Understanding inflation trends in Israel: A univariate approach

NYONI, THABANI

UNIVERSITY OF ZIMBABWE, DEPARTMENT OF ECONOMICS

25 February 2019

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Nyoni, Thabani

Department of Economics

University of Zimbabwe

Harare, Zimbabwe

Email: nyonithabani35@gmail.com

ABSTRACT

This paper uses annual time series data on inflation in Israel from 1960 to 2017, to model and forecast inflation using the Box – Jenkins ARIMA technique. Diagnostic tests indicate that Q is I (1). The study presents the ARIMA (1, 1, 2) model for predicting inflation in Israel. The diagnostic tests further show that the presented parsimonious model is stable and acceptable for predicting inflation in Israel. The results of the study apparently show that inflation in Israel is likely to be hovering around 1.6% over the next decade. Basically, the study encourages the Bank of Israel to continue being transparent and independent in order to retain credibility and boost its ability to engineer successful macroeconomic policy actions.

Key Words: Forecasting, Inflation

JEL Codes: C53, E31, E37, E47

INTRODUCTION & BACKGROUND

The Bank of Israel (BOI) was founded in August 1954 after a substantial inflationary bulge due to high monetary expansion cum initially suppressed inflation during the early statehood years had largely subsided. Although the its legal independence was reasonable, by international standards of the time, its actual ability to confront the remaining inflationary pressures was severely limited because it was directed by the government to function as a development bank allocating credit to various industries in the economy. The first four to five decades following the Bank's foundation were characterized by inflation rates above the current 2% international norm, at times very much so (Cukierman & Melnick, 2015). Throughout the 1970s, the economy of Israel suffered from persistent inflation, which turned into hyperinflation in the early 1980s (Helpman, 2003). This period was dubbed Israel's "lost decade" with near zero per capita growth. In 1985, with annual inflation rate approaching 450%, the government implemented a stabilization program, bringing inflation down to about 20% in the early 1990s. Israel was the third country in the world to formally adopt inflation targeting in the late 1991, following New Zealand (1990) and Canada (1991). The target range for 1992 was set at 14 – 15%, relative to the Consumer Price Index (CPI). Israel was very index-dependent at the time, and many contracts in the economy were indexed to the CPI: rents, mortgages, government bonds and wages. The dis-inflationary process in Israel was completed in 1997 with capital flows fully liberalized and a floating exchange rate regime instituted. Overall, over the course of the 1990s, annual inflation rate decreased from 18% to 4% (Kazinnik, 2017).

Following a successful heterodox stabilization program in July 1985, and after a prolonged stabilization that followed, Israel finally reached price stability on a permanent basis at the beginning of the twenty-first century (Cukierman & Melnick, 2015). With price stability in the late 1990s, and having gained some credibility, policy makers in Israel adopted an element of inflation forecast targeting. Inflation forecast targeting is needed because the lags in transmission mechanism of monetary policy require policy makers to act in response to current and expected future developments that could lead to deviations of inflation from target. In the early 2000s, inflation in Israel reached low single digits, and for 2001 the inflation target was set to a 3% to 4% band (Kazinnik, 2017). Since then, inflation in Israel has always been a single digit figure, well below 6% as clearly shown below in figure 1. In fact inflation in Israel, as revealed in figure 1; as of 2017 is estimated to be have been approximately 0.2%.

Inflation is the sustained increase in the general level of prices and services over time (Blanchard, 2000). The negative effects of inflation are widely recognized (Fenira, 2014). 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). To prevent the aforementioned undesirable outcomes of price instability, central banks require proper understanding of the future path of inflation to anchor expectations and ensure policy credibility; the key aspects of an effective monetary policy transmission mechanism (King, 2005). Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialized economies is mandated to maintain price stability over the medium term (Buelens, 2012). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012). Israel's economy continues to register remarkable macroeconomic and fiscal performance. Growth is strong and unemployment low and falling. With low interest rates and price stability, financial policy is prudent, and public debt is comparatively low and declining (OECD, 2018).

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). The Bank of Israel relied on inflation forecasts as early as 1998 (Bufman & Leiderman, 1998; Leiderman & Bar-Or, 2000). Inflation forecasting in Israel is based on a market-based measure, where inflation expectations for the term are derived from the spread between yields to maturity on non-linked *shekel* bonds and CPI linked bonds (Kazinnik, 2017). The main objective of this study is to model and forecast inflation in Israel using ARIMA models.

