Forecasting Australian CPI using ARIMA models

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ABSTRACT

This research uses annual time series data on CPI in Australia from 1960 to 2017, to model and forecast CPI using the Box – Jenkins ARIMA technique. Diagnostic tests indicate that the A series is I (1). The study presents the ARIMA (1, 1, 0) model for predicting CPI in Australia. The diagnostic tests further imply that the presented optimal model is stable and acceptable. The results of the study apparently show that CPI in Australia is likely to continue on an upwards trend in the next decade. The study basically encourages policy makers to make use of tight monetary and fiscal policy measures in order to control inflation in Australia.

Key Words: Forecasting, Inflation, Australia

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). This study, whose major objective is to model and forecast CPI; uses CPI as an indicator of inflation in Australia.

LITERATURE REVIEW

Meyler *et al* (1998) forecasted Irish inflation using ARIMA models with quarterly data ranging over the period 1976 to 1998 and illustrated some practical issues in ARIMA time series forecasting. Kock & Terasvirta (2013) forecasted Finnish consumer price inflation using Artificial Neural Network models with a data set ranging over the period March 1960 – December 2009 and established that direct forecasts are more accurate then their recursive counterparts. Kharimah *et al* (2015) analyzed the CPI in Malaysia using ARIMA models with a data set ranging over the period January 2009 to December 2013 and revealed that the ARIMA (1, 1, 0) was the best model to forecast CPI in Malaysia. 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. Sarangi *et al* (2018) analyzed the consumer price index using Neural Network models with 159 data points and revealed that ANNs are better methods of forecasting CPI in India. 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 Australia, ARIMA models were specified and estimated. If the sequence $\Delta^d A_t$ satisfies an ARMA (p, q) process; then the sequence of A_t also satisfies the ARIMA (p, d, q) process such that:

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

which we can also re – write as:

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

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

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 in Australia (A) 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
A	1.296997	0.9984	-3.552666	@1%	Non-stationary
			-2.914517	@5%	Non-stationary
			-2.595033	@10%	Non-stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-3.076188	0.1220	-4.130526	@1%	Non-stationary
			-3.492149	@5%	Non-stationary
			-3.174802	@10%	Non-stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	2.668796	0.9978	-2.606911	@1%	Non-stationary
			-1.946764	@5%	Non-stationary
			-1.613062	@10%	Non-stationary

Tables 1 – 3 indicate that A is non-stationary in levels.

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-3.799737	0.0050	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-4.247395	0.0072	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

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

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-1.675040	0.0885	-2.606911	@1%	Non-stationary
			-1.946764	@5%	Non-stationary
			-1.613062	@10%	Stationary

Tables 4 – 6 indicate that the A series is stationary after taking first differences.

Evaluation of ARIMA models (with constant)

Table 7

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	171.5925	0.61509	0.041747	0.83831	1.0226	3.1661
ARIMA (1, 1, 0)	**171.0231**	0.6824	0.019859	0.85433	1.0359	3.3245
ARIMA (0, 1, 1)	179.7215	0.92306	0.0048615	0.91252	1.1138	4.013
ARIMA (2, 1, 1)	172.662	0.60277	0.062987	0.83144	1.014	3.121
ARIMA (1, 1, 2)	172.7572	0.59949	0.063032	0.82776	1.0146	3.0962
ARIMA (2, 1, 2)	174.6483	0.60222	0.0635546	0.83052	1.0138	3.1163

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 Australia. Therefore, the ARIMA (1, 1, 0) model is finally selected.

