EXPONENTIAL SMOOTHING METHODS IN FORECASTING NIGERIA CONSUMER PRICE INDEX

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ABSTRACT: The consumer price index (CPI) measure the average change over a time in price of goods and services consumed by people, this study is focus to determine the best smoothing technique, to remove the irregularity in the series and to use the smoothed data to fit the model for future prediction. The data used for this study are monthly data, extracted from the record of CBN via www.cbn .gov.ng. The data spanned from January 1995 to December 2017. The behavioral pattern of the associated time plot exhibits the existence of trend and non-seasonality in the data. In view of this, non-seasonal Exponential Smoothing Techniques were adopted and the Holt's Smoothing Exponential Technique was proved to be the best techniques to use for this study because, the accuracy measure i.e. MAPE (2.457), MAE (0.9352), MSE (4.5512), are relatively smallest compare with others used smoothing techniques, using the smoothing constant α(0.933) and β(0.07) The future value of Nigeria CPI for year 2018 was predicted using fitted equation. In view of this study, it was discovered that Nigeria CPI will be gradually increasing over times.
KEYWORDS: Consumer Price Index, Smoothing Technique, Accuracy Measurement.

1. INTRODUCTION

Consumer price index (CPI) measures changes in the price level of market basket of consume goods and services and service purchased by household.
The consumer price index is a statistical estimate constructed using price of the sample of representative items whose are price are collected periodically. Sub-indices and sub-sub-indices are computed for different categories and sub-categories of goods and service being combined to produce the overall index with weight reflecting their share in the total of the consumer expenditures covered by index. It is one of several price index calculated by most National Statistical Agencies. The annual percentage change in CPI is used as a measure of inflation
A CPI can be used to index (i.e. adjust for the effect of inflation).
The real value of wages, salaries, pension for regulating prices and dealing with monetary magnitude to show changes in real value. In most countries, the CPI along with the population census is one of the closely watched National Economics Statistic.
The index is usually computed monthly or quarterly in some countries as a weighted average of sub-indices for different components of consumer expenditure, such as food, house, shoes, clothing, each of which is turn a weighted average. In view of the nature of this data, there must be existence of trend and some irregularities within the data, for the purpose of forecast it is necessary to smooth out some effect within data the data and forecast with smoothed data to see the truth behaviors of the data. Some authors have discourses on time series analysis on CPI with different methods and techniques, e.g ARMA, SARIMA etc.
Note that, the annual percentage change in a CPI is used as a measure of inflation. A CPI can be used to index (i.e., adjust for the effect of inflation) the real value of wages, salaries, pensions, for regulating prices and for deflating monetary magnitudes to show changes in real values. Therefore, CPI and inflation are related nature in data form.
No wonder Akpanta and Okorie ([AO16]) examined 18 years data on Consumer Price Index (CPI) from 1996 to 2013 obtained in months from the CBN website. The basic statistics shows that the indicator has neither fallen below 21.19 nor risen above 152.29 within the period under consideration. The major analysis was done using Time Series approach. Although the diagnostic plots carried out showed that ARIMA (11, 2, 1) $(0,0,1)_{12}$ provides a good fit to the CPI data, the model seems to be over-parameterized hence the need to drop statistically insignificant ones became inevitable. This resulted to a parsimonious seasonal ARIMA (1, 2, 1) $(0, 0, 1)_{12}$ for the non-differenced CPI data. Forecasts were made using the model and a scientific comparison carried out showed that there is no significant difference between the observed and the forecast values of the CPI data.
Iwok and Udoh ([IU16]) compared the performances between the autoregressive integrated moving average (ARIMA) – Fourier model and the wavelet model. The methods were applied to a consumer price index (CPI) series.

Doguwa and Alade ([DA13]) working together modeled CPI using SARIMA and SARIMAX model and compared their performance using pseudo – out – of - sample forecasting procedure covering the period July 2011 to September 2013. On the course of the research, it was strongly recommended that SARIMA model be used in forecasting core inflationary situations.

