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Forecasting Inflation in Nigeria by State Space Modeling

Raphael A. Yemitan, Olanrewaju I. Shittu

Abstract— *In recent times, inflation figures used by policy makers and investors are usually at lag one (i.e. previous month's inflation rate). The reality of the present day situation where changes in the economy increases with a high degree of uncertainty, decision of monetary policy tools requires the use of current figures of macroeconomic indicators such as inflation. This paper, therefore aims at modelling and forecasting Nigeria's inflation rate for the current period, using the Kalman filter methodology. This paper reveals that estimating the Nigerian headline inflation rate using the Kalman filter approach is more efficient than the popular Box-Jenkins ARIMA(0,1,0). The efficiency of the Kalman Filter was mainly as a result of its built in specification for updating the estimation with the latest available information. This is evident the unbiased insample estimation of the headline inflation as well as the significant result of the results of the diagnostics test. Hence, the result imply that switches in the inflation series could cause the regime of the series to shift from a linear space to a non-linear regime. Therefore, an introduction of non-linear estimation methodologies may provide a starting point for further research and development of a modified state space methodology by redefining Kalman filter transition equation and its estimation procedure..*

Index Terms— State Space, Regime Switching, Kalman Filter, ARIMA, Nigerian Inflation, Monetary Policy, Non-Linear Time Series

1 Introduction

THe Central Bank of Nigeria (CBN) constantly uses a variety of models to analyze and forecast inflationary trends. This is because inflation remains a central issue to policy makers and analysts. Its importance is premised on the distortions that unexpected spike in the headline inflation rate can have on the economy. Hence, the need to gain insight into the dynamics of inflation using a variety of models to provide a relatively precise and reliable forecast of the headline, food and core inflation. This will help the CBN and its monetary policy committee (MPC) to react in time and neutralize inflationary or deflationary pressures that could appear in the future. Furthermore, several researches on the dynamic of Nigeria's inflation have also contributed to study of Nigeria's inflation rate.

The main objective of this paper is to add to the set of forecasting methodologies of the Nigerian inflation rate through the state space models. The state space methodology is useful and important because it estimates unobserved variables that are often encountered in statistical modeling while forecasting the state of interest more efficiently. Therefore, the purpose of this paper is to compare the out-of-sample forecasts obtained using the state space models relative to the result from a simple Box-Jenkins approach.

State space modeling has been found useful in evaluating and estimating relationships that might have been subject to important changes in a review period. In 2014 the Nigerian economic data was rebased to capture sectors and industry that were previously not considered. Prior to the rebasing, the economy has undergone a series of structural changes which was constantly addressed by the formulation and implementation of monetary policy as well as an inflation targeting regime. A major feature of the Nigerian monetary policy has been the aggressive approach to price and currency stable since 2009 and the adoption of an inflation targeting framework in 2013. The target was achieved with great precision. The CBN after a series of measures to curb rising inflationary pressures was determined and achieved a single digit inflation rate in 2013. In November 2013, the CBN announced an inflation target band which will range between 6% and 9% in 2014..

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2 Review of Literature

Detailed Over the years, various structural statistical models that have been used to examine the inflation behavior in Nigeria include Shittu and Yemitan (2014), Doguwa and Alade (2013), Shittu, Yaya, Yemitan (2012), Mordi et. al (2007), Essien (2002), Ojo (2000), Gil-Alana, Shittu and Yaya (2011), Olubusoye and Oyaromade (2008), Adebiyi et. al (2010) and Akdogan et. al (2012). However, there are limited studies on time varying-parameter of inflation model for the Nigerian case. An evidence of inflation persistence over different regime shifts in Nigeria can be found in Gil-Alana, Shittu and Yaya (2011) confirmed the presence of time-varying parameter of the Nigerian inflation series. While majority of the literature on Nigeria's inflation rate focused on the dynamics, the result of Shittu and Yemitan (2014) reveal provided an inflation forecasting model for Nigeria. However, studies on the inflation behavior by capturing different expectation behaviors or regimes are new area of research needing attention in Nigeria.

