WP/15/7

SAMA Working Paper

INFLATION FORECASTING MODELS FOR SAUDI ARABIA

October 2015

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Abstract

This study consists of one essay related to modeling and out-of sample forecasting monthly headline and core inflation for the economy of Saudi Arabia. The primary contribution is to provide a short term inflation forecast (STIF) model based on disaggregated consumer price index data of Saudi Arabia. The study predicts headline and core inflation rates and CPI for the period from February 2015 until June 2015. For headline inflation, the expected rates are 2.33, 2.29, 2.26, 2.33, 2.33 for the period from February 2015 to June 2015 respectively. Moreover, the forecasted core inflation rates for the same period are 2.21,2.16,2.16, 2.34,2.37 respectively. Thus, headline and core inflation rates will be increasing in February, decreasing in March and April and eventually increasing again in May and June. Also, core inflation will be higher than headline inflation in May and June. We can conclude that the study's estimation and forecasting are consistent and provide stable and accurate results.

Keywords: Headline Inflation, Core Inflation, consumer Price Index,

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1. Introduction

Monetary policymakers focus on economic predictions of only a few crucial macroeconomics variables such as GDP, inflation and unemployment rate. However, many other variables should be looked into when creating these forecasts. In principle, information extracted from other economic variables should be useful and add some prediction power when forecasting macroeconomic variables. Recent studies such as [Stock and Watson, 2005] have shown that inflation has become hard to forecast. Also, if we follow the literature over the last 20 years on inflation modeling and forecasting, the reader will notice that these forecasting models range from simple to very complicated ones. The goal of these models is to come up with a precise and accurate model to predict inflation in short and medium terms.

In 2001, [Atkeson and Ohanian, 2001] concluded their study onforecasting inflation, showing that for the period between 1985 and 1999, simple random walk forecasting would outperform more sophisticated and complicated models. Moreover, Brave and Fisher (2004) expanded on the work of [Atkeson and Ohanian, 2001], finding that it might work well for time periods other than 1985 to 1999. However, they also suggested that it would be hard to come up with a unique model that performs better than the random walk in different sample periods.

In this paper, I will concentrate on short term inflation forecast (STIF) based on disaggregated consumer price index data of Saudi Arabia. It is worth mentioning that there is a lack of literature related to forecasting short term inflation in Saudi Arabia. Thus most references go back to original economists work on the economy of United States or Euro area such as [Blake and Rummel, 2013].

2. Background

There are many ways to forecast future inflation, ranging from the most sophisticated statistical models, involving a lot of variables, to simple models based on past experience. This paper provides an example of a short-term inflation forecast (STIF) in Saudi Arabia.

The aim is to construct a STIF on a disaggregated consumer price index CPI data for Saudi Arabia. In particular, it generates a STIF for the total CPI index or the headline and core inflation. The forecasting model can predict in-sample headline and core inflation up to six months ahead, which can then be compared to the actual inflation numbers. Moreover, it is predicted out-of sample headline and core inflation up to five months ahead

The methodology of the STIF is straightforward: a time-series model is constructed for each CPI component at a chosen level of disaggregation. Each of these models is then used to produce a short-term forecast for the respective CPI component. The individual forecasts are then (re-)aggregated into the CPI index, using the weights of each component in the all-items CPI index. The forecast for the CPI index in levels can then be used to calculate (short-term) inflation forecasts. This analysis uses an example of a STIF first applied by the Bank of England when forecasting inflation in South Africa.

3. Data

The data consist of a monthly dataset of 12 disaggregated Saudi Arabia CPI components, spanning the period from January 2011 through November 2014. Depending on the respective sample periods, we have approximately 47 observations. The data are taken from Saudi Arabian Monetary Agency.

The 12 disaggregate components of Saudi Arabia CPI basket are: food and beverages, tobacco, clothing and footwear, housing; water; electricity and other fuels, furnishing, household equipment and maintenance, health, transport, communications, recreation and culture, education, restaurants and hotels, and finally miscellaneous goods and services. The weights of the 12 components are shown in Table (1).

Table 1:The weights of the 12 components of CPI.

Number	CPI component	weight	number	CPI component	weight
1	Food and Beverages	21.7	**7**	Transport	10.4
2	Tobacco	0.5	**8**	Communications	8.1
3	Clothing and Footwear	8.4	**9**	Recreation and Culture	3.5
4	Housing	20.5	**10**	Education	2.7
5	Furnishing	9.1	**11**	Restaurants and Hotels	5.7
6	Health	2.6	**12**	Miscellaneous	6.8

The three components with the largest weights are food (21.7 percent), housing, water, electricity and other fuels (20.5 percent) and transport (10.4 percent). Altogether, these three components account for more than 50 percent of the Saudi Arabia all-items CPI index. The time series of the price levels for the 12 components are given in Figures (1) and (2).

Figure1 : Monthly Dataset of the First 6 Saudi Arabia CPI Components, Spanning from the Period January 2011 through November 2014.