LITERATURE REVIEW

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 (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) 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 inflation rate in Israel, ARIMA models were specified and estimated. If the sequence $\Delta^d Q_t$ satisfies an ARMA (p, q) process; then the sequence of Q_t also satisfies the ARIMA (p, d, q) process such that:

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

which we can also re – write as:

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

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, 2018).

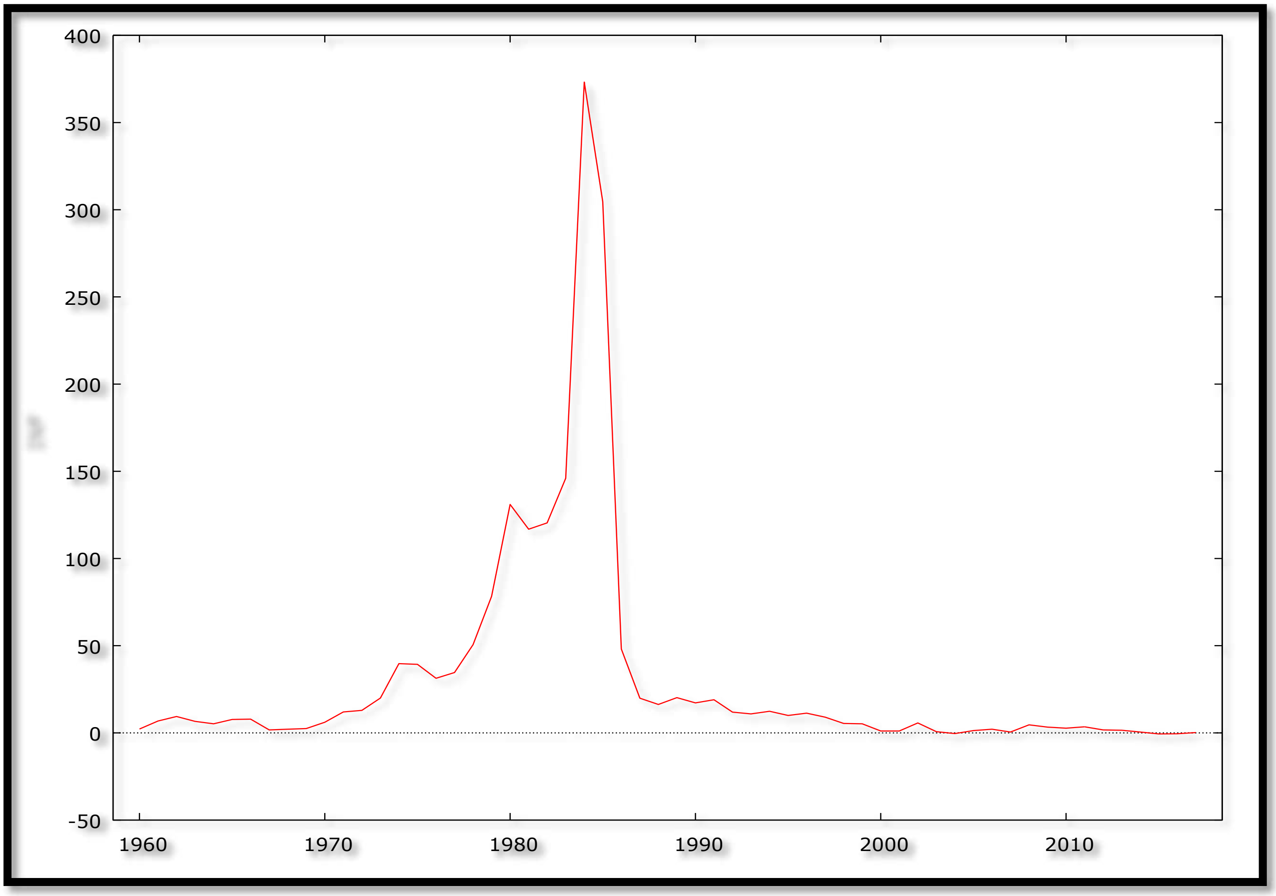
Data Collection

This study is based on a data set of annual rates of inflation in Israel (INF or simply Q) ranging over the period 1960 – 2017. All the data was taken from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Autocorrelation function for INF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF	PACF	Q-stat. [p-value]
1	0.7513 ***	0.7513 ***	34.4631 [0.000]
2	0.4401 ***	-0.2855 **	46.5006 [0.000]
3	0.3444 ***	0.3345 **	54.0035 [0.000]

