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Univariate Time Series Modelling of Cedi-Dollar Nominal Exchange Rate

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Authors' contributions

This work was carried out in collaboration between all authors. Author SY designed the study, wrote the protocol and wrote the first draft of the manuscript. Authors JT and FM managed the literature searches and analyses of the study. All authors read and approved the final manuscript.

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ABSTRACT

This paper seeks to develop a statistical model capable of forecasting the Ghanaian Cedi US Dollar nominal exchange rate. The study uses end-of-month interbank exchange rate between January, 1994 and May, 2016. We employed the Autoregressive Integrated Moving Average (ARIMA) scheme in analysing the data. The study reveals that the exchange rate has a unit root implying that shocks to the exchange rate have a long term permanent effect. We have established that the end-of-month Cedi-Dollar rate follows ARIMA (0,1,2) process. The 12-month ahead forecast indicates that the value of the Cedi to the Dollar would decline in line with its past trend. The forecasts from the model compared favourably with actual realizations of the exchange rate. It is recommended that businesses whose cost is in Cedi but their revenue in Dollar should use the lower limit of the forecasts for the purposes of planning their business activities and vice versa.

Keywords: Cedi; Dollar; nominal exchange rate; ARIMA process; unit root.

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1. INTRODUCTION

Exchange rate is one of the crucial macroeconomic indicators. Exchange rate has been defined as the price of one currency in relation to another [1]. According to researchers; [2,3,4]; exchange rates and the choice of the exchange rate regime retain a centre stage in the post-crisis environment especially for emerging economies including Ghana. Actually, there is a significant divide between policy-makers and economists regarding the impact of foreign exchange policies on growth of an economy. Its (exchange rate) importance lies in the fact that it serves as a link between a country's economy and the economies of her trading partners. The large volume of empirical studies on the subject confirms this assertion [5,6,7,8,9,10]. It is the channel by which economic and commercial policies of one country are transmitted to her trading partners and vice versa.

Exchange rate regime in Ghana until 1983 was generally fixed with occasional adjustments. This meant the exchange rate was to a large extent determined at the discretion of the Bank of Ghana together with the government of the day. Ghana embarked on an economic recovery programme (ERP) in April, 1983 with the aim of removing distortions in the economy which had prevented efficient allocation of resources. The reforms sought to arrest and reverse the economic decay witnessed in the late 1970s and early 1980s as well as structurally transform the various sectors of the economy (Dordoonu, 1994).

As part of the measures embarked on under the reform programme, trade was liberalised, price controls were dismantled and exchange rate policy reforms were introduced. The reforms sought to replace controls with the market in resource allocation. This recovery programme involved several structural reforms including the exchange rate regime.

By 1992, the entire foreign exchange reform process came to its logical end with the replacement of Wholesale auction by the Interbank Market. Under the interbank market, authorised dealer banks could trade in foreign exchange among themselves or with their final-user clients.

Following the completion of the deregulation of the exchange rates, the Ghanaian Cedi has witnessed great volatility. Fig. 1 depicts the annual depreciation of the Cedi spanning 1994 to 2016.

Between January, 1994 and December, 2000, the Cedi has depreciated averagely by 34.4%. The depreciation was remarkable in the years 1999 and 2000, registering 50.9% and 81.5% respectively. The rate of depreciation moderated between 2001 and 2010, with the local currency depreciating on the average by 6.8% with 2008 recording the highest depreciation of 23.6% and 2005 witnessing the lowest of 0.2% depreciation. From 2011 to February, 2016, the Cedi has depreciated averagely by 14% with 2014 recording the highest fall in the value of the Cedi by 33.4%.

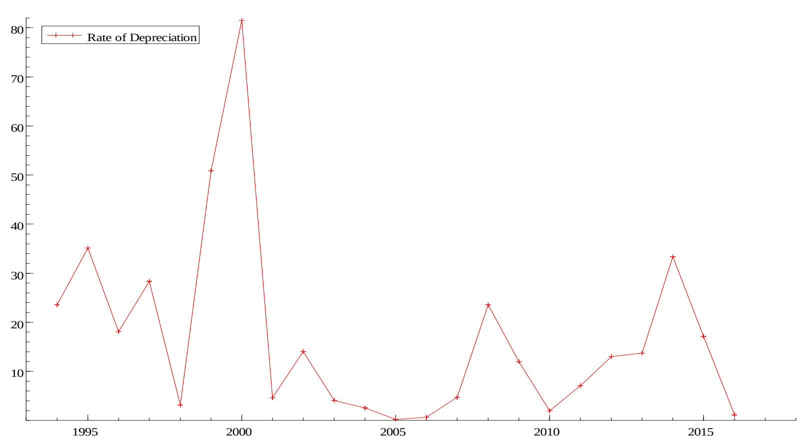

Fig. 1. Depreciation of the Cedi

It can be observed that the rate of depreciation from year to year is quite volatile with about 19.3% standard deviation. The volatile nature of the exchange rate movement makes it difficult to predict using annual percentage changes, thereby making business planning and budgeting extremely difficult (Fig. 1). This calls for a robust statistical technique that can greatly model the nominal Cedi-Dollar exchange rate.

