Predicting consumer price index in Saudi Arabia

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ABSTRACT

This paper uses annual time series data on CPI in Japan from 1963 to 2017, to model and forecast CPI using the Box – Jenkins ARIMA technique. Diagnostic tests indicate that the Y series is I (2). The study presents the ARIMA (0, 2, 1) model for predicting CPI in Saudi Arabia. The diagnostic tests further imply that the presented optimal model is actually stable and acceptable for predicting CPI in Saudi Arabia. The results of the study apparently show that CPI in Saudi Arabia is likely to be relatively high in the next decade. The study encourages policy makers to make use of tight monetary and fiscal policy measures in order to deal with inflation in Saudi Arabia.

Key Words: Forecasting, Inflation, Saudi Arabia

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) as it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado *et al*, 2013). As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004). Consumer Price Index (CPI) may be regarded as a summary statistic for frequency distribution of relative prices (Kharimah *et al*, 2015). CPI number measures changes in the general level of prices of a group of commodities. It thus measures changes in the purchasing power of money (Monga, 1977; Subhani & Panjwani, 2009). As it is a prominent reflector of inflationary trends in the economy, it is often treated as a litmus test of the effectiveness of economic policies of the government of the day (Sarangi *et al*, 2018). The CPI program focuses on consumer expenditures on goods and services out of disposable income (Boskin *et al*, 1998). Hence, it excludes non-market activity, broader quality of life issues, and the costs and benefits of most government programs (Kharimah *et al*, 2015). To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability (Enke & Mehdiyev, 2014). Precisely forecasting the change of CPI is significant to many aspects of economics, some examples include fiscal policy, financial markets and productivity. Also, building a stable and accurate model to forecast the CPI will have great significance for the public, policy makers and research scholars (Du *et al*, 2014). In this study we use CPI as an indicator of inflation in Saudi Arabia. This paper seeks to model and forecast CPI in Saudi Arabia.

LITERATURE REVIEW

Alvarez-Diaz & Gupta (2015) studied US CPI using RW, AR, SARIMA, ANN and GP models with a data set ranging over the period January 1980 to December 2013 and revealed that SARIMA models were the best models to forecast US inflation. Nyoni (2018k) studied inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni (2018n) modeled inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; studied inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

MATERIALS & METHODS

Box – Jenkins ARIMA Models

One of the methods that are commonly used for forecasting time series data is the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976; Brocwell & Davis, 2002; Chatfield, 2004; Wei, 2006; Cryer & Chan, 2008). For the purpose of forecasting Consumer Price Index (CPI) in Saudi Arabia, ARIMA models were specified and estimated. If the sequence $\Delta^d Y_t$ satisfies an ARMA (p, q) process; then the sequence of Y_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d Y_t = \sum_{i=1}^{p} \beta_i \Delta^d Y_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

which we can also re – write as:

$$\Delta^d Y_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i Y_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018i).

Data Collection

This study is based on a data set of annual CPI (denoted as Y) in Saudi Arabia; ranging over the period 1963 – 2017. All the data was gathered from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests

The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-1.129071	0.6978	-3.560019	@1%	Non-stationary
			-2.917650	@5%	Non-stationary
			-2.596689	@10%	Non-stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-2.797770	0.2046	-4.140858	@1%	Non-stationary
			-3.496960	@5%	Non-stationary
			-3.177579	@10%	Non-stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	0.818666	0.8857	-2.609324	@1%	Non-stationary
			-1.947119	@5%	Non-stationary
			-1.612867	@10%	Non-stationary

Table 4: 1^{st} Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-2.914401	0.0504	-3.560019	@1%	Non-stationary
			-2.917650	@5%	Non-stationary
			-2.596689	@10%	Stationary

Table 5: 1^{st} Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-2.872347	0.1795	-4.140858	@1%	Non-stationary
			-3.496960	@5%	Non-stationary
			-3.177579	@10%	Non-stationary

Table 6: 1^{st} Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values	Conclusion

Y	-2.501171	0.0133	-2.609324	@1%	Non-stationary
			-1.947119	@5%	Stationary
			-1.612867	@10%	Stationary

Table 7: 2^{nd} Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-6.760902	0.0000	-3.562669	@1%	Stationary
			-2.918778	@5%	Stationary
			-2.597285	@10%	Stationary

Table 8: 2^{nd} Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-6.695425	0.0000	-4.144584	@1%	Stationary
			-3.498692	@5%	Stationary
			-3.178578	@10%	Stationary

Table 9: 2^{nd} Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-6.830234	0.0000	-2.610192	@1%	Stationary
			-1.947248	@5%	Stationary
			-1.612797	@10%	Stationary

Tables 1 – 6 show that Y is neither I (0) nor I (1). Tables 7 – 9 reveal that Y is I (2).