In light of lack of the time-varying parameters models for the Nigerian inflation, utilizing state space model has the advantages of integrating both the expectation theories. Therefore, this paper estimates the time-varying parameters of the AR(1) parameter of the random walk inflation model as identified by Shittu and Yemitan (2014) utilizing Kalman filter under state space model.

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3 Conceptual Framework and Methodology

As State space modelling consists of a measurement (observation) equation and a state (transition) equation where the state equation formulates the dynamics of the state variables while the measurement equation relates the observed variables to the unobserved state vector. Let y_t denote a $Nx1$ time series of observations whose development over time can be characterized in terms of an unobserved state vector β_t of dimension $Mx1$. Based on this, a standard state space formulation can be represented as follows:

$$y_t = Hx_t + v_t, \quad v_t \sim N(0, H_t) \quad \dots (1)$$
$$x_t = \varphi x_{t-1} + \omega_t, \quad \omega_t \sim N(0, Q_t) \quad \dots (2)$$

Equation (1) is the measurement equation, where, y_t is a vector of measured variables of dimension nx1, x_t is the state vector of unobserved variables of dimension $px1$, H is a matrix of parameters of dimension nxp and $v_t \sim N(0, H_t)$. Similarly, equation (2) is the state equation, where φ is a matrix of parameters and $\omega_t \sim N(0, Q_t)$. The H and φ refer to the hyper-parameters of the model. The initial vector of parameter and covariance matrix are assumed ξ_0 and P_0 respectively. The disturbances v_t and ω_t are assumed uncorrelated with each other in all time periods and also uncorrelated with the initial state.

Once a model is put into state space form, the Kalman filter can be used to estimate state vector by filtering. The Kalman filter will provide estimates of the unobserved variable which plays a central role in estimating changes. The purpose of filtering is to update our knowledge of the state vector as soon as a new observation y_t becomes available. Hence, the Kalman filter can be described as an algorithm for the unobserved components at time t based on the available information at the same date. The estimates of any other desired parameters including hyper parameters can be obtained by Maximum Likelihood Estimation (MLE) algorithm as adapted by Shumway and Stoffer (1982). Estimating the states through Kalman filter encompasses three step processes:

The initial states

$$x_{0\backslash 0}, P_{0\backslash 0}$$

The predict states

$$\hat{x}_{t\backslash t-1} = \hat{x}_{t-1\backslash t-1} \quad \dots (3)$$
$$P_{t\backslash t-1} = E\{(x_{t-1\backslash t-1} - \hat{x}_{t-1\backslash t-1})(x_{t-1\backslash t-1} - \hat{x}_{t-1\backslash t-1})'\} \dots (4)$$

The update states

$$K_t = \left(H_t P_{t\backslash t-1}\right)\left(H_t P_{t\backslash t-1} H_t' + R_t\right)^{-1} \quad \dots (5)$$
$$\hat{x}_{t\backslash t} = \hat{x}_{t\backslash t-1} + K_t(y_t - H\hat{x}_{t\backslash t-1}) \quad \dots (6)$$
$$P_{t\backslash t} = P_{t\backslash t-1} - K_t H_{t+1} P_{t\backslash t-1} \quad \dots (7)$$

Where, $\hat{x}_{t\backslash t-1}$ is the estimated state, $P_{t\backslash t-1}$ State variance matrix (i.e., error due to process), $y_t$is the measurement variable, H_t measurement matrix (i.e., mapping measurements onto state), K_t Kalman gain, and R_t is the measurement variance matrix (i.e., error from measurements). Subscripts, t \ t current time period, t−1\t−1 previous time period, and t\t−1 are intermediate steps.

The $x_{0\backslash 0}$ and $P_{0\backslash 0}$ are the vectors of initial state and covariance matrix respectively. The covariance matrix $P_{0\backslash 0}$ depicts noise of the $x_{0\backslash 0}$. If vector of $x_{0\backslash 0}$ and covariance matrix $P_{0\backslash 0}$ are not given prior, $x_{0\backslash 0}$ is assumed zero and large number for diagonal elements of matrix $P_{0\backslash 0}$. Equation (3) is simply the expected value of the transition equation $E\{x_t\} = E\{\varphi x_{t-1} + \omega_t\}$ whereas Equation (4) can be described as $Var\{x_t\} = Var\{\varphi x_{t-1} + \omega_t\}$. Equations (5), (6) and (7) are the set of update equations. The K_t in Equation (5) is termed as Kalman gain which is the weight given to new information. The term in the parenthesis is prediction error. It contains information that is new relative to the previous one. When K_t increases due to uncertainty about state (model noise), it is said to have heavy weight on new information. When K_t falls due to increase in R_t , the shock is said to be less informative. Similarly, Equation (6) updates information of $t-1$ adjusted by K_t which is determined by the equation of prediction error $(y_t - H\hat{x}_{t\backslash t-1})$. Equation (5) is the update states of covariance matrix for the state vector.