1.1 Motivation for the Study

No country is an island onto itself. Nations all over the world have become interdependent on each other since all countries are not equally endowed with all the natural resources. Therefore, they have to trade in both goods and natural resources. Exchange rate plays an important role in this interaction among countries as trade occurs.

The objective of this study is to develop a univariate statistical model that best characterizes the behavior of the Cedi-Dollar nominal exchange rate. As shown in Figure 1, the rate of depreciation is quite unstable and hence unpredictable. This makes planning in business very difficult. This model can be useful in business planning as it forecasts the exchange rate into the future. The forecasts then become a good foundation upon which business planning is undertaken.

1.2 Review of Literature

As indicated earlier, the exchange rate is one of the most important macroeconomic variables both at the national and international levels. At the international level, it has attracted the needed attention leading to the adoption of the Gold Standard fixed exchange rate and the establishment of the International Monetary Fund to supervise the “adjustable-peg” exchange rate regime adopted in 1944 at the Bretton Woods conference.

Following the demise of the adjustable-peg exchange rate system and the decision of many countries to float their currencies, many currencies have witnessed large fluctuations during the 1970s. This phenomenon of wide currency fluctuations have prompted substantial research interest in studying the major determinants of equilibrium exchange rates [10] There have been various theories propounded to explain the exchange rate behavior, notable among them are the purchasing power parity (PPP), the monetary, the portfolio balance, and the Dornbusch sticky price models.

Many of these theoretical models have been subjected to substantial empirical studies. [11] investigated the PPP doctrine by using a two-stage least squares. The choice of this approach is informed by the conviction that both the exchange rate and the relative prices are endogenously determined. The results from this study support the PPP hypothesis.

Researchers [7] investigated the purchasing power parity hypothesis using long spans of data. They have argued that the earlier studies of PPP hypothesis and their conclusions were flawed because of the use of naive techniques. Using Autoregressive Integrated Moving Average analytical tool, their study revealed that purchasing power parity holds in the long run for each of the currencies studied.

[12] in a working paper did a study on the determinants of the Cedi/Dollar exchange rate in Ghana by employing a modified flexible price monetary model. In the study, they added an election as an additional regressor. Monthly macro time series data for the period December, 1992 to November, 2003 were used. They employed the techniques of cointegration and error correction modeling and found that all the variables except the political factor were significant in explaining variation in the nominal exchange rate.

According to [13] examined the Cedi Dollar exchange rate using the ARIMA modelling technique. Their study discovered that the Cedi would continue to depreciate in line with its past trend. For a comprehensive review of exchange rate studies, consult [14], and [10].

Even though the researchers are not looking at the exchange risk because of the importance of this study to the businesses we take a brief look at it. An exchange rate risk relates to the effect of unanticipated exchange rate changes on the value of the firm. The three main types of exchange rate risk (Transaction risk, Translation risk, Economic risk) that the authors consider in this paper are [15]; and [11].):

1. Transaction risk which is basically cash flow risk and deals with the effect of exchange rate moves on transactional account exposure related to receivables (export contracts), payables (import

contracts) or repatriation of dividends. An exchange rate change in the currency of denomination of any such contract will result in a direct transaction exchange rate risk to the firm;

2. Translation risk refers to the impact of exchange rate changes on the valuation of foreign assets (mainly foreign subsidiaries) and liabilities on a multinational company's consolidated balance sheet. Usually, translation risk is measured in net terms, i.e. net foreign assets minus net foreign liabilities.
3. Economic risk refers to the impact of exchange rate movements on the present value of uncertain future cash flows. It comprises the impact of exchange rate variation on future revenues and expenses through both variations in price and volume.

1.3 Data

The study makes use of a secondary data, which is a monthly end of period interbank nominal Ghanaian Cedi United States Dollar exchange rate spanning January, 1994 and May, 2016, obtainable from the Bank of Ghana. This period was chosen because it marked the final phase of the exchange rate deregulation. It is the period in which market forces have been allowed to determine the nominal exchange rate to a large extent.

2. METHODOLOGY

This study seeks to construct a statistical model that best characterizes nominal Cedi-Dollar exchange rate behavior in Ghana. Nominal Cedi Dollar exchange rate is the quantity of Ghana Cedi needed to purchase one unit of United States Dollar. The methodology was employed by Researchers [16] in analyzing the data. This methodology is also known as autoregressive integrated moving average ARIMA (p, d, q) process. The method consists of four steps of identification, estimation, diagnostic checking, and forecasting.

