Modeling and forecasting CPI in Iran: A univariate analysis

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ABSTRACT

This paper uses annual time series data on CPI in Iran from 1960 to 2017, to model and forecast CPI using the Box – Jenkins ARIMA technique. Diagnostic tests indicate that the I series is I (2). The study presents the ARIMA (1, 2, 1) model for predicting CPI in Iran. The diagnostic tests further imply that the presented optimal model is actually stable and acceptable for predicting CPI in Iran. The results of the study apparently show that CPI in Iran is likely to continue on an upwards trajectory in the next ten years. The study basically encourages Iranian policy makers to make use of tight monetary and fiscal policy measures in order to control inflation in Iran.

Key Words: Forecasting, Iran, Inflation

JEL Codes: C53, E31, E37, E47

INTRODUCTION

A continued sustained rise in the general price level, as measured by the consumer price index (CPI) is a typical definition of inflation (Pahlavani & Rahini, 2009). Inflation is the process in which the price index is rising and money is losing its value (Hemmati *et al*, 2018). 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). Thus, the inflation rate is usually considered an important economic indicator to assess the economic performance (Kun *et al*, 2015). 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). Thus, accurate prediction of CPI plays a significant role for better planning of economic strategies in almost every institution such as government, financial institutions, investors in industries and agriculture, savings and credit cooperative unions, and individual consumer as well (Ambukege *et al*, 2017). The issue of inflation takes primary importance in Iran as the rising inflation has far reaching economic and social implications (Hemmati *et al*, 2018). In this study we use CPI as an indicator of inflation in Iran. The main motive behind this study is to model and forecast CPI in Iran.

LITERATURE REVIEW

Alvarez-Diaz & Gupta (2015) modeled and forecasted 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 (2018) 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 (2018) also 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 Iran, ARIMA models were specified and estimated. If the sequence $\Delta^d I_t$ satisfies an ARMA (p, q) process; then the sequence of I_t also satisfies the ARIMA (p, d, q) process such that:

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

which we can also re – write as:

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

where Δ is the difference operator, vector β ∈ ℝ^p and α ∈ 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, 2018).

Data Collection

This study is based on a data set of annual Iranian CPI (I) ranging over the period 1960 – 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
I	4.050081	1.0000	-3.577723	@1%	Non-stationary
			-2.925169	@5%	Non-stationary
			-2.600658	@10%	Non-stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	3.953523	1.0000	-4.165756	@1%	Non-stationary
			-3.508508	@5%	Non-stationary
			-3.184230	@10%	Non-stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	4.140895	1.0000	-2.615093	@1%	Non-stationary
			-1.947975	@5%	Non-stationary
			-1.612408	@10%	Non-stationary

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	3.584148	1.0000	-3.568308	@1%	Non-stationary

| | | -2.921175 | @5% | Non-stationary |
| | | -2.598551 | @10% | Non-stationary |

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	2.883464	1.0000	-4.152511	@1%	Non-stationary
			-3.502373	@5%	Non-stationary
			-3.180699	@10%	Non-stationary

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

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	3.827100	0.9999	-2.612033	@1%	Non-stationary
			-1.947520	@5%	Non-stationary
			-1.612650	@10%	Non-stationary

Table 7: 2nd Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	2.108331	0.9999	-3.571310	@1%	Non-stationary
			-2.922449	@5%	Non-stationary
			-2.599224	@10%	Non-stationary

Table 8: 2nd Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	1.282058	0.9999	-4.156734	@1%	Stationary
			-3.504330	@5%	Stationary
			-3.181826	@10%	Stationary

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

Variable	ADF Statistic	Probability	Critical Values		Conclusion
I	2.439065	0.9959	-2.613010	@1%	Non-stationary
			-1.947665	@5%	Non-stationary
			-1.612573	@10%	Non-stationary

All the above tables, with the exception of table 8; indicate that the I series is non-stationary. For the purposes of our estimations, we will consider I to be integrated of order 2 as shown in table 8.