4 0.3086 ** -0.1135 60.1417 [0.000]

5 0.2286 * 0.0219 63.5717 [0.000]

6 0.1178 -0.1126 64.5009 [0.000]

7 0.0416 0.0151 64.6189 [0.000]

8 -0.0050 -0.0801 64.6207 [0.000]

9 -0.0182 0.0754 64.6442 [0.000]

10 -0.0328 -0.0810 64.7221 [0.000]

11 -0.0733 -0.0143 65.1197 [0.000]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Q	-2.122808	0.2368	-3.555023	@1%	Non-stationary
			-2.915522	@5%	Non-stationary
			-2.595565	@10%	Non-stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Q	-2.234918	0.4613	-4.133838	@1%	Non-stationary
			-3.493692	@5%	Non-stationary
			-3.175693	@10%	Non-stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Q	-1.860278	0.0603	-2.607686	@1%	Non-stationary
			-1.946878	@5%	Non-stationary
			-1.612999	@10%	Non-stationary

Figure 1 and tables 1 – 4 show that Q is non-stationary in levels.

The Correlogram (at 1st Differences)

Autocorrelation function for d_INF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 5

LAG ACF PACF Q-stat. [p-value]

1 0.1283 0.1283 0.9893 [0.320]

2 -0.4387 *** -0.4628 *** 12.7577 [0.002]

3 -0.1228 0.0246 13.6964 [0.003]

4	0.0903	-0.1210	14.2139 [0.007]
5	0.0631	0.0229	14.4716 [0.013]
6	-0.0698	-0.1130	14.7930 [0.022]
7	-0.0620	-0.0101	15.0515 [0.035]
8	-0.0681	-0.1634	15.3694 [0.052]
9	0.0034	0.0050	15.3702 [0.081]
10	0.0526	-0.0702	15.5682 [0.113]
11	0.0058	-0.0069	15.5707 [0.158]

ADF test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Q	-7.856813	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Q	-7.802844	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

Table 8: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Q	-7.931893	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Tables 6 – 8 reveal that Q became stationary after taking first differences.

Evaluation of ARIMA models (without a constant)

Table 9

Model	AIC	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	598.4706	-0.022672	14.921	43.557	88.98
ARIMA (1, 1, 0)	604.8797	-0.029112	14.868	47.078	85.396
ARIMA (0, 1, 1)	601.2218	-0.015571	17.068	45.492	108.61
ARIMA (2, 1, 1)	595.5348	-0.039874	15.483	41.712	100.88
ARIMA (1, 1, 2)	**593.3766**	-0.073434	17.108	40.788	153.04
ARIMA (3, 1, 1)	595.9521	-0.040806	15.428	41.069	105.95
ARIMA (4, 1, 1)	597.7	-0.044401	15.679	40.968	98.411

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). The study will only consider the AIC as the criteria for choosing the best model for predicting inflation in Israel. Hence, the ARIMA (1, 1, 2) model is selected finally.

95% Confidence Ellipse & 95% 95% Marginal Intervals of the ARIMA (1, 1, 2) model

Figure 2 [*AR (1) & MA (1) components*]