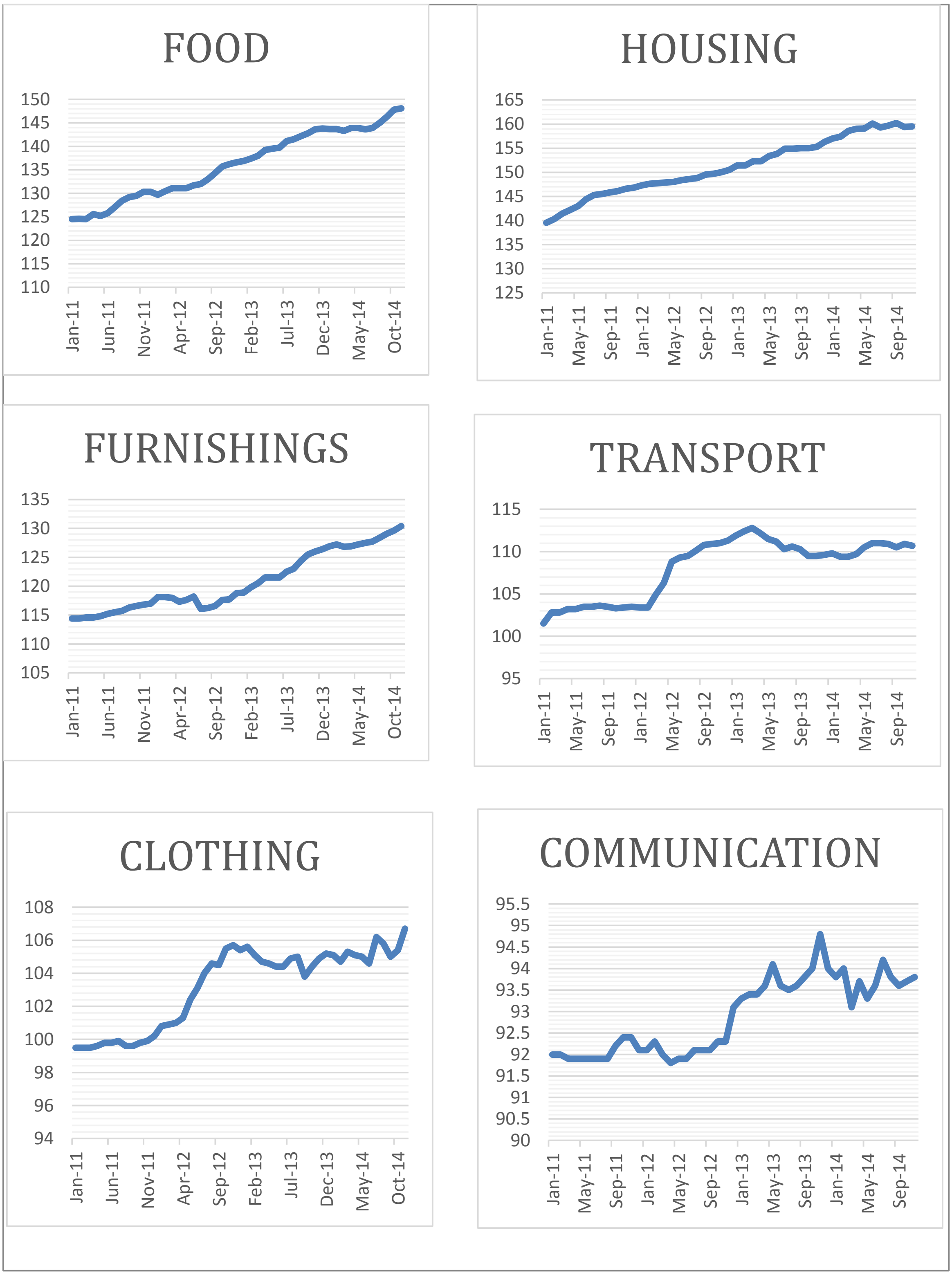
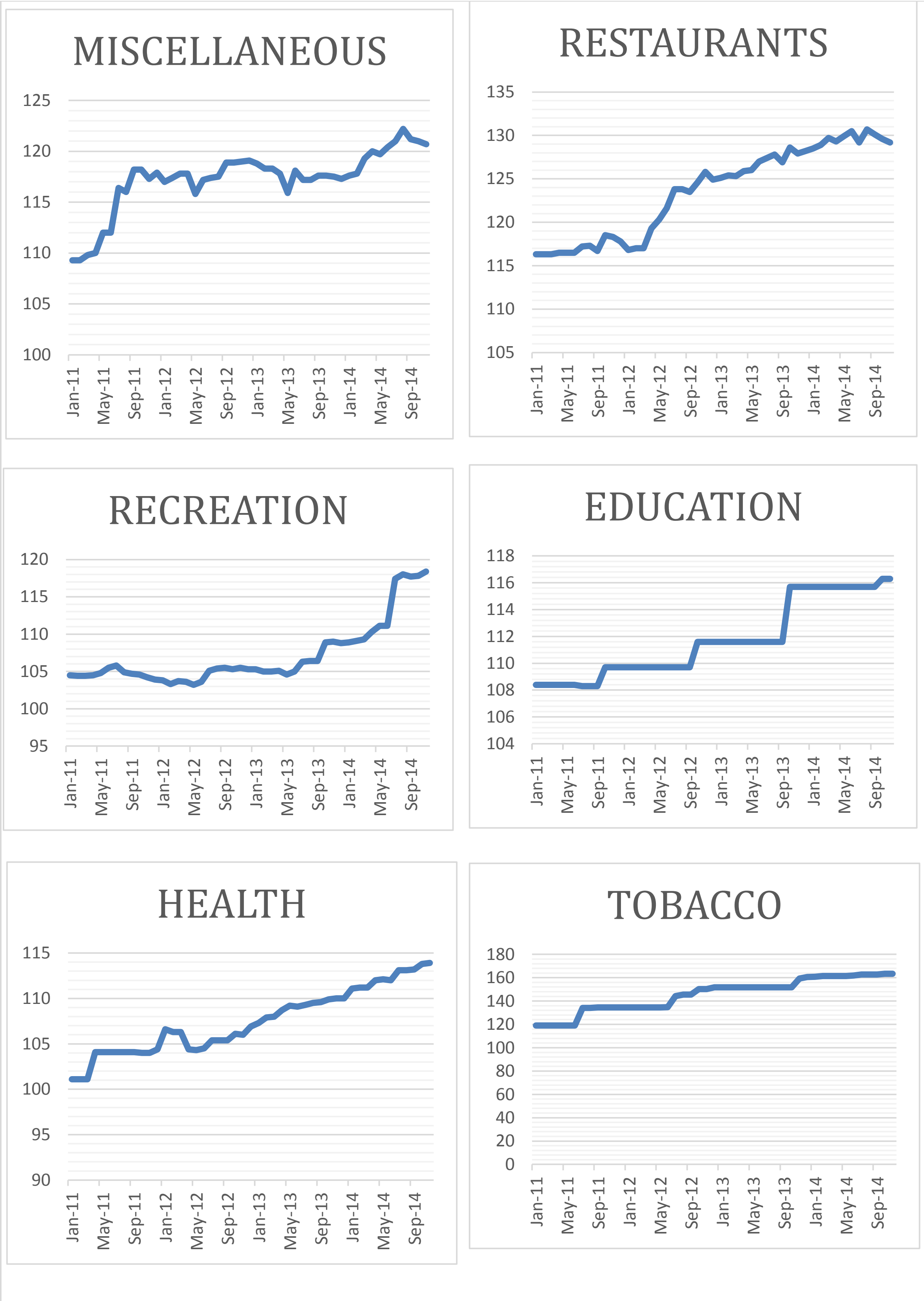