As the objective of the paper is to estimate and present the time-varying coefficient of random walk model of inflation in Nigeria, the following model as identified by Shittu and Yemitan (2014) has been specified for the analysis.

$$x_t = \varphi_t x_{t-1} + \omega_t, \quad Var\,(\omega_t) = R \quad \dots(8)$$

Assuming x_t is a stochastic process (inflation series) generated based on an unobserved process of x_{t-1} (Shittu and Yemitan, 2014) with φ_t as the time-varying autoregressive coefficient.

The computation of time-varying parameters in this paper has been programmed in Eviews7 and the codes of Kalman filter have been presented in the appendices and are available with the author.

4 Results And Discussion

The analysis in this paper is based on monthly inflation series starting from January, 1995 to December, 2014. The selected data frame covers different complete cycles formed based on political, monetary and macroeconomic events and policies of this period in Nigeria. Fig 1 shows the trend of the monthly inflation series over the study period. The increasing trend of inflation during the transition period could have been due to the weak monetary policy of the military regime and high currency pressures caused by round tripping and illegal transactions. Notably, every political business cycle in Nigeria is associated with a lower trend in the inflation rate relative to periods after the elections (Fig, 2). The inflation rate generally tends to moderate towards major political events and spikes thereafter.

Two models of inflation are compared for their in-sample as well as their out-of-sample forecast performance of the Nigerian inflation. The first model is the ARIMA(0,1,0) identified to fit the Nigerian CPI by Shittu and Yemitan (2014) but with a monthly update of the series before re-estimation. The second model is the state space model which captures the time varying and regime switching characteristics of the inflation series

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and as a result requires no re-estimation of the series.