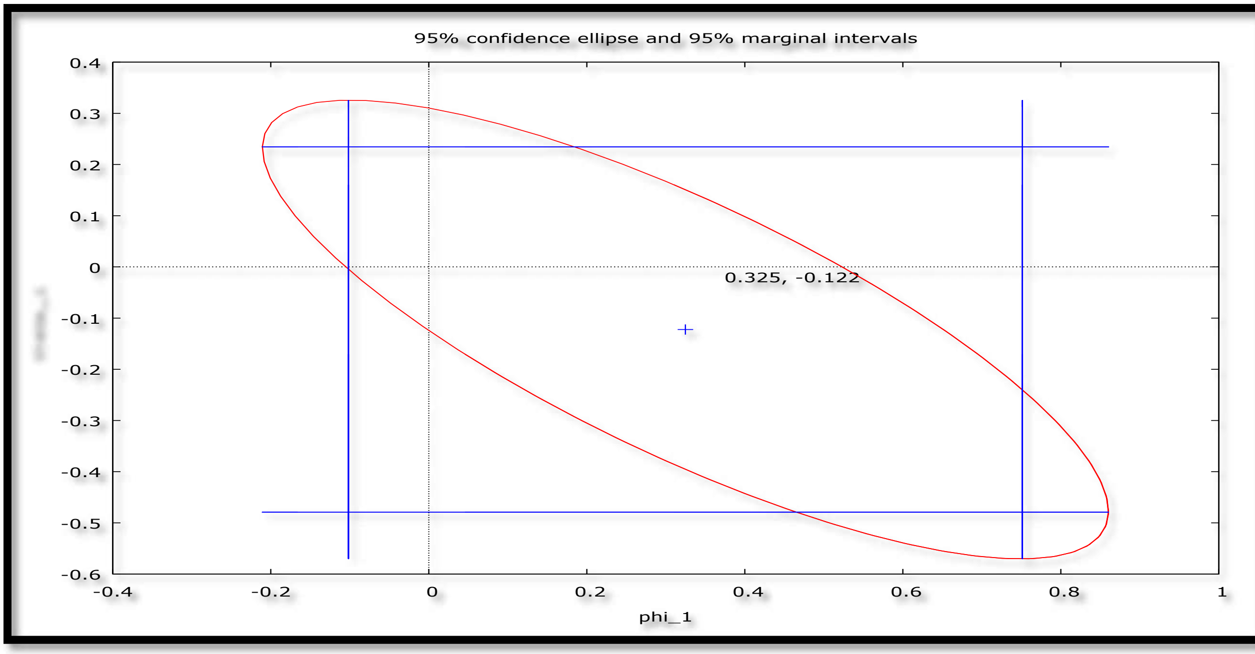


Figure 3 [*AR (1) & MA (2) components*]