Al-Eideh, Al-Refai and Sbeiti ([AAS04]) used Maximum Likelihood estimator within a lognormal diffusion process with closed form analytical solutions to obtain the monthly CPI forecasts for the period between 1970 and 2002. The quarterly estimates of inflation rates are obtained from these monthly forecasts rather than from quarterly data. This procedure significantly improved the estimates of inflation rates. The model also produced a superior fit as compared to random walk and GARCH (p,q)-M models. The adopted approach is found to be simple, economical and generally suitable for modelling stochastic processes that reflect aggregation over time stemming from many factors, and in which the transition path between consecutive states is relatively smooth.

ARIMA models for forecasting the Irish inflation were outlined by Meyler, Kenny and Quinn ([MKQ98]). The study considered two alternative approaches to the issue of identifying ARIMA models, namely, the Box-Jenkins approach and the objective penalty function methods. The emphasis was on forecast performance, which suggests that ARIMA forecast outperformed the other approach.

Malliaris and Malliaris ([MM95]) presented a decomposition of inflation and its volatility. According to the traditional quantity theory of money, the rate of inflation is decomposed into three components: the rate of change in the money supply, plus the rate of change in the velocity of circulation, minus the rate of change in real output. They derived a generalization of this decomposition by postulating that the rate of change of money supply, velocity, and output follow diffusion equations. Using stochastic calculus techniques, two expressions are obtained decomposing inflation and its volatility as a sum of several economically important terms. Two sets of U.S. data are used to illustrate these decompositions with actual numbers.

An autoregressive model with a deterministically shifting intercept was introduced by Gonzalez and Terasvirta ([GT08]). This implies that the model has a shifting mean and is thus nonstationary but stationary around a nonlinear deterministic component. The shifting intercept is defined as a linear combination of logistic transition functions with time as the transition variables. The number of transition functions was determined by selecting the appropriate functions from a possibly large set of alternatives using a sequence of specification tests. This selection procedure is in ([J+18]). A Monte Carlo experiment was conducted to show how the proposed modelling procedure and some of its variants work in practice. The paper contains two applications in which the results are compared with what is obtained by assuming that the time series used as examples may contain structural breaks instead of smooth transitions and selecting the number of breaks following the technique of Bai and Perron ([BP98]).

Kang et al ([KKM09]) investigated the existence and timing of changes in U.S. inflation persistence. To do so, they developed an unobserved components model of inflation with Markov-switching parameters and measured persistence using impulse response functions based on the model. An important feature of their model is its allowance for multiple regime shifts in parameters related to the size and propagation of shocks. Inflation persistence depends on the configuration of these parameters, although it need not change even I f the parameters change. Using the GDP deflator for the sample period of 1959-2006, Kang et al ([KKM09]) found that U.S. inflation underwent two sudden permanent regime shifts, both of which corresponded to changes in persistence.

Much of these works done in modelling and forecasting of Inflation, which is measured by Consumer Price Index, have used ARIMA models and perhaps made comparisons with some other models. In this study we shall use different approach which is smoothing techniques. This study shall compare the performance of different smoothing techniques to Nigerian All Items Consumer Price Index (NAICPI).

2. MATERIALS AND METHODOLOGY

2.1. Smoothing techniques

When data collected over time displays random variation, smoothing techniques can be used to reduce or cancel the effect of these variations. When properly applied, these techniques smooth out the random variation in the time series data to reveal underlying trends and some irregularities.

XL Miner features four different smoothing techniques: Exponential, Moving Average, Double Exponential, and Holt-Winters. Exponential and Moving Average are relatively simple smoothing techniques and should not be performed on data sets involving seasonality. Double Exponential is also known as Holt's smoothing technique is an advanced smoothing technique that can be used on data sets involving trend and no seasonality and

Holt-Winters are more advanced techniques that can be used on data sets involving trend and seasonality.