Figure2 : Monthly Dataset of the second 6 Saudi Arabia CPI Components, Spanning from the Period January 2011 through November 2014.



4. Analyzing the Data

4.1 Unit Root test

Figures (1) and (2) above show that all 12 Saudi Arabia CPI components have unit roots and suffer from autocorrelations, since most of the components are likely to have a random walk pattern. Thus, they move up and down in the line graph above. Also, in the correlogram, it is clear that the 12 disaggregated Saudi Arabia CPI components suffer autocorrelations as shown in Figure (3).[1]

Mandatory initial step in modern time series analysis is testing for unit roots to check whether data are stationary. The food time series has to be tested for a unite root using Augmented Dickey-Fuller (D-F) test as follows:

The hypothesis in the Augmented Dickey-Fuller (D-F) test are:

- H0: There is a Unit Root
- H1: There is no Unit Root
- Decision rule:

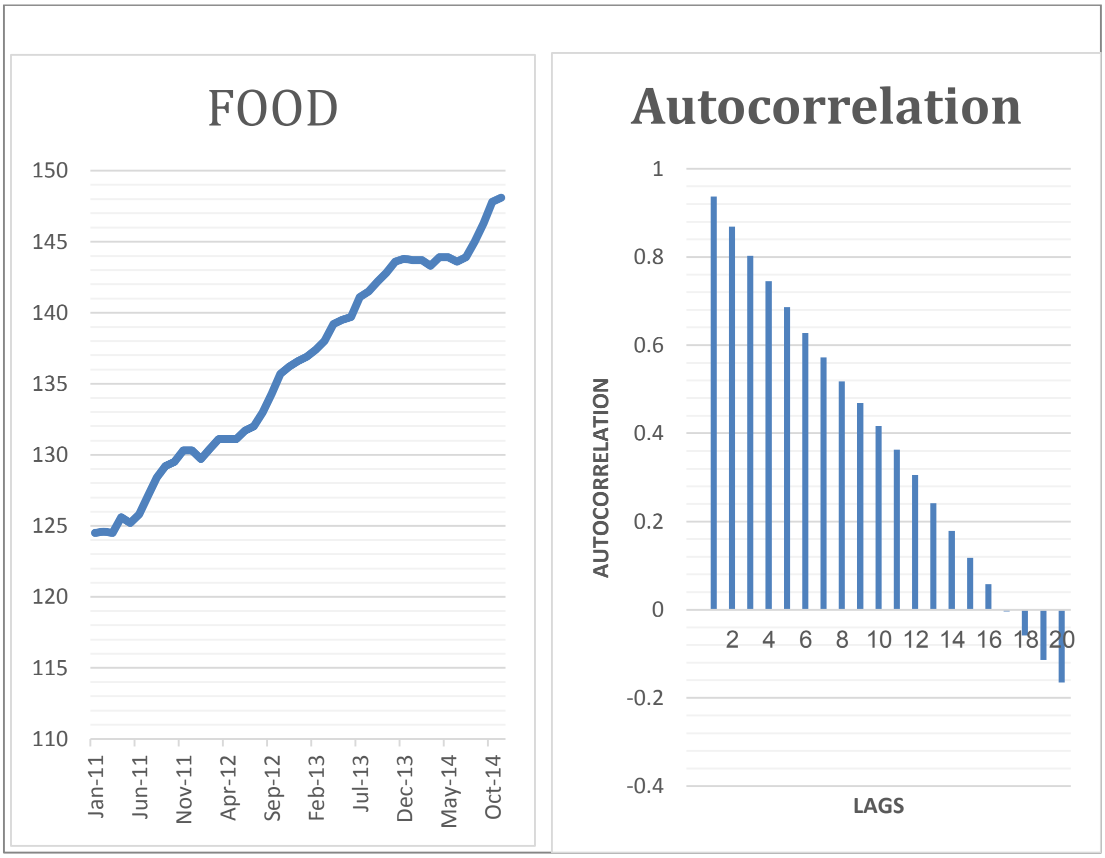
1. If Augmented Dickey-Fuller-t.value > Augmented Dickey-Fuller critical value. Thus, do not reject null hypothesis, i.e., a unit root exists.