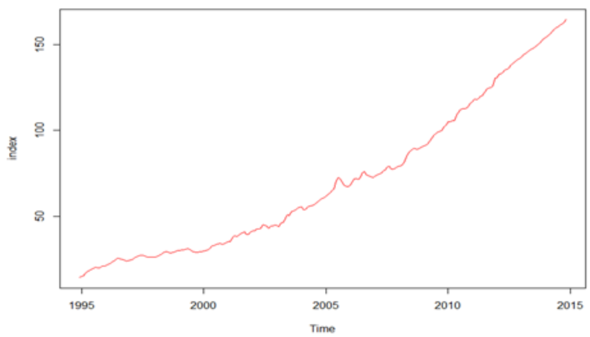

Fig. 1. **Time Plot of Nigeria's CPI (1995-2014)**

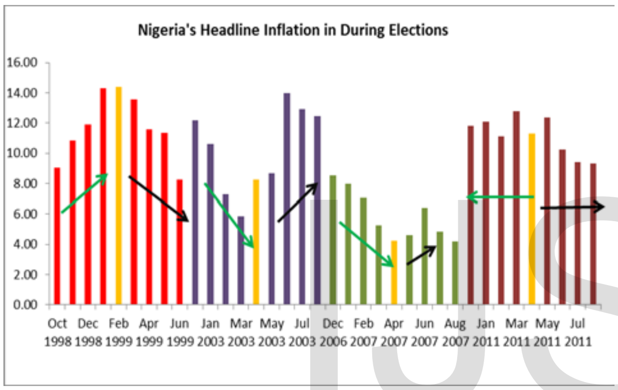

Fig. 2. **Plot of Nigeria's Headline Inflation in periods of Elections**

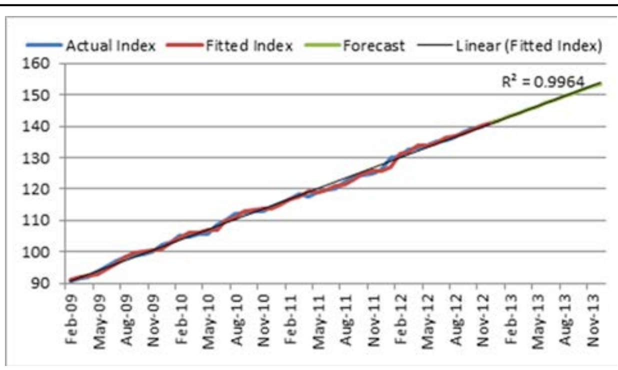

Fig. 3. **Actual Vs Projected Headline Inflation Rate in Nigeria ARIMA (0,1,0)**

The in-sample performance of the state space model for forecasting the Nigerian inflation series appears to be more favorable to the model identified by Shittu and Yemitan (2014). This is evident in Table 1 and Fig 3.

TABLE 1
NIGERIA'S HEADLINE INFLATION RATE BY ARIMA(0,1,0)

	Predicted (ARIMA(0,1,0))(%)	NBS actual (%)
Jan-13	9.1	9.0
Feb-13	9.6	9.5
Mar-13	8.7	8.6
Apr-13	9.1	9.1
May-13	9.1	9.0
Jun-13	8.5	8.4
Jul-13	8.8	8.7
Aug-13	9.0	8.2
Sep-13	8.6	8.0
Oct-13	8.6	7.8
Nov-13	8.9	7.9
Dec-13	9.0	8.0
Average	**8.9**	**8.5**

NBS Actual was collected from the Monthly consumer price report by the National Bureau of Statictics

TABLE 2
NIGERIA'S HEADLINE INFLATION RATE BY ARIMA(0,1,0)

	Predicted (SSM)	Actual
Jan-13	9.0%	9.0%
Feb-13	9.5%	9.5%
Mar-13	8.6%	8.6%
Apr-13	9.1%	9.1%
May-13	9.0%	9.0%
Jun-13	8.4%	8.4%
Jul-13	8.7%	8.7%
Aug-13	8.2%	8.2%
Sep-13	8.0%	8.0%
Oct-13	7.8%	7.8%
Nov-13	7.9%	7.9%
Dec-13	8.0%	8.0%
Jan-14	8.0%	8.0%
Feb-14	7.7%	7.7%
Mar-14	7.8%	7.8%
Apr-14	7.9%	7.9%
May-14	8.0%	8.0%
Jun-14	8.2%	8.1%
Jul-14	8.3%	8.3%
Aug-14	8.5%	8.5%
Sep-14	8.3%	8.3%
Oct-14	8.1%	8.1%
Nov-14	7.9%	7.9%
Dec-14	7.9%	7.9%

For the out-of-sample forecast, Table 2, and Fig 4 depict the efficient prediction of the inflation series using the state space model. This is further improved by the smoothed state space model. Furthermore, the out of sample forecast estimates Nigeria's Headline inflation rate at 8.9% for 2015 and 7.2% in 2016 (Result in Table X3). The diagnostics tests showed normality of residuals.

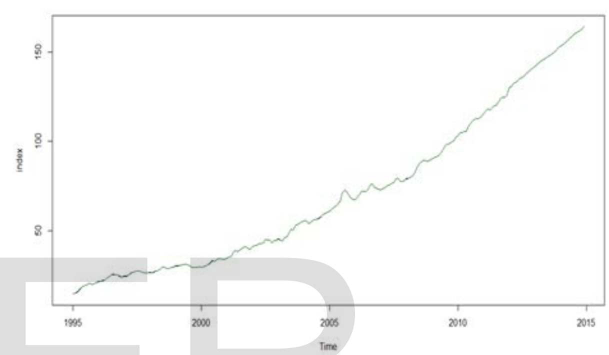

Fig. 4. Insample Prediction by State Space Model Vs Actual

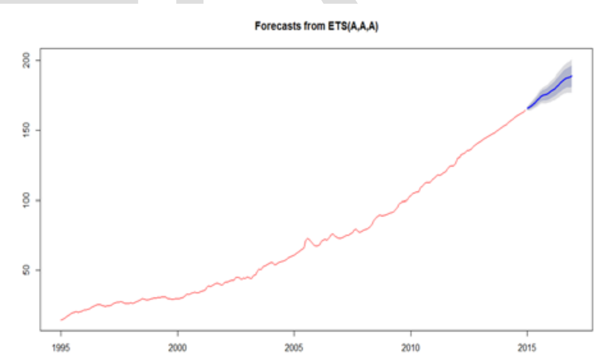

Fig. 5. Nigeria Headline Inflation Rate – Prediction and Forecast by Kalman Filter (1995-2015)