The general ARIMA(p, d, q) model is of the form:

$$\boldsymbol{Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} +, \dots, + \beta_p Y_{t-p} + \alpha_1 u_{t-1} + \alpha_2 u_{t-2} + \cdots + \alpha_q u_{t-q} + v_t} \quad (1)$$

where $\boldsymbol{p}$ refers to the order of the autoregressive (AR) part, $\boldsymbol{d}$ referring to the number of times the time series $\boldsymbol{Y_t}$ be differenced in order to achieve stationarity, and $\boldsymbol{q}$ **,** the order of the moving average (MA) part.

Identification phase seeks to establish numerical figures for $\boldsymbol{p, d, q}$. The first step in modelling the Cedi Dollar exchange rate is to determine the order of integration, $\boldsymbol{d}$ **,** of the time series concerned. This is very crucial because standard statistical tests (such as t, χ^2 and F) would be invalid if the exchange rate is found to be integrated [17]. In other words, we seek to avoid spurious regression phenomenon. We used Augmented Dickey-Fuller (ADF) test to determine the order of integration. If the series is integrated of order $\boldsymbol{d}$, it means we have to difference the data $\boldsymbol{d}$ times in order to achieve stationary series. Consider a time series process

$$\boldsymbol{Y_t = \beta_0 + \beta_1 Y_{t-1} + u_t} \quad (2)$$

where $\boldsymbol{u_t} \backsim \boldsymbol{N}(0, \sigma^2)$. The null hypothesis we seek to test is $\beta_1 = 1$ (i.e. Y_t has a unit root) against the alternative $\beta_1 < 1$. The series $\boldsymbol{Y_t}$ is stationary if $\beta_1 < 1$. Accepting the null hypothesis of $\beta_1 = 1$ implies that the time series in its levels is nonstationary and first differencing may produce stationary process. If the test fails to reject the null hypothesis in the first and second cases but rejects the null hypothesis of unit root in the third case of using the second differenced data, then it means that one needed to difference that series twice in order to achieve stationary.

After rendering the series stationary, one way of determining the order of the autoregressive (AR) part of equation (1) is to make use of partial autocorrelation functions ($\boldsymbol{\beta_i}$). Given that the true order of the **AR** is $\boldsymbol{p}$, then we expect the partial autocorrelations beyond it be zero. In other words, given that the true order of the **AR** is $\boldsymbol{p}$, we expect $\boldsymbol{\beta_{p+1}}, \boldsymbol{\beta_{p+2}}, \boldsymbol{\beta_{p+3}}, \dots = \boldsymbol{0}$ theoretically. Again, $\boldsymbol{\beta_i} \sim \boldsymbol{N}\left(\boldsymbol{0}, \frac{\boldsymbol{1}}{\boldsymbol{T}}\right)$ where T is the sample size.

To determine the lag length of the moving average (MA) part, we make use of autocorrelation functions (ACF). The major feature of a moving average process is an ACF that abruptly drops to zero at one lag past the order of the process [18]. In general, the autocorrelation function for an $\boldsymbol{MA}(\boldsymbol{q})$ can be calculated between $\boldsymbol{Y_t}$ and $\boldsymbol{Y_{t-k}}$ for $\boldsymbol{k} > 0$ by

$$\boldsymbol{\rho(k)} = \frac{a_k + \sum_{i=1}^{q-k} a_{(k+i)}\alpha_i}{1+\sum_{i=1}^{q} a_i^2}.$$

For $\boldsymbol{k} < q$, $\boldsymbol{\rho(k)} \neq 0$. Otherwise, $\boldsymbol{\rho(k)} = 0$ if $\boldsymbol{k} > q$ **,** where it is understood that for $\boldsymbol{k = q}$ **,** the numerator is just $\boldsymbol{a_k}$.

Having identified the appropriate values of ***p***, ***d***, and ***q****,* the next stage is to estimate the parameters of the autoregressive and moving average terms included in the model, $\boldsymbol{ARMA\ (p, q)}$. The method of maximum likelihood is used to estimate the parameters. It is important to note that having identified the reference model, we needed to compare it to other ARIMA (p,d,q) models. This is done by varying the lag length of the reference model. This is to ensure that the model chosen is the best representation of the data generating process when compared to other models describing the same data.

We examine all the models and select one that fits the data reasonably well. For this, we choose the model with the maximum value of log-likelihood and minimum values of Akaike Information Criterion (AIC), modified Akaike Information Criterion (AICc), Root Mean Square Error (RMSE), Bayesian Information Criterion (BIC) and Mean Absolute Error (MAE) as the best model.

2.1 Akaike Information Criterion

The Akaike information criterion (AIC) is a measure of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection.

The AIC is an estimator of the expected Kullback-Leibler divergence, which measures the closeness of a candidate model to the truth. The smaller this divergence, the better the model. The Akaike Information Criterion (AIC) says choose the ARIMA (***p, d, q***) model which minimizes $\boldsymbol{AIC = -2lnL + 2k}$, where $\boldsymbol{InL}$ is the natural logarithm of the estimated likelihood function and $\boldsymbol{k = p + q}$ is the number of parameters in the model. AIC is a large sample estimator and hence biased in small samples. As a result, AIC is corrected for small sample sizes. The corrected AIC is as follows:

$$\boldsymbol{AIC_c = AIC + (n - k - 1)^{-1}\{2k(k + 1)\}}$$

where ***n*** denotes the sample size and ***k*** the number of parameters.

