Forecasting CPI in Sweden

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15 February 2019

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ABSTRACT

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

Key Words: Forecasting, Inflation, Sweden

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). Decisions basing on impractical inflation predictions result in ineffective resource allocation and weaker macroeconomic activities (Khanh, 2012). 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 Sweden as we model and forecast CPI using the generalized ARIMA framework.

LITERATURE REVIEW

In Lithuania, Cuvak & Kalinauskas (2009), analyzed inflation using VAR models and concluded that VAR models could provide good forecasting accuracy for Lithuanian inflation. Zhou (2017) analyzed Swedish inflation using market data and employed ARIMA as well as DLM techniques and found out that the RFDLM was the best approach to model inflation in Sweden. 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 Sweden, ARIMA models were specified and estimated. If the sequence $\Delta^d W_t$ satisfies an ARMA (p, q) process; then the sequence of W_t also satisfies the ARIMA (p, d, q) process such that:

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

which we can also re – write as:

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

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 (W) in Sweden 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
W	-0.774384	0.8184	-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
W	-1.412199	0.8467	-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
W	1.321639	0.9514	-2.606911	@1%	Non-stationary
			-1.946764	@5%	Non-stationary
			-1.613062	@10%	Non-stationary

Tables 1 – 3 reveal that the W series is non-stationary in levels.

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
W	-3.365882	0.0165	-3.552666	@1%	Non-stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
W	-3.348315	0.0691	-4.130526	@1%	Non-stationary
			-3.492149	@5%	Non-stationary
			-3.174802	@10%	Stationary

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

Variable	ADF Statistic	Probability	Critical Values		Conclusion
W	-2.073594	0.0376	-2.606911	@1%	Non-stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

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

Evaluation of ARIMA models (with a constant)

Table 7

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	185.0382	0.5124	0.026757	0.86433	1.1459	2.3337
ARIMA (1, 1, 0)	**184.1016**	0.53273	0.018953	0.88382	1.1571	2.4378
ARIMA (0, 1, 1)	194.7236	0.64772	0.0072197	0.9965	1.2678	2.8288
ARIMA (2, 1, 1)	186.8551	0.50721	0.030917	0.86465	1.1437	2.3035
ARIMA (1, 1, 2)	186.7074	0.50306	0.032174	0.8647	1.1422	2.2833
ARIMA (2, 1, 2)	188.2542	0.49887	0.030742	0.8635	1.1377	2.2807

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 Sweden. Hence, the ARIMA (1, 1, 0) model is preferred.

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	-7.833623	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	-7.791681	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

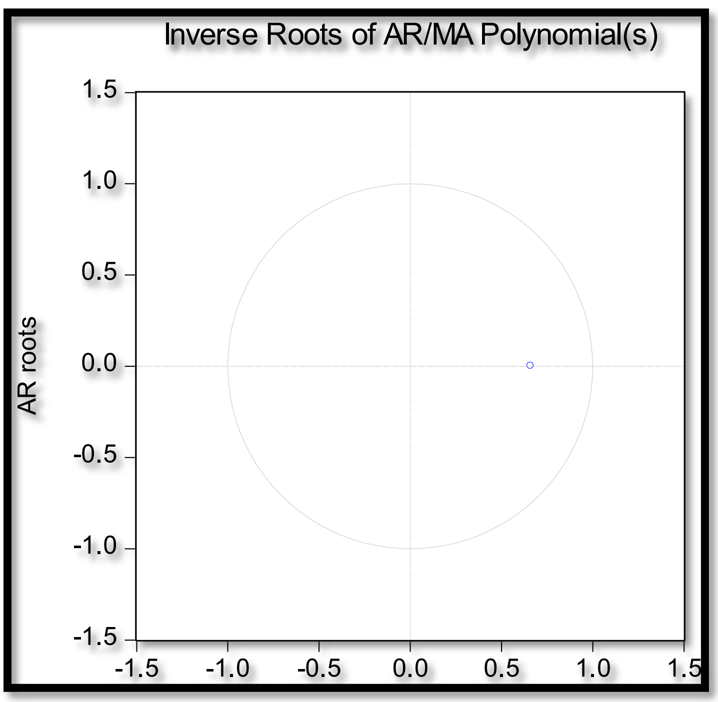
Table 10: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.907281	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Tables 8 – 10 tell us 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 stable and suitable for predicting CPI in Sweden over the period under study.

FINDINGS

Descriptive Statistics

Table 11

Description	Statistic
Mean	58.103
Median	60
Minimum	9
Maximum	106
Standard deviation	36.056
Skewness	-0.10217
Excess kurtosis	-1.6174

As shown above, the mean is positive, i.e. 58.103. The minimum is 9 while the maximum is 106. The skewness is -0.10217 and the most striking characteristic is that it is positive, indicating that the W series is positively skewed and non-symmetric. Excess kurtosis is -1.6174; showing that the W series is not normally distributed.