TABLE 3
NIGERIA HEADLINE INFLATION FORECAST BY KALMAN FILTER

	CPI Forecast	Estimated Inflation Rate		CPI Forecast	Estimated Inflation Rate
Jan-15	165.6	8.0%	Jan-16	177.9	7.5%
Feb-15	166.5	8.1%	Feb-16	178.8	7.4%
Mar-15	167.4	7.9%	Mar-16	179.8	7.4%
Apr-15	168.8	8.1%	Apr-16	181.1	7.3%
May-15	170.1	8.0%	May-16	182.4	7.3%
Jun-15	171.5	8.1%	Jun-16	183.9	7.2%
Jul-15	173.0	8.4%	Jul-16	185.4	7.2%
Aug-15	174.2	8.6%	Aug-16	186.6	7.1%
Sep-15	175.0	8.5%	Sep-16	187.4	7.1%
Oct-15	175.4	8.2%	Oct-16	187.7	7.1%
Nov-15	175.9	7.9%	Nov-16	188.3	7.0%
Dec-15	176.8	7.5%	Dec-16	189.1	7.0%
Average		**8.10%**			**7.21%**

Given the relative accuracy of the model by Shittu and Yemitan (2014), the improvement achieved by the Kalman filter method is mainly as a result of the built in specification for updating the estimation based on latest available information. Hence, the Nigeria CPI exhibits elements of time varying or

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regime switching characteristics over the study period. As a result, it is an indication and a signal that the Nigeria CPI may be best estimated using non-linear time series methodologies.

5 Conclusion

The main empirical result of this paper is the volatility recorded in Nigeria consumer prices and the efficiency of the state space model. But there is evidence from the empirical method used in the paper as well as in Shittu and Yemitan (2014), that there is instability from a linear point of view due to structural breaks found in the data to be associated with political and major economic events. The structural breaks seem irreversible and suggest a nonlinearity structure in the Nigeria inflation series. Hence, the instability and possible nonlinearity in the estimations can be interpreted as an asymmetry in the Nigerian consumer price series.

The Kalman filter model result gave a more efficient result when compared to the ARIMA(0,1,0) model (Result in Table 1 and 2). Hence, the estimation and projection of the Nigerian CPI was improved despite the result achieved in the earlier work of Shittu and Yemitan. Notable is the result of the out-of-sample forecast which effectively estimated the three months ahead forecast of the series when compared with the officially announced result by the National Bureau of Statistics (See Table 2). The result takes away the need update the CPI data before re-estimating and forecasting using Shittu and Yemitan (2014).

As outlined above the effectiveness of the state space model in forecasting relative to the ARIMA(0,1,0) model would be beneficial to monetary policy authorities in an inflation targeting framework. However, switches in the inflation series could cause the regime of the series to shift from a linear space to a non-linear regime. Hence the efficiency of the Kalman Filter through its built in specification for updating the estimation with the latest available information is evident. Further study on the effectiveness of non-linear estimation methodologies may provide a starting point for further research and development of a new state space methodology by redefining Kalman filter transition equation and its estimation procedure