Residual & Stability Tests

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

Table 8: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.941434	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 9: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-8.196294	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

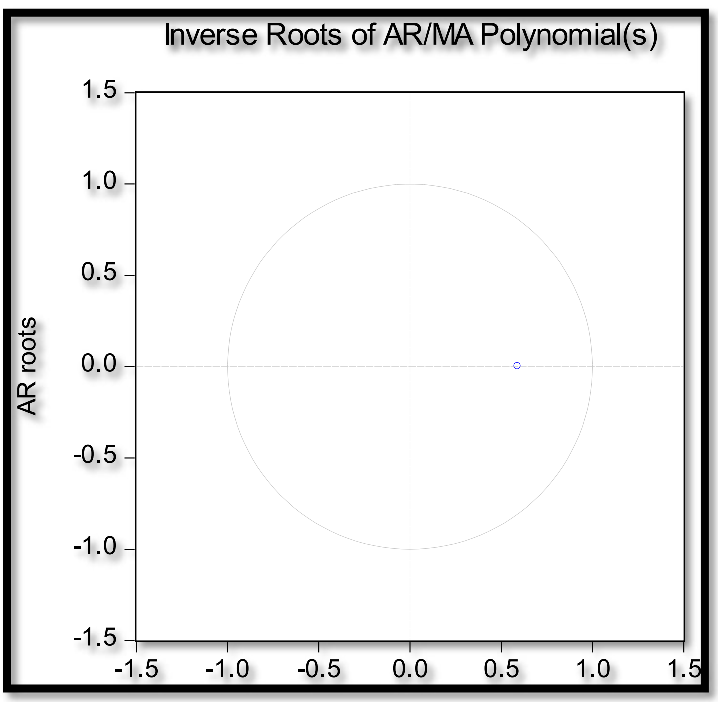
Table 10: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-8.021300	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Tables 8 to 10 reveal that the residuals of the ARIMA (1, 1, 0) model are stationary.

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

Figure 1



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

FINDINGS

Descriptive Statistics

Table 11

Description	Statistic
Mean	52.414
Median	54
Minimum	8
Maximum	116
Standard deviation	35.88
Skewness	0.19282
Excess kurtosis	-1.3316

As shown above, the mean is positive, i.e. 52.414. The minimum is 8 while the maximum is 116. The skewness is 0.19282 and the most striking characteristic is that it is positive, indicating that the A series is positively skewed and non-symmetric. Excess kurtosis is -1.3316; showing that the A series is not normally distributed.

Results Presentation[1]

Table 12

ARIMA (1, 1, 0) Model:

$$\Delta A_{t-1} = 1.8747 + 0.603796\Delta A_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

P: (0.0000) (0.0000)

