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Sarima Modelling of Nigerian Bank Prime Lending Rates

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Abstract

The monthly Prime Lending Rates of Nigerian Banks are modeled herein by SARIMA methods. The realization considered here spans from January 2006 to July 2014. The original series called herein PLR has a generally horizontal secular trend. Its correlogram reveals some seasonality of period 12 months. Moreover, preliminary data analysis shows that yearly maximums are mostly between October and the next March, and the minimums mostly between April and September. That means that the maximums tend to lie in the first and the fourth quarters of the year and the minimums in the second and third quarters of the year. That means that the series is seasonal of 12 monthly period. Twelve-monthly differencing of PLR yields the series called SDPLR which also has a generally horizontal trend. Augmented Dickey Fuller (ADF) Tests consider both PLR and SDPLR to be non-stationary. A non-seasonal differencing of SDPLR yields the series DSDPLR which is considered stationary by the ADF tests. Its correlogram attests to a 12-monthly seasonality as well as the presence of a seasonal moving average component of order one. The autocorrelation structure suggests the proposal of the following models: (1) a SARIMA$(0,1,1)\text{x}(0,1,1)_{12}$ (2) a SARIMA$(0,1,1)\text{x}(1,1,1)_{12}$ and (3) a SARIMA$(0,1,1)\text{x}(2,1,1)_{12}$. The foregoing models following a descending order of degree of adequacy on AIC grounds. However, from the SARIMA$(0,1,1)\text{x}(2,1,1)_{12}$ model, a SARIMA$(0,1,0)\text{x}(2,1,1)_{12}$ model becomes suggestive and it outdoes the rest on all counts. Its residuals are mostly uncorrelated and also follow a normal distribution with mean zero. Hence it is adequate and may be used to forecast the prime lending rates.

Mathematics Subject Classification: 62P05
Keywords: Prime Lending Rates, Sarima Models, Seasonal Time Series, Nigeria

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1 Introduction

Prime lending rates are rates at which banks give loans to their best customers. These customers are called best in the sense of having a long term relationship and credit reputation with the bank and are often big-time and well-established clients. These rates are usually minimal and they fluctuate according to the economic realities of the nation. The aim of this work is to fit a seasonal autoregressive integrated moving average (SARIMA) model to the monthly prime lending rates of Nigerian banks.

The rates are herein observed to show some seasonality of period 12 months as many other economic and financial time series. Hence, the proposal of a SARIMA fit. In the literature time series that have been modeled by SARIMA techniques because of their intrinsically seasonal nature include temperature (Khajavi *et al.,* [1]), tourism patronage (Padhan, [2]), airways patronage (Box and Jenkins, [3]), inflation (Fannoh *et al.* [4]), savings deposit rates (Etuk *et al.*, [5]), rice prices (Hassan *et al.*, [6]), tuberculosis incidence (Moosazadeh *et al.*, [7]), stock prices (Etuk, [8]), cucumber prices (Luo *et al.*, [9]), internally generated revenues (Etuk *et al.*, [10]), dengue numbers (Martinez *et al.*, [11]), and tomato prices (Adanacioglu and Yercan, [12]), to mention but a few.

2 Materials and Methods

2.1 Data

The data analyzed in this work are 103 prime lending rates from January 2006 to July 2014 retrievable from the website of the Central Bank of Nigeria, www.cenbank.org. They are published under the Money Market indicators subsection of the Data and Statistics section.

2.2 Sarima Models

A stationary time series $\{X_t\}$ is said to follow an *autoregressive integrated moving average model of order p and q* denoted by ARMA(p,q) if it satisfies the following difference equation

$$X_t - \alpha_1 X_{t-1} - \alpha_2 X_{t-2} - ... - \alpha_p X_{t-p} = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + ... + \beta_q \varepsilon_{t-q} \qquad (1)$$

where the sequence of random variables $\{\varepsilon_t\}$ is a white noise process. The α's and β's are constants such that the model is both stationary and invertible. Suppose that the model (1) is written as

$$A(L)X_t = B(L)\varepsilon_t \qquad (2)$$

where A(L) and B(L) are the autoregressive (AR) and the moving average (MA) operators respectively defined by $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha_p L^p$ and $B(L) = 1 + \beta_1 L + \beta_2 L^2 + \ldots + \beta_q L^q$ and L is the backward shift operator defined by $L^k X_t = X_{t-k}$.

