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EXPONENTIAL SMOOTHING STATE SPACE INNOVATION MODEL FOR FORECASTING EXPORT COMMODITY PRICE INDEX IN NIGERIA

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ABSTRACT: *Commodity price forecasts play an important role in terms of guidance to economic agents and policymakers in developing countries. This paper focuses on the development of exponential smoothing state space (ETS) innovation models for forecasting monthly export price indexes of four different commodities in Nigeria for the period 2000-2021. The data are secondary and collected from the Central Bank of Nigeria (CBN) Statistical Bulletin. After examining the possible models using the computed information criteria, the results showed that the exponential smoothing state space model (M, Ad, N), (M, N, M), (M, N, M), and (M, N, N) are suitable for forecasting Commodity 1, Commodity 2, Commodity 3, and Commodity 4 respectively.*

KEYWORDS: Exponential smoothing state space, export price index, forecasting, information criteria

INTRODUCTION

The commodity market has been growing substantially because of its influence on inflation and macroeconomic environments (Bernanke, 2008). Moreover, commodity assets play a crucial role in portfolio management and asset allocation (Gospodinov & Ng, 2013; Marquis & Cunningham, 1990; Ftiti et al., 2016; Kablan et al., 2017; Klein, 2017). However, forecasting the dynamic of the commodity market is very important to businesses, investors, and policymakers. In developing countries like Nigeria, the commodity market plays an important role because these countries depend on commodity exportation (Kablan et al., 2017).

Time series observations usually occur in regular intervals, and the major objective is to prepare and fit a suitable mathematical model for the observed data. However, the fitted model is usually used to predict future outcomes of the given event. Dutta et al.(2020) discussed the importance of the forecasting technique, which is usually applied to controlling past and present operations which may assist with any long-term planning or decision-making. Unlike other forecast methods, the exponential smoothing technique is usually used for forecasting purposes. Thus, in the exponential smoothing technique, the weights on the observations decrease exponentially as the observations become older. However, one of the limitations of exponential smoothing is that only point forecasts are obtained. To address this limitation, Hyndman et al. (2008) developed the exponential smoothing state space model, which provides maximum likelihood estimation, procedures for model selection, and prediction intervals. Here, the triplet (E, T, S) represents three components: error, trend and seasonality, respectively. This technique was first developed by Pegels (1969) and was later extended by Gardner (1985), who used damped trends to classify the models. This extension was later modified by Hyndman et al. (2002) and extended again by Taylor (2003) for a multiplicative damped trend. Dutta et al. (2022) developed an exponential smoothing state space (A, A, A) model for forecasting annual deaths due to road accidents in India.

In this paper, we develop exponential smoothing state space innovation models for forecasting monthly export commodity price index for the period 2000-2021 in Nigeria. The major objective of this paper is to obtain the most adequate exponential smoothing state space models for four different export commodity price indexes. The rest of the paper is structured as follows. Section 2 discusses the data and methods used in the analysis of data in this study. The results of the study are discussed in section 3. Finally, the study's conclusion is presented in section 4.

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DATA AND METHODS

The data of this study are secondary and collected from the Central Bank of Nigeria (CBN) Statistical Bulletin. The data cover the period 2000M1 -2021M12. The data comprises of four (4) commodities: Commodity 1 is described as "Live animals, animal products"; Commodity 2 is described as "Vegetable products"; Commodity 3 is described as "Prepared foodstuffs, beverages, spirit and vinegar, tobacco"; and Commodity 4 is described as "Mineral product".

