	0.015543	14.08029	0.0000
	6	0.241651	0.015081	16.02395	0.0000
GU_US	2	-7.06E-05	0.000527	-0.134080	0.8933
	3	-0.000142	0.001171	-0.120877	0.9038
	4	-0.000248	0.001948	-0.127408	0.8986
	5	-0.000391	0.002835	-0.137862	0.8903
	6	-0.000570	0.003817	-0.149295	0.8813
LI_US	2	0.033898	0.008204	4.132158	0.0000
	3	0.084330	0.013133	6.421036	0.0000
	4	0.120370	0.015765	7.635285	0.0000
	5	0.135481	0.016569	8.176637	0.0000
	6	0.136888	0.016117	8.493583	0.0000
NG_US	2	0.046633	0.007629	6.112594	0.0000
	3	0.075250	0.012204	6.165967	0.0000
	4	0.098805	0.014636	6.750681	0.0000
	5	0.108449	0.015368	7.056908	0.0000
	6	0.112605	0.014933	7.540851	0.0000
SI_US	2	0.078147	0.008189	9.543005	0.0000
	3	0.135832	0.013111	10.35982	0.0000
	4	0.179710	0.015741	11.41687	0.0000
	5	0.210726	0.016546	12.73587	0.0000
	6	0.228260	0.016096	14.18112	0.0000

4.4 Exploring the forecast performance of individual models over various forecast horizons

Table 5. Composite table of forecasting accuracy measured using RMSE

	GB_US	GH_US	GU_US	LI_US	NG_US	SI_US
One month						
ARIMA	0.828467	0.003696	23.09351	0.204043	0.009575	20.04135
RWM	0.909132	0.002594	0.783893	0.307489	0.209846	8.810909
GARCH(-M)	0.882829	0.002833	8.355045	0.398910	0.580994	3.995569
VAR		0.004521	10.80650	0.106401	0.116475	12.83658
Three months						
ARIMA	0.494345	0.010775	19.13473	0.337736	0.327648	19.00570
RWM	0.834794	0.029741	0.626797	0.519590	0.430052	17.68353
GARCH(-M)	0.758140	0.016219	49.85752	0.700638	1.148238	7.822234
VAR		0.011399	14.20282	0.429432	0.508073	15.39242
Six months						
ARIMA	1.831937	0.013507	46.82105	0.791520	0.622405	16.94604
RWM	1.818191	0.079474	1.526718	1.177414	0.980623	22.68563
GARCH(-M)	1.668452	0.046683	46.66874	1.525769	2.289623	6.962326
VAR		0.019470	46.08303	0.432046	0.787301	14.90809
Twelve months						
ARIMA	1.922646	0.022722	53.09616	2.787207	2.183316	16.49220
RWM	2.981627	0.244234	2.408738	3.532694	1.347499	25.13553
GARCH-M	2.526971	0.133605	38.96499	4.196263	2.798994	15.89180
VAR		0.038493	52.84433	0.685094	1.089101	15.44404

All discussions below are done with respect to Table 5 above.

Results of ARIMA Forecasts

An ARIMA model was fitted for each country based on the best ARIMA model selected from the automatic ARIMA selection add-in in eviews. The Schwarz information criterion assisted in the model selection process. The AR and MA terms in the ARIMA models range from 1 to 4. The results of the forecast are shown in Table 5.

We compare the forecast over four forecast horizons namely one month (1-step ahead) three months (3-steps ahead), six months (six-steps ahead), and twelve months (12-steps ahead). For Ghana, Liberia and Nigeria, consistently, the one month forecast is better than the three month forecast, which in turn is better than the six month forecast, which is also better than the twelve month forecast. The implication is that for these countries, the farther we look into the future the more inaccurate our prediction. In the case of Sierra Leone, the reverse is the case. The further we look into the future the clearer our vision, which is a bit strange. For Gambia, the one month forecast is better than all the horizons except for the three month forecast. Thus, apart from the Sierra Leonean case, in all the WAMZ countries the ARIMA forecast is more accurate over the short run than in the long run.