If a time series is non-stationary, Box and Jenkins [3] proposed that differencing of the series a number of times may make it stationary. Let ∇ be the difference operator. Then $\nabla = 1 - L$. If d is the minimum number of times for which the d^{th} difference $\{\nabla^d X_t\}$ of $\{X_t\}$ is stationary and $\{\nabla^d X_t\}$ follows model (1) or (2) the original series $\{X_t\}$ is said to follow an *autoregressive integrated moving average model of order p, d and q,* denoted by ARIMA(p,d,q).

If in addition the time series $\{X_t\}$ is seasonal of period s, Box and Jenkins [3] moreover proposed that it may be modeled by

$$A(L)\Phi(L^s)\nabla^d \nabla_s^D X_t = B(L)\Theta(L^s)\varepsilon_t \tag{3}$$

where ∇_s is the seasonal differencing operator defined by $\nabla_s = 1 - L^s$, D is the minimum number of times of seasonal differencing for stationarity and $\Phi(L)$ and $\Theta(L)$ are the seasonal AR and MA operators respectively. Suppose $\Phi(L)$ and $\Theta(L)$ are polynomials of orders P and Q respectively model (3) is called a *multiplicative seasonal autoregressive integrated moving average model of order (p,d,q)x(P,D,Q)$_s$,* denoted by SARIMA(p,d,q)x(P,D,Q)$_s$ model.

2.3 Sarima Model Fitting

The fitting of a SARIMA model of the form (3) starts invariably with the determination of the orders p, d, q, P, D, Q and s. The seasonal period might be directly suggestive by knowledge of the seasonal nature of the series as with monthly rainfall for which s = 12 or hourly atmospheric temperature for which s = 24. An inspection of the series could reveal an otherwise unclear seasonality. Moreover the correlogram could reveal seasonality if the autocorrelation function (ACF) has a sinusoidal pattern. In this case the period of seasonality is the same as that of the ACF. The differencing orders d and D are often chosen so that $d + D < 3$. This is usually enough to make the series stationary. Before and after differencing at each stage the series is tested for stationarity using the Augmented Dickey Fuller (ADF) Test. The AR orders p and P are estimated by the non-seasonal and the seasonal cut-off lags of the partial autocorrelation function function (PACF) respectively and the MA orders q and Q are estimated by the non-seasonal and the seasonal cut-off lags of the ACF respectively.
The model parameters may be estimated by the use of a nonlinear optimization technique like the least squares procedure or the maximum likelihood technique. This is due to the presence of items of the white noise process in the model. The best of competing models shall be chosen on minimum Akaike's Information Criterion (AIC) grounds. Any chosen model is tested for goodness-of-fit to the data by analysis of its residuals. An adequate model must have residuals that are uncorrelated and/or follow the Gaussian distribution.

2.4 Statistical Software

The software used here is Eviews 7. It employs the least error sum of squares criterion for model estimation.

3 Results and Discussion

The time plot of the realization of the prime lending rates called herein PLR in Figure 1 shows a generally horizontal trend with a big hunch between 2009 and 2010. It is observed that yearly minimums tend to lie in the second and third quarters of the year and the maximums in the first and fourth quarters of the year.