Evaluation of ARIMA models (without a constant)

Table 10

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 2, 1)	**357.8337**	0.45912	0.57598	2.1559	5.5877	5.2417
ARIMA (2, 2, 2)	360.8145	0.4665	0.82924	2.0872	5.5352	5.2427
ARIMA (2, 2, 0)	359.93	0.45079	0.6044	2.2338	5.703	5.1366
ARIMA (1, 2, 0)	358.0068	0.44895	0.62885	2.2162	5.707	5.0914
ARIMA (0, 2, 1)	357.9892	0.44883	0.64551	2.2071	5.706	5.0818
ARIMA (2, 2, 1)	359.4523	0.46106	0.52744	2.1323	5.5677	5.3001

ARIMA (1, 2, 2)	360.5368	0.45557	0.90087	2.081	5.6292	5.0743
ARIMA (0, 2, 2)	359.7438	0.45048	0.75207	2.1452	5.692	5.0453

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 only consider the AIC as the criteria for choosing the best model for forecasting CPI in Iran. Therefore, the ARIMA (1, 2, 1) model is eventually considered.

Stability Tests

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

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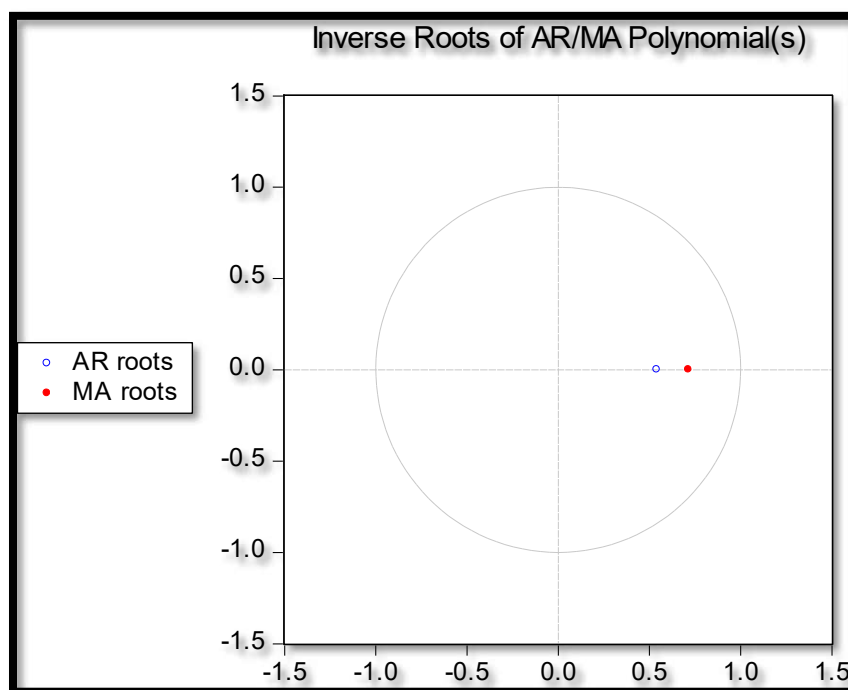
Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (1, 2, 1) model is indeed stable and suitable for predicting CPI in Iran over the period under study.