2. If Augmented Dickey-Fuller-t.value < Augmented Dickey-Fuller critical value. Thus, reject null hypothesis, i.e., a unit root does not exist.

[1] To avoid redundancy, the paper concentrates on food time series only and the other 11 Saudi Arabia CPI components will be discussed in the appendix.

The autocorrelation function (ACF)[2] in figure (3) confirms that food time series has a unit root since the values of ACF are very large and persist for many lags (The ACF of food is slowly declining which is an indicator of non-stationary time series). In addition, Augmented Dickey-Fuller test confirms that the food time series has a unit root as shown in figure (4). The computed Augmented Dickey -Fuller t-statistic for the food time series is -0.409974 which is greater than Augmented Dickey-Fuller critical value -2.602225, -2.928142 and -3.584743 at 10%, 5% and 1% significant level, respectively. Thus Ho cannot be rejected and the food time series has a unit root problem (not stationary).

Figure3 : The autocorrelation function (ACF) for Food.



[2] The ACF is a plot of ρk for k lags that measures to what extent the value of yt in one period is correlated with values in previous periods yt-k

Null Hypothesis: FOOD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=9)

Prob.*	t-Statistic		
0.8986	-0.409974	Augmented Dickey-Fuller test statistic	
	-3.584743	1% level	Test critical values:
	-2.928142	5% level	
	-2.602225	10% level	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOOD)
Method: Least Squares
Date: 12/16/14 Time: 09:45
Sample (adjusted): 2011M03 2014M11
Included observations: 45 after adjustments

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.6839	-0.409974	0.011688	-0.004792	FOOD(-1)
0.0913	1.727999	0.148765	0.257065	D(FOOD(-1))
0.5156	0.655661	1.588077	1.041241	C

0.522222	Mean dependent var	0.067849	R-squared
0.542255	S.D. dependent var	0.023461	Adjusted R-squared
1.654439	Akaike info criterion	0.535856	S.E. of regression
1.774883	Schwarz criterion	12.05996	Sum squared resid
1.699340	Hannan-Quinn criter.	-34.22488	Log likelihood
1.964808	Durbin-Watson stat	1.528535	F-statistic
		0.228672	Prob(F-statistic)

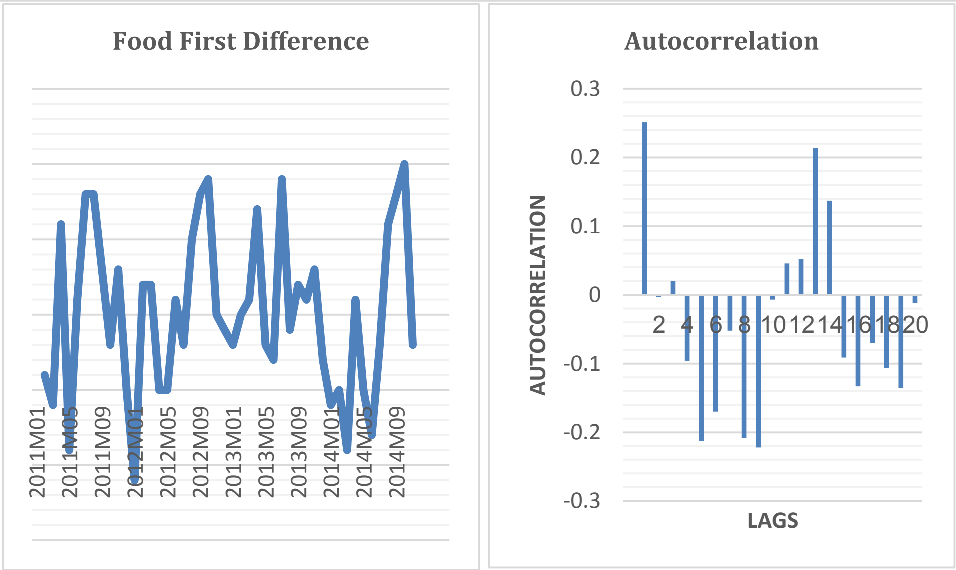
Figure: 4 Augmented Dickey-Fuller Test Equation for food time series.

4.2 Solving Unit Root Problem

To solve the unit root problem, first it is better to check if the first difference can attain level-stationary time series. If the answer is yes, then the Auto-Regressive Integrated Moving Average (ARIMA) (p,d,q) can be used. More precisely, ARIMA (1, 1, 0) = differenced first-order autoregressive model is used, which makes the first component a stationary time series. Otherwise, it is advised to move to the second difference. Fortunately, all 12 disaggregated Saudi Arabia CPI components are stationary when the transform is made to the first difference form.

