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MODELLING INFLATION WITH RANDOM WALK MODELS: SHORT AND LONG HORIZONS

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Abstract: This study is aimed at modelling and forecasting inflation at shorter and longer horizons using random walk models and therefore evaluate the forecast capability of random walk models at shorter and longer horizons. Taking into account seasonality of data, the author estimated the SARIMA models and found that indeed random walk models have strong ability in forecasting financial variables at shorter than longer time horizons. The study also established that previous values of the inflation and the error terms contain information that is necessary for predicting the future values of inflation.

Keywords: Random walk models, ARIMA, SARIMA models, Inflation

I. Introduction

The finding of Meese and Rogof (1983) in their empirical study showed that a number of structural models could not outperform ARIMA models in forecasting exchange rate brought an empirical question on economic fundamentals in explaining financial variables. As Hilde and Havard (2003) site, the empirical finding by Meese and Rogof (1983) led to a number of researchers such as MacDonald and Taylor (1994), Chrystal and MacDonald (1995), Kim and Mo (1995), Reinton and Ogena (1999) and others to compare many monetary models with random walk models like ARIMA models. However, their finding showed that ARIMA models have strong predictive ability in forecasting financial variables at shorter horizons but are quiet poor at longer horizons. Their findings also showed that structural models are quiet good at forecasting financial variables at longer horizons than shorter horizons.

The major objective of this study is to test the forecast ability of ARIMA models at shorter and longer horizons and empirically test whether inflation modelling with ARIMA models can produce good forecast at shorter horizons than at longer horizons. Other than comparing forecast ability at shorter and longer horizons, the study will also forecast inflation in the Zambian context. In addition, because of use of monthly data which exhibits seasonality features, the study extends ARIMA models to seasonal ARIMA models.

II. Literature

A number of authors consider ARIMA models to be good in forecasting financial variables at shorter time horizons while structural models are said to have good forecast ability at longer horizons. This section therefore, presents literature on empirical findings on ARIMA models in comparisons with other structural models.

Macco and Daniel (2013) carried out a study in which they used ARIMA model to forecast inflation for Swiss National Bank. Their findings indicated that ARIMA models are quiet accurate in forecasting inflation and that ARIMA models actually out-performed other models. Mark (1995) on the other hand investigated exchange rate movement in US dollar against the four major currencies for the period of eighteen years. He compared random walk models (ARIMA model) and structural model in the quest to determine which models would do better at different time horizons. His findings showed that exchange rate models based on random walk had good forecast ability at shorter horizons while exchange rate models based on economic fundamentals forecasted better at longer horizons. Like Mark (1995), Meese and Chin (1995) did a study in which they were investigating exchange rate movement of US dollar against other major currencies for the period of 17 years using parametric models and non-parametric models. Their findings also indicated that random walk models performed better than structural models for shorter horizons. However, at longer horizons beyond 36 months, their results showed that structural models did far much better than random walk models.

Meyler and Kenny (1998) conducted a study in which they compared ARIMA models and Bayesian autoregressive model (BVAR) in forecasting Irish inflation. Their findings were that for the sample period 1993Q1 to 1998Q4, the ARIMA models and the BVAR compared relatively well although they cautioned that the reason why ARIMA models and BVARs compared relatively well in their study could be due to the fact the time period under consideration was characterised by stable inflation hence reason for good performance of the ARIMA model. They pointed out that ARIMA models are backward looking and are quiet poor in forecasting

data that has turning points. Golderg and Frydman (1996) conducted a study in which the dual were forecasting Gernam Mark against the US dollar for 15 years using ARIMA models which they compared with structural models. Their findings showed that random walk models outperformed the structural models.

Qizhi & Hong & Zhongwen (2012) investigated inflation forecasting were they compared performance of ARIMA models with other models like ARIMA-GARCH, ARIMA, Artificial Neural Networks (ANN) and exponential smoothing and other models. They discovered that the best model in order of ranking were ARIMA-GARCH, ARIMA, ANN and exponential smoothing. In forecasting and modelling inflation in Pakistan, Bokhari and Feridun (2006) compared ARIMA and VAR models. Of the ARIMA models that were estimated, they picked ARIMA (2,1,2) as the best ARIMA model and compared it with the VAR model. They found that the VAR model could not outperform the ARIMA (2,1,2).