Results of Non-linear RWM Forecasts

We estimate a non-linear version of the random walk model except in the case of Guinea where a linear version is fitted. We use an ARCH type non-linear RWM. The results are shown in Table 5. The forecasts from the non-linear RWM follows a similar pattern as the ARIMA case above. For Ghana, Liberia, Guinea, Nigeria, and Sierra Leone, the short term forecasts are generally more accurate than the long term ones. Also, in the case of Gambia, the shorter the forecast horizon the better the forecast, though the three month forecast is slightly better than the one month forecast.

Results of GARCH Forecasts

The best GARCH model has been fitted for each country. Because all the exchange rate series are not normally distributed, estimating the GARCH(-M) model under the assumption of normality will yield consistent but inefficient estimators. To overcome this problem, we assume a Generalised Error Distribution (GED) which accommodates a continuum of both platykurtic and leptokurtic densities. Thus, the GED is able to model variables that are either normally distributed, or right sewed or left skewed relative to the normal distribution.

We choose the GARCH model over the other volatility based models because of the empirical tractability and ease of interpretation of the GARCH model. The analysis shows that for Ghana, Guinea and Sierra Leon, the GARCH-M model fits better than the ordinarily GARCH model. This means that, for these countries, volatility in the exchange rate affects the returns of the same. However, for Liberia and Nigeria the ordinary GARCH model fits the data better than the GARCH-M model. The results of the GARCH(-M) model show that, for Ghana, Liberia, Nigeria, and Sierra Leone, the short term forecasts are consistently better than the long term forecast. In the case of Gambia and Guinea the 1-step ahead forecast is more accurate than all the other steps ahead forecast with the exception of the 3-steps ahead forecasts. In the particular case of Guinea, the forecast error rate increases sharply over the long horizon. The implication of the forecast from the GARCH(-M) model is that, generally, short term forecast are more precise than long term forecast for WAMZ countries. The detailed results are shown in Table 5.

Results of VAR Forecasts

The forecast results of the unrestricted VAR model are presented in Table 5. It is clear from the results that for WAMZ countries, the VAR model produces a forecast that consistently reduces in accuracy as we move far into the future. This is consistent with results of the ARIMA, RWM and GARCH(-M) models.

4.5 Comparing the forecast performance of time series models for WAMZ exchange rates

Table 5 contains the forecast of exchange rate series of the four time series models for all WAMZ countries. We discuss for each country the performance of the models and judge the unbeatableness of the RWM. All the discussions that follow are based on results provided in Table 5. In some cases graphs are used for clarity.