Taking the first difference of the food time series and calculating Augmented Dickey -Fuller proves that the first difference of food time series is stationary at the mean and variance since the computed Augmented Dickey -Fuller t-statistics -5.095407 which is less than the Augmented Dickey-Fuller critical value -2.602225, -2.928142 and -3.584743 at 10%, 5% and 1% significant level, respectively as shown in figure (6). Thus Ho is rejected and the food time series does not have a unit root problem (stationary). The autocorrelation function (ACF) in figure (4) confirms that first difference of food time series does not have a unit root since the values of ACF are very small and decay rather quickly.

Figure5 : The autocorrelation function (ACF) for Food first difference.



The same conclusion can be derived for all other 11 disaggregated Saudi Arabia CPI components. Thus, all 12 disaggregated Saudi Arabia CPI components have a unit root problem, and this obstacle can be avoided by taking the first difference. Also, The recommended model is ARIMA (1, 1, 0).

Null Hypothesis: D(FOOD) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=9)

Prob.*	t-Statistic		
0.0001	-5.095407	Augmented Dickey-Fuller test statistic	
	-3.584743	1% level	Test critical values:
	-2.928142	5% level	
	-2.602225	10% level	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOOD,2)
Method: Least Squares
Date: 12/16/14 Time: 11:31
Sample (adjusted): 2011M03 2014M11
Included observations: 45 after adjustments

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.0000	-5.095407	0.146804	-0.748027	D(FOOD(-1))
0.0009	3.570981	0.109706	0.391756	C

0.004444	Mean dependent var	0.376479	R-squared
0.664337	S.D. dependent var	0.361978	Adjusted R-squared
1.613989	Akaike info criterion	0.530647	S.E. of regression
1.694285	Schwarz criterion	12.10823	Sum squared resid
1.643922	Hannan-Quinn criter.	-34.31474	Log likelihood
1.957467	Durbin-Watson stat	25.96318	F-statistic
		0.000007	Prob(F-statistic)

Figure6 : Augmented Dickey-Fuller Test Equation for the first difference of food time series.

5. Forecasting Evaluation and Forecasting Accuracy Criteria

5.1 Headline Inflation

It is advisable to retain some observations at the end of the sample period, which are not included in the estimation model, to test the out-of sample forecasting ability of the model. However, in this paper, in-sample forecasts and out-of sample forecasts were used. First, the entire period from January 2011 to January 2015 was used to model each of the 12 disaggregated Saudi Arabia CPI components, then, in-sample forecasts were computed for the period from August 2014 to January 2015 and out- of sample forecasts were computed for the period from February 2015 to June 2015. Figure (7) shows the forecasted food time series with minus and plus one standard deviation.

