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Modeling Consumer Price Index in Zambia: A Comparative Study between Multicointegration and Arima Approach

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Abstract

Consumer Price Index (CPI) is an important indicator used to determine inflation. The main objective of this research was to compare the forecasting ability of two time-series models using Zambia Monthly Consumer Price Index. We used monthly CPI data which were collected from January 2003 to December 2017. The models that were compared are the Autoregressive Integrated Moving average (ARIMA) model and Multicointegration (ECM) model. Results show that the ECM was the best fit model of CPI in Zambia since it showed smallest errors measures. Lastly, a forecast was done using the ECM and results show an average growth rate for food CPI at 6.63% and an average growth rate for nonfood CPI at 7.41%. Forecasting CPI is an important factor for any economy because it is essential in economic planning for the future. Hence, identifying a more accurate forecasting model is a major contribution to the development of Zambia.

Keywords

Consumer Price Index, Multicointegration, ARIMA, ECM, Forecast

1. Introduction

Rising prices affect everyone in terms of purchasing power especially if wages remain constant. This lowers the living standards. Generally, it is difficult to detect change in price levels across product in the absence of a systematic approach. The consumer price measures the weighted average of prices of a basket of goods and services, which include fuel, transport, food and medical care purchased by households. CPI identifies price changes across product categories relevant to the consumer. According to [1], CPI is a weighted aggregate index that is computed and published monthly. The CPI may not adequately explain actual movements in the costs of living according to [2]. This may be as a result of some biases which may include inaccurate data. Thus, the Engel curve method introduced by [3] addresses the above bias.

In Zambia, the consumer price index is recorded monthly by the Central Statistics Office (CSO). In order to come up with the monthly CPI, products that are essential to human needs such as fuel, food, medical services and so on are categorized in two major categories as; foods which are edible products needed to sustain humans and nonfood products such as fuel, education and so on. The two groups are further used to calculate the monthly CPI as an average.

Forecasts of CPI are important because they affect many economic decisions. Without knowing future CPI rates, future inflation rates cannot be estimated which would make it difficult for lenders to price loans, which in turn have a negative impact on the economy. Investors require good inflation forecasts, since the returns to stocks and bonds depend totally on what happens to inflation. Businesses need inflation forecasts to price their goods and services as well as plan production. Modelling inflation is important from the point of view of poverty alleviation and social justice [4].

2. Literature Review

The study by [5] stated that the CPI is one of the main indicators of economic performance and also the key indicator of the results of the monetary policy of the country, because of its wide use as a measure of inflation. The ARIMA (4, 1, 6) was selected as a potential model which fits the data as well as for accurate forecasting. Hence, the forecast was made for 12 months ahead of the year 2016, and the findings showed that the CPI was likely to continue rising up with time.

A research by [6] also further described CPI as a measure of changes in the general level of prices of a group of commodities. The best model was found to be the ARIMA (1, 1, 0) compare to ARIMA (0, 1, 1), and ARIMA (1, 1, 1).

The study by [7] relates between CPI and oil prices in Turkey using the Error Correction Model (ECM). Their study revealed that a 1% increase in fuel prices caused the CPI to rise by 1.26% with an approximate one-year lag.

According to [8], cointegration was actually present in the long run equilibrium relationship of different time series which is a key basic thought and theory in the current econometric field and also an important theoretical cornerstone in current researches on combination forecasting launched by time series.

The paper by [9] modelled inflation using a structural cointegration approach. This paper used cointegration and error-correction models to analyze the relative impact of the monetary, labor and external sectors on Polish inflation from 1990 to 1999. Results showed that the labor and external sectors dominated the determination of Polish inflation during the above period, but their effects have been opposite since 1994. The monetary sector appears not to have exerted influence on inflation, suggesting monetary policy has been passive.

3. Methodology

To carry out this study, monthly food and nonfood CPI collected from January 2003 to December 2017 was used. We used the monthly CPI (which is the average of the food and nonfood CPI) for the ARIMA model while food and nonfood CPI for Multicointegration to develop the error correction model. Statistical software package R (version 0.99.903) was used in obtaining results.

1) Variable Definition

We let, Monthly CPI be denoted by U_t, Food be denoted by X_t and Nonfood be denoted by Y_t.

2) Relationship among the Variables

$$U_t = \frac{X_t + Y_t}{2} \quad (1)$$

3) ARIMA (Box and Jenkins) Model

George Box and Jenkins developed a practical approach to build ARIMA model. The Box-Jenkins methodology uses a three-step approach of model identification, parameter estimation and diagnostic checking to determine the best model from a general class of ARIMA model. ARIMA model is used to fit historical time series expressed in terms of past values of itself plus current and lagged values of error term. Once the series is confirmed to be stationary, one may proceed by tentatively choosing the appropriate order of models through visual inspection of plots, both the Autocorrelation Function (ACF) and Partial Autocorrelation Functions (PACF). The relevant properties are set out as follows: The series show an AR (*p*) process, if the ACF decays exponentially (either direct or oscillatory) and PACF cut off after lag *p*. The series show a MA (*q*) process, if the PACF decays exponentially (either direct or oscillatory) and ACF cut off after lag *q*. The series show an ARMA (*p*, *q*) process, if the PACF decays exponentially (either direct or oscillatory) and ACF decays exponentially (either direct or oscillatory).