III. Methodology

A. Data

Monthly inflation data denoted as inf that was used in this study was obtained from Bank of Zambia (BOZ).

B. Seasonal ARIMA model

The generic autoregressive integrated moving average (ARIMA) model that was introduced by Box and Jenkins (1976) has characteristics of both autoregressive model of order p denoted as AR(p) and moving average of order q denoted as MA(q) but also includes differencing in the model. The ARIMA model is therefore, written as ARIMA (p,d,q) where p is the autoregressive order and d is the number of times the series ought to be differenced to make them stationary while q is the order of the moving average. The ARIMA (p,d,q) can be represented as follows;

$$\Delta Y_t = \mu + \sum_{i=1}^p \theta_i \Delta Y_{t-i} + \sum_{i=1}^q \gamma_i \varepsilon_{t-i} + \varepsilon_t \quad (1)$$

Where Δ is the difference operator

Y_t = series of Y

ΔY_{t-i} = lagged series of Y

ε_t = is the white noise error term

ε_{t-i} = the lagged values of the error term

Monthly data series in certain variables may have seasonal components. If that is the case, then seasonality in data must be accounted for by adding seasonal structure to ARIMA model. It should be noted that seasonal ARIMA (SARIMA) model could be multiplicative and thus would be expressed as ARIMA (p,d,q) X (P,D,Q)_s. Where P means that there are P number of autoregressive seasonal terms and D is the number of times of seasonal differencing and Q entails that there are Q number of moving average seasonal terms and s denotes time in which seasonal pattern is observed. For instance if a researcher is working with monthly data, s could be 12 and if the researcher is dealing with quarterly data, s could be 4. Mathematically ARIMA (p,d,q) X (P,D,Q) can be expressed as follows;

$$\Delta Y_t = \mu + \sum_{i=1}^p \theta_i \Delta Y_{t-i} + \sum_{i=1}^p \theta_{12,i} \Delta Y_{t-i} + \sum_{i=1}^p \theta_i \theta_{13,i} \Delta Y_{t-i} + \sum_{i=1}^q \gamma_i \varepsilon_{t-i} + \sum_{i=1}^q \gamma_{12,i} \varepsilon_{t-i} + \sum_{i=1}^q \gamma_i \gamma_{13,i} \varepsilon_{t-i} + \varepsilon_t \quad (2)$$

Where;

$\sum_{i=1}^p \theta_{12,i} \Delta Y_{t-i}$ = Seasonal component of AR at month twelve

$\sum_{i=1}^q \gamma_{12,i} \varepsilon_{t-i}$ = Seasonal component of MA (q) at month twelve

$\sum_{i=1}^p \theta_i \theta_{13,i} \Delta Y_{t-i}$ = multiplicative component of seasonal AR(p)

$\sum_{i=1}^q \gamma_i \gamma_{13,i} \varepsilon_{t-i}$ = multiplicative component of seasonal structure MA (q)

It is also possible to have an additive seasonal ARIMA also called additive SARIMA model other than the multiplicative one where the lagged terms of AR(p) and MA(q) do not interact with their respective seasonal terms. In that case the multiplicative components will fall out and then equation (2) is reduced to the following equation;

$$\Delta Y_t = \mu + \sum_{i=1}^p \theta_i \Delta Y_{t-i} + \sum_{i=1}^p \theta_{12,i} \Delta Y_{t-i} + \sum_{i=1}^q \gamma_i \varepsilon_{t-i} + \sum_{i=1}^q \gamma_{12,i} \varepsilon_{t-i} + \varepsilon_t \quad (3)$$

C. Building ARIMA Model

Building ARIMA model involves three steps according to Box and Jenkins (1994) namely, identification of ARIMA model, estimation of parameters and diagnostic checking of the model.