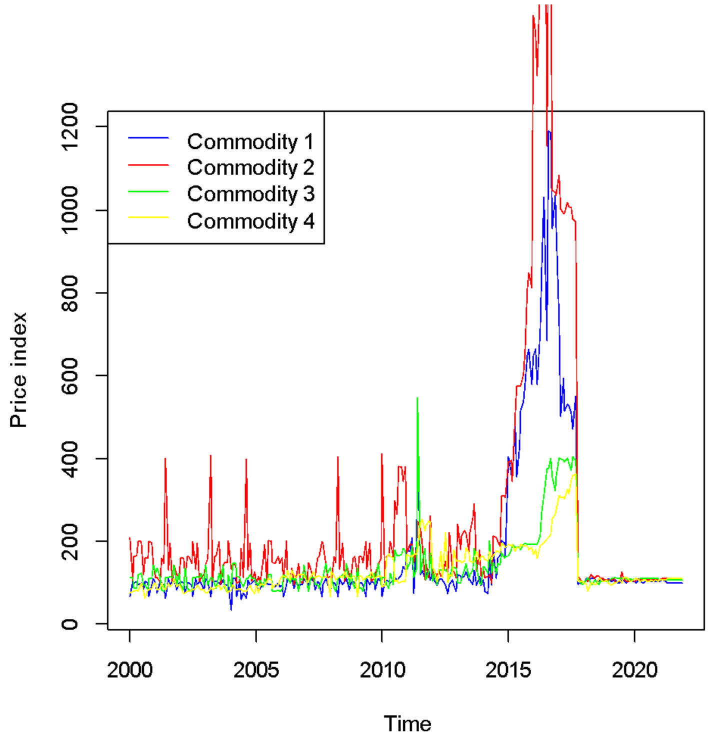

Figure 1. Export commodity price indexes for the period 2000M1-2021M12

This study uses the exponential smoothing state space (ETS) method developed by Hyndman et al. (2008). The ETS(error, trend, seasonal) model provides an automatic technique of selecting among the competing models the best forecasting model and also provides the predictive intervals. The model we generate either has additive or multiplicative errors. Hyndman et al. (2008) suggested a total of thirty (30) ETS models. Thus, in the model ETS(error, trend, seasonal), the 'error' as mentioned earlier, can be additive or multiplicative; the "trend" can be none, additive, additive damped, multiplicative, or multiplicative damped; and the 'seasonal' can be none, additive, or multiplicative. Table 1 shows the classification of EST models as propounded by Hyndman et al. (2008).

In this paper, we use a total of nine (9) ETS models. These models are: ETS(A,N,N), ETS(M,N,N), ETS(A,A,N), ETS(M,A,N), ETS(A,N,A), ETS(M,N,A), ETS(M,N,M), ETS(A,Ad,N), and ETS(M,Ad,N). For Commodity 1, we use four models: ETS(A,A,N), ETS(M,A,N), ETS(A,Ad,N), and ETS(M,Ad,N); for

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Table 1. ETS model classification

	Seasonal component		
Trend component	None (N)	Additive (A)	Multiplicative (M)
None (N)	(A,N,N)/(M,N,N)	(A,N,A)/(M,N,A)	(A,N,M)/(M,N,M)
Additive (A)	(A,A,N)/(M,A,N)	(A,A,A)/(M,A,A)	(A,A,M)/(M,A,M)
Additive damped (AD)	(A,AD,N)/(M,AD, N)	(A,AD,A)/(M,AD, A)	(A,AD,M)/(M,AD, M)
Multiplicative (M)	(A,M,N)/(M,M,N)	(A,M,A)/(M,M,A)	(A,M,M)/(M,M,M)
Multiplicative damped (MD)	(A,MD,N)/(M,MD, N)	(A,MD,A)/(M,MD, A)	(A,MD,M)/(M,MD, M)

Commodity 2 and 3, we use three models each: ETS(A,N,A), ETS(M,N,A), and ETS(M,N,M); and for Commodity 4, we use two models: ETS(A,N,N) and ETS(M,N,N). The models were selected after the data of the respective commodities were tested for seasonality and also for adjusted in the case of seasonality.

Generally, the ETS framework involves a state vector x_t and state space equations written as follows:

$$Y_t = h(x_{t-1}) + k(x_{t-1})\varepsilon_t \tag{1}$$

$$X_t = f(x_{t-1}) + g(x_{t-1})\varepsilon_t \tag{2}$$

where $\varepsilon_t \sim NID(0,\sigma^2)$ and with $x_t = (l_t, b_t, s_t, \cdots, s_{t-(m-1)})$, $k(x_{t-1})\varepsilon_t = e_t$ and $h(x_{t-1}) = \mu_t$, then equation (1) can be written as $y_t = \mu_t + e_t$. The exponential smoothing state space (ETS) models we applied in this study are presented in Table 2.