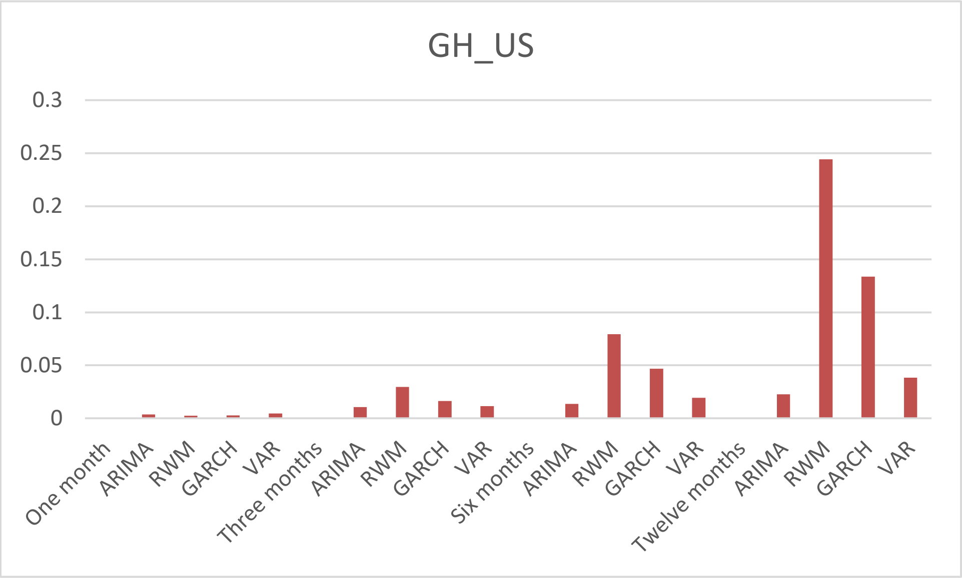
Forecast Comparison for Gambia

In the case of Gambia, for all the forecast horizons, the GARCH-M model outperforms the benchmark non-linear RWM while the ARIMA model fails to outperform the nonlinear RWM in only one instance (six month forecast horizon). This clearly debunks the notion held by Meese and Rogoff (1983) that the RWM is unbeatable. Between the GARCH-M and the ARIMA models, while the former slightly outperforms the latter in the six months forecasts, the latter outperforms the former in the one month, three months and twelve months forecast. The implication is that, if the objective is to perform a 6-steps ahead forecast for Gambia the best model to use is GARCH-M. But if the objective is to perform 1-step ahead, 3-steps ahead or 12-steps ahead forecast, the best model to use is the ARIMA model.

Forecast Comparison for Ghana

In the case of Ghana, the benchmark non-linear RWM is unbeatable in the 1-step ahead forecast lending some credence to the Meese and Rogoff (1983) postulation. Over the rest of the forecast horizons however, all the models outperform the benchmark model. The ARIMA and VAR models outperform the GARCH-M model over the medium to long term forecast horizons. See details in Table 5 and Figure 2.

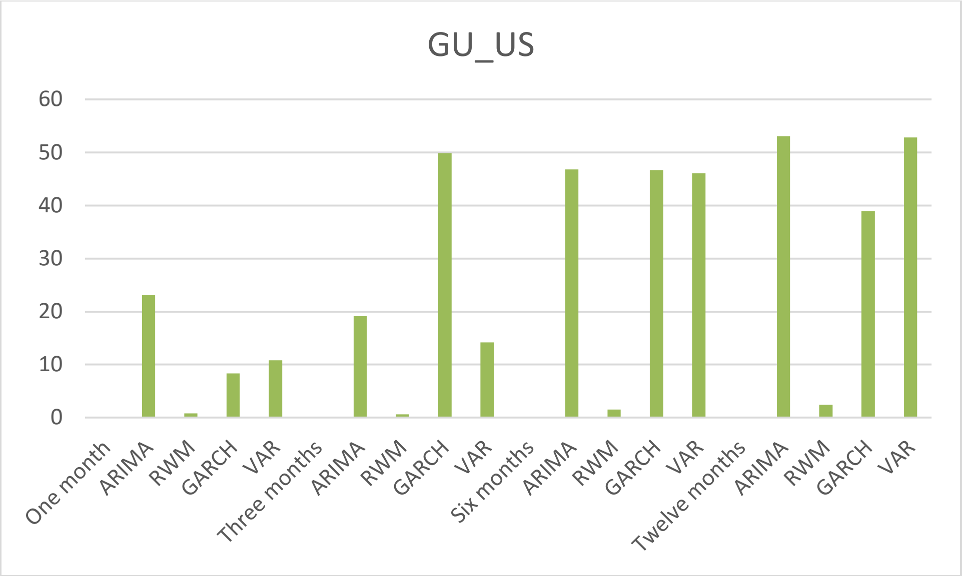
Figure 2. Forecast Comparison for Ghana



Forecast Comparison for Guinea

The benchmark linear RWM outperforms all the models over all forecast horizons. This provides full support for the Meese and Rogoff (1983) supposition. Thus, in forecasting exchange rate for Guinea, the best model to use is the linear RWM. Figure 3 shows clearly that the RMSE of the linear RWM is far smaller than that of the other models.