Evaluation of ARIMA models (without a constant)

Table 10

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (2, 2, 0)	249.7051	0.57947	-0.017646	1.7049	2.4104	2.7241
ARIMA (1, 2, 0)	248.8484	0.57141	-0.019985	2.7374	2.4374	2.7374
ARIMA (0, 2, 1)	**248.8403**	0.57101	-0.020419	1.7259	2.4372	2.7404
ARIMA (0, 2, 2)	249.3747	0.58763	-0.0080474	1.6937	2.402	2.7278

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018l). The study will consider the AIC and U as the benchmark for choosing the best model and hence the ARIMA (0, 2, 1) model is carefully selected.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (0, 2, 1) Model

Table 11: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.921942	0.0000	-3.562669	@1%	Stationary
			-2.918778	@5%	Stationary
			-2.597285	@10%	Stationary

Table 12: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.854920	0.0000	-4.144584	@1%	Stationary
			-3.498692	@5%	Stationary
			-3.178578	@10%	Stationary

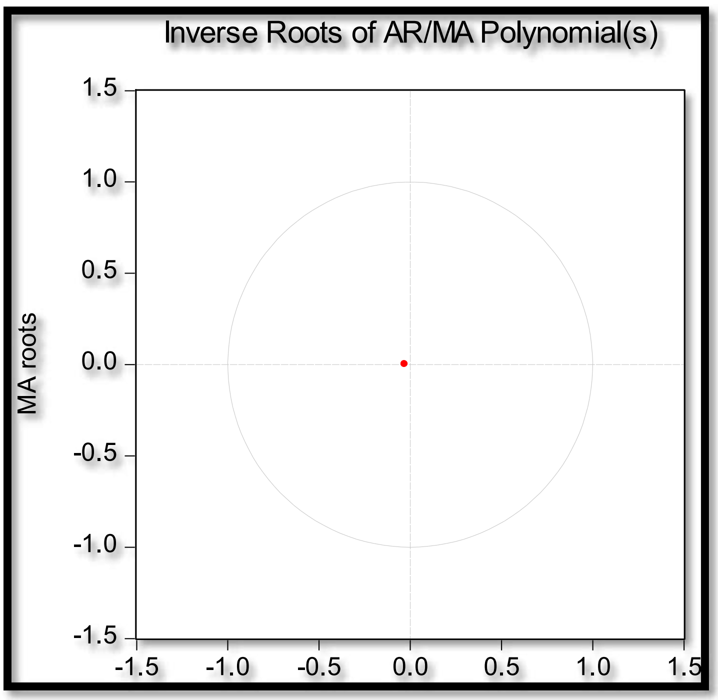
Table 13: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.992908	0.0000	-2.610192	@1%	Stationary
			-1.947248	@5%	Stationary
			-1.612797	@10%	Stationary

Tables 11 – 13 demonstrate that the residuals of the ARIMA (0, 2, 1) model are stationary.

Stability Test of the ARIMA (0, 2, 1) Model

Figure 1



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (0, 2, 1) model is indeed stable and suitable for predicting CPI in Saudi Arabia over the period under study.

FINDINGS

Descriptive Statistics

Table 14

Description	Statistic
Mean	68.473

Median	73
Minimum	20
Maximum	122
Standard deviation	28.59
Skewness	-0.25427
Excess kurtosis	-0.46212

As shown above, the mean is positive, i.e. 68.473. The minimum is 20 while the maximum is 122. The skewness is -0.25427 and the most striking characteristic is that it is positive, indicating that the Y series is positively skewed and non-symmetric. Excess kurtosis is -0.46212; showing that the Y series is not normally distributed.