2.2 Bayesian Information Criterion

The Bayesian information criterion (BIC) or Schwarz criterion is a criterion for model selection among a finite set of models. It is based, in part, on the residual sum of squares and it is closely related to the Akaike information criterion (AIC). When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in overfitting. Both **BIC** and **AIC** resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in BIC than in AIC.

$$\boldsymbol{BIC} = log\left(\frac{e'e}{n}\right) + \frac{Klog(n)}{n}; \quad K = q + p$$

where $\boldsymbol{e'e}\ and\ \boldsymbol{n}$ are the residual sum of squares and sample size respectively. The model with the lowest BIC is preferred.

2.3 Root Mean Square Error

The Root Mean Square Error (RMSE) represents the sample standard deviation of the differences between predicted values and observed values. These individual differences are called residuals when the calculations are performed over the data sample that was used for estimation, and are called *prediction errors* when computed out-of-sample. The RMSE serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. It is calculated using the formula:

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \hat{Y})^2}{n}}$$

where n is the sample size.

2.4 Mean Absolute Error

The mean absolute error (MAE) is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The mean absolute error is given by:

$$\boldsymbol{MAE} = \frac{\sum_{t=1}^{n}|Y_t - \hat{Y}|}{n}$$ where ***n*** is the sample size.

In diagnostic checking, we examine the residuals of the identified model that best fits the data to determine whether they are random ($i.e. N(o, \sigma^2)$) or not by using revised Ljung-Box **Q** statistic and whether the residuals have a constant variance by using Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test. The residuals of the model provide important information for testing. If an adequate model has been fitted, the residuals should be approximately white noise. In other words, it is expected that the residuals of the estimated model are independent, uncorrelated, have mean zero and a finite variance.

Test statistics have been developed to test the joint hypothesis that all the correlation coefficients of the residuals up to certain lags are simultaneously equal to zero. One of such test is Box-Pierce **Q** statistic, defined as

$$\boldsymbol{Q = n \sum_{k=1}^{m} r^2}$$

where n =sample size, r =correlation coefficient between the residuals (e_t, e_{t-k}) $for\ k = 1, 2, 3, \dots m,$ and $m =$ the total lag length being tested.

The **Q** statistic is often used as a test of whether the residuals are white noise. In large samples, **Q** is approximately distributed as a χ^2 with **m** degrees of freedom. In an application, if the computed **Q** exceeds the χ^2 distribution with **m** degrees of freedom at a chosen level of significance, one can reject the null hypothesis that all the true correlation coefficients are zero; at least some of them must be nonzero (i.e. the residuals are not white noise or random). Box-Pierce **Q** statistic has been modified for finite samples by [19]. Ljung-Box statistic is defined as

$$Q_m = n(n+2) \sum_{k}^{m} r_k^2 / (n-k) \sim \chi_m^2.$$

where *n* is the sample size, (i.e. the number of residuals used), r_k^2 is the sample autocorrelation at lag *k*, and *m* is the number of lags being tested. In this study, Ljung-Box statistic is used to test whether the residuals are white noise.

Another crucial characteristic of an adequate fit is to have a model that has homoscedastic residuals. An Autoregressive Conditional Heteroscedasticity Lagrange Multiplier (ARCH-LM) test has been performed on the residuals to ascertain the presence of heteroscedasticity. The test is carried out as follows:

i. Estimate the ARIMA (p,d,q) model and obtain the residuals.
ii. Compute the OLS regression $u_t^2 = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1} u_{t-1}^2 + \boldsymbol{\alpha_2} u_{t-2}^2 + \cdots + \boldsymbol{\alpha_j} u_{t-j}^2 + \boldsymbol{v_t}$.
iii. Compute the $\boldsymbol{R_j^2}$ from (ii) where *j* is the lag length.
iv. Calculate the **LM** test statistic, $\boldsymbol{nR_j^2}$.
v. Test the joint significance of $\boldsymbol{\alpha_1}, \dots, \boldsymbol{\alpha_j}$.

If these coefficients are significantly different from zero (i.e. $\boldsymbol{nR_j}^2 > \boldsymbol{\chi_j}^2$), the assumption of conditionally homoscedastic disturbances is rejected in favour of ARCH disturbances.

2.5 Forecasting

The main purpose of fitting ARMA schemes is to project the series forward beyond the sample period. We forecast the Cedi Dollar rate for a 12-month time horizon with 95% confidence interval.

3. RESULTS AND DISCUSSION

3.1 Identification

We started the analysis by plotting the Cedi Dollar exchange rate against time as shown in Fig. 2. This is to enable us examine the time series properties of the data. It can be observed that the series is nonstationary in the mean, suggesting that we cannot proceed with the analysis unless the data is differenced.