2.2. Exponential smoothing

Exponential smoothing was proposed in the late 1950s. Brown, Holt and Winters are key pioneering works and have motivated some of the most successful forecasting methods. Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words the more recent the observation the higher the associated weight. This framework generates reliable forecasts quickly and for a wide spectrum of time series which is a great advantage and of major importance to applications in industry. Exponential Smoothing is one of the more popular smoothing techniques due to its flexibility, ease in calculation, and good performance. Exponential Smoothing uses a simple average calculation to assign exponentially decreasing weights starting with the most recent observations. New observations are given relatively more weight in the average calculation than older observations.

$$\hat{Y}_t = \alpha(y_t + \sum_{i=1}^{r}(1-\alpha)^{i}\ y_{t-j})$$

where $\hat{Y}_t$ is the forecasted value of the series at time t and α is the smoothing constant. Note that $r < t$, but r does not have to equal $t-1$.From the above equation, we see that the method constructs a weighted average of the observations. The weight of each observation decreases exponentially as we move back in time. Hence, since the weights decrease exponentially and averaging is a form of smoothing, the technique was named exponential smoothing. An equivalent ARIMA (0,1,1) model can be constructed to represent the single exponential smoother.

2.3. Double exponential smoothing

This exponential smoothing technique, also known as **Holt's method** and its use to smooths the data when a trend is present and no seasonal. The double exponential smoothing equations and forecasted equation is:

$$L_t = \alpha\, y_t + (1-\alpha)\, L_{t-1} + T_{t-1} \quad (1)$$
$$T_t = \beta\,(L_t - L_{t-1}) + (1-\beta)\, T_{t-1} \quad (2)$$

And forecasted equations is

$$F_{1+k} = L_t + kT_{t.} \quad (3)$$

where Lt is the level at time t, α is the weight (or smoothing constant) for the level, Tt is the trend at time t, β is the weight (or smoothing constant) for the trend, and F_k is the forecasted values.

Finally, **Holt-Winters exponential smoothing** smooths the data when trend and seasonality are present; however, these two components can be either additive or multiplicative. For the additive model, the equations are:

$$L_t = \alpha(Y_t - S_{t-P}) + (1-\alpha)\,(L_{t-1} + T_{t-1}) \quad (4)$$
$$T_t = \beta\,(L_t - L_{t-1}) + (1-\beta)\, T_{t-1} \quad (5)$$
$$S_t = \delta(Y_t + L_t) + (1-\delta)S_{t-P.} \quad (6)$$
$$F_t = L_{t-1} + T_{t-1} + S_{t-P.} \quad (7)$$

For the multiplicative model, the equations are:

$$L_t = \alpha(Y_t/S_{t-P.}) + (1-\alpha)\,(L_{t-1} + T_{t-1}) \quad (8)$$
$$S_t = \delta(Y_t/L_{t.}) + (1-\delta)S_{t-P.} \quad (9)$$
$$F_t = (L_{t-1} + T_{t-1}) + S_{t-P.} \quad (10)$$

For both sets of equations, all quantities are the same as they were defined in the previous models, except now we also have that St, St is the seasonal component at time t, δ is the weight (or smoothing constant) for the seasonal component, and p is the seasonal period.

3. MEASURE OF PERFORMANCES ACCURACY OF THE MODEL

There are several statistical properties normally uses to measure the accuracy or performance of the fitted model. Proper care have to be taking while selecting the best model as important of time series forecasting process in many economics situation in any nation. There are various statistics need to be compared, the minimum value of these statistic corresponding to each model will be regarded the best model. For this research work three accuracy measures were employed to minimize the error of the fitted equations. These are:

(i) Mean Absolute Percentage Error (MAPE).
(ii) Mean Absolute Error (MAE).
(iii) Mean Square Error (MSE).

4. RESULT AND DISCUSION

The data used in this research work is secondary data extracted from the CBN website; the data comprise twenty five years monthly data of consumer price index collected from various Nigeria markets basket from 1995 to 2017.