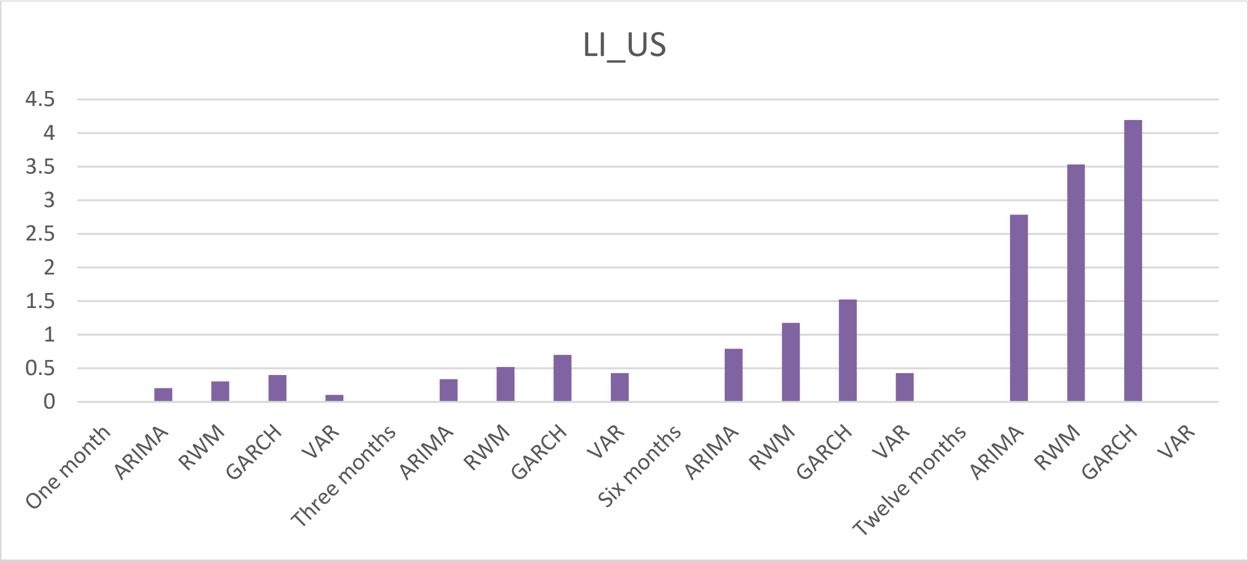
Figure 3. Forecast Comparison for Guinea



Forecast Comparison for Liberia

Apart from the GARCH model, all other models outperform the benchmark model over the forecast horizons. This partially supports the position of Moosa and Burn (2014) but refutes the Meese and Rogoff (1983) prognosis. Moosa and Burn's (2014) assert that dynamic models are likely to outperform the RWM. The VAR model performs better than all the models over all the horizons except in the case of the three months forecast where the ARIMA model slightly performs better. Refer to Table 5 and Figure 4 for more details.

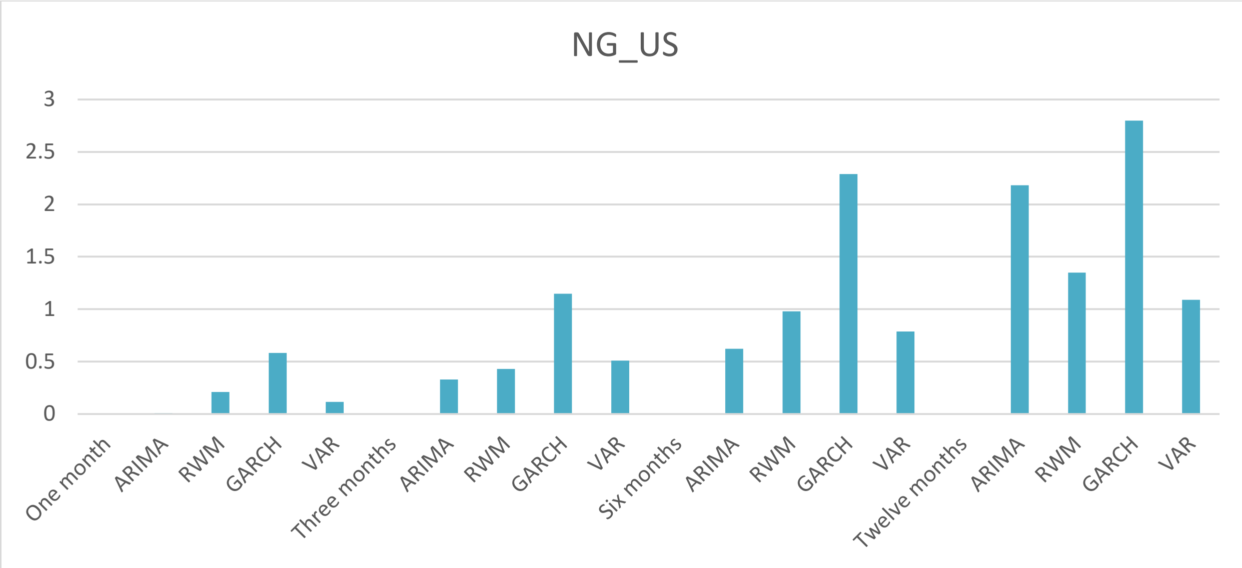
Figure 4. Forecast Comparison for Liberia



