SARIMA MODELLING OF NIGERIAN BANK PRIME LENDING RATES

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ABSTRACT

The monthly Prime Lending Rates of Nigerian Banks are modelled 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 the 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)x(0, 1, 1)12 (2) a SARIMA(0,1,1)x(1,1,1)12 and (3) a SARIMA(0, 1, 1)x(2, 1, 1)12 . The foregoing models follow a descending order of degree of adequacy on AIC grounds. However, from the SARIMA(0, 1, 1)x(2, 1, 1)12 model, a SARIMA(0,1,0)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.

KEY WORDS: Prime Lending rates, Sarima Models, Seasonal Time Series, Nigeria

**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 modelled by SARIMA techniques because of their intrinsically seasonal nature include temperature (Khajavi *et al.,* 2012), tourism patronage (Padhan, 2011), airways patronage (Box and Jenkins, 1976), inflation (Fannoh *et al.,* 2012), savings deposit rates (Etuk *et al.*, 2014), rice prices (Hassan *et al.,* 2013), tuberculosis incidence (Moosazadeh *et al.*, 2014), stock prices (Etuk, 2012), cucumber prices (Luo *et al.,* 2013), internally generated revenues (Etuk *et al.*, 2014), dengue numbers (Martinez *et al.,*  2011) and tomato prices (Adanacioglu and Yercan, 2012), to mention but a few.

**MATERIALS AND METHODS**

**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 **Ba**nk of Nigeria, [www.cenbank.org](http://www.cenbank.org). They are published under the Money Market Indicators subsection of the Data and Statistics section.

**Sarima Models**: A stationary time series {Xt} is said to follow an *autoregressive model of order p and q* denoted by ARMA(p, q) if it satisfies the following difference equation

Xt - α1Xt-1 - α2Xt-2 - ... - αpXt-p = εt + β1εt-1 + β2εt-2 + ... + βqεt-q (1)

where the sequence of random variables {εt} is a white noise process. The α’s and β’s are constants such that the model is both stationary and invertible. Suppose that we write model (1) as

A(L)Xt = B(L)εt (2)

where A(L) and B(L) are the autoregressive (AR) and the moving average (MA) operators respectively defined by A(L) = 1 - α1L - α2L2 - ... - αpLp and B(L) = 1 + β1L + β2L2 + ... + βqLq and L is the backward shift operator defined by LkXt = Xt-k.

If a time series is non-stationary, Box and Jenkins (1976) proposed that differencing of the series a certain number of times may make it stationary. Let ∇ be the differencing operator. Then ∇ = 1 – L. If d is the minimum number of times for which the dth difference {∇dXt} of {Xt} is stationary and {∇dXt} follows model (1) or (2) the original series {Xt} 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 {Xt} is seasonal of period s, Box and Jenkins (1976) moreover proposed that it may be modelled by

A(L)Φ(Ls)∇d∇DsXt = B(L)Θ(Ls)εt (3)

where ∇s is the seasonal differencing operator defined by ∇s = 1 – Ls , D is the minimum number of times of seasonal differencing for stationarity and Φ(L) and Θ(L) are the seasonal AR and MA operators respectively. Suppose Φ(L) and Θ(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.

**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 (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.

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

**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. It has a sinusoidally 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. The ADF test statistic for PLR, SDPLR and DSDPLR are respectively equal to -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. The correlogram of DSDPLR shows an ACF of a series with a SARIMA(0,1,1)x(0,1,1)12 component and a seasonal AR component of order 2. The models proposed are (1) a SARIMA(0,1,1)x(0,1,1)12 model (2) a SARIMA(0,1,1)x(1,1,1)12 model (3) a SARIMA(0,1,1)x(2,1,1) model and (4) a SARIMA(0,1,0)x(2,1,1)12 model .

The SARIMA(0,1,1)x(0,1,1)12 model as estimated in Table 1 is given by

Xt = 0.3046εt-1 – 0.6386εt-12 + 0.0563εt-13 + εt (4)

 (±0.1076) (±0.1007) (±0.1107)

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

Xt = 0.2486εt-1 – 0.7512εt-12 + εt (5)

 (±0.0987) (±0.0893)

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

Xt + 0.3085Xt-12 = 0.2773εt-1 – 0.6114εt-12 – 0.5619εt-12 + εt (6)

 (±0.1021) (±0.0965) (±0.0731) (±0.0945)

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

Xt + 0.9314Xt-12 + 0.3833Xt-24 = 0.1165εt-1 + 0.9484εt-12 + 0.0847εt-13 + εt (7)

 (±0.0805) (±0.0650) (±0.1246) (±0.0223) (±0.1215)

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

Xt + 0.9329Xt-12 + 0.3849Xt-24 = 0.9330εt-12 + εt (8)

 (±0.0750) (±0.0612) (±0.0200)

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.

**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 the model.

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FIGURE 2: CORRELOGRAM OF PLR







FIGURE 5: CORRELOGRAM OF DSDPLR

TABLE 1: ESTIMATION OF THE SARIMA(0,1,1)X(0,1,1)12 MODEL



TABLE 2: ESTIMATION OF THE ADDITIVE SARIMA MODEL



TABLE 3: ESTIMATION OF THE SARIMA(0,1,1)X(1,1,1)12 MODEL



TABLE 4: ESTIMATION OF THE SARIMA(0,1,1)X(2,1,1)12 MODEL



TABLE 5: ESTIMATION OF THE SARIMA(0,1,0)X(2,1,1)12 MODEL





 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