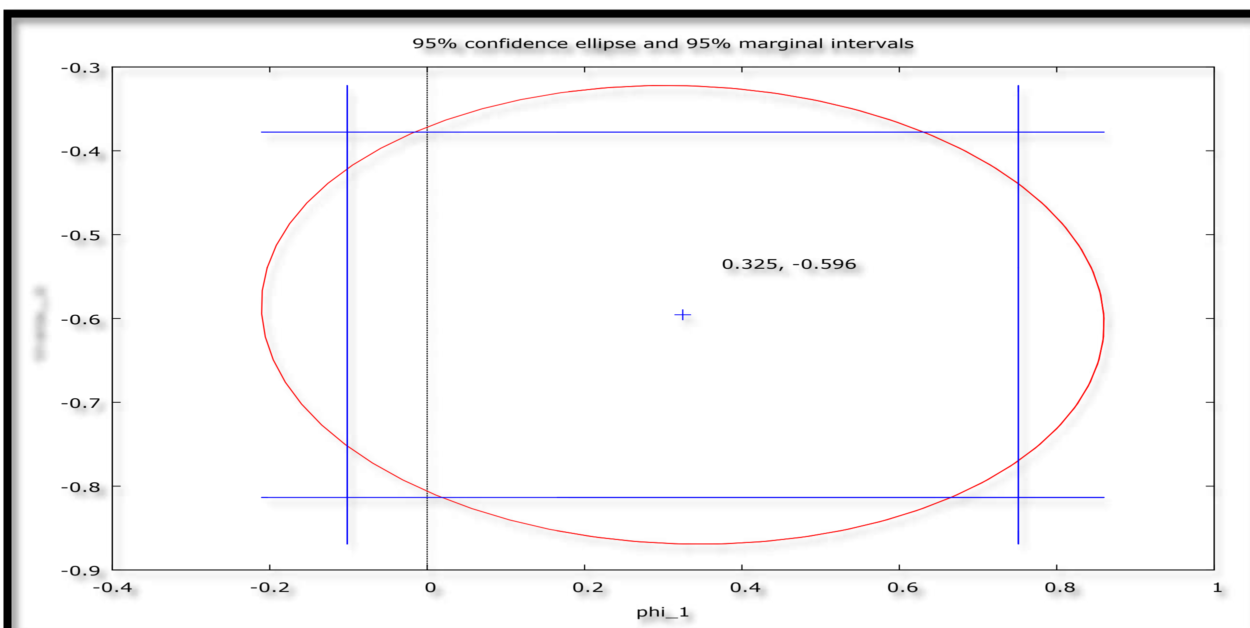
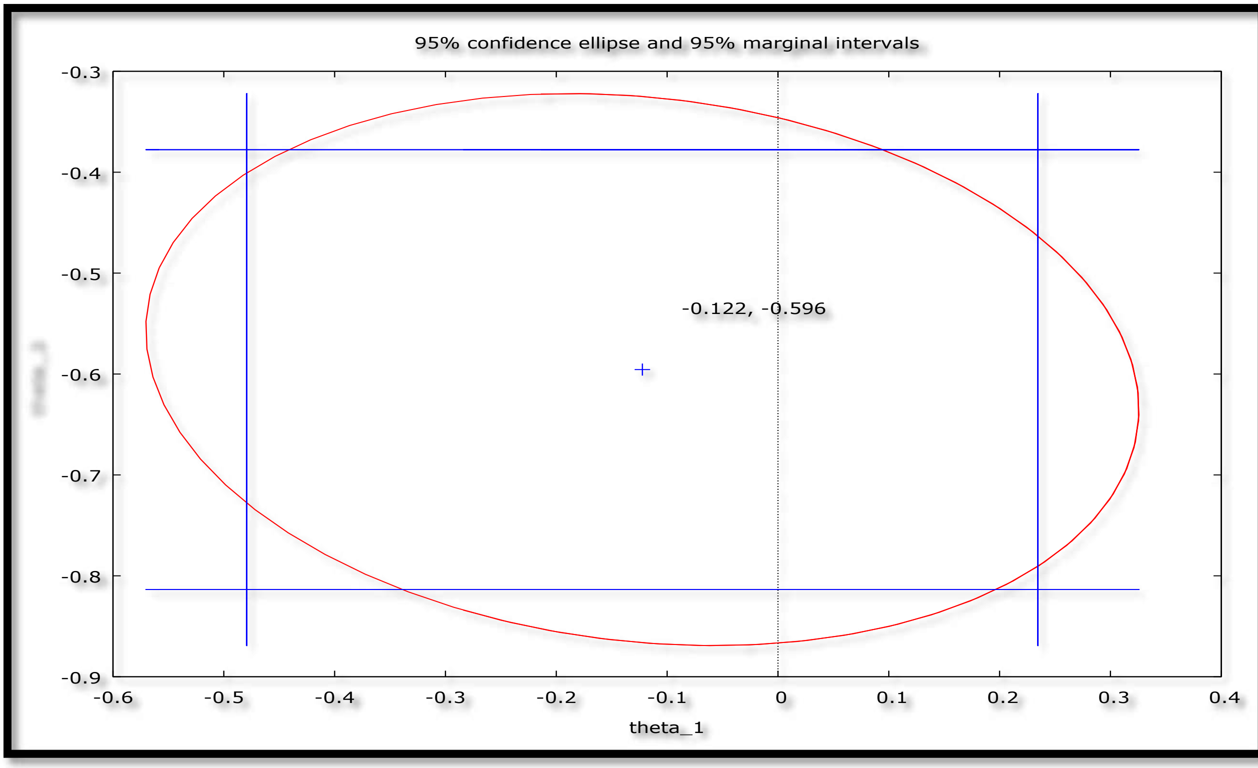


Figure 4 [*MA (1) & MA (2) components*]



Figures 2 – 4 indicate that the accuracy of our forecast is satisfactory since it falls within the 95% confidence interval.

Residual & Stability Tests

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

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.556239	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.658528	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

Table 12: without intercept and trend & intercept

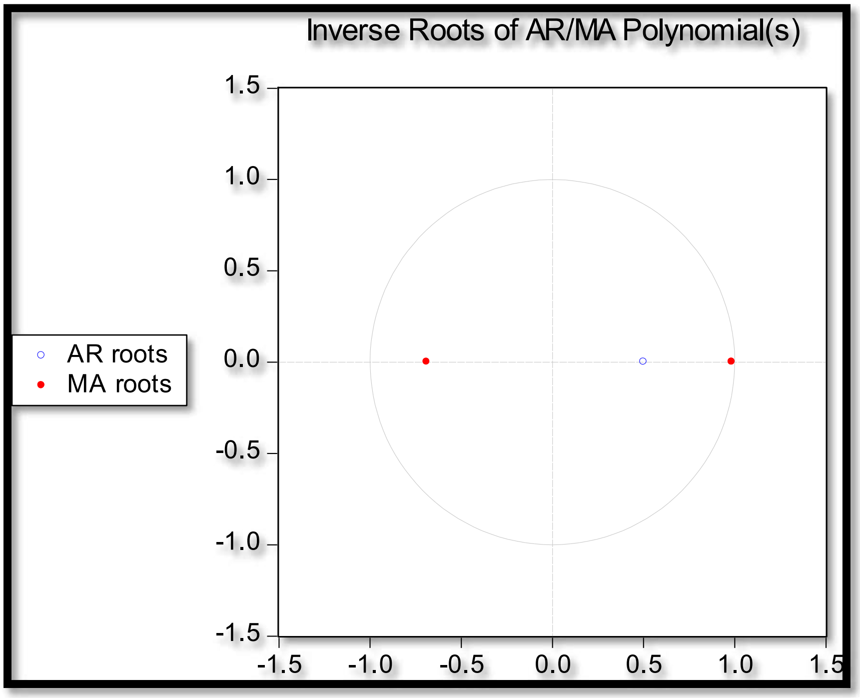
Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.614423	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary