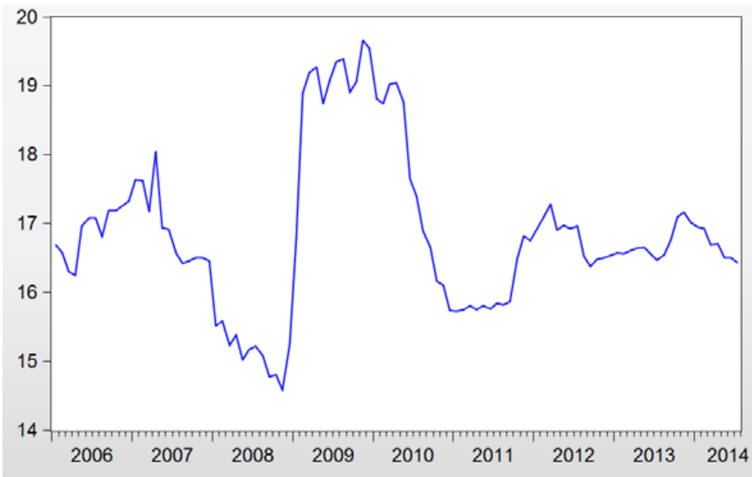


Figure 1: PLR

It has a sinusoidal patterned ACF (see Figure 2) revealing a seasonal tendency of period 12 months. A 12-monthly differencing produces the series SDPLR which also has a fairly horizontal trend with a hunch between 2009 and 2010 (See Figure 3). A non-seasonal differencing of SDPLR yields the series DSDPLR which has a generally horizontal trend (See Figure 4).

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.938	0.938	93.198	0.000
		2	0.843	-0.300	169.23	0.000
		3	0.729	-0.149	226.74	0.000
		4	0.628	0.105	269.82	0.000
		5	0.512	-0.255	298.71	0.000
		6	0.390	-0.090	315.67	0.000
		7	0.268	-0.014	323.74	0.000
		8	0.152	-0.095	326.37	0.000
		9	0.028	-0.203	326.46	0.000
		10	-0.096	-0.069	327.53	0.000
		11	-0.223	-0.163	333.39	0.000
		12	-0.328	0.034	346.15	0.000
		13	-0.409	0.026	366.28	0.000
		14	-0.468	-0.053	392.87	0.000
		15	-0.522	-0.125	426.36	0.000
		16	-0.568	-0.086	466.47	0.000
		17	-0.595	0.025	511.00	0.000
		18	-0.596	0.013	556.19	0.000
		19	-0.573	0.057	598.43	0.000
		20	-0.528	0.051	634.75	0.000
		21	-0.461	0.067	662.75	0.000
		22	-0.377	-0.008	681.74	0.000
		23	-0.293	-0.069	693.32	0.000
		24	-0.208	0.034	699.22	0.000
		25	-0.134	-0.101	701.73	0.000
		26	-0.066	-0.058	702.35	0.000
		27	-0.003	-0.017	702.35	0.000
		28	0.049	-0.175	702.70	0.000
		29	0.098	0.034	704.11	0.000
		30	0.142	0.034	707.09	0.000
		31	0.189	0.048	712.46	0.000
		32	0.214	-0.158	719.45	0.000
		33	0.218	-0.075	726.77	0.000
		34	0.200	-0.092	733.03	0.000
		35	0.178	-0.017	738.08	0.000
		36	0.150	-0.026	741.73	0.000