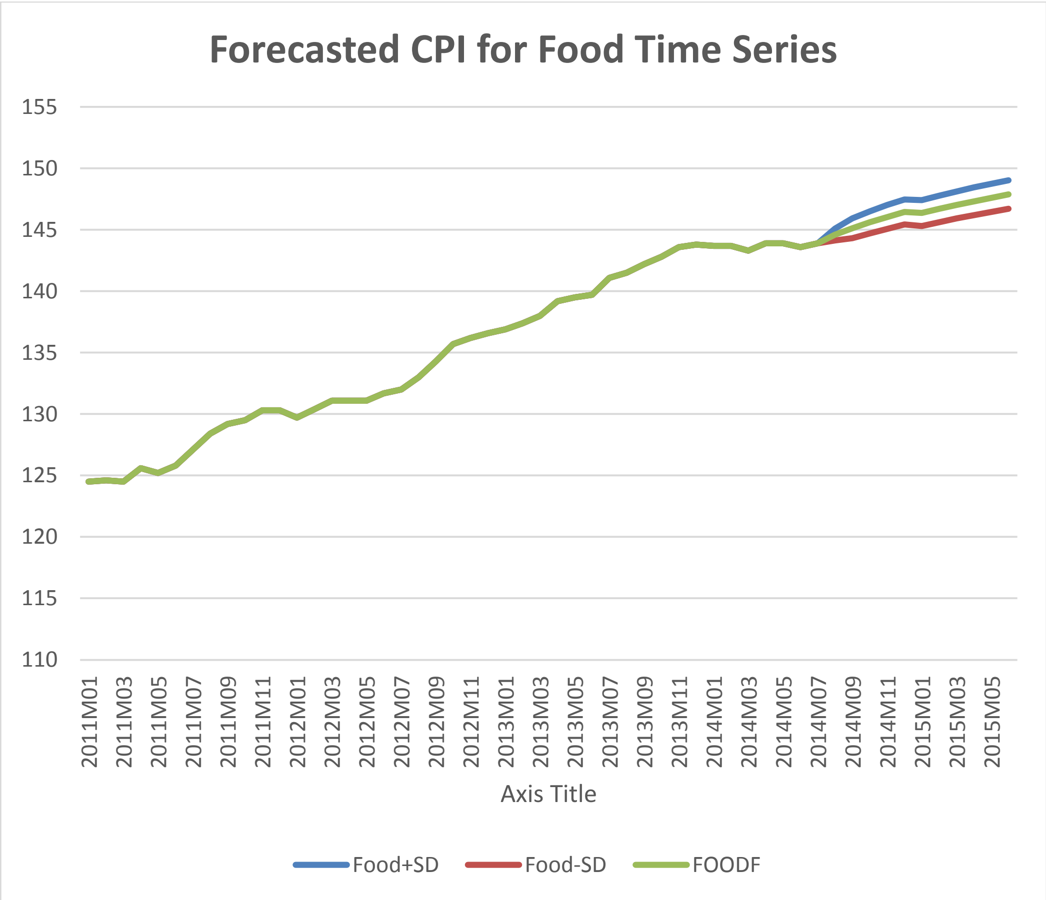


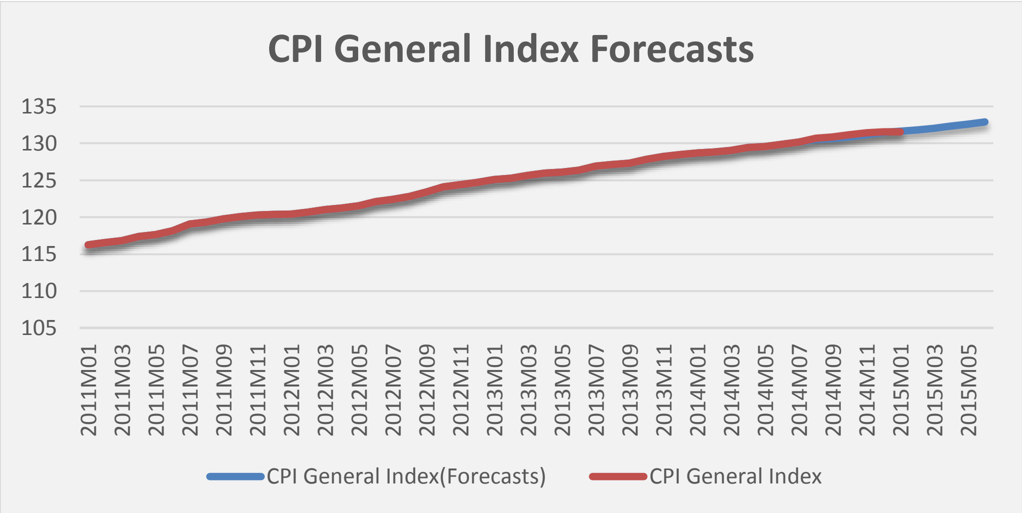
Figure 7 Forecasted CPI for food time series

Forecasting all CPI components is now straightforward: we simply weigh together the 12 disaggregated Saudi Arabia CPI components using the CPI weights as a model of the all-items CPI inflation rate. The underlying weights are defined as the weights of the 12 disaggregate components are 21.7,0.5, 8.4, 20.5,9.1,2.6,10.4.8.1,3.5,2.7,5.7 and 6.8 for the following CPI components: food and beverages, tobacco, clothing and footwear, housing, water, electricity and other fuels, furnishing, household equipment and maintenance, health, transport, communications, recreation and culture, education, restaurants and hotels, and finally miscellaneous goods and services respectively. Forecasted CPI can be calculated as follows:

$$
\begin{aligned}
CPI\ General\ Index &= Weight_1 * CPI^t_{Food} + Weight_2 * CPI^t_{Tobacco} + Weight_3 \\
&* CPI^t_{Clothing} + Weight_4 * CPI^t_{Housing} + Weight_5 \\
&* CPI^t_{Furnishing} + Weight_6 * CPI^t_{Health} + Weight_7 \\
&* CPI^t_{Transport} + Weight_8 * CPI^t_{Communications} + Weight_9 \\
&* CPI^t_{Recreation} + Weight_{10} * CPI^t_{Education} + Weight_{11} \\
&* CPI^t_{Resaurants} + Weight_{12} \ * CPI^t_{Miscellaneous}
\end{aligned}
$$

Figure (8) shows the forecasted CPI general index time series, in-sample forecasts for the period from August 2014 to January 2015 and out-of sample for the period from February 2015 to June 2015.

Figure8 : CPI General index forecasts



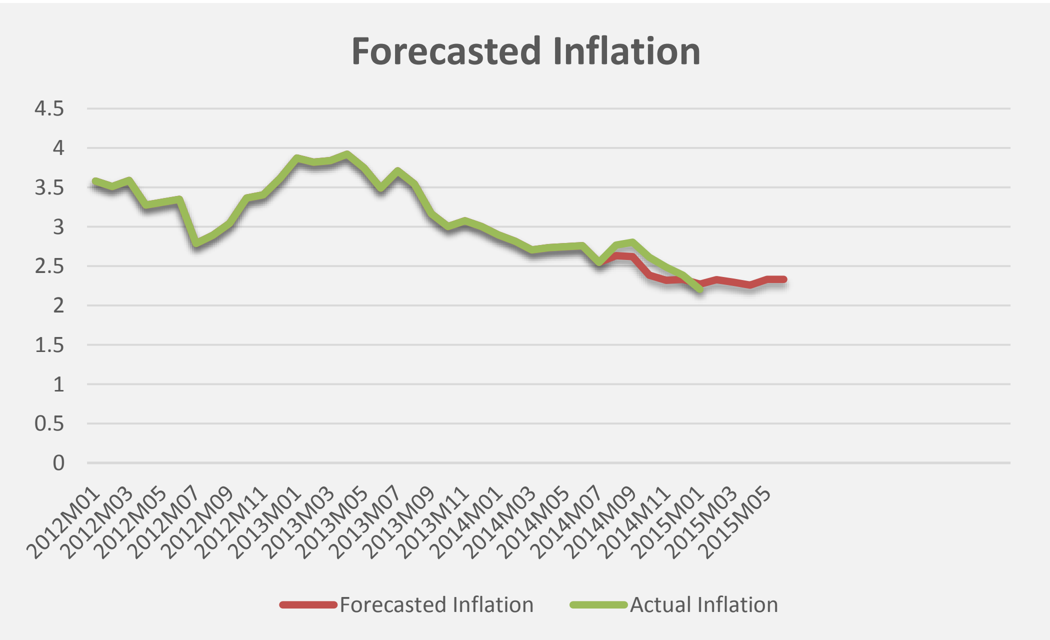
Also, table(2) gives a summary of the forecasted errors in CPI general index (in-sample) for the period from August 2014 to January 2015. It is clear that the maximum forecasted error in absolute value is 0.29 in October 2014, and the minimum value of error in absolute value is 0.07 in December 2014.