The ETS model with an additive error is written as follows: $Y_t = \mu_t + \varepsilon_t, where\ k(x) = 1$; a model with multiplicative error is written as follows: $Y_t = \mu_t(1+\varepsilon_t)$, where $k(x_{t-1}) = \mu_t$, this model produces a relative error $\varepsilon_t = \frac{(y_t-\mu_t)}{\mu_t}$.

Table 2. Selected state space models

A,N,N $Y_t = l_{t-1} + \varepsilon_t$ $l_t = l_{t-1} + \alpha\varepsilon_t$	**M,N,A** $Y_t = (l_{t-1} + s_{t-m})(1+\varepsilon_t)$ $l_t = l_{t-1} + \alpha(l_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(l_{t-1} + s_{t-m})\varepsilon_t$	**M,A,N** $Y_t = (l_{t-1} + b_{t-1})(1+\varepsilon_t)$ $l_t = (l_{t-1} + b_{t-1})(1+\alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(l_{t-1} + b_{t-1})\varepsilon_t$
M,N,N $Y_t = l_{t-1}(1+\varepsilon_t)$ $l_t = l_{t-1}(1+\alpha\varepsilon_t)$	**M,N,M** $Y_t = (l_{t-1}s_{t-m})(1+\varepsilon_t)$ $l_t = l_{t-1}(1+\alpha\varepsilon_t)$ $s_t = s_{t-m}(1+\gamma\varepsilon_t)$	**A,Ad,N** $Y_t = l_{t-1} + \phi b_{t-1} + \varepsilon_t$ $l_t = l_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$
A,N,A $Y_t = l_{t-1} + s_{t-m} + \varepsilon_t$ $l_t = l_{t-1} + \alpha\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	**A,A,N** $Y_t = l_{t-1} + b_{t-1} + \varepsilon_t$ $l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$	**M,Ad,N** $Y_t = (l_{t-1} + \phi b_{t-1})(1+\varepsilon_t)$ $l_t = (l_{t-1} + \phi b_{t-1})(1+\alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(l_{t-1} + \phi b_{t-1})\varepsilon_t$

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The parameters of the innovation state space models are obtained by computing the maximum likelihood of the models. Let's consider the likelihood to be

$$L(\theta; X_0) = n\, log\, log \left[\sum_{t=1}^{T} \frac{\varepsilon_t^2}{k^2(x_{t-1})}\right] + 2\sum_{t=1}^{T} log\, log\, |k(x_{t-1})| \qquad (3)$$

However, the initial states of ETS model $x_0 = (l_0, b_0, s_0, \cdots, s_{-m+1})$ and the parameters in the ETS model $\omega = \alpha, \beta, \gamma, \phi$ can be estimated by minimising the likelihood function $L(\theta; X_0)$. Furthermore, the ETS model with the least Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) is selected as the most optimised model. AIC and BIC are defined as follows:

$$AIC = -2\, log\, log\, (L) + 2k\, ; \quad BIC = AIC + k[log\, log\, (T) - 2] \qquad (4)$$

where: L is the likelihood of the ETS model; k is the number of parameters initial states estimated in the model; and T is the time period. The forecast performance of the appropriate model selected is examined by Mean Absolute Percentage Error (MAPE), and it is defined as follows:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} \left|\frac{e_t}{y_t}\right| \times 100 \qquad (5)$$

where: T is the number of time period, y_t is the actual observation at time t, and e_t is the forecast error at time period t.

RESULTS AND DISCUSSION

In this study, we investigate some descriptive statistics like the mean and standard deviation of the different commodities, as shown in Table 3. Under the period 2000M1-2021M12, the average price index of Commodity 1 is 172.58 with standard deviation 198.8882; the average price index of Commodity 2 is 263.9339 with standard deviation 339.3877; the average price index of Commodity 3 is 137.6907 with standard deviation 73.1597; and the average price index of Commodity 4 is 130.6788 with standard deviation 55.909. The findings of the descriptive statistics show that variation in Commodity 4 is lower compared to the other commodities.