To confirm the assertion that the data is nonstationary in the means, we subjected the series to a more formal test. The results of the Augmented Dickey-Fuller test, which is a unit root test, is shown in Table 1. Nine models were run with varying degrees of differenced lag terms added. The model with three differenced lag terms appears to have the least Akaike Information Criterion. Looking at the critical value of 2.425 suggests that the series has a unit root. In other words, we failed to reject the null hypothesis of unit root in the data.

As a result of the nonstationarity of the series in levels, we first differenced the data and examined its characteristics as depicted in Fig. 3.

The series appears to be stationary when differenced once. This is confirmed by the unit root test as shown in Table 2. The null hypothesis of unit root in the differenced data is rejected at all conventional levels of significance.

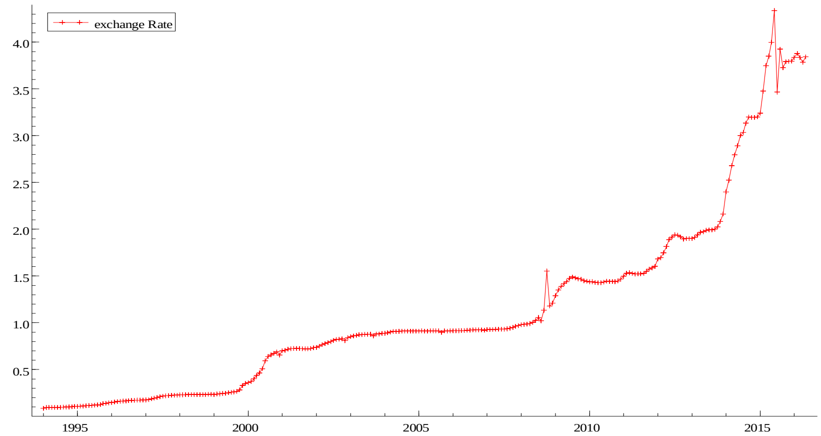

Fig. 2. Time series plot of Cedi-Dollar exchange rate in levels

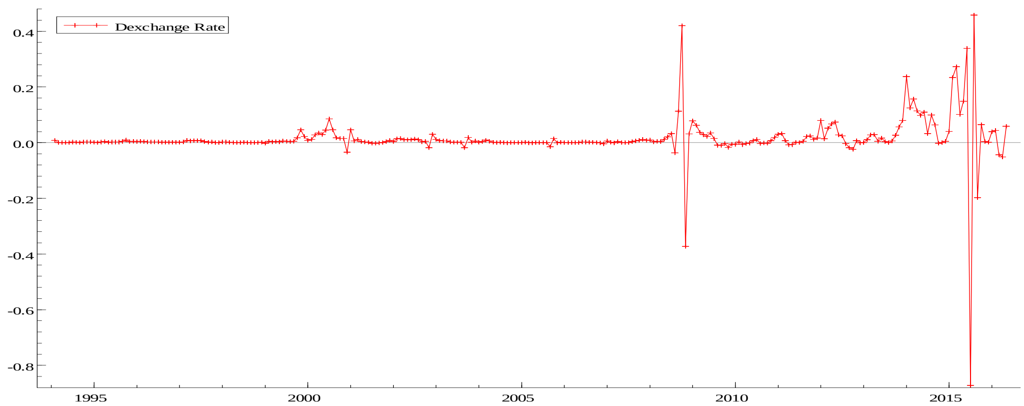

Fig. 3. Plot of Cedi-Dollar exchange rate in first differences

Table 1. Augmented Dickey-Fuller test of Cedi Dollar rate in levels

D-lag	t-adf	t-prob	AIC
8	1.784	0.4040	-5.096
7	2.052	0.7628	-5.100
6	2.201	0.7197	-5.108
5	2.182	0.1531	-5.115
4	1.904	0.8772	-5.115
3	1.999	0.0149	-5.122***
2	2.681	0.4395	-5.107
1	2.967	0.0000	-5.112
0	1.654	-	-4.964

**** the model with the least AIC*

Having established that the series is weakly stationary in the mean, we can now determine the order of the MA and AR components of the ARIMA $(p, 1, q)$ model. If the model is formulated as a pure moving average process, it will have its order being two (2). As can be observed from the autocorrelation function ACF), it is only at lags 1 and 2 that the ACF are significantly different from zero (i.e they have exceeded the confidence band). This is depicted in Fig. 4.

Table 2. Augmented Dickey-Fuller test of first differenced Cedi Dollar rate

D-lag	t-adf	t-prob	AIC
8	-3.865	0.0255	-5.099
7	-4.669	0.0255	-5.087
6	-5.358	0.4053	-5.087
5	-6.054	0.8668	-5.092
4	-6.642	0.3389	-5.100
3	-6.814	0.5437	-5.104
2	-7.924	0.0027	-5.110+++
1	-12.01	0.1454	-5.083
0	-23.17		-5.082

+++ the model with the least AIC

For the AR part, we examine the partial autocorrelation function (PACF) as shown in Fig. 5. Fig. 5 suggests that if the model is formulated as a pure autoregressive process, it would have an order of 3 with coefficients significantly different from zero occurring at lags 1 and 3 (i.e. the coefficients have exceeded the confidence band). We also have a spike at lag 9 but this may be due to random influence.