D. Identification of ARIMA and Analysis

To identify ARIMA model, ACF and PACF functions are used to identify MA(q) and AR(p) respectively (Box and Jenkins, 1994). In addition, to identify seasonal pattern of data, the ACF and PACF are again used. Box, Jenkins and Reinsel (1994) suggest that if data does exhibit seasonal patterns, it could be better to start with multiplicative SARIMA model and if data does not fit the multiplicative SARIMA well then one can proceed to fit data with additive SARIMA model. Chatfield (2004) on the other end recommend that taking log of the series can make the seasonal effect additive and therefore, a researcher can now use additive SARIMA to fit data.

What is suggested in literature is that a researcher should try additive and multiplicative SARIMA models for analysis and see which one fit data well (STATA CORP LP, 2011).

In this study both multiplicative and additive SARIMA were fitted but the multiplicative SARIMA models produced better results and the results are in table 2.

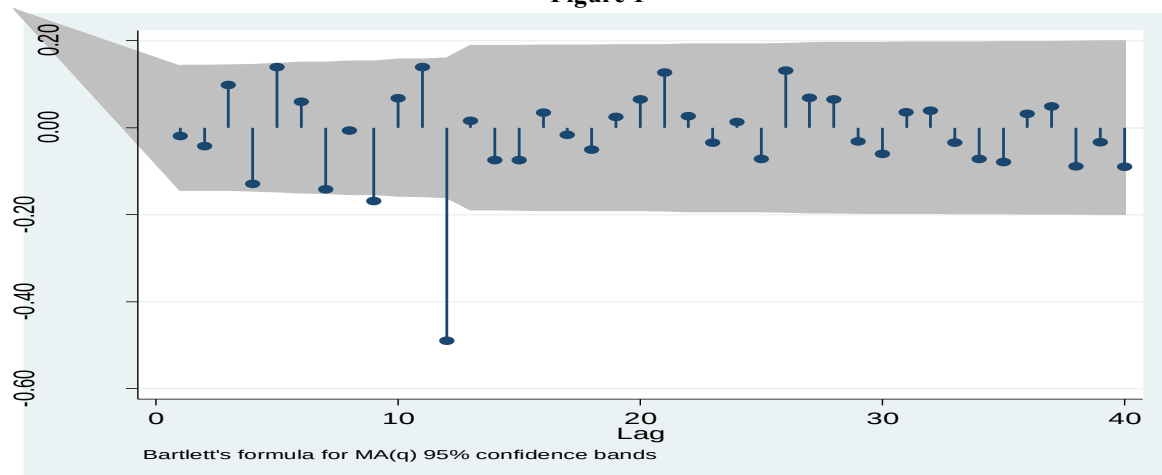
In analysis, the author, started by testing for unit root to establish the order of integration. The results are tabulated in table1. What is observed in table 1 is that inflation is non stationary in levels because the ADF statistic is less negative than the critical value at all levels of significance (1%, 5% and 10%). However, in first difference inflation is stationary because the ADF statistics is more negative than the critical values at all levels of significance. The unit root test results therefore, indicate that the ARMA model is integrated of order one

Table 1: Augmented Dick Fuller Test For Unit Root Test

Variable	Levels	Differenced		Order of Integration	
	ADF-Statistics	Critical Values 1%, 5% & 10 %	ADF-Statistics	Critical Values 1%, 5% & 10 %	
inf	-1.051469	-3.467851 -2.877919 -2.575581	-6.798373	-3.467851 -2.877919 -2.575581	I(1)