Forecast Comparison for Nigeria

The ARIMA model outperforms the benchmark model in all forecast horizons except the 12 months forecast. While the benchmark model outperforms the VAR model in the three month and twelve months forecast, the latter outperforms the former in the one month and six month forecast horizons. These findings further cast doubt on the unbeatableness of the RWM. The error rate of the GARCH model increases rapidly over the forecast horizon. This makes the GARCH model the most error prone forecast model for Nigeria. The ARIMA model appears to be the best model for the 1-step, 3-step, and 6-steps ahead forecast. For long term forecast, the VAR model is the most accurate. Refer to Table 5 and Figure 5 for precise details.

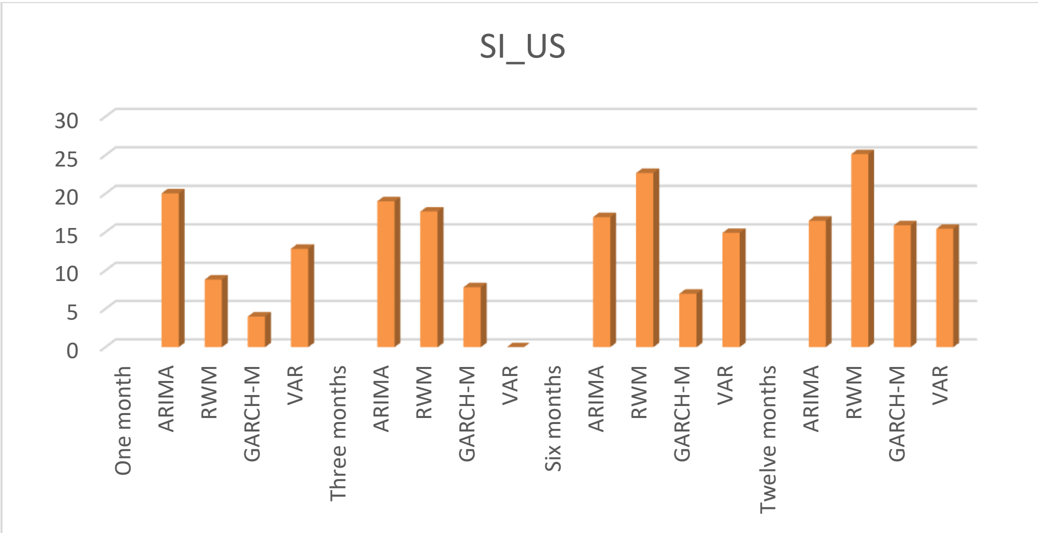
Figure 5. Forecast Comparison for Nigeria



Forecast Comparison for Sierra Leone

Apart from the one and three month forecast horizons, all the models beat the nonlinear RWM. The GARCH-M model is the most accurate time series model for forecasting exchange rate series in Sierra Leone for all forecast horizons except for three month forecast where it is beaten by the VAR model. The RWM is able to beat the VAR model only in the short term. See details in Table 5 and Figure 6.