Results Presentation[1]

Table 12

ARIMA (1, 1, 0) Model:

$$\Delta W_{t-1} = 1.62331 + 0.665581\Delta W_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

P: (0.00001) (0.0000)

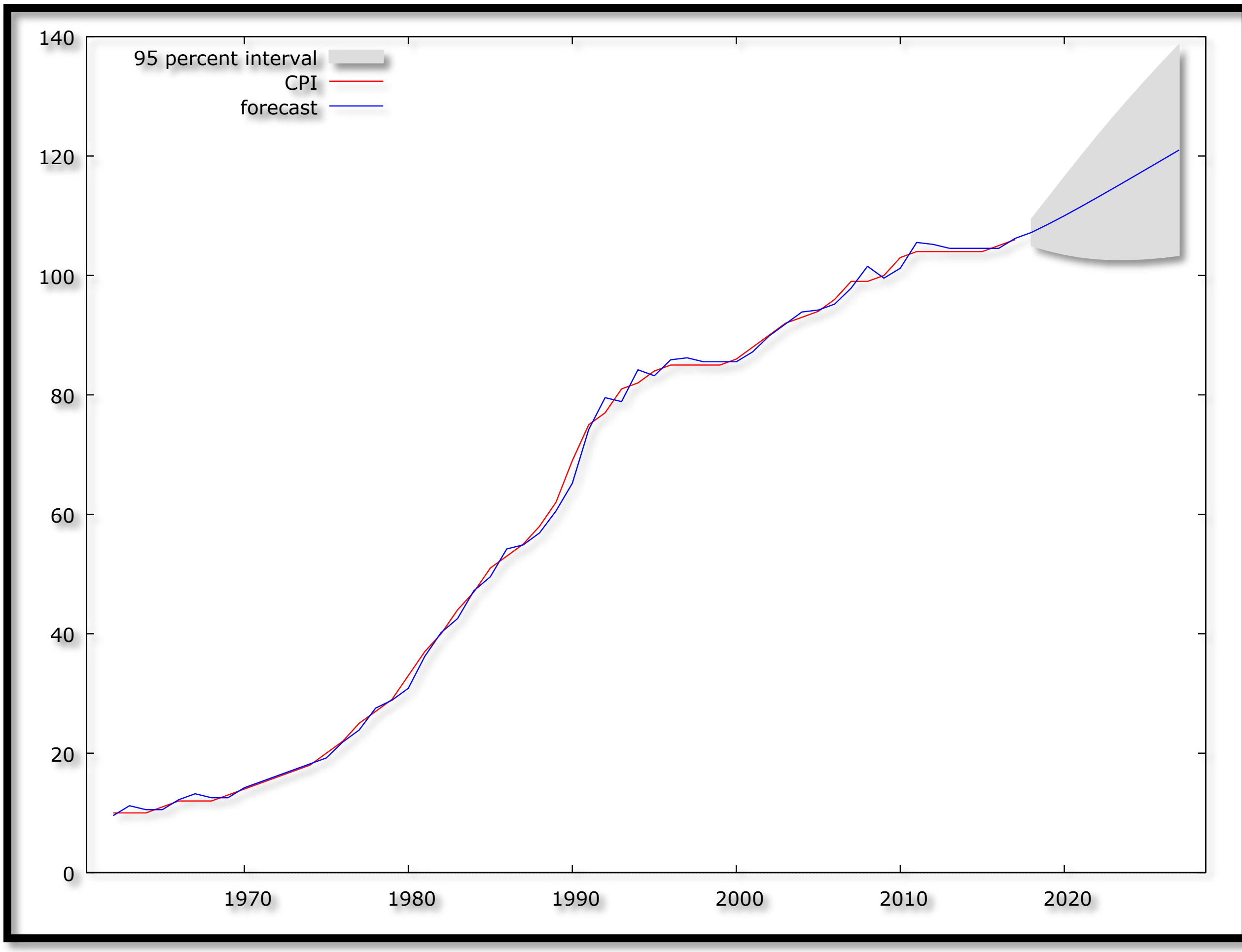
S. E: (0.426694) (0.0986443)

Variable	Coefficient	Standard Error	z	p-value
Constant	1.62331	0.426694	3.804	0.00001**
AR (1)	0.665581	0.0986443	6.747	0.0000***

Forecast Graph

Figure 2

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



Predicted Annual CPI in Sweden

Table 13

Year	Prediction	Std. Error	95% Confidence Interval
2018	107.21	1.148	104.96 - 109.46
2019	108.56	2.231	104.18 - 112.93
2020	110.00	3.292	103.54 - 116.45
2021	111.50	4.296	103.08 - 119.92
2022	113.04	5.231	102.79 - 123.29
2023	114.61	6.099	102.65 - 126.56
2024	116.19	6.903	102.66 - 129.72
2025	117.79	7.652	102.80 - 132.79

2026	119.40	8.351	103.03 -	135.77
2027	121.01	9.008	103.36 -	138.67

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

POLICY IMPLICATION & CONCLUSION

After performing the Box-Jenkins approach, the ARIMA was engaged to investigate annual CPI of Sweden from 1960 to 2017. The study mostly planned to forecast the annual CPI in Sweden 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 is not only stable but also the most suitable model to forecast the CPI of Sweden for the next ten years. In general, CPI in Sweden; showed an upwards trend over the forecasted period. Based on the results, policy makers in Sweden should engage more proper economic and monetary policies in order to fight such increase in inflation as reflected in the forecasts. In this regard, Swedish policy makers are challenged to consider a tight monetary policy stance, 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] Cuvak, A & Kalinauskas, Z (2009). Application of Vector Autoregression Model for Lithuanian inflation, *Economics and Management*, pp: 145 – 150.

[7] 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.

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

[9] 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.

[10] Khanh, P. V (2012). Comparisons of VAR model and models created by Genetic Programming in Consumer Price Index Prediction in Vietnam, *Open Journal of Statistics*, 2 (2012): 237 – 250.

[11] 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.

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

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

[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.

[22] Zhou, Y (2017). Modeling Swedish inflation using market data, *Masters Thesis*, KTH.