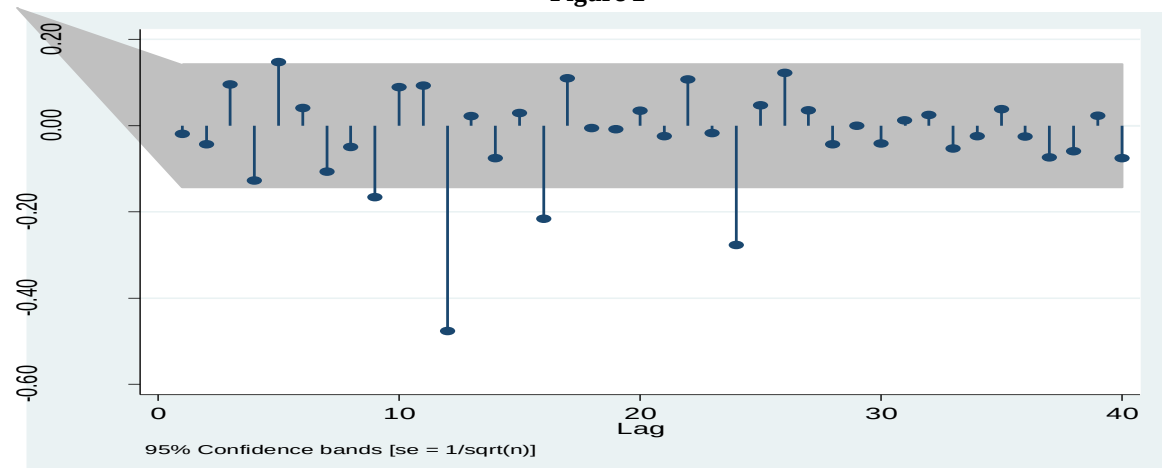
To determine the order of the ARIMA models to be estimated, the study made use of the ACF and ACF graphs in order to have picture of the order of MA(q) and AR (p) respectively. Below are the graphs for both ACF and PACF.

Figure 1



An examination of the ACF graphs in figure 1 shows that the MA is of order one since there is only one significant spike. However, since the significant spike occurs at lag 12, this is indicative of the presence of seasonality. Thus, there could be one seasonal moving average (SMA(1)) at lag twelve. The graph for PACF in figure 2 shows that data may exhibit AR(1) process, but also the significant spike occurs at lag 12 and therefore, the author had reason to suspect the presence of seasonal autoregressive term, SAR(1). However, selection criterion must be applied to the data to correctly select the best models for forecasting.

Figure 2



It should also be mentioned here that, usually estimating ARIMA with either SAR (1) or SMA (1) should be able to capture seasonality in data. Therefore, the author, estimated a number of SARIMA models and using information criterion, the best model was picked. Table 2 below presents results for different SARIMA models.

As table 2 indicates; of all the five seasonal ARIMA models that were estimated, ARIMA (0,1,1) X SMA(1)₁₂ has the lowest values of information criterion followed by ARIMA (1,1,1) X SMA(1)₁₂. Hence these two models were picked for further analysis. Actually, what is observed is that all the variables are significant for both models.

ARIMA (1,1,1) SMA(1)₁₂, by interpretation means that the model has one integrated non-seasonal autoregressive term, one non-seasonal moving average term and one seasonal multiplicative moving average term. Further, all the integrated non-seasonal autoregressive term, the non-seasonal moving average term and the multiplicative seasonal moving average terms are significant and this implies that previous values of inflation and the error terms contain vital information that could be used to predict the future values of inflation taking into account seasonality. On the other hand ARIMA (0,1,1) X SMA(1)₁₂ has an ARIMA with only one non-seasonal moving average term with a multiplicative seasonal moving average term. Both the non-seasonal moving average and the seasonal moving average are significant. This entails that in this model, future values of inflation can be predicted by only the previous values of the error terms of course accounting for seasonality. This means that the errors in the inflation equation contain important information that is important for forecasting future values of inflation.