From the above analyses, our reference model is ARIMA (3,1,2). Having identified the reference model, we estimated several models in its neighbourhood and computed their model selection criteria as shown in Table 3.

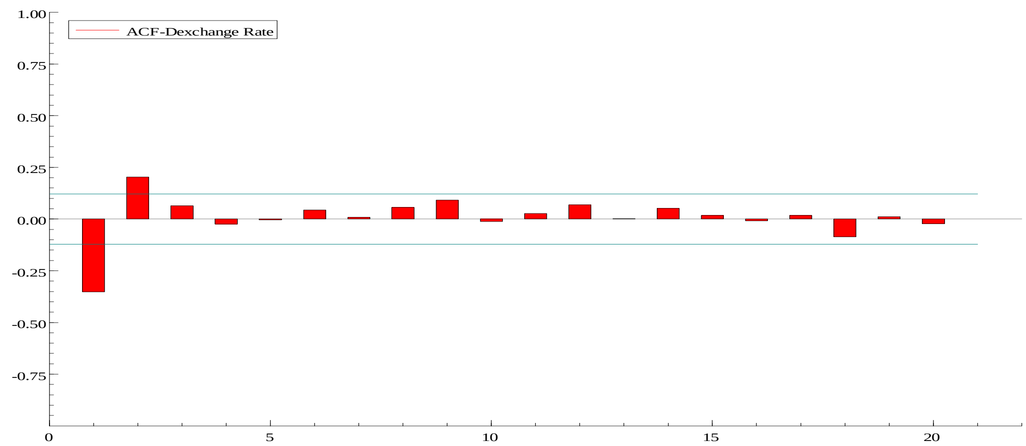

Fig. 4. Autocorrelation function of the differenced data

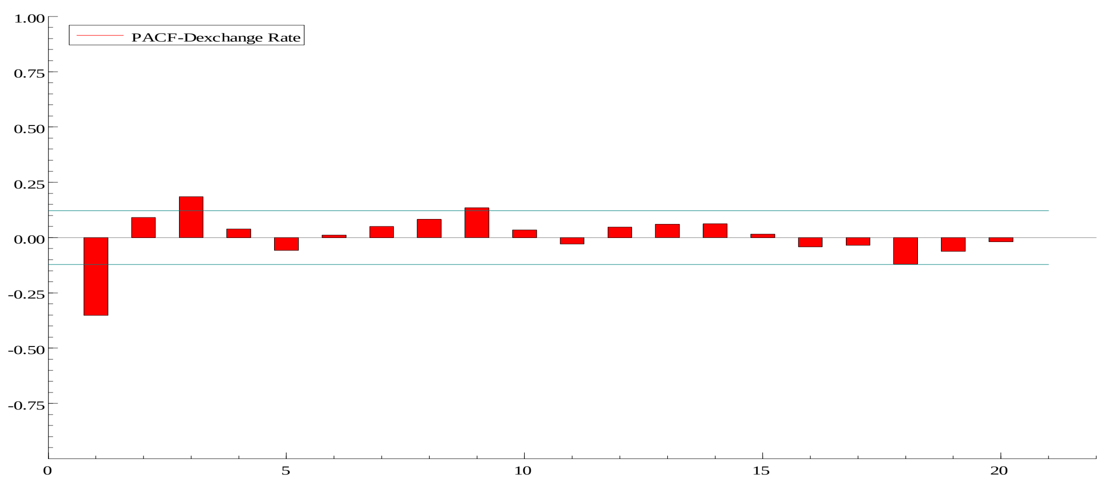

Fig. 5. Partial autocorrelation function of the first differenced data

Table 3. Information criteria and estimated ARIMA $(p, 1, q)$ models

Model	AIC	AICc	loglikelihood	RMSE	RMSE	BIC
ARIMA (0,1,2)	-2.3081*	1.5583*	313.2871	0.0751367	0.0302	-5.1352*
ARIMA (3,1,0)	-2.2982	1.6077	312.9631	0.0752315	0.0295	-5.1118
ARIMA (1,1,1)	-2.2661	1.6241	307.6535	0.0767535	0.0327	-5.0926
ARIMA (2,1,1)	-2.2908	1.6189	311.9676	0.0755085	0.0282*	-5.1044
ARIMA (2,1,2)	-2.2988	1.6564	314.0438	0.0749204	0.0301	-5.0992
ARIMA (3,1,1)	-2.2917	1.6675	313.0846	0.0751969	0.0291	-5.0918
ARIMA (3,1,2)	-2.2941	1.7289	314.4114*	0.0748096*	0.0308	-5.0813
ARIMA (1,1,2)	-2.3027	1.6008	313.5625	0.0750585	0.0296	-5.1164

** Optimal model selection statistic*

From Table 3, it can be seen that ARIMA (0,1,2) is the only model to have satisfied three of the model selection criteria, namely AIC, AICc and BIC. ARIMA (3,1,2) only met two of the model selection criteria. While ARIMA (0,1,2) model has the least values of AIC, AICc and BIC, the highest loglikelihood and the least RMSE occurred in ARIMA (3,1,2). In model selection, premium is placed on a model with the least AICc and parsimony. Going by this selection criteria, we choose ARIMA (0,1,2) as the best model that fits the data.