Table 3. Descriptive statistics

	Commodity 1	Commodity 2	Commodity 3	Commodity 4
Mean	172.5827	263.9339	137.6907	130.6788
Std. Dev.	198.8882	339.3877	73.15970	55.90901

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Table 4. AIC, BIC values, accuracy measures, and forecast performance for ETS models for commodity 1

Model	AIC	BIC	MAPE	Ljung-Box test
ETS(A,A,N)	3694.313	3712.193	17.60543	62.399 (0.0000)
ETS(M,A,N)	3619.593	3637.473	22.78679	19.979 (0.6980)*
ETS(A,Ad,N)	3691.350	3712.806	17.84471	60.621 (0.0000)
ETS(M,Ad,N)	3297.136	3318.592	17.01728	22.311 (0.5607)*

Note: Under the Ljung-Box test, the p-value in parentheses; * means the forecast performance is adequate

Table 5. AIC, BIC values, accuracy measures, and forecast performance for ETS models for commodity 2

Model	AIC	BIC	MAPE	Ljung-Box test
ETS(A,N,A)	4082.870	4136.510	33.57780	59.518 (0.0000)
ETS(M,N,A)	4080.862	4134.501	67.77045	331.62 (0.0000)
ETS(M,N,M)	3717.173	3770.812	27.80114	106.180 (0.000)

Note: Under the Ljung-Box test, the p-value in parentheses; * means the forecast performance is adequate

Table 6. AIC, BIC values, accuracy measures, and forecast performance for ETS models for commodity 3

Model	AIC	BIC	MAPE	Ljung-Box test
ETS(A,N,A)	3465.413	3519.052	16.64425	27.066 (0.3014)*
ETS(M,N,A)	3327.863	3381.502	18.22468	26.918 (0.3083)*
ETS(M,N,M)	3302.619	3356.258	18.02689	26.117 (0.3472)*

Note: Under the Ljung-Box test, the p-value in parentheses; * means the forecast performance is adequate

Table 7. AIC, BIC values, accuracy measures, and forecast performance for ETS models for commodity 4

Model	AIC	BIC	MAPE	Ljung-Box test
ETS(A,N,N)	3175.539	3186.267	9.491281	15.825 (0.8943)*
ETS(M,N,N)	3008.979	3019.706	9.337025	24.255 (0.4471)*

Note: Under the Ljung-Box test, the p-value in parentheses; * means the forecast performance is adequate

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DISCUSSION

We first applied all the ETS models that are appropriate for the data of the different commodities and optimise the parameters of the ETS models using likelihood criterion. In order to select the best ETS model, we compute the Information Criteria (AIC and BIC), we also compute the Ljung-Box test for evaluating the selected model performance, and the MAPE for accuracy measures (forecast precision), which are shown in Table 4 through Table 7. The estimated states of the selected models for the commodities are shown in Figures 2 through 5. The comparison of the actual data (Commodity 1 through 4) and the forecasts are shown in Figure 6.

For Commodity 1, four of the thirty ETS models are appropriate for the data, as shown in Table 4. This selection is due to the fact that the data contains a trend component that is suspected to be additive or damped additive, with no seasonal component. Therefore, with this, we ignored all ETS models with multiplicative or multiplicative damped trend components and with seasonal components. The suitable models are ETS(A,A,N), ETS(M,A,N), ETS(A,Ad,N), and ETS(M,Ad,N). We compared all the ETS models and found out that ETS(M,Ad,N) model has the least AIC and BIC. Thus, we select ETS(M,Ad,N) as the most suitable model for Commodity 1 from this result. Next, ETS(M,Ad,N) model has the least forecast precision, and its performance is adequate based on the p-value of the Ljung-Box test, which is greater than 0.05.