Table 2: Results for Seasonal ARIMA Models

	ARIMA (1,1,1) X SAR(1) ₁₂	ARIMA (1,1,1) X SARIMA(1) ₁₂	ARIMA (1,1,1)X SMA(1) ₁₂	ARIMA (0,1,1) X SMA(1) ₁₂	ARIMA (1,1,0) X SAR(1) ₁₂
Constant	-0.109677***	-0.105482***	-0.106885***	-0.103563***	-0.102635
AR(1)	-0.886280*	0.189735	-0.729274***		0.060706
AR(2)					
MA(1)	0.994932*	-0.076040	0.863249***	0.153281***	
SAR (1) ₁₂	-0.477134*	0.094205			-0.494202***
SMA(1) ₁₂		-0.942018***	-0.932460***	-0.940044***	
AIC	3.252205	3.075599	3.069059	3.068442	3.290956
SIC	3.324827	3.166376	3.13843	3.120277	3.345422
HQIC	3.281665	3.112424	3.097171	3.089445	3.313051

*** Coefficient is significant at 1%, 5% & 10%
 ** Coefficient is significant at 5% & 10%
 * Coefficient is significant at 10%

Table 3 below shows results for forecasting the two models. As can be observed in table 3, ARIMA (0,1,1)x(SMA(1)₁₂) is the best model for forecasting because all the forecast statistics; Root Means Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil Inequality Coefficient (TIC) error are lower than those of ARIMA (1,1,1) x SMA(1)₁₂. Therefore, ARIMA (0,1,1) x SMA(1)₁₂ fit data and forecast very well as compared to the other model. Actually ARIMA (0,1,1) x SMA(1)₁₂ has the lowest values of information criterion than all the seasonal ARIMA models estimated in this study. Therefore, the finding that ARIMA (0,1,1) x SMA(1)₁₂ is the best model should not come as a surprise.

Table 3: Forecast Statistics for Seasonal ARIMA Models For 18 months Step Ahead

Forecast statistics	Seasonal ARIMA Model	
	ARIMA (1,1,1) SMA(1) ₁₂	ARIMA (0,1,1) X SMA(1) ₁₂
RMSE	2.609442	2.321305
MAE	2.515944	2.228328
MAPE	34.29903	30.45505
TIC	0.213983	0.185941

In trying to compare forecast ability of SARIMA models at different time horizons, 18 and 12 and 3 months step ahead forecast were computed and compared and the results are presented in table 4 below

Table 4: Forecast Statistics for Seasonal ARIMA Models For 18,12 & 3 months Step Ahead

Forecast Statistics	Seasonal ARIMA Model					
	ARIMA (1,1,1) SMA(1) ₁₂			ARIMA (0,1,1) X SMA(1) ₁₂		
	18 months step ahead forecast	12 months step ahead forecast	3 months step ahead forecast	18 months step ahead forecast	12 months step ahead forecast	3 months step ahead forecast
RMSE	2.609442	1.366341	1.085202	2.321305	1.224622	0.986774
MAE	2.515944	1.069495	0.989725	2.228328	1.013446	0.905312
MAPE	34.29903	13.8491	12.39205	30.45505	13.22602	11.33740
TIC	0.213983	0.092651	0.072563	0.185941	0.081538	0.065624

What is being observed in table 4 is that the seasonal ARIMA models under comparison, forecast better for a period of 3 months than at 12 and 18 months step ahead forecast. What one observes in table 4, is that the forecast statistics are decreasing for each model as one moves from 18 to 12 and to 3 months step forecast. This finding is consistent with the findings of other researchers like Meese and Rogof (1998), and Chinn and Meese (1995) and (Fandamu et al; 2015) who also found that ARIMA models have good forecast ability at shorter horizons than longer horizons. Another thing that is observed in table 4 is that ARIMA(0,1,1) x SMA(1)₁₂ which

is the best model in this study forecast better than ARIMA (1,1,1) x SMA(1)₁₂ for all forecast periods because the forecast statistics are lower for the former than the later.

IV. Diagnostic checks for the models

Box and Jenkins (1994) proposed test for serial correlation for diagnostic purposes. Therefore, Breush Godfrey test for both models was performed. The test for both models indicate that both models do not have serial correlation since probability of the Chi-square statistics are higher than 1% which implies that the null hypothesis of no serial correlation in the residuals cannot be rejected as table 5 indicates.