Figure 6. Forecast Comparison for Sierra Leone



4.6. Robustness Checks

Due to the fact that the RMSE is deemed defective when exchange rate follows a non-normal Paretian process with infinite variance (Meese and Rogoff, 1983), we use the Mean Absolute Error (MAE) as an alternative measure of forecast accuracy. The results are shown in Table 6. The values of the MAE are consistently smaller than the RMSE values suggesting a possible bias associated with the RMSE. However, the results from the MAE consistently confirm the conclusions drawn from the RMSE. Generally, the shorter the forecast horizon, the more accurate the forecast. Forecasts from the nonlinear RWM are generally inferior to the ARIMA, GARCH(M), and VAR models. However, forecasts from the linear RWM (in the case of Guinea) are superior to all model forecast in all forecast horizons. Thus, when linear, the RWM is unbeatable. However, when linearity is violated, the RWM is easily outperformed by other models.

Table 6. Composite table of forecasting accuracy measured using Mean Absolute Error (MAE)

	GB_US	GH_US	GU_US	LI_US	NG_US	SI_US
One month						
ARIMA	0.828467	0.003696	23.09351	0.204043	0.009575	20.04135
RWM	0.909132	0.002594	0.783893	0.307489	0.209846	8.810909
GARCH(-M)	0.882829	0.002833	19.26405	0.398910	0.580994	3.995569
VAR		0.004521	10.80650	0.106401	0.116475	12.83658
Three months						
ARIMA	0.377648	0.007764	17.87983	0.289362	0.264200	18.89369
RWM	0.832718	0.023951	0.611737	0.408311	0.345225	16.67348
GARCH(-M)	0.750845	0.013248	8.355045	0.591153	1.087522	7.431898
VAR		0.010554	12.71064	0.362226	0.388572	15.25993
Six months						
ARIMA	1.282492	0.011540	39.06817	0.674789	0.489888	16.53019
RWM	1.382686	0.064754	1.036887	0.992878	0.764049	21.58968
GARCH(-M)	1.206968	0.037858	41.34810	1.312850	1.920163	6.533101
VAR		0.017049	36.63817	0.372441	0.632578	14.61574
Twelve months						
ARIMA	1.124770	0.018731	43.42533	2.199099	1.479070	15.64846
RWM	2.143364	0.194429	1.681330	2.849511	1.150530	22.57974
GARCH(-M)	1.789779	0.108737	37.66042	3.443746	2.482228	10.80094
VAR		0.032144	42.21268	0.563349	0.826328	14.63954

5. Conclusion

Our findings provide evidence using monthly exchange rate data from WAMZ countries, to support the long held fact that time series models are more accurate in forecasting short term than long term horizons. We also find evidence to refute the body of economic literature that supports the view that the forecasts from the RWM are second to none. We show that if a non-linear RWM is estimated, and the RMSE is used as the measure of forecast performance, the VAR model, the ARIMA model, and the GARCH(-M) model outperform the RWM. However, when the assumption of linearity is met, the RWM is superior to all models for all forecast horizons.

We further find that, for some time horizons and for some countries, the RWM is able to outperform the ARIMA, VAR and GARCH-M models lending partial support for the Meese and Rogoff (1983) prognosis. We find only one instance where the RWM beats all the models for all forecast horizons. This is the case of Guinea where the (linear) RWM outperforms all the models in all forecast horizons. This scenario provides full support for the Meese and Rogoff (1983) thesis. Thus, we show that in most cases, the RWM is more beatable than it is not when the assumption of linearity is violated. The study, though not in all cases, corroborates the findings of Moosa and Burns (2014) that the VAR model given its dynamic nature is more likely to outperform the RWM. The above findings remain robust when the MAE is used as an alternative measure of forecast accuracy.

Our findings imply that, there is no "one model fits all" for forecasting exchange rate either for each WAMZ country or for all WAMZ countries. The type of model to use to achieve forecast accuracy depends on the time horizon for which the forecast is needed, and the country for which the forecast is to be made. This point must be noted by economists in performing forecast for WAMZ countries if accurate and reliable forecast are to be achieved. We recommend that future research work in the WAMZ on the subject should look at comparing the forecast of time series models to forecast from structural models.