Figure 2: Correlogram of PLR

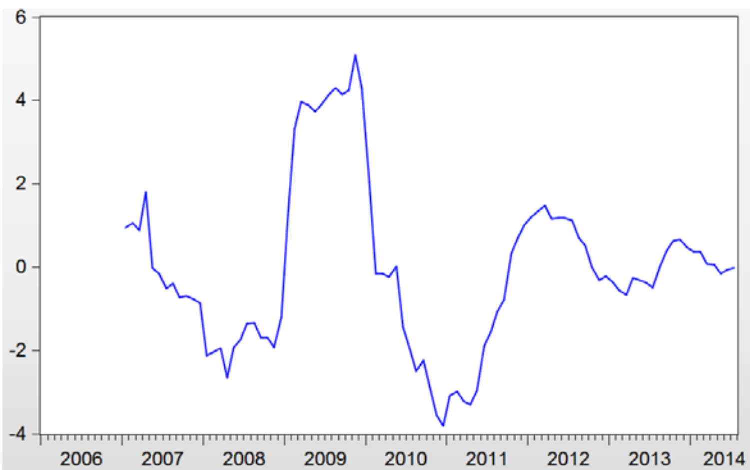


Figure 3: SDPLR

The ADF test statistic for PLR, SDPLR and DSDPLR are respectively -2.4, -2.4 and -5.8. With the 1%, 5% and 10% critical values of -3.5, -2.9 and -2.6 respectively the ADF test considers both PLR and SDPLR non-stationary and DSDPLR as stationary.

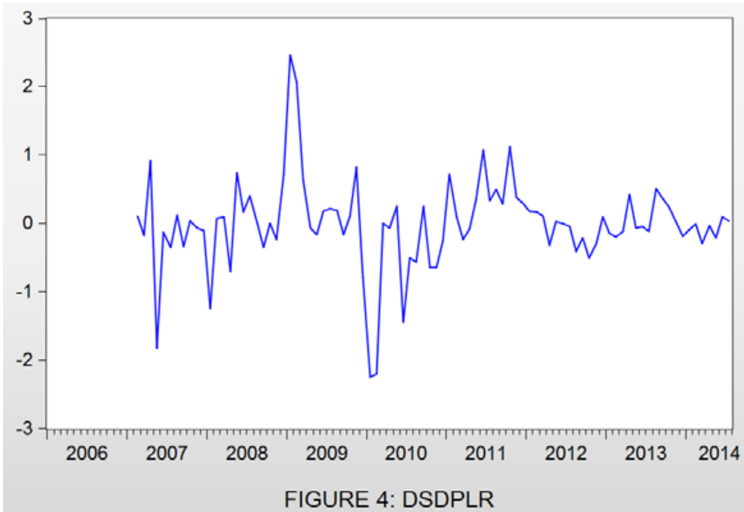
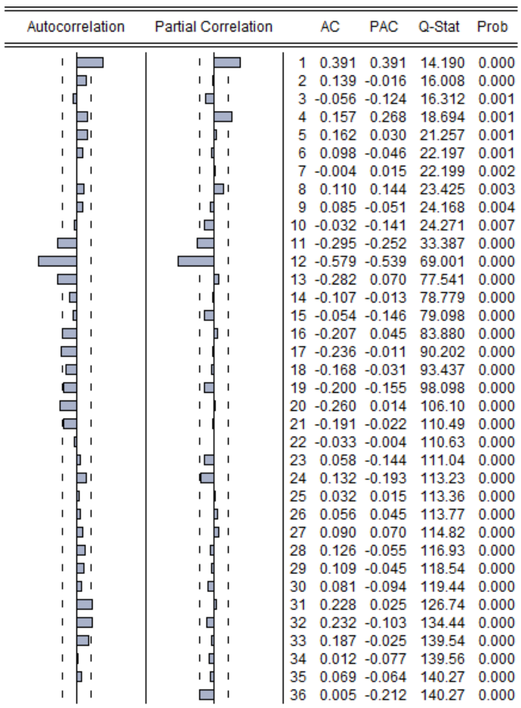