Table 2: CPI General index forecasted errors

Date	Actual CPI	Forecasted CPI	Forecasted Errors
2014M08	130.50	130.67	0.17
2014M09	130.65	130.89	0.24
2014M10	130.88	131.17	0.29
2014M11	131.19	131.41	0.22
2014M12	131.47	131.54	0.07
2015M01	131.63	131.55	-0.08

Inflation rate can be computed as a percentage change in CPI. Figure (9) shows the forecasted inflation rates time, in-sample forecasts for the period from August 2014 to January 2015 and out-of sample for the period from February 2015 to June 2015.

Figure9 : Forecasted Inflation



Also, table(3) gives a summary of the forecasted errors in inflation rates (in-sample) for the period from August 2014 to January 2015. It is clear that the maximum forecasted error in absolute value is 0.23 in October 2014, and the minimum value of error in absolute value is 0.05 in December 2014 which is consistent with the forecasted errors in CPI general index . it is better to keep in mind that the level of disaggregation matters. On many occasions, it is useful to monitor even more disaggregated sub-components.

Table 3: In- sample forecasted inflation

Date	Actual Inflation	Forecasted Inflation	Forecasted Errors
2014M08	2.77	2.63	-0.14
2014M09	2.81	2.62	-0.19
2014M10	2.61	2.38	-0.23
2014M11	2.49	2.32	-0.17
2014M12	2.39	2.33	-0.05
2015M01	2.21	2.27	0.06

5.2 Core Inflation

Core inflation in Saudi Arabia can be calculated by excluding the most volatile components in the general CPI index at first difference level (stationary time series).The sum of the weights of the excluding components should not exceed 20% of the general CPI index so that the core inflation maintains the main characteristics implied in the headline inflation. The excluded components are education, recreation, transportation and tobacco. The sum of the weights of these components is 10.5.

The new CPI and their respective adjusted weights for core inflation are: food (26.18%); clothing and footwear (10.13%); housing (24.73%); furnishing, household equipment and maintenance (10.98%); health

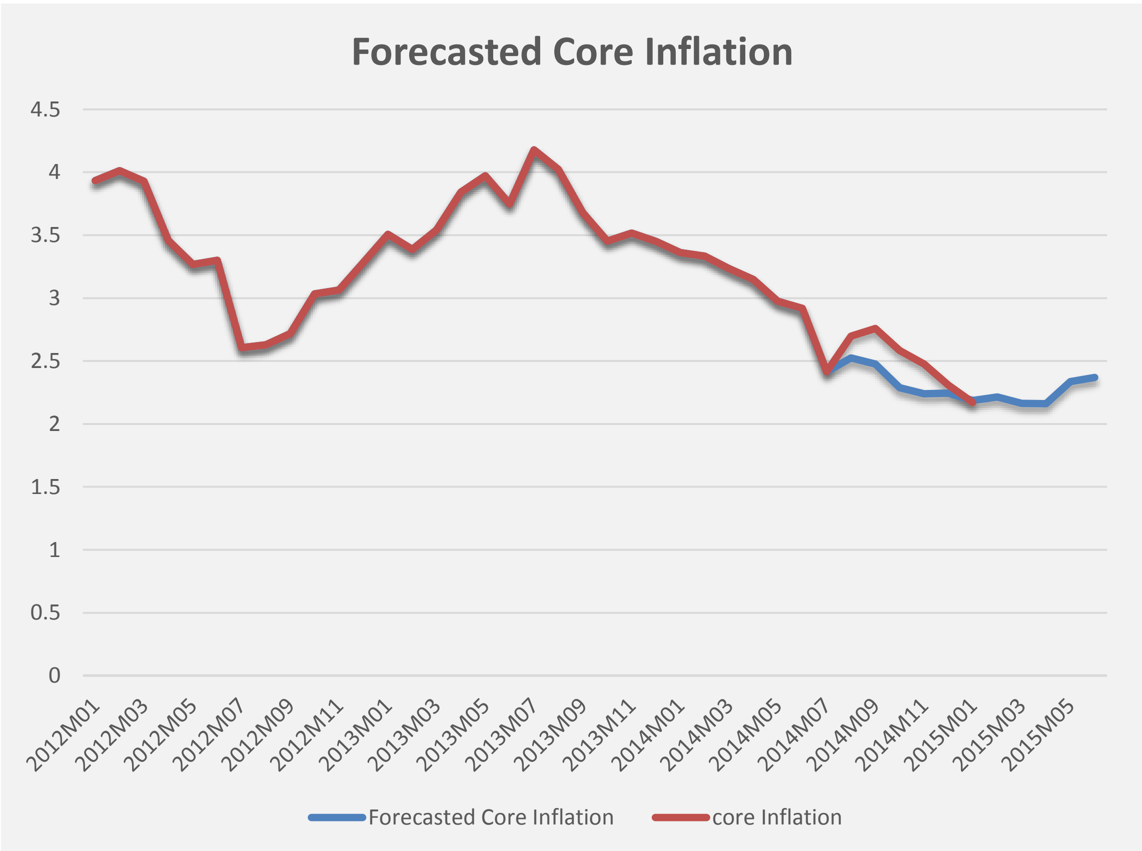
(3.14%); communications (9.77%); restaurants and hotels (6.88%); and finally miscellaneous goods and services (8.2%).