For Commodity 2, out of the thirty ETS models, three models are appropriate for the data, as shown in Table 5. Our selection was based on the fact that the data does not contain a trend component but a seasonal component. The suitable models are: ETS(M,N,M), ETS(A,N,A), and ETS(M,N,A). After comparing the models, we found out that ETS(M,N,M) model has the least AIC and BIC. However, with this result, we select ETS(M,N,M) as the most appropriate model for Commodity 2.

For Commodity 3, out of the thirty ETS models, three models are appropriate for the data, as shown in Table 6. Our selection was based on the fact that the data does not contain a trend component but contains a seasonal component. The suitable models are: ETS(M,N,M), ETS(A,N,A), and ETS(M,N,A). After comparing the models, we found out that ETS (M,N,M) model has the least AIC and BIC. However, with this result, we select ETS(M,N,M) as the most appropriate model for Commodity 3. The results of the Ljung-Box test for forecast adequacy show that the model is adequate for Commodity 3.

For Commodity 4, two of the thirty ETS models are appropriate for the data, as shown in Table 7. Our selection was based on the fact that the data does not contain trend components and seasonal components. The suitable models are: ETS(M,N,N) and ETS(A,N,N). After comparing the models, we found out that ETS(M,N,N) model has the least AIC and BIC. However, with this result, we select ETS(M,N,M) as the most appropriate model for Commodity 2. The results of the Ljung-Box test for forecast adequacy show that the model is adequate for Commodity 2.

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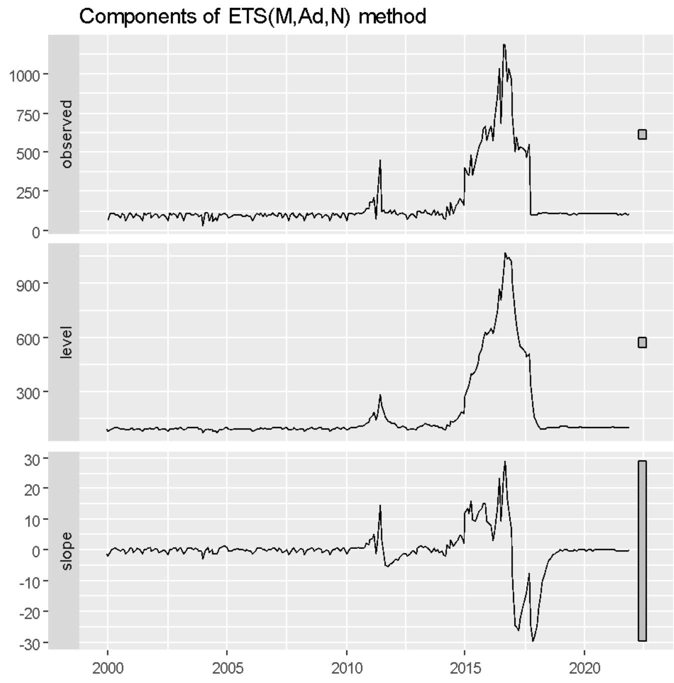