FIGURE 4: DSDPLR

Figure 4: DSDPLR



Lag	AC	PAC	Q-Stat	Prob
1	0.391	0.391	14.190	0.000
2	0.139	-0.016	16.008	0.000
3	-0.056	-0.124	16.312	0.001
4	0.157	0.268	18.694	0.001
5	0.162	0.030	21.257	0.001
6	0.098	-0.046	22.197	0.001
7	-0.004	0.015	22.199	0.002
8	0.110	0.144	23.425	0.003
9	0.085	-0.051	24.168	0.004
10	-0.032	-0.141	24.271	0.007
11	-0.295	-0.252	33.387	0.000
12	-0.579	-0.539	69.001	0.000
13	-0.282	0.070	77.541	0.000
14	-0.107	-0.013	78.779	0.000
15	-0.054	-0.146	79.098	0.000
16	-0.207	0.045	83.880	0.000
17	-0.236	-0.011	90.202	0.000
18	-0.168	-0.031	93.437	0.000
19	-0.200	-0.155	98.098	0.000
20	-0.260	0.014	106.10	0.000
21	-0.191	-0.022	110.49	0.000
22	-0.033	-0.004	110.63	0.000
23	0.058	-0.144	111.04	0.000
24	0.132	-0.193	113.23	0.000
25	0.032	0.015	113.36	0.000
26	0.056	0.045	113.77	0.000
27	0.090	0.070	114.82	0.000
28	0.126	-0.055	116.93	0.000
29	0.109	-0.045	118.54	0.000
30	0.081	-0.094	119.44	0.000
31	0.228	0.025	126.74	0.000
32	0.232	-0.103	134.44	0.000
33	0.187	-0.025	139.54	0.000
34	0.012	-0.077	139.56	0.000
35	0.069	-0.064	140.27	0.000
36	0.005	-0.212	140.27	0.000

Figure 5: Correlogram of DSDPLR

The correlogram of DSDPLR in Figure 5 shows an ACF of a series with a SARIMA$(0,1,1)\text{x}(0,1,1)_{12}$ component and a seasonal AR component of order 2. The models proposed are (1) a SARIMA$(0,1,1)\text{x}(0,1,1)_{12}$ model (2) a SARIMA$(0,1,1)\text{x}(1,1,1)_{12}$ model (3) a SARIMA$(0,1,1)\text{x}(2,1,1)_{12}$ model and (4) a SARIMA$(0,1,0)\text{x}(2,1,1)_{12}$ model.

The SARIMA$(0,1,1)\mathrm{x}(0,1,1)_{12}$ model as estimated in Table 1 is given by

$$X_t = 3046\varepsilon_{t-1} - .6386\varepsilon_{t-12} + .0563\varepsilon_{t-13} \tag{4}$$

The additive SARIMA model suggestive by model (4) is estimated in Table 2 by

$$X_t = .2486\varepsilon_{t-1} - .7512\varepsilon_{t-12} + \varepsilon_t \tag{5}$$

Table 1: Estimation of the SARIMA$(0,1,1)\mathrm{x}(0,1,1)_{12}$ Model

Dependent Variable: DSDPLR
Method: Least Squares
Date: 09/10/14 Time: 19:43
Sample (adjusted): 2007M02 2014M07
Included observations: 90 after adjustments
Failure to improve SSR after 8 iterations
MA Backcast: 2006M01 2007M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	0.304640	0.107625	2.830573	0.0058
MA(12)	-0.638577	0.100668	-6.343388	0.0000
MA(13)	0.056343	0.110166	0.511443	0.6103

R-squared	0.514087	Mean dependent var	-0.010889
Adjusted R-squared	0.502917	S.D. dependent var	0.664303
S.E. of regression	0.468361	Akaike info criterion	1.353610
Sum squared resid	19.08449	Schwarz criterion	1.436937
Log likelihood	-57.91246	Hannan-Quinn criter.	1.387212
Durbin-Watson stat	1.720081		

Inverted MA Roots	.93	.80+.48i	.80-.48i	.45+.83i
	.45-.83i	.09	-.03+.96i	-.03-.96i
	-.52+.83i	-.52-.83i	-.87-.48i	-.87+.48i
	-1.00			

Table 2: Estimation of the Additive Sarima Model

Dependent Variable: DSDPLR
Method: Least Squares
Date: 09/10/14 Time: 19:51
Sample (adjusted): 2007M02 2014M07
Included observations: 90 after adjustments
Failure to improve SSR after 9 iterations
MA Backcast: 2006M02 2007M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	0.248570	0.098703	2.518356	0.0136
MA(12)	-0.751223	0.089345	-8.408096	0.0000