Firstly, time plot of the series were examined and the series contained trend and no seasonality, therefore double (Holt's) exponential smoothing technique were used in the analysis. The time plot revealed that the series contained the trend and no seasonality, the Holt's linear trend exponential smoothing techniques have to be used. In that case, two equations have to be fitted, level and trend which symbolized α and β respectively'

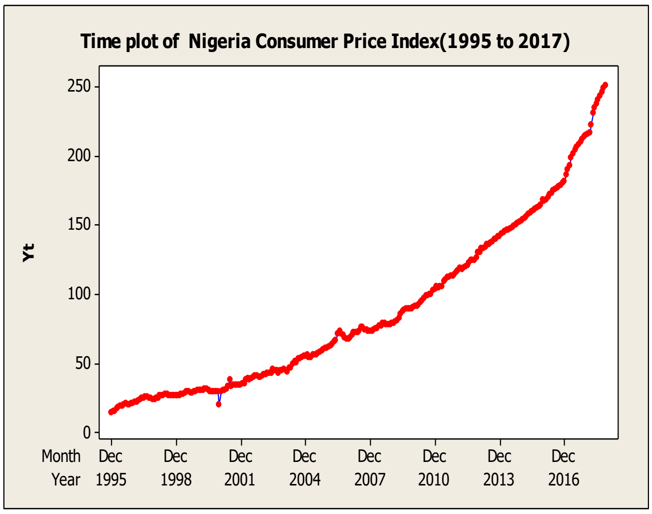

Figure 1. Time plot for Nigeria Consumer Price Index (1995 to 2017)

4.1. Selecting of Smoothing Constant

In selecting the smoothing constant, Try and error method were adopted to choose the best smoothing constant. Therefore, α and β used interchangeably in the equations to obtain minimum value of error. (i.e MAPE, MAE MSE). In this process of selecting smoothing constant, 0.93 and 0.07 were fund to be best smoothing parameter for α and β respectively, the constants minimized the error as MAPE (2.457), MAE(0.9352,) and MSE(4.5512) compare to others.

$$L_t = \alpha\, y_t + (1-\alpha)\, L_{t-1} + T_{t-1} = 0.093Y_t + (1\text{-}0.093)\,(L_{t-1}+T_{t-1})$$

$$T_t = \beta\,(L_t - L_{t-1}) + (1-\beta)\, T_t = 0.071(L_t - L_{t-1}) + (1-0.071)\, T_t$$

$$Y_t = L_t + T_t$$

In modelling the smoothing parameter, the α that used to estimate level which is 0.933 and its standard error is 0.06 is proved to be significant by obtained the p-value (0.001), and Betta that is used to estimate trend which is 0.071 and its standard error is 0.026 obtained the p-value (0.007) which is significantly difference, therefore, the two equations are significantly difference from zero, which mean they impact on forecasted o predicted value.

Table 1: Smoothed, Level, Trend and Residual

t	Y_t	Smoothed	Level (L_t)	Trend (T_t)	Fitted	Residual
Jan,95	14.36082	12.59109	12.59109	2.476219	-12.053	26.41386
Feb,95	15.01978	15.02296	15.02296	2.473071	15.06731	-0.04753
Mar, 95	15.55548	15.6855	15.6855	2.344523	17.49603	-1.94055
Apr, 95	16.95309	17.02524	17.02524	2.273184	18.03002	-1.07693
May, 95	17.99757	18.08473	18.08473	2.187011	19.29843	-1.30085
Jun, 95	18.81197	18.90978	18.90978	2.090312	20.27174	-1.45977
Jul, 95	19.43492	19.53978	19.53978	1.98663	21.00009	-1.56517
Aug, 95	20.12022	20.21443	20.21443	1.893479	21.52641	-1.4062
Sep, 95	20.46407	20.57421	20.57421	1.784586	22.10791	-1.64384
Oct, 95	19.9586	20.11941	20.11941	1.62559	22.35879	-2.40019
Nov, 95	20.2293	20.33085	20.33085	1.525185	21.745	-1.51571
Dec, 95	20.96472	21.02444	21.02444	1.466142	21.85603	-0.89132
Jan, 96	21.19138	21.27842	21.27842	1.380079	22.49058	-1.2992
Feb, 96	21.57553	21.64809	21.64809	1.308339	22.6585	-1.08298
Mar, 96	22.07399	22.13311	22.13311	1.249884	22.95643	-0.88244
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
Sep.16	207.9632	207.9913	207.9913	2.068855	208.3828	-0.41958
Oct,16	209.681	209.7064	209.7064	2.043735	210.0602	-0.3792
Nov,16	211.327	211.3553	211.3553	2.015704	211.7501	-0.42316