7 End Sections

7.1 Appendices

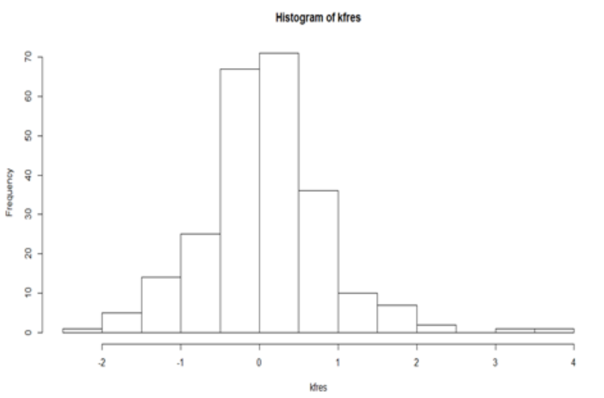

Fig. 5. **Histogram of Residuals**

7.2 R-Code and Results

```
library(tsDyn)
library(KFAS)
data <- read.table("~/gretl/inflation index .R", header=TRUE, quote="\"")
xt.ts <- ts(data, frequency=12, start=1995)
xt <- xt.ts
xt <- na.omit(xt.ts)
yt <- xt
xt.L <- lag(xt)

# Kalman filtering
fitInflation <- StructTS(xt)
kffit <- fitted(fitInflation)
kffit <- kffit[,1]
kftssmt <- tsSmooth(fitInflation)
kftssmt <- kftssmt[,1]

#Forecasts
library(forecast)
fkffit <- forecast(kffit)
fkftssmt <- forecast(kftssmt)

#Forecast Plot
plot(fkffit, type="l", col="red")
plot(fkftssmt, type="l", col="darkblue")

#Residual
kfres <- residuals(fkffit)
kfrests <- residuals(fkftssmt)

#Residual Plot
lines(kfres, type="l", col="darkblue")
lines(kfrests, type="l", col="darkgreen")

hist(kfres)
hist(kfrests)

#Time Plot
plot(xt, type="l", col="red")
#Series Summary
summary(xt)

#Kalman Filter results
fitInflation

#Filtered result
kffit

#Plots of Fits
plot(xt.L, type="l", col="red")
lines(kffit, type="l", col="darkgreen")

#Predicted filtered and smoothed State using Kalman filter
predict(kffit)
predict(kftssmt)

#Summary of results for the different models
summary(fkffit)

#Diagnostics Tests
shapiro.test(kffit)
shapiro.test(kftssmt)

library(nortest)
library(normtest)
ad.test(kffit)
ad.test(kftssmt)

Kfmos <- kffit-xt
Kfsres<-kftssmt-xt

# Mean Squared Error
kmse <- sum((Kfmos) ^ 2) / length(Kfmos)
ksmse <- sum((Kfsres) ^ 2) / length(Kfsres)
kmse
ksmse

# Mean Absolute Deviation
kmad <- sum(abs(Kfmos) )/ length(Kfmos)
ksmad <- sum(abs(Kfsres) )/ length(Kfsres)
kmad
ksmad

# Mean Squared Deviation
kmsd <- sum(abs(Kfmos) ^ 2) / length(Kfmos)
ksmsd <- sum(abs(Kfsres) ^ 2) / length(Kfsres)
kmsd
ksmsd

# Mean Absolute Percentage Error
kmape <- ((sum(abs(Kfmos)/ xt)) / length(Kfmos))*100
ksmape <- ((sum(abs(Kfsres)/ xt)) / length(Kfsres))*100
kmape
ksmape
```

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```
# Root Mean Squared Error
krmse <- sqrt(kmse)
ksrmse <- sqrt(ksmse)

# ACF
acf(Kfmos)acf(arres)

#PACF
pacf(Kfmos)

#Residual Analysis
hist(kfres)