Results Presentation[1]

Table 15

ARIMA (0, 2, 1) Model:

$$\Delta^2 Y_{t-1} = 0.0276402\mu_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots. [3]$$

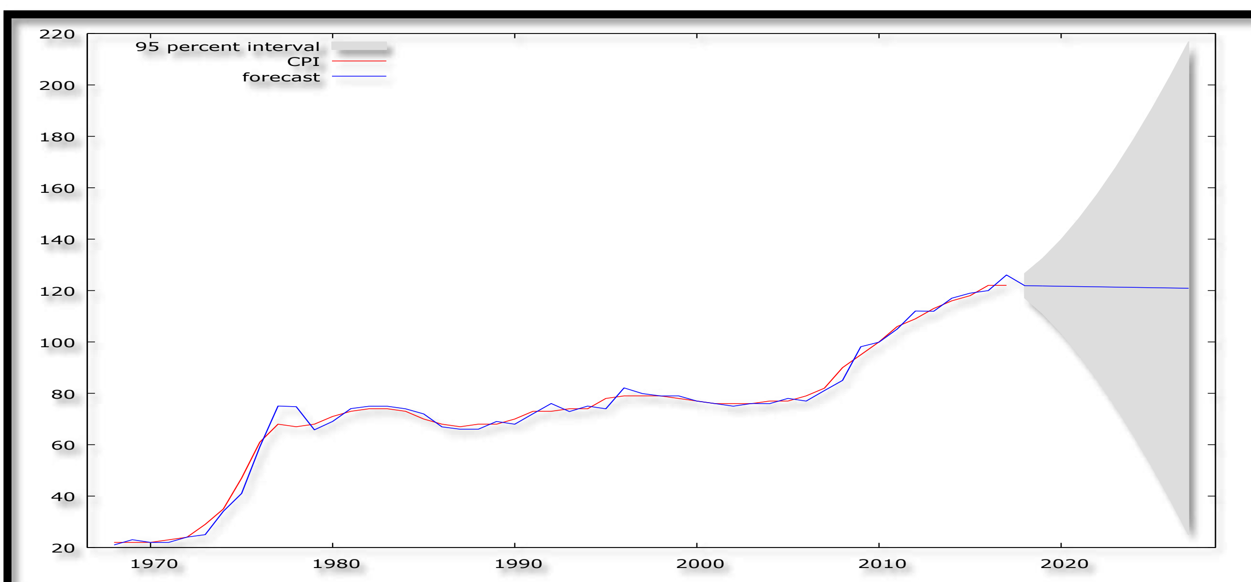
P: (0.8448)

S. E: (0.141155)

Variable	Coefficient	Standard Error	z	p-value
MA (1)	0.0276402	0.141155	0.1958	0.8448

Forecast Graph

Figure 2



[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

Predicted Annual CPI in Saudi Arabia

Table 16

Year	Prediction	Std. Error	95% Confidence Interval
2018	121.89	2.437	117.11 - 126.66
2019	121.78	5.510	110.98 - 132.58
2020	121.66	9.263	103.51 - 139.82
2021	121.55	13.595	94.90 - 148.20
2022	121.44	18.439	85.30 - 157.58
2023	121.33	23.744	74.79 - 167.87
2024	121.22	29.476	63.44 - 178.99
2025	121.10	35.603	51.32 - 190.88
2026	120.99	42.103	38.47 - 203.51
2027	120.88	48.955	24.93 - 216.83

Figure 2 (with a forecast range from 2018 – 2027) and table 16, clearly show that CPI in Saudi Arabia is indeed set to be relatively high in the next decade.

POLICY IMPLICATION & CONCLUSION

After performing the Box-Jenkins approach, the ARIMA was engaged to investigate annual CPI of Saudi Arabia from 1960 to 2017. The study mostly planned to forecast the annual CPI in Saudi Arabia for the upcoming period from 2018 to 2027 and the best fitting model was selected based on how well the model captures the stochastic variation in the data. The ARIMA (0, 2, 1) model, as indicated by the AIC statistic; is not only stable but also the most suitable model to forecast the CPI of Saudi Arabia for the next ten years. In general, CPI in Saudi Arabia; showed an upwards trend over the forecasted period. Based on the results, policy makers in Saudi Arabia should engage more proper economic and monetary policies in order to fight such increase in inflation as reflected in the forecasts. In this regard, the government of Saudi Arabia, through its relevant departments, is encouraged to rely more on contractionary monetary policy, which should be complimented by a tighter fiscal policy stance.

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