3.2 Estimation

The selected model is estimated using maximum likelihood procedure. The parameters and their respective t-ratios are shown in Table 4.

As can be observed from Table 4, all the variables in the model are statistically different from zero at 1% level of significance.

3.3 Diagnostic Checking

One way of checking if ARIMA (p,d,q) model fits the data at hand is to examine the residuals resulting from the estimated model. A first step in diagnostic checking of fitted models is to analyze the residuals from the fit for any signs of non–randomness. It is based on the notion that the residuals of a correctly specified model are independently distributed. If the residuals are not, then they come from a miss–specified model.

The residuals from the model is shown in Fig. 6. Visual inspection of the graph suggests that the residuals are zero mean and uncorrelated. The assumption of homoscedastic disturbances is not clear cut from Fig. 6 as few spikes can be observed. To ascertain that there is no serial correlation, we performed the Ljung-Box test of no autocorrelation and the results are shown in Table 5.

At 5% level of significance, the theoretical $\chi^2(10)$ is 18.31. Since the computed critical value is less than the theoretical critical value, we fail to reject the null hypothesis of no autocorrelation in the residuals. In other words, the test suggests that the residuals are random and independently distributed, and that the model ARIMA (0,1,2) is correctly specified.

Table 4. Output from estimated ARIMA $(0,1,2)$ model

Variable	Coefficient	Std error	t-ratio	P-value
MA-1	-0.360073	0.05845	-6.16	0.000**
MA-2	0.311186	0.06294	4.94	0.000**
Constant	0.0138905	0.004360	3.19	0.002**

*** significant at 1%*

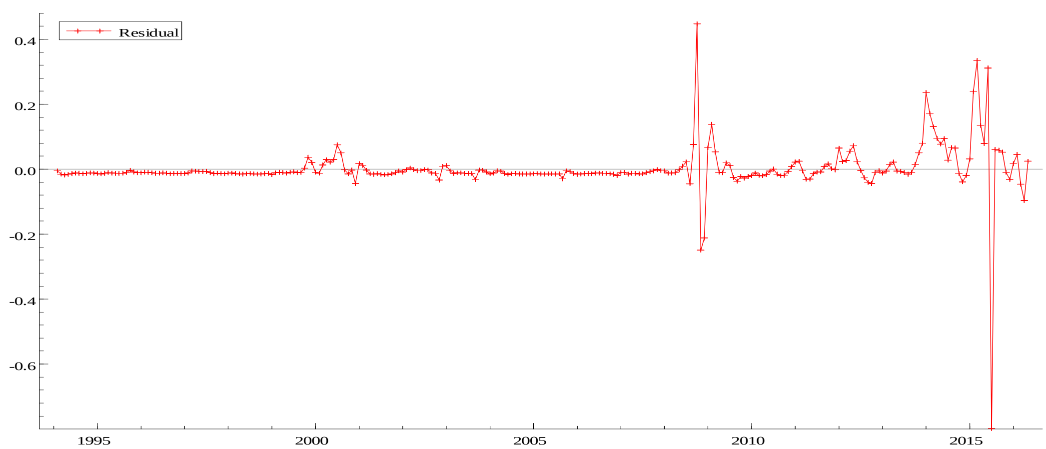

Fig. 6. Plot of residuals from the estimated ARIMA (0,1,2) model

Table 5. Test of no autocorrelation in the residuals

Variable	Chi-squared (calculated)	P-value	Chi-squared (tabubated)	df
Residuals	15.407,	0.1179	18.31	10

Source: From the study

Table 6. ARCH–LM test for homoscedasticity

Variable	Chi-squared (computed)	n	R_j^2	nR_j^2	df	Chi-squared (tabulated)
ARIMA (0,1,2)	14.391498	258	0.055781	14.3915	df=10	18.31

Source: From the study

We also test for ARCH effect in the residuals by making use of Lagrange Multiplier test which has Chi-squared distribution of $\boldsymbol{m}$ degrees of freedom(χ_m^2), $\boldsymbol{m}$ being the lag length of residuals used in the test. The test results of homoscedastic disturbances are shown in Table 6.