#Filtered result
> kffit
```

	Jan	Feb	Mar	Apr	May	Jun	Jul
1995	14.36	14.99	15.52	16.91	17.95	18.76	19.38
1996	21.54	21.55	22.04	22.32	23.55	24.21	25.13
1997	24.49	24.44	25.09	26.15	26.60	27.04	27.24
1998	26.60	26.44	26.83	27.47	27.77	28.76	29.58
1999	30.29	30.25	30.48	30.66	30.94	31.15	30.77
2000	29.53	29.73	30.05	30.65	31.61	32.97	32.81
2001	34.68	35.26	35.52	37.77	38.87	38.28	39.06
2002	41.04	41.60	41.69	42.59	42.83	42.96	45.14
2003	45.36	44.64	44.15	46.12	46.56	48.98	50.99
2004	55.46	55.73	54.06	54.21	55.77	55.88	56.43
2005	60.91	61.83	62.86	63.94	65.15	66.26	71.18
2006	67.46	68.53	70.43	71.97	72.02	71.88	73.31
2007	72.89	73.37	74.11	75.00	75.35	76.50	76.85
2008	79.11	79.27	79.89	81.13	82.67	85.72	87.58
2009	90.19	90.83	91.36	91.90	93.59	95.32	97.29
2010	103.16	105.03	104.89	105.71	105.67	108.75	109.93
2011	115.64	116.69	118.29	117.65	118.72	119.88	120.26
2012	130.16	130.55	132.63	132.80	133.80	135.34	135.66
2013	141.90	143.01	144.03	144.82	145.79	146.65	147.44
2014	153.26	154.00	155.20	156.20	157.40	158.60	159.70

	Aug	Sep	Oct	Nov	Dec
1995	19.89	20.41	19.91	20.18	20.90
1996	25.46	25.27	24.83	24.42	23.94
1997	27.44	26.94	26.43	26.41	26.39
1998	29.45	28.82	28.82	29.28	29.54
1999	29.69	29.47	29.25	29.28	29.62
2000	33.57	34.04	34.24	33.77	33.91
2001	39.86	40.56	40.88	39.67	39.52
2002	44.76	44.60	43.07	44.50	44.33
2003	50.34	52.81	53.25	53.98	54.89
2004	56.89	57.63	58.96	59.40	60.39
2005	72.94	71.64	69.93	68.39	67.37
2006	75.67	76.12	74.22	73.69	73.13
2007	78.85	79.24	77.59	77.49	77.92
2008	88.60	89.58	89.04	88.99	89.66
2009	98.39	98.88	99.35	100.00	102.15
2010	111.86	112.37	112.71	112.76	114.21
2011	122.26	123.99	124.59	124.64	125.96
2012	136.57	137.95	139.17	140.01	141.06
2013	147.81	148.92	150.00	151.10	152.30
2014	160.40	161.30	162.10	163.10	164.40