t	Y_t	Smoothed	Level (L_t)	Trend (T_t)	Fitted	Residual
Dec,16	213.557	213.5445	213.5445	2.028023	213.371	0.185967
Jan,17	214.7265	214.7832	214.7832	1.97198	215.5726	-0.84602
Feb, 17	215.9542	216.0079	216.0079	1.91892	216.7552	-0.80099
Mar, 17	216.7123	216.7937	216.7937	1.838469	217.9268	-1.21449
Apr, 17	222.4255	222.1713	222.1713	2.089749	218.6322	3.793303
May, 17	230.5362	230.1158	230.1158	2.505436	224.2611	6.275188
Jun, 17	234.1745	234.0705	234.0705	2.608332	232.6212	1.553307
Jul, 17	237.0215	236.9986	236.9986	2.631035	236.6788	0.342736
Aug, 17	239.8725	239.8562	239.8562	2.647122	239.6296	0.242841
Sep, 17	242.7255	242.7106	242.7106	2.661838	242.5033	0.222155
Oct, 17	245.5745	245.561	245.561	2.675226	245.3724	0.202107
Nov, 17	248.3956	248.385	248.385	2.685788	248.2362	0.159438
Dec, 17	250.7454	250.7672	250.7672	2.664237	251.0708	-0.32533

Table 2. Accuracy measurement of the model

LEVEL/TREND	MAPE	MAE	MSE
α =0.2, β = 0.2	5.4608	1.9091	11.6655
α =0.2, β = 0.15	5.5319	1.9230	11.8208
α =0.2, β = 0.25	5.3560	1.8997	117014
α =0.2, β = 0.30	5.4389	1.9411	11.8518
α =0.25, β = 0.2	4.8406	1.7320	9.8669
α =0.25, β = 0.25	4.8219	1.7495	9.97726
α =0.15, β = 0.30	4.4998	1.6563	8.7559
α =0.30, β = 0.25	3.8999	1.4642	7.1086
α=0.93, β = 0.07	**2.457**	**0.9352**	**4.5512**
α =0.45, β = 0.2	3.4339	1.29165	6.0212
α =0.55, β = 0.2	3.1362	1.18115	5.4004
α =0.9, β = 0.2	2.61717	0.97768	4.7813
α =0.9, β = 0.3	2.6952	0.9852	4.9971
α =0.9, β = 0.15	2.5689	0.9640	4.6821
α =0.9, β = 0.10	2.5129	0.9482	4.5993
α =0.9, β = 0.01	2.4181	1.0048	4.7540

Table 3. Model Smoothing Parameter

Model	S.C	Estimation	S.E.	T	Sig
Consumer Price Index	Alph(Level)	0.933	0.061	15.252	0.000
	Betta(Trend)	0.071	0.026	2.701	0.007

Table 4. Model statistics

Model	MAPE	MAE	MSE
CONSUMER PRICE INDEX	2.4574	0.9351	4.5512

Table 5. Residual ACF

MODEL		1	2	3	4	5	6	7	8	9	10	11	12
CONSUMER PRICE INDEX	ACF	-0.011	0.39	-0.23	-0.058	0.053	-0.268	0.043	-0.115	-0.064	0.035	0.064	0.163
	S.E	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060

Table 6. Forecast value for 2018

MODEL		Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept.	Oct	Nov	Dec.
Consumer Price Index	Forecast	253.43	256.09	258.75	261.92	264.08	266.74	269.40	272.06	274.39	277.39	280.05	282.7
	UCL	256.15	259.94	263.58	267.15	270.68	274.19	277.19	277.69	284.68	288.19	291.68	295.18
	LCL	250.70	252.23	253.92	255.68	257.48	259.29	261.12	262.94	264.9	266.60	268.42	270.23