R-squared	0.561111	Mean dependent var	-0.010889
Adjusted R-squared	0.556123	S.D. dependent var	0.664303
S.E. of regression	0.442586	Akaike info criterion	1.229606
Sum squared resid	17.23761	Schwarz criterion	1.285157
Log likelihood	-53.33225	Hannan-Quinn criter.	1.252007
Durbin-Watson stat	1.683168		

Inverted MA Roots	.96	.83+.49i	.83-.49i	.47+.84i
	.47-.84i	-.02+.97i	-.02-.97i	-.51+.84i
	-.51-.84i	-.87+.49i	-.87-.49i	-1.00

Table 3: Estimation of the SARIMA$(0,1,1)x(1,1,1)_{12}$ Model

Dependent Variable: DSDPLR
Method: Least Squares
Date: 11/03/14 Time: 07:09
Sample (adjusted): 2008M02 2014M07
Included observations: 78 after adjustments
Convergence achieved after 27 iterations
MA Backcast: 2007M01 2008M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	-0.308461	0.102135	-3.020138	0.0035
MA(1)	0.277314	0.096452	2.875154	0.0053
MA(12)	-0.619369	0.073079	-8.475350	0.0000
MA(13)	-0.561941	0.094494	-5.946816	0.0000

R-squared	0.626500	Mean dependent var	0.026795
Adjusted R-squared	0.611358	S.D. dependent var	0.656040
S.E. of regression	0.408983	Akaike info criterion	1.099633
Sum squared resid	12.37775	Schwarz criterion	1.220490
Log likelihood	-38.88569	Hannan-Quinn criter.	1.148014
Durbin-Watson stat	1.940528		

Inverted AR Roots	.88-.23i	.88+.23i	.64-.64i	.64+.64i
	.23-.88i	.23+.88i	-.23+.88i	-.23-.88i
	-.64-.64i	-.64-.64i	-.88-.23i	-.88+.23i
Inverted MA Roots	.99	.87+.49i	.87-.49i	.51-.85i
	.51+.85i	.04-.98i	.04+.98i	-.44-.87i
	-.44+.87i	-.77+.54i	-.77-.54i	-.84-.13i
	-.84+.13i			

Table 4: Estimation of the SARIMA$(0,1,1)x(2,1,1)_{12}$ Model

Dependent Variable: DSDPLR
Method: Least Squares
Date: 09/10/14 Time: 20:27
Sample (adjusted): 2009M02 2014M07
Included observations: 66 after adjustments
Convergence achieved after 26 iterations
MA Backcast: 2008M01 2009M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	-0.931393	0.080534	-11.56521	0.0000
AR(24)	-0.383290	0.064961	-5.900332	0.0000
MA(1)	0.116502	0.124558	0.935326	0.3533
MA(12)	0.948391	0.022273	42.58032	0.0000
MA(13)	0.084726	0.121475	0.697481	0.4882

R-squared	0.777617	Mean dependent var	-0.019545
Adjusted R-squared	0.763034	S.D. dependent var	0.622275
S.E. of regression	0.302918	Akaike info criterion	0.522025
Sum squared resid	5.597318	Schwarz criterion	0.687908
Log likelihood	-12.22683	Hannan-Quinn criter.	0.587573
Durbin-Watson stat	1.810596		

Inverted AR Roots	.94-.19i	.94+.19i	.91+.30i	.91-.30i
	.72-.64i	.72+.64i	.64+.72i	.64-.72i
	.30+.91i	.30-.91i	.19-.94i	.19+.94i
	-.19+.94i	-.19-.94i	-.30-.91i	-.30+.91i
	-.64+.72i	-.64-.72i	-.72+.64i	-.72-.64i
	-.91-.30i	-.91+.30i	-.94+.19i	-.94-.19i
Inverted MA Roots	.96+.26i	.96-.26i	.70-.70i	.70+.70i
	.26-.96i	.26+.96i	-.09	-.26-.96i
	-.26+.96i	-.71+.70i	-.71-.70i	-.96+.26i
	-.96-.26i			