		-1.612999	@10%	Stationary

Tables 10, 11 and 12 show that the residuals of the ARIMA (1, 1, 2) model are stationary and hence the ARIMA (1, 1, 2) model is suitable for forecasting inflation in Israel.

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

Figure 5



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

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	31.288
Median	7.8
Minimum	-0.6
Maximum	373.2
Standard deviation	67.784
Skewness	3.6111
Excess kurtosis	13.626

As shown above, the mean is positive, i.e. 31.288%. The minimum is -0.6% and the maximum is 373.2%. The skewness is 3.611 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis was found to be 13.626; implying that the inflation series is not normally distributed.

Results Presentation[1]

Table 14

ARIMA (1, 1, 2) Model:

$$\Delta Q_{t-1} = 0.324834\Delta Q_{t-1} - 0.122321\mu_{t-1} - 0.59561\mu_{t-2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

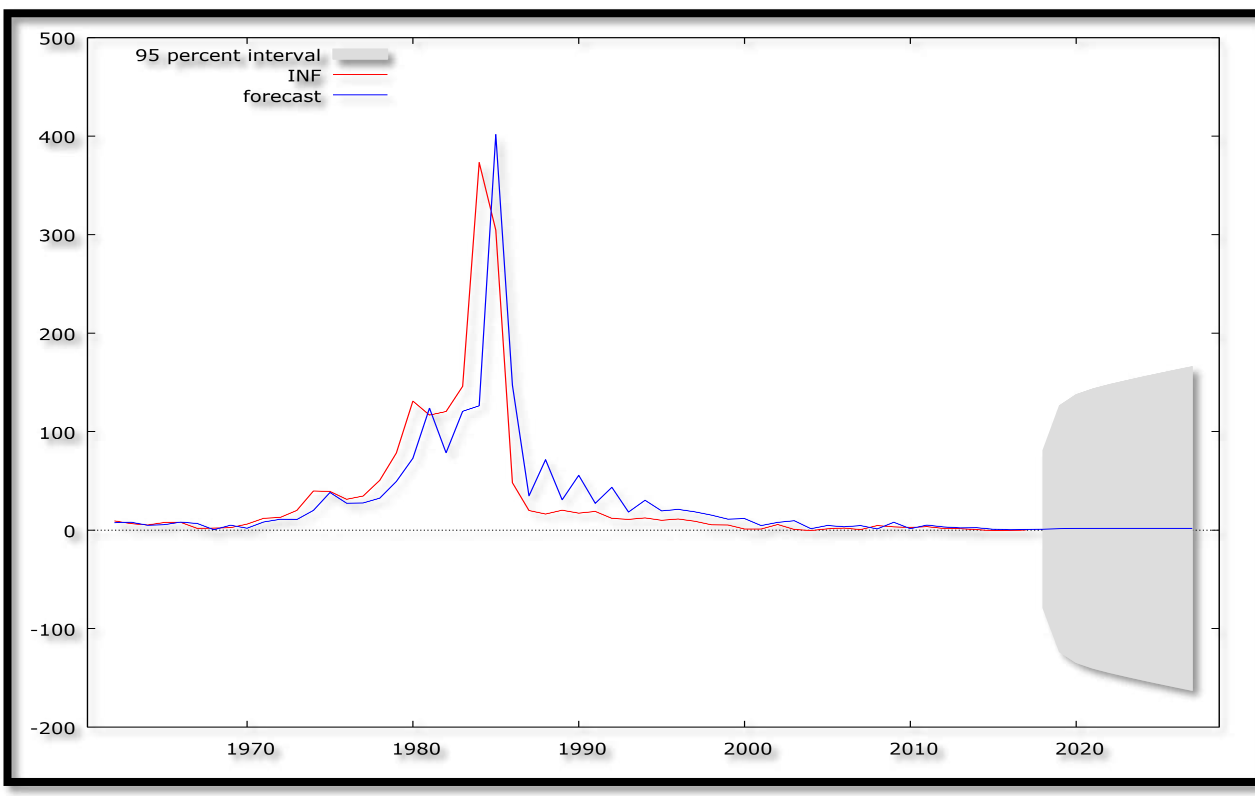
P: (0.1268) (0.492) (0.0000)