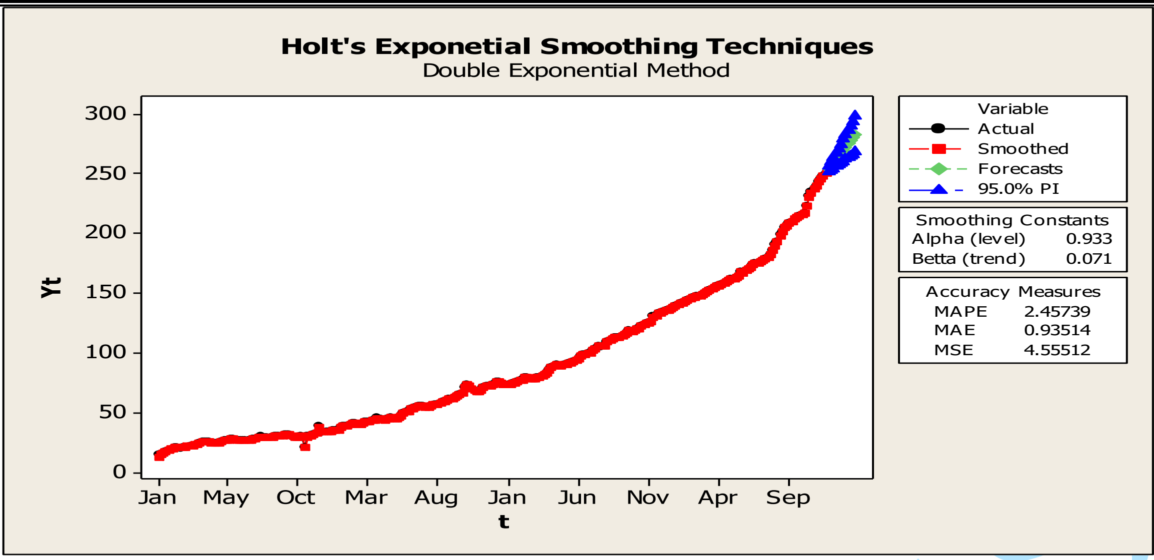

Figure 2. The plot exhibited the actual, smoothed, and forecasted value of Nigeria consumer price index

5. DISCUSSION AND CONCLUSION

Consumer Price Index is measures the changes in the price of level of market basket of goods and services purchase by households the cost of obtaining subjected to monthly collection of market price of goods and service. To remove some irregularities and forecast the future occurrences in such series, exponential smoothing techniques is among the best tools to be used. In view of this, Double exponential smoothing method which is knows as Holt's smoothing techniques was used for Nigeria Consumer Price Index for the period (1995 to 2017) after its time plot revealed that the series contained trends but no seasonality.

The two smoothing equations were obtained, level denoted by L_t and trend denoted by T_t, with smoothing constant α and β respectively. Try and error method were adopted and eventually α (0.093) used to obtain level and β (0.071) used to obtain trend, both of them provide smoothed value (Y_t) that minimize the error compare to others. The following accuracy of the model: MAPE (2.457), MAE (0.952) and MSE (4.5512), are the minimum error obtained through the process. Then, the analysis of smoothing parameters level and trend have the p-value (0.000) and p-value (0.007) respectively which both are significantly difference. Then, the equation (F_{t+k}) used to forecast for year 2018.

This research work purposely designed for researchers and statistical Agencies who's annually dealing with Nigeria Consumer Price Index to be considered all the smoothing parameters including smoothing constant and the fitted equations as their tools to forecast or predict future occurrence, this will enable the cost, strength and unbiasedness that may occurred during the survey be reduced.

Finally, this researched work help the students and research personnel to employ the Holt's exponential smoothing technique as the best smoothing techniques for forecast future occurrence of Nigeria Consumer Price Index.

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