Figure 2. Estimated states of ETS(M, Ad, N) for commodity 1 over time

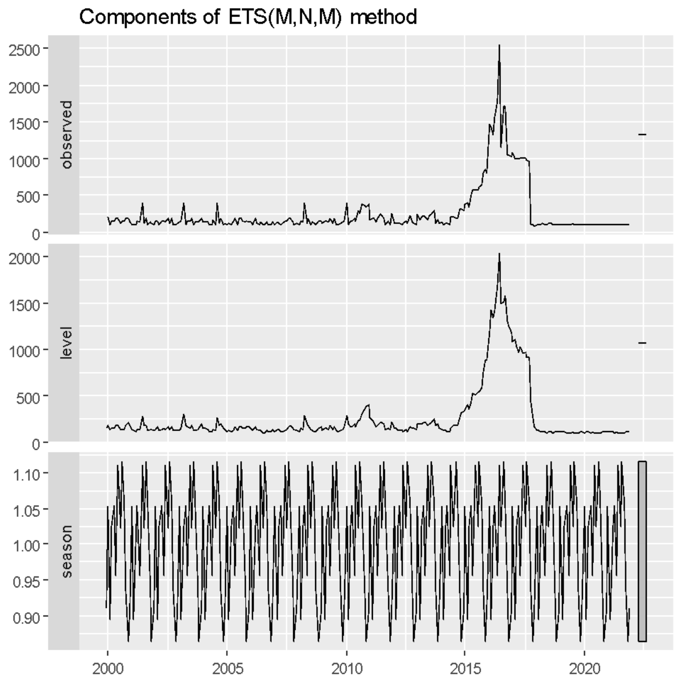

Figure 3. Estimated states of ETS(M, N, M) for commodity 2 over time

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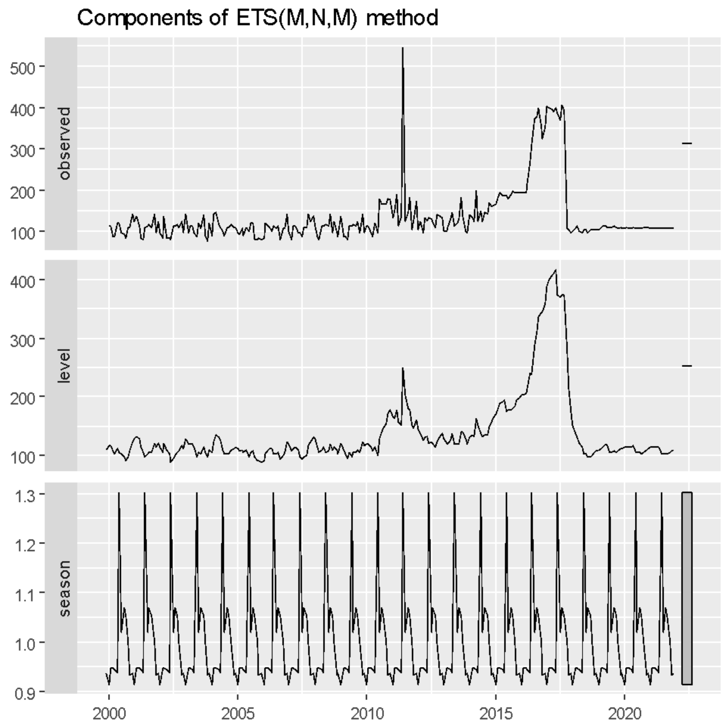