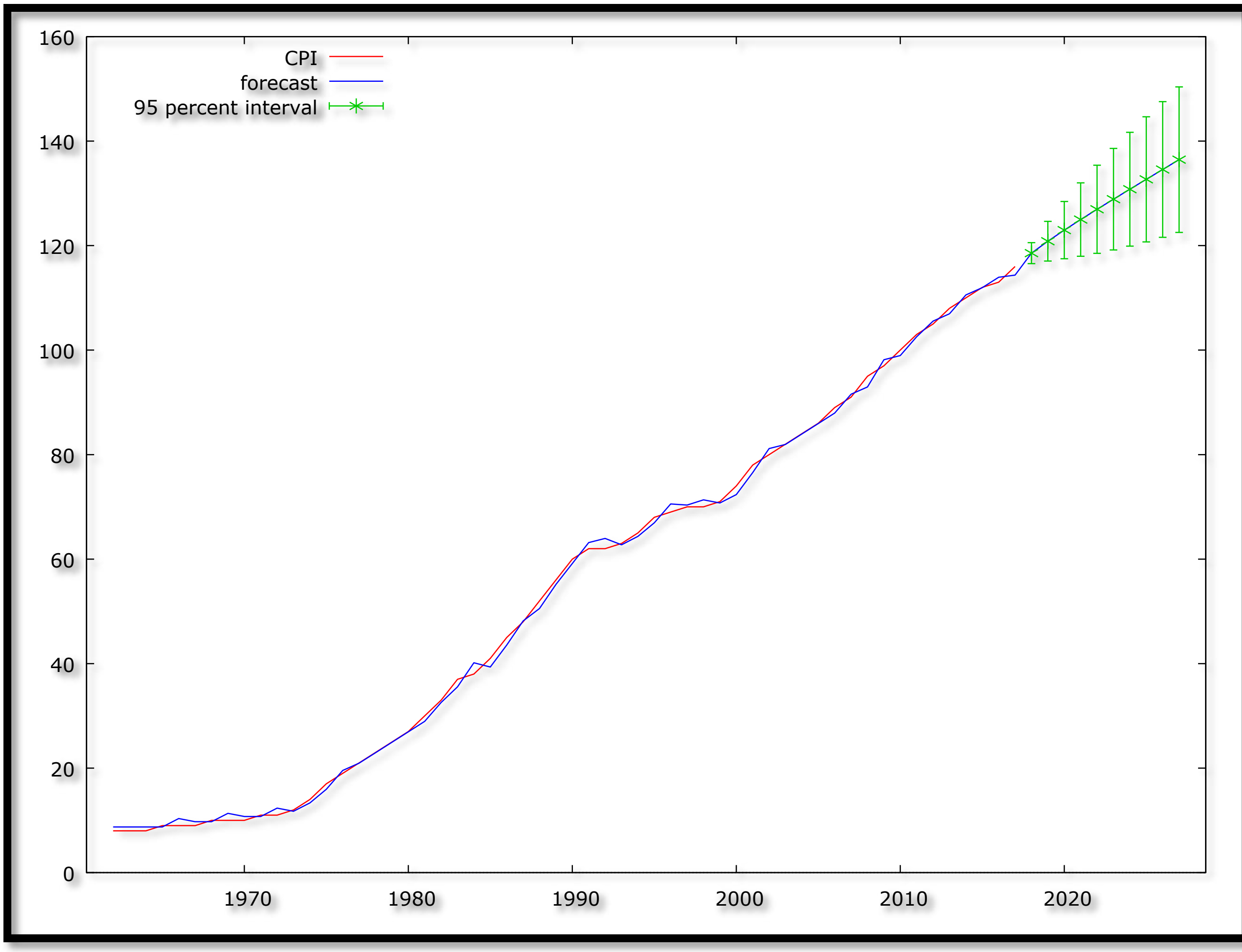
S. E: (0.327507) (0.106787)

Variable	Coefficient	Standard Error	z	p-value
Constant	1.8747	0.327567	5.723	0.0000***
AR (1)	0.603796	0.106787	5.654	0.0000***

Forecast Graph

Figure 2

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



Predicted Annual CPI in Australia

Table 13

Year	Prediction	Std. Error	95% Confidence Interval
2018	118.55	1.025	116.55 - 120.56
2019	120.84	1.937	117.04 - 124.64
2020	122.96	2.797	117.48 - 128.44
2021	124.99	3.585	117.96 - 132.01
2022	126.95	4.303	118.52 - 135.38
2023	128.88	4.957	119.16 - 138.60
2024	130.79	5.557	119.90 - 141.68
2025	132.68	6.111	120.71 - 144.66

2026	134.57	6.625	121.58 - 147.55
2027	136.45	7.106	122.52 - 150.38

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

POLICY IMPLICATION & CONCLUSION

After performing the Box-Jenkins approach, the ARIMA was engaged to investigate annual CPI of Australia from 1960 to 2017. The study mostly planned to forecast the annual CPI in Australia 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, 1, 0) model, as indicated by the AIC statistic; is not only stable but also the most suitable model to forecast the CPI of Australia for the next ten years. In general, CPI in Australia; showed an upwards trend over the forecasted period. Based on the results, policy makers in Australia should engage more proper economic and monetary policies in order to fight such increase in inflation as reflected in the forecasts. In this regard, relevant authorities in Australia are encouraged to rely more on tight monetary policy, which should be complimented by a tight fiscal policy stance.