FINDINGS

Descriptive Statistics

Table 11

Description	Statistic
Mean	41.162
Median	2.475
Minimum	0.14
Maximum	339.72

Standard deviation	81.438
Skewness	2.4124
Excess kurtosis	4.8915

As shown above, the mean is positive, i.e. 41.162. The minimum is 0.14 while the maximum is 339.72. The skewness is 2.4124 and the most striking characteristic is that it is positive, indicating that the I series is positively skewed and non-symmetric. Excess kurtosis is 4.8915; showing that the I series is not normally distributed.
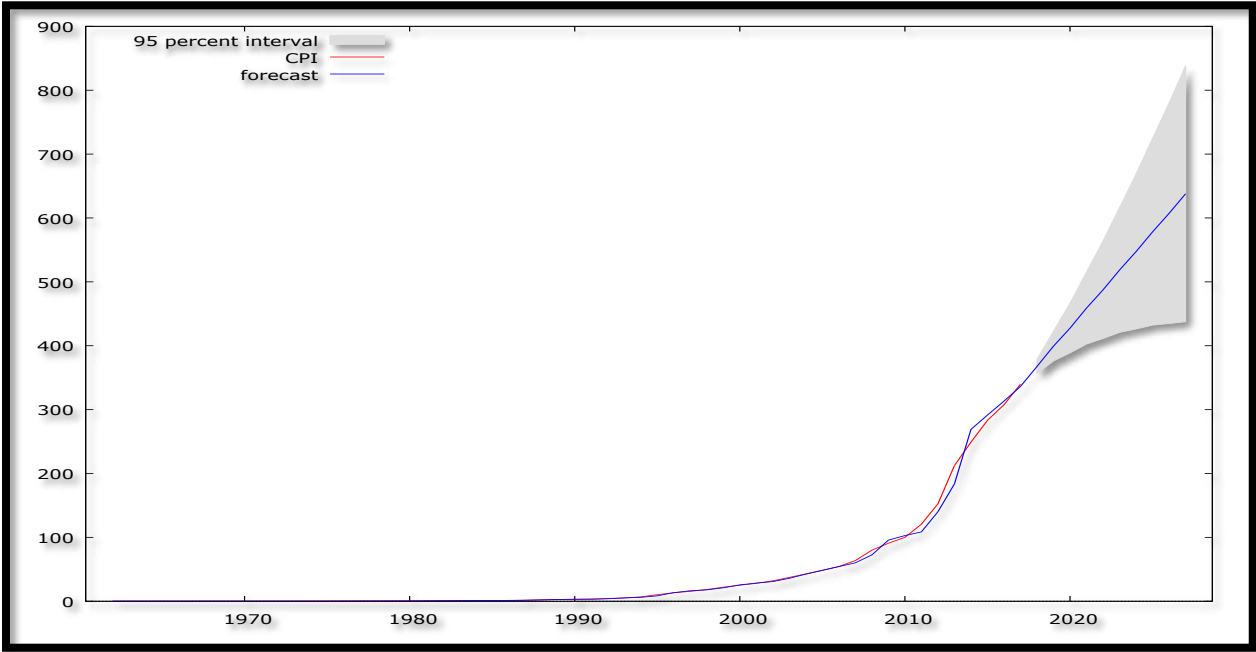
Results Presentation[1]

Table 12

ARIMA (1, 2, 1) Model:

$$\Delta^2 I_{t-1} = -0.896413\Delta^2 X_{t-1} + 0.757118\mu_{t-1} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots [3]$$

P: (0.0923)   (0.2172)

S. E: (0.532568)   (0.613576)

Variable	Coefficient	Standard Error	z	p-value
AR (1)	-0.896413	0.532568	-1.683	0.0923*
MA (1)	0.757118	0.613576	1.234	0.2172

Forecast Graph

Figure 2

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

Predicted Annual CPI in Iran

Table 13

Year	Prediction	Std. Error	95% Confidence Interval
2018	367.50	5.588	356.55 - 378.46
2019	399.27	11.804	376.14 - 422.41
2020	427.47	19.806	388.65 - 466.29
2021	458.87	28.711	402.60 - 515.14
2022	487.40	38.888	411.18 - 563.62
2023	518.50	49.837	420.82 - 616.18
2024	547.29	61.808	426.15 - 668.44
2025	578.16	74.472	432.19 - 724.12
2026	607.17	88.006	434.68 - 779.66
2027	637.84	102.179	437.57 - 838.10

Figure 2 (with a forecast range from 2018 – 2027) and table 13, clearly show that CPI in Iran is indeed set to continue rising sharply, in the next decade.

POLICY IMPLICATION & CONCLUSION

After performing the Box-Jenkins approach, the ARIMA model was engaged to investigate annual CPI of Iran from 1960 to 2017. The study mostly planned to forecast the annual CPI in Iran 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 (1, 2, 1) model, as indicated by the AIC statistic; is not only stable but also the most suitable model to forecast the CPI of Iran for the next ten years. In general, CPI in Iran; showed a sharply upwards trend over the forecasted period. Based on the results, policy makers in Iran 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 Iranian government, through the relevant authorities is encouraged to rely more on tight monetary policy, which must be complimented by a tight fiscal policy stance.

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