Figure 4. Estimated states of ETS(M, N, M) for commodity 3 over time

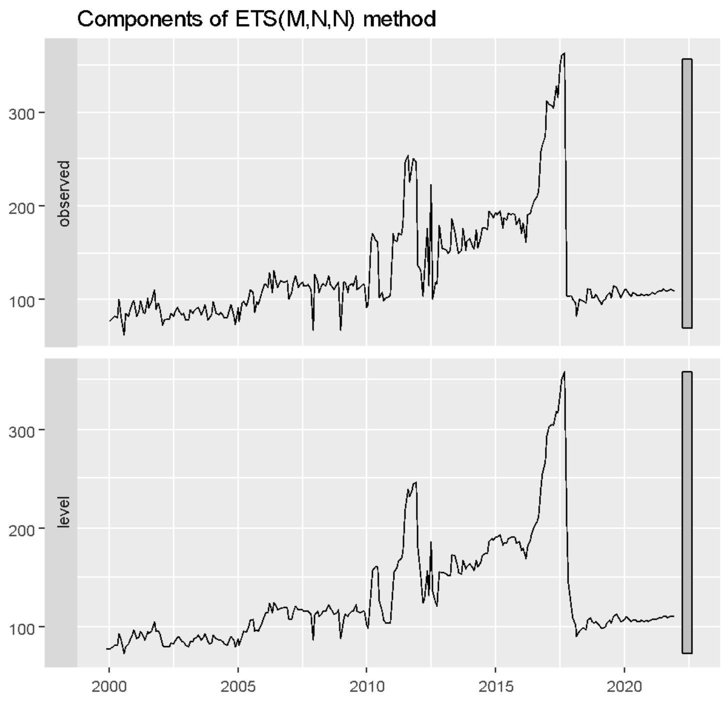

Figure 5. Estimated states of ETS(M, N, N) for commodity 4 over time

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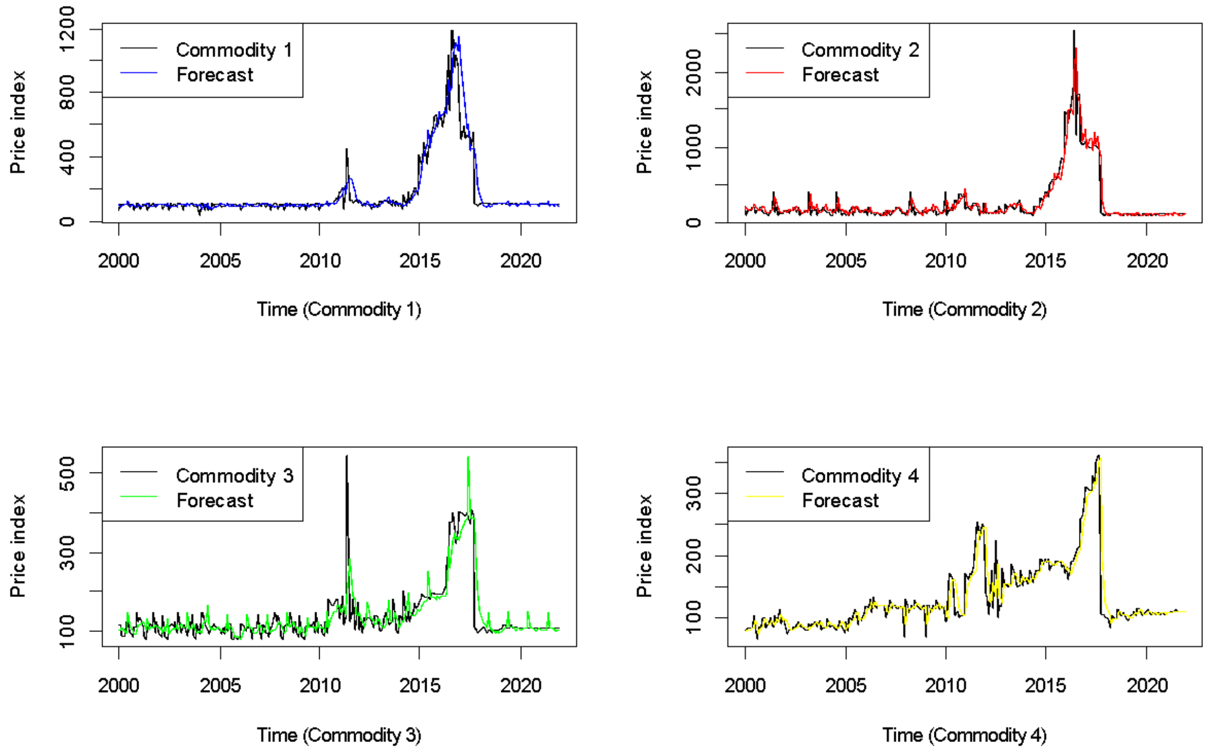

Figure 6. Commodity VS Forecast (commodity 1 through 4)

CONCLUSION

In this paper, we examine the price indexes of four different export commodities in Nigeria using the methods of exponential smoothing state space (ETS). The information criteria were computed and used to select adequate models for each commodity. The results showed that the dataset of Commodity 1 has damped additive trend and no seasonal components, Commodity 2 and 3 both does not have trend component, and Commodity 4 does not have both trend and seasonal components. Finally, the results of this study show that ETS(M,Ad,N) is adequate for Commodity 1, ETS(M,N,M) is adequate for both Commodity 2 and 3, while ETS(M,N,N) is adequate for Commodity 4. However, there is every indication that this study contains gaps, which may be filled by further researches. For instance, the ETS(M,N,M) for Commodity 2 does not show adequacy since the p-value obtained from the Ljung-Box test is less than 0.05. Thus, we recommend further analysis using other forecast methods.

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