The SARIMA(0,1,1)x(1,1,1)$_{12}$ model as estimated in Table 3 is given by

$$X_t + .3085X_{t-12} = .2773\varepsilon_{t-1} - .6114\varepsilon_{t-12} - .5619\varepsilon_{t-13} + \varepsilon_t \qquad (6)$$

The SARIMA(0,1,1)x(2,1,1)$_{12}$ model as estimated in Table 4 is given by

$$X_t + .9314X_{t-12} + .3833X_{t-24} = .1165\varepsilon_{t-1} + .9484\varepsilon_{t-12} + .0847\varepsilon_{t-13} + \varepsilon_t \qquad (7)$$

which suggests a SARIMA(0,1,0)x(2,1,1)$_{12}$ model. This is estimated in Table 5 as

$$X_t + .9329X_{t-12} + .3849X_{t-24} = .9330\varepsilon_{t-12} + \varepsilon_t \qquad (8)$$

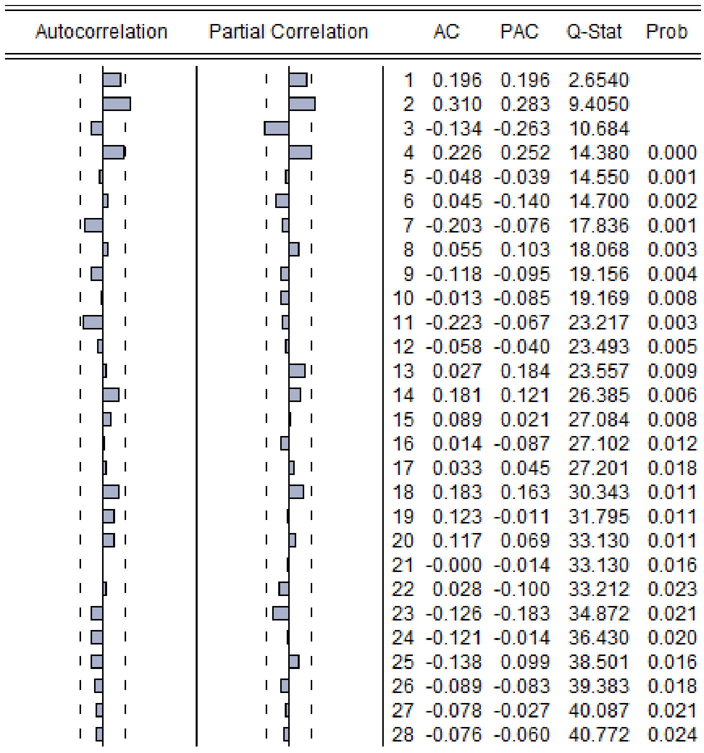
Table 5: Estimation of the SARIMA(0,1,0)x(2,1,1)$_{12}$ Model

Dependent Variable: DSDPLR
Method: Least Squares
Date: 09/25/14 Time: 10:50
Sample (adjusted): 2009M02 2014M07
Included observations: 66 after adjustments
Convergence achieved after 7 iterations
MA Backcast: 2008M02 2009M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	-0.932895	0.074960	-12.44531	0.0000
AR(24)	-0.384935	0.061179	-6.291917	0.0000
MA(12)	0.932951	0.019998	46.65244	0.0000

R-squared	0.767978	Mean dependent var	-0.019545
Adjusted R-squared	0.760612	S.D. dependent var	0.622275
S.E. of regression	0.304462	Akaike info criterion	0.503849
Sum squared resid	5.839924	Schwarz criterion	0.603379
Log likelihood	-13.62702	Hannan-Quinn criter.	0.543178
Durbin-Watson stat	1.534540		