Table 5: Breusch Godfrey LM test for serial correlation in residuals

Model	Chi-square statistics	probability
ARIMA (0,1,1) x SMA(1) ₁₂	0.0000	1.0000
ARIMA (1,1,1) x SMA(1) ₁₂	0.248666	0.8673

V. Conclusion

The major objective of the paper was to model inflation with random walk models and also to assess the forecast ability of random walk models both at longer and shorter horizons. Since the data used was monthly data, the author used both ACF and PACF to check not only for the order of AR and MA but also the seasonal structure of data. The findings showed that the data generating process had AR of order one, MA of order one and seasonal components and thus based on this finding, the author estimated five seasonal ARIMA models and picked the best two seasonal ARIMA models namely ARIMA (1,1,1) x SMA(1)₁₂ and ARIMA(0,1,10 x SMA(1)₁₂ because these two models had the lowest values of information criterion. The two seasonal ARIMA models which were compared showed that past values of inflation and error terms indeed contain information needed to predict the future values of inflation. The author also forecasted inflation using the two models so as to compare them and pick the best. Out of the two models, seasonal ARIMA(0,1,1) x SMA(1)₁₂ had the lowest values of forecast statistics namely RMSE, MAE, MAPE and TIC. Thus the model for forecasting was chosen as ARIMA(0,1,1) x SMA(1)₁₂ based on forecast error statistics.

Furthermore, the author wanted to evaluate the forecast capabilities of seasonal ARIMA models both at longer and shorter horizons. For this reason, the author compared the forecast ability of the two seasonal ARIMA models at 18, 12 and 3 months. The findings of the author is that random walk models (seasonal ARIMA model in this case) have stronger forecast ability at shorter horizons (3 months) than longer horizons (12 and 18 months).

VI. References

- [1] Bokari, S.M.H & Feridun.M (2006), "Forecasting, inflation through econometric models: an empirical study on Pakistan data," Dogus University Dergis, 7(1), 2006, pp. 39-47.
- [2] Box, G.E & Jenkins & Reinsel, G (1994), "Time series analysis: Forecasting and Control," third edition, Englewood Cliffs, Prentice Hall.
- [3] Chatfield, C (2004), "The Analysis of Time series: An introduction sixth edition, Boca Raton," FL: Chapman and Hall/CRC
- [4] Chinn & Meese (1995), "Banking on currency forecast: how predictable is the change in money," Journal of International Economics, 38, pp. 161-178.
- [5] Fandamu, H. & Fandamu, M. & Phiri, W, (2015), "Forecasting exchange rate with ARIMA model," unpublished paper.
- [6] Hilde, C.B & Havard, B (2003), "The importance of interest rates in Forecasting Exchange rate," Disucssion Paper 340, Statistics Norway, Research Department.
- [7] Kim, B.J.C & Mo, S (1995), "Cointegration and the long run forecast of exchange rates, Economics-Letters," 48, pp. 352-359.
- [8] MacDonald, R. & Taylor, M.P (1995), "The monetary model of the exchange rate; long run relationship, short run dynamics & how to beat a random walk," Journal of international money & finance, 13, pp. 276-290.
- [9] Macco, H and Daniel, K (2013), "Combining disaggregate forecasts for inflation: The SNB's ARIMA model," Swiss National Bank (SNB), available at www.snb.ch
- [10] Meese, R and Rogoff, K (1983), "The out of sample failure of Empirical Exchange rate: sampling error or misspecification?" University of Chikago press.
- [11] Meyler, A and Kenny, g (1999), "Forecasting Irish inflation using ARIMA," Article; 1999, @ www.researchgate.net/publication/23543270.
- [12] Qizhi, H, Hong, S & Zhongwen, T (2012), "Investigation of inflation forecasting, Journal of applied mathematics and information sciences," 6, (3), pp. 649-655.
- [13] Reinton . H & Ongena.S (1994), "Out of sample forecasting performance of single equation monetary exchange rate models in Norwegian currency markets," Applied financial econometrics, 9, pp. 545-550.
- [14] Rogoff .K. (1996), "The purchasing Power Parity Puzzle," Journal of economic literature, 34,647-668.
- [15] Stata Corporation LP (2011), "Stata Time series reference Manual Release," Stata Press, Texas, USA.