Forecasted core CPI can be calculated by using the estimated CPI components and weights as follow:

$$Core\ CPI = \text{adjusted weight}_1 * CPI^t_{food} + \text{adjusted weight}_2 * CPI^t_{clothing} + \text{adjusted weight}_3 * CPI^t_{housing} + \text{adjusted weight}_4 * CPI^t_{\text{furnishing}} + \text{adjusted weight}_5 * CPI^t_{\text{health}} + \text{adjusted weight}_6 * CPI^t_{\text{communications}} + \text{adjusted weight}_7 * CPI^t_{\text{restaurants}} + \text{adjusted weight}_8 * CPI^t_{\text{miscellaneous}}$$

Core Inflation rate can be computed as a percentage change in core CPI. Figure (10) shows the forecasted core inflation rates time, in-sample forecasts for the period from August 2014 to January 2015 and out-of sample for the period from February 2015 to June 2015.

Figure10 : Forecasted Core Inflation



Moreover, table(4) gives a summary of the forecasted errors in core inflation rates (in-sample) for the period from August 2014 to January 2015. It is clear that the maximum forecasted error in absolute value is 0.23 in October 2014, and the minimum value of error in absolute value is 0.05 in December 2014.

Table 4: In- sample forecasted core inflation

Date	Actual Core Inflation	Forecasted Core Inflation	Forecasted Errors
2014M08	2.52	2.70	0.17
2014M09	2.48	2.76	0.28
2014M10	2.29	2.58	0.30
2014M11	2.24	2.48	0.24
2014M12	2.25	2.31	0.06
2015M01	2.19	2.17	-0.01

Figure (10) shows the forecasted core inflation rates time, in-sample forecasts for the period from August 2014 to January 2015 and out-of sample for the period from February 2015 to June 2015.

6. Results

Figure (10) and table (5) show out-of sample forecasted headline and core inflation rates for the period from February 2015 to June 2015 (we don't know the actual data yet). It is clear that headline and core inflation rates will be increasing in February, decreasing in March and April and eventually increasing again in May and June. Also, core inflation will be higher than headline inflation in May and June.

Figure11 : Forecasted headline and core inflation rates

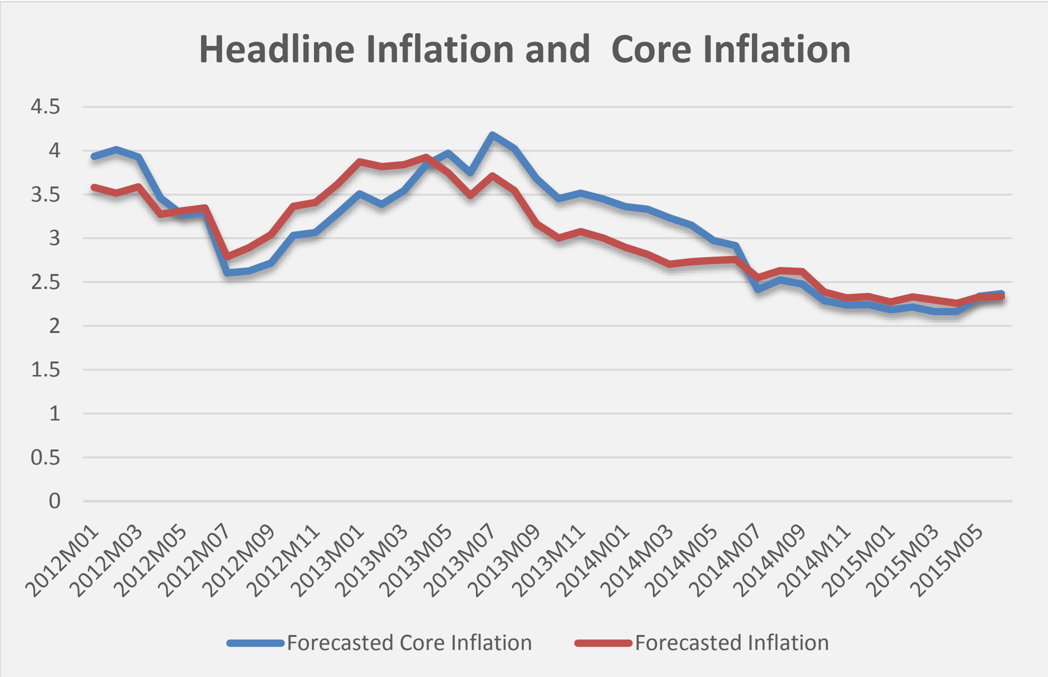


Table 5: Forecasted headline and core inflation rates for the period from February 2015 to June 2015

Date	Forecasted Core Inflation	Forecasted Inflation
2015M02	2.21	2.33
2015M03	2.16	2.29
2015M04	2.16	2.26
2015M05	2.34	2.33
2015M06	2.37	2.33

Table6 Out- of sample forecastedheadline and core inflation

Reference

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