The computed critical value (**14.39**) is less than the theoretical critical value (**18.31**) at 5% level of significance. We therefore fail to reject the null hypothesis of constant residual variance. The test suggests that the residuals are coming from a model with homoscedastic disturbance. Having established that our chosen ARIMA (0,1,2) model satisfied all assumptions underlying the analysis, we can conclude that the model adequately represents the data generating process. Our ARIMA (0,1,2) model can now be written as:

$$\widehat{\boldsymbol{\Delta Y_t}} = 0.0138905 - 0.360073\boldsymbol{u_{t-1}} + 0.311186\boldsymbol{u_{t-2}} \quad (3)$$

Our focus is to model the nominal exchange rate and not its changes. We therefore redefine $\boldsymbol{\Delta Y_t = Y_t - Y_{t-1}}$ and substituting back into equation (3), we have:

$$\boldsymbol{Y_t} - \boldsymbol{Y_{t-1}} = 0.0138905 - 0.360073\boldsymbol{u_{t-1}} + 0.311186u_{t-2} \quad (4)$$

Making $\boldsymbol{Y_t}$ the subject, we now have our final model as:

$$\widehat{\boldsymbol{Y_t}} = 0.0138905 + \boldsymbol{Y_{t-1}} - 0.360073\boldsymbol{u_{t-1}} + 0.311186\boldsymbol{u_{t-2}} \quad (5)$$

3.4 Forecasting

We now use our model as in equation (5) to forecast the Cedi-Dollar exchange rate over twelve-month period at 95% confidence interval as shown in Table 7.

Comparing the actual Cedi-Dollar exchange rates 3.9279, 3.9470 and 3.9465 from June, July and August, 2016, to the forecast interval as shown in Table 7, it can be observed that all the realizations fall within the confidence interval. This suggests that the model can be quite relied upon in forecasting the exchange rate.

We also ran a random walk with drift model of the Cedi-Dollar exchange rate (i.e. $y_t = \gamma + \beta y_{t-1} + e_t$) and used the model to forecast a 12-month period for the Cedi-Dollar exchange rate at 95% confidence interval as shown in **Table 8**. The purpose is to compare the forecasts from this model to that of ARIMA (0,1,2).

It can be observed from **Tables 7** and **8** that while the point forecasts of the Cedi-Dollar exchange rate from the random walk model are declining, the point forecasts from the ARIMA (0,1,2) model are moving in an upward direction. Again, comparing the forecasts from the two models to the actual Cedi-Dollar exchange rate realisations, it could be observed that all the forecasts from ARIMA (0,1,2) are closer to the actual realisations than the forecasts from the random walk model (3.9279>3.8551>3.841; 3.9470>3.8766>3.839, and 3.9465>3.89>3.8367). One can conclude from the above comparisons that ARIMA (0,1,2) model provides better forecasts than the random walk model.

Table 7. ARIMA (0,1,2) forecast results for Cedi-Dollar exchange rate

Year / Month	Forecast	Lower limit	Upper limit
2016 June	3.8551	3.7800	3.93023
2016 July	3.8766	3.7874	3.96580
2016 August	3.8905	3.7762	4.0048
2016 September	3.9043	3.7695	4.0391
2016 October	3.9182	3.76563	4.07077
2016 November	3.9321	3.76362	4.10058
2016 December	3.9460	3.76299	4.12901
2017 January	3.9599	3.76343	4.15637
2017 February	3.9738	3.76474	4.18286
2017 March	3.9877	3.76676	4.20864
2017 April	4.0016	3.76939	4.23381
2017 May	4.0155	3.77254	4.25846

Source: From the study (2016)

Table 8. Forecasts from random walk model of Cedi-Dollar exchange rate

Year/ Month	Forecast	Lower limit	Upper limit
2016 June	3.8412	3.757857	3.924543
2016 July	3.839	3.7212	3.9568
2016 August	3.8367	3.69251	3.98089
2016 September	**3.8345**	3.6681	4.0009
2016 October	3.8322	3.64626	4.01814
2016 November	3.83	3.62643	4.03357
2016 December	3.8277	3.60795	4.04745
2017 January	3.8255	3.59071	4.06029
2017 February	3.8232	3.5743	4.0721
2017 March	3.821	3.55879	4.08321
2017 April	3.8188	3.54395	4.09365
2017 May	3.8165	3.52959	4.10341

Source: From the Study

4. CONCLUSIONS

The study revealed that the nominal Cedi-Dollar exchange rate is nonstationary. The implication is that the effect of any shock to the rate will take a longer time to diminish. In other words, any random shocks in the foreign exchange market will affect the value of the Cedi permanently.

The study has also shown that the international value of the Cedi in relation to the Dollar will fall going into the future. This is to say that the Cedi will experience depreciation going into the future, barring any unforeseen major shocks.

5. RECOMMENDATIONS

It is suggested that businesses in Ghana whose cost is in US Dollars while their revenue is in Ghana Cedi should use the upper limits of the forecast for the purposes of planning. On the other hand, businesses in Ghana whose cost is in Ghana Cedis but their revenue in US Dollars should use the lower limits of the forecast in their business planning.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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