REFERENCES

Abhyankar, A, Sarno, L. and Valente, G. (2005). Exchange rates and fundamentals: evidence on the economic value of predictability, *Journal of International Economics,* 66, pp.325–348.

Adjasi C. K. D., Biekpe N. B. and Osei, K. A. (2011). Stock prices and Exchange Rate Dynamics in Selected African Countries: a bivariate Analysis, *African Journal of Economic and Management Studies*, 2(2), pp.143-161.

Alagidede, P. (2011). Return behaviour in Africa's emerging equity markets, *The Quarterly Review of Economics and Finance*, 51(2), pp.133–140.

Balaban, E. (2004). Comparative Forecasting Performance of Symmetric and Asymmetric Conditional Volatility models of an exchange rate, *Economic Letters,* 83, pp.99-105.

Balogun, E. D. (2007). Effects of Exchange Rate Policy on Bilateral Export Trade of West African Monetary Zone (WAMZ) Countries, *West African Journal of Monetary and Economic Integration,* 8(2). Also available at http://mpra.ub.uni.muenchen.de/6234.

Bollerslev, T. (1986). Generalised autoregressive conditional heteroskedasticity, *Journal of Econometrics,* 31, pp.307-327.

Brock, W. A., Dechert, W. D and J.A. Scheinkman (1987). A Test for Independence Based on the Correlation Dimension, mimeo.

Engle R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, *Econometrica,* 50(4), pp.987-1007.

Faust, J, Rogers J. H. and Wright, J. H. (2003). Exchange Rate Forecasting: the errors we've really made, *Journal of International Economics,* 60, pp.35-59.

Fullerton, T. M., Hattori, M. and Calderon, C. (2001). Error correction exchange rate modelling: evidence for Mexico, *Journal of Economics and Finance,* 25, pp.358–368.

Jhingan, M. L. (2005). *The Economics of Development Planning.* Vrinda Publications Ltd, New Delhi.

Kilian, L. and Taylor, M. P. (2003). Why is it so difficult to beat the random walk forecast of exchange rates? *Journal of International Economics,* 60, pp.85-107.

Kim, H. (2012). Nonlinearity, macroeconomic factors and the dollar-sterling real exchange rate, *International Journal of Finance and Economics,* Vol. 17, pp.337–346.

MacDonald, R. (1999). Exchange rate behaviour: are the fundamentals important? *Economics Journal,* 109, pp.673–691.

Madura, J., Martin, A. D. and Wiley, M. (1999). Forecast Bias and Accuracy of Exchange Rates in Emerging Markets, *Journal of Multinational Financial Management,* 9, pp.27-43.

Mark, N. and Sul, D. (2001). Nominal exchange rates and monetary fundamentals: evidence from a small post-Bretton Woods panel, *Journal of International Economics,* 53, pp.29–52.

Meese, R. and Rogoff, K. (1983). Empirical exchange rate models of the seventies: do they fit out of sample? *Journal of International Economics,* 14, pp.3–24.

Moosa, I. and Burns, K. (2014). The unbeatable random walk in exchange rate forecasting: Reality or myth? *Journal of Macroeconomics,* 40, pp.69–81.

Ono, S. (2013). The effects of foreign exchange and monetary policies in Russia, *Economic Systems,* 37, pp.522–541.

Simpson, M. W. and Grossmann, A. (2011). Can a relative purchasing power parity-based model outperform a random walk in forecasting short-term exchange rates? *International Journal of Finance and Economics,* 16, pp.375–392.

Sissoko, Y. and Dibooglu, S. (2006). The exchange rate system and macroeconomic fluctuations in Sub-Saharan Africa, *Economic Systems,* 30, pp.141–156.

Tsay, R. S. (2005). *Analysis of financial time series*. 2nd edn. Wiley, New Jersey.

Vilasuso, J. (2002). Forecasting Exchange Rate Volatility, *Economic Letters*, 76, pp.59-64.

West, K. D. and Cho, D. (1995). The Predictive Ability of Several Models of Exchange Rate Volatility, *Journal of Econometrics,* 69, pp.367-391.