REFERENCES

[1] Boskin, M. J., Ellen, R. D., Gordon, R. J., Grilliches, Z & Jorgenson, D. W (1998). Consumer Price Index and the Cost of Living, *The Journal of Economic Perspectives*, 12 (1): 3 – 26.

[2] Box, G. E. P & Jenkins, G. M (1976). Time Series Analysis: Forecasting and Control, *Holden Day*, San Francisco.

[3] Brocwell, P. J & Davis, R. A (2002). Introduction to Time Series and Forecasting, *Springer*, New York.

[4] Chatfield, C (2004). The Analysis of Time Series: An Introduction, 6th Edition, *Chapman & Hall*, New York.

[5] Cryer, J. D & Chan, K. S (2008). Time Series Analysis with Application in R, *Springer*, New York.

[6] Du, Y., Cai, Y., Chen, M., Xu, W., Yuan, H & Li, T (2014). A novel divide-and-conquer model for CPI prediction using ARIMA, Gray Model and BPNN, *Procedia Computer Science*, 31 (2014): 842 – 851.

[7] Enke, D & Mehdiyev, N (2014). A Hybrid Neuro-Fuzzy Model to Forecast Inflation, *Procedia Computer Science*, 36 (2014): 254 – 260.

[8] Hurtado, C., Luis, J., Fregoso, C & Hector, J (2013). Forecasting Mexican Inflation Using Neural Networks, *International Conference on Electronics, Communications and Computing*, 2013: 32 – 35.

[9] Kharimah, F., Usman, M., Elfaki, W & Elfaki, F. A. M (2015). Time Series Modelling and Forecasting of the Consumer Price Bandar Lampung, *Sci. Int (Lahore).*, 27 (5): 4119 – 4624.

[10] Kock, A. B & Terasvirta, T (2013). Forecasting the Finnish Consumer Price Inflation using Artificial Network Models and Three Automated Model Section Techniques, *Finnish Economic Papers*, 26 (1): 13 – 24.

[11] Manga, G. S (1977). Mathematics and Statistics for Economics, *Vikas Publishing House*, New Delhi.

[12] Mcnelis, P. D & Mcadam, P (2004). Forecasting Inflation with Think Models and Neural Networks, *Working Paper Series*, European Central Bank.

[13] Meyler, A., Kenny, G & Quinn, T (1998). Forecasting Irish Inflation using ARIMA models, *Research and Publications Department*, Central Bank of Ireland.

[14] Nyoni, T & Nathaniel, S. P (2019). Modeling Rates of Inflation in Nigeria: An Application of ARMA, ARIMA and GARCH models, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 91351.

[15] Nyoni, T (2018k). Modeling and Forecasting Inflation in Zimbabwe: a Generalized Autoregressive Conditionally Heteroskedastic (GARCH) approach, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88132.

[16] Nyoni, T (2018l). Modeling Forecasting Naira / USD Exchange Rate in Nigeria: a Box – Jenkins ARIMA approach, *University of Munich Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88622.

[17] Nyoni, T (2018n). Modeling and Forecasting Inflation in Kenya: Recent Insights from ARIMA and GARCH analysis, *Dimorian Review*, 5 (6): 16 – 40.

[18] Nyoni, T. (2018i). Box – Jenkins ARIMA Approach to Predicting net FDI inflows in Zimbabwe, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 87737.

[19] Sarangi, P. K., Sinha, D., Sinha, S & Sharma, M (2018). Forecasting Consumer Price Index using Neural Networks models, *Innovative Practices in Operations Management and Information Technology* – Apeejay School of Management, pp: 84 – 93.

[20] Subhani, M. I & Panjwani, K (2009). Relationship between Consumer Price Index (CPI) and Government Bonds, *South Asian Journal of Management Sciences*, 3 (1): 11 – 17.

[21] Wei, W. S (2006). Time Series Analysis: Univariate and Multivariate Methods, 2nd Edition, Pearson Education Inc, Canada.