S. E: (0.21274) (0.178022) (0.108694)

Variable	Coefficient	Standard Error	z	p-value
AR (1)	0.324834	0.21274	1.527	0.1268
MA (1)	-0.122321	0.178022	-0.6871	0.492
MA (2)	-0.59561	0.108694	-5.48	0.0000***

Forecast Graph

Figure 6



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

Predicted Annual Inflation in Israel

Table 15

Year	Prediction	Std. Error	95% Confidence Interval	
2018	1.0	40.79	-79.0 -	80.9
2019	1.4	63.79	-123.6 -	126.4
2020	1.6	69.44	-134.5 -	137.7
2021	1.6	72.38	-140.2 -	143.5
2022	1.6	74.62	-144.6 -	147.9
2023	1.6	76.62	-148.5 -	151.8
2024	1.6	78.51	-152.3 -	155.5
2025	1.6	80.35	-155.8 -	159.1
2026	1.6	82.14	-159.4 -	162.6
2027	1.6	83.89	-162.8 -	166.1

Figure 6 (with a forecast range from 2018 – 2027) and table 15, clearly show that inflation in Israel is projected to be hovering around 1.6% in the next 10 years. This is clear testimony to the fact that there is price stability in Israel since 1999 and this is indeed predicted to exist over the next decade, ceteris paribus. The current and projected price stability in Israel could be attributed to prudent macroeconomic policy formulation and implementation.

CONCLUSION

The ARIMA model was employed to investigate annual inflation rates in Israel from 1960 to 2017. The study planned to forecast inflation for the upcoming period from 2018 to 2027 and the best fitting model was carefully selected. The ARIMA (1, 1, 2) model is stable and most suitable model to forecast inflation in Israel for the next ten years. Based on the results, policy makers in Israel should continue to engage proper economic policies in order to fight against any inflationary pressures in the economy. In this regard, the Bank of Israel is encouraged to continue being transparent and independent in order to foster macroeconomic policy credibility and maintain confidence in the economy. By so doing, policy makers will be able to engineer and maintain price stability along with sustainable economic growth and development.

REFERENCES

[1] Blanchard, O (2000). Macroeconomics, 2nd Edition, *Prentice Hall*, New York.

[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] Buelens, C (2012). Inflation modeling and the crisis: assessing the impact on the performance of different forecasting models and methods, *European Commission*, Economic Paper No. 451.

[5] Bufman, G & Leiderman, L (1998). Monetary policy and inflation in Israel, in Leiderman L (Ed)., Inflation and Disinflation, *The Bank of Israel*, 187 – 239.

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

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

[8] Cukierman, A & Melnick, R (2015). The quest for Israel inflation and current policy dilemmas, *CEPR*, Discussion Paper Series No. 10955.

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

[10] Fenira, M (2014). Democracy: a determinant factor in reducing inflation, *International Journal of Economics and Financial Issues*, 4 (2): 363 – 375.

[11] Hector, A & Valle, S (2002). Inflation forecasts with ARIMA and Vector Autoregressive models in Guatemala, *Economic Research Department*, Banco de Guatemala.

[12] Helpman, E (2003). Israel's growth: An international comparison, The Economic Quarterly, 46: 7 – 17.

[13] 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.

[14] Kazinnik, S (2017). Essays on monetary policy in Israel, PhD Thesis, *Department of Economics*, University of Houston.

[15] 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.

[16] King, M (2005). Monetary Policy: Practice Ahead of Theory, *Bank of England*.

[17] 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.

[18] Leiderman, L & Bar-Or, H (2000). Monetary policy rules and transmission mechanisms under inflationary targeting in Israel, *Bank of Israel*, Discussion Paper No. 1

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

[20] 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.

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

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

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

[24] OECD (2018). OECD Economic Surveys – Israel, *OECD*, Economic & Development Review Committee.

[25] 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.

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