```
> #Smoothed Kalman Filter result
> kftssmt
```

	Jan	Feb	Mar	Apr	May	Jun	Jul
1995	14.32	15.02	15.56	16.95	18.00	18.81	19.43
1996	21.15	21.58	22.07	22.35	23.58	24.24	25.17
1997	24.19	24.46	25.11	26.17	26.62	27.06	27.26
1998	26.32	26.46	26.85	27.49	27.79	28.78	29.60
1999	30.09	30.26	30.49	30.67	30.95	31.16	30.78
2000	29.34	29.74	30.06	30.66	31.62	32.99	32.83
2001	34.52	35.27	35.53	37.78	38.88	38.29	39.07
2002	40.93	41.61	41.70	42.60	42.84	42.97	45.15
2003	45.27	44.64	44.15	46.12	46.56	48.98	50.99
2004	55.42	55.73	54.06	54.21	55.77	55.88	56.43
2005	60.88	61.83	62.86	63.94	65.15	66.26	71.18
2006	67.40	68.53	70.43	71.97	72.02	71.88	73.31
2007	72.78	73.38	74.12	75.01	75.36	76.51	76.86
2008	79.02	79.27	79.89	81.13	82.67	85.72	87.58
2009	90.11	90.83	91.36	91.90	93.59	95.32	97.29
2010	103.09	105.04	104.90	105.72	105.68	108.76	109.94
2011	115.55	116.70	118.30	117.66	118.73	119.89	120.27
2012	130.15	130.55	132.63	132.80	133.80	135.34	135.66
2013	141.90	143.01	144.03	144.82	145.79	146.65	147.44
2014	153.26	154.00	155.20	156.20	157.40	158.60	159.70

	Aug	Sep	Oct	Nov	Dec
1995	19.95	20.46	19.96	20.23	20.96
1996	25.50	25.31	24.87	24.45	23.97
1997	27.46	26.96	26.45	26.43	26.41
1998	29.47	28.84	28.84	29.30	29.56
1999	29.70	29.48	29.26	29.29	29.63
2000	33.59	34.06	34.26	33.79	33.93
2001	39.87	40.57	40.89	39.68	39.53
2002	44.77	44.61	43.08	44.51	44.34
2003	50.34	52.81	53.25	53.98	54.89
2004	56.89	57.63	58.96	59.40	60.39
2005	72.94	71.64	69.93	68.39	67.37
2006	75.67	76.12	74.22	73.69	73.13
2007	78.86	79.25	77.60	77.50	77.93
2008	88.60	89.58	89.04	88.99	89.66
2009	98.39	98.88	99.35	100.00	102.15
2010	111.87	112.38	112.72	112.77	114.22
2011	122.27	124.00	124.60	124.65	125.97
2012	136.57	137.95	139.17	140.01	141.06
2013	147.81	148.92	150.00	151.10	152.30
2014	160.40	161.30	162.10	163.10	164.40

> #Predicted filtered and smoothed State using Kalman

> predict(kffit)

	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan	2015	165.57	164.55	166.58	164.01	167.12
Feb	2015	166.46	164.95	167.96	164.16	168.76
Mar	2015	167.44	165.55	169.33	164.55	170.34
Apr	2015	168.77	166.54	171.01	165.35	172.20
May	2015	170.06	167.50	172.62	166.15	173.97
Jun	2015	171.51	168.65	174.37	167.13	175.88
Jul	2015	173.05	169.90	176.20	168.23	177.87
Aug	2015	174.20	170.76	177.63	168.94	179.45
Sep	2015	175.01	171.30	178.73	169.33	180.70
Oct	2015	175.38	171.39	179.37	169.27	181.48
Nov	2015	175.92	171.66	180.18	169.40	182.44
Dec	2015	176.77	172.24	181.31	169.84	183.71
Jan	2016	177.94	173.13	182.74	170.59	185.28
Feb	2016	178.83	173.76	183.90	171.07	186.59
Mar	2016	179.81	174.47	185.15	171.64	187.98
Apr	2016	181.14	175.53	186.76	172.56	189.73
May	2016	182.43	176.55	188.31	173.44	191.43
Jun	2016	183.88	177.73	190.03	174.47	193.29
Jul	2016	185.42	179.00	191.84	175.59	195.25
Aug	2016	186.57	179.87	193.27	176.32	196.81
Sep	2016	187.39	180.41	194.36	176.72	198.05
Oct	2016	187.75	180.50	195.00	176.66	198.83
Nov	2016	188.29	180.76	195.81	176.78	199.80
Dec	2016	189.15	181.34	196.95	177.21	201.08

> predict(kftssmt)

	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95	Lo
Jan	2015	165.47	164.45	166.49	163.91	167.03	
Feb	2015	166.52	165.02	168.02	164.23	168.82	
Mar	2015	167.55	165.67	169.44	164.67	170.44	
Apr	2015	168.84	166.61	171.07	165.43	172.25	
May	2015	170.07	167.53	172.62	166.18	173.97	
Jun	2015	171.58	168.73	174.42	167.23	175.93	
Jul	2015	173.11	169.97	176.24	168.31	177.90	
Aug	2015	174.20	170.79	177.62	168.98	179.42	
Sep	2015	175.05	171.36	178.74	169.41	180.69	
Oct	2015	175.30	171.34	179.26	169.25	181.36	
Nov	2015	175.83	171.61	180.06	169.37	182.30	
Dec	2015	176.75	172.26	181.25	169.88	183.62	
Jan	2016	177.82	173.06	182.58	170.54	185.10	
Feb	2016	178.87	173.85	183.89	171.19	186.55	
Mar	2016	179.90	174.62	185.19	171.82	187.99	
Apr	2016	181.19	175.64	186.74	172.70	189.67	
May	2016	182.42	176.61	188.24	173.53	191.32	
Jun	2016	183.93	177.85	190.01	174.63	193.23	
Jul	2016	185.45	179.11	191.80	175.75	195.16	
Aug	2016	186.55	179.94	193.16	176.44	196.66	
Sep	2016	187.40	180.52	194.28	176.88	197.92	
Oct	2016	187.65	180.50	194.80	176.72	198.59	
Nov	2016	188.18	180.76	195.60	176.83	199.53	
Dec	2016	189.10	181.41	196.79	177.34	200.87	

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