Inverted AR Roots	.94-.19i	.94+.19i	.91+.30i	.91-.30i
	.72-.64i	.72+.64i	.64+.72i	.64-.72i
	.30+.91i	.30-.91i	.19-.94i	.19+.94i
	-.19+.94i	-.19-.94i	-.30-.91i	-.30+.91i
	-.64+.72i	-.64-.72i	-.72+.64i	-.72-.64i
	-.91-.30i	-.91+.30i	-.94+.19i	-.94-.19i
Inverted MA Roots	.96+.26i	.96-.26i	.70+.70i	.70-.70i
	.26-.96i	.26+.96i	-.26+.96i	-.26-.96i
	-.70-.70i	-.70-.70i	-.96-.26i	-.96+.26i



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.196	0.196	2.6540	
		2	0.310	0.283	9.4050	
		3	-0.134	-0.263	10.684	
		4	0.226	0.252	14.380	0.000
		5	-0.048	-0.039	14.550	0.001
		6	0.045	-0.140	14.700	0.002
		7	-0.203	-0.076	17.836	0.001
		8	0.055	0.103	18.068	0.003
		9	-0.118	-0.095	19.156	0.004
		10	-0.013	-0.085	19.169	0.008
		11	-0.223	-0.067	23.217	0.003
		12	-0.058	-0.040	23.493	0.005
		13	0.027	0.184	23.557	0.009
		14	0.181	0.121	26.385	0.006
		15	0.089	0.021	27.084	0.008
		16	0.014	-0.087	27.102	0.012
		17	0.033	0.045	27.201	0.018
		18	0.183	0.163	30.343	0.011
		19	0.123	-0.011	31.795	0.011
		20	0.117	0.069	33.130	0.011
		21	-0.000	-0.014	33.130	0.016
		22	0.028	-0.100	33.212	0.023
		23	-0.126	-0.183	34.872	0.021
		24	-0.121	-0.014	36.430	0.020
		25	-0.138	0.099	38.501	0.016
		26	-0.089	-0.083	39.383	0.018
		27	-0.078	-0.027	40.087	0.021
		28	-0.076	-0.060	40.772	0.024

Figure 6: Correlogram of the SARIMA(0,1,0)x(2,1,1)$_{12}$ Residuals

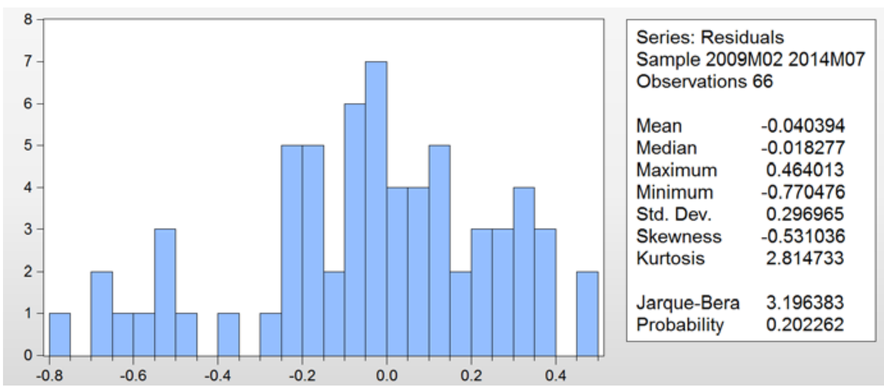


Figure 7: Histogram of the SARIMA(0,1,0)x(2,1,1)$_{12}$ Residuals

In models (4) through (8), X represents DSDPLR. Model (8) is the most adequate on minimum AIC grounds.

The residuals of model (8) are mostly uncorrelated (See Figure 6) and normally distributed (See the Jarque Bera test of Figure 7) implying that model (8) is adequate.

4 Conclusion

It may be concluded that the prime lending rates of Nigerian banks follow a SARIMA$(0,1,0)x(2,1,1)_{12}$ model. Forecasting of these rates may be done on the basis of this model.

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