The MA, AR and ARMA are defined as follows:

$$\text{AR model: } Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t, \quad (2)$$

$$\text{MA model: } Y_t = \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \quad (3)$$

The combination of AR and MA gives

$$\text{ARMA model: } Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (4)$$

where ϕ_t is the autoregressive parameter at time *t*, ε_t is the error term at time *t* and θ_t is the moving-average parameter at time *t*.

In order to build our tentative model, we will follow the three highlighted steps which are: **Model Identification**, **Parameter Estimation** and **Diagnostic Checking**.

4) Multicointegration Model

According to [10], Cointegration, occurs if two non-stationary variables X_t and Y_t are combined into a unique linear relationship. Under Multicointegration we will consider two variables food and nonfood to model the consumer price index level. Therefore, let X_t denote the food variable at time *t* and let Y_t denote the nonfood variable at time *t* to fit a short run and long run dynamic relationship and estimate an error correction model (ECM).

In order to build the tentative model, we will follow the two highlighted steps which are:

Step 1, **Unit root test**

To test for unit root for each variable (X_t) and (Y_t), we used the Augmented Dickey-Fuller test (ADF) based on the hypothesis that

H_0: *the series has a unit root*

H_1: *the series has no unit root.*

Step 2, **Two-step method**

This is based on the idea that cointegration between X_t and Y_t is tested using standard cointegration techniques before testing for multicointegration. We test for a cointegrating relationship between (X_t) and (Y_t) using a proposed cointegrating regression of

$$X_t = \alpha_0 + \alpha_1 Y_t + z_t \tag{5}$$

where X_t is food in time *t*, Y_t is nonfood in time *t*, α_0, α_1 are parameters and z_t is the residual. If z_t is stationary then a cointegraion relationship exists between X_t and Y_t.

5) Error Correction Models (ECM)

Following the two step method above, we estimate the error correction model for X_t and Y_t. The ECM model is given by

$$\Delta U_t = \alpha_3 + \beta_1 z_{t-1} + \beta_2 \varepsilon_{t-1} + \mu_1 \Delta Y_t + \text{lagged}\left(\Delta X_t, \Delta Y_t\right) + \text{residual} \tag{6}$$

where z_{t-1} is the residual from the first cointegrating relationship between X_{t-1} and Y_{t-1}, α_3, β_1, β_2, μ_1 are parameters, ε_{t-1} is the residual from the cointegrating relationship between CPI (U_t) and Y_t. $\Delta X_t = X_t - X_{t-1}$, and $\Delta Y_t = Y_t - Y_{t-1}$ are lagged values.

4. Results

Table 1 shows the summary statistics of the variables Food, Nonfood and monthly CPI. For food CPI, the minimum CPI was 48.4 with a maximum of 197.8.

Then 25% of the data was less or equal to 74.53 while 50% of the data was less of equal 106.2 and 75% of the data was less or equal to 134.32. On average, the food CPI was 109.64 with a standard deviation of 41.93263.

Table 1. Summary statistics.

Data/summary	Min	1st Qu	Median	3rd Qu	Mean	Std. dev	Max
Food	48.4	74.53	106.2	134.32	109.64	41.93263	197.8
Non-food	38.6	72.58	110.25	144.22	111.72	46.34205	205.1
Monthly CPI	44.2	72.47	108.2	138.93	110.53	43.98698	201.2

For non-food CPI, the minimum was 38.6 with a maximum of 205.1. Then 25% of the data were less or equal to 72.58 while 50% of the data was less or equal to 110.25 and 75% of the data was less or equal to 144.22. On average the non-food CPI was 111.72 with standard deviation of 46.34205.

For monthly CPI, the minimum was 44.2 with a maximum of 201.2. Then 25% of the data was less or equal to 72.47 while 50% of it was less or equal to 108.2 and 75% of it was 110.53. On average, the monthly CPI was 110.53 with standard deviation of 43.98698.

Figure 1 shows time plots for the variables considered in this study from January 2003 to December 2017. The figure clearly shows an upward trend in the monthly CPI, Food and Non Food.

Table 2 shows the ADF test for monthly CPI and differenced monthly CPI which shows that the monthly CPI data is stationary at difference order 1 ($d = 1$).

Figure 2 shows the time plot of the differenced data of order 1.

Figure 3 shows the ACF (left) and PACF (right) respectively for $d = 1$.

The error measures for selecting the best fit model were used in this study though there are several ways to determine best forecasting model. The best fit model is one with minimal errors. The error indicators for our study are MPE, MAE, MASE, RMSE and MAPE defined in Table 3.

Table 4 shows the measure of accuracy for selected ARIMA models. An ARIMA model with the smallest errors is the best model. The ARIMA (3, 1, 3) has been identified as the model with the smallest AIC, RMSE, MAE and MASE as can be seen in Table 4. Next, we proceed to estimate the parameters.

Table 5 shows the estimated parameters for ARIMA (3, 1, 3) model.

Table 6 shows the Box-Ljung test results of the residues. Since the test fails to reject the null hypothesis at 5% level of significance, we conclude that the model is a good fit since the data is independent and uncorrelated.

Figure 4 shows the ACF of residuals plot. It is clear that there is no significant spike. So there is no residual correlation left in our data.

Figure 5 shows that the residuals are approximately normally distributed, and there is no correlation in the residuals implying ARIMA (3, 1, 3) was successfully selected as the tentative model to be used for Forecasting.

1) Multicointegration

Table 7 shows the Augmented Dickey-Fuller Test results for food and non-food variables before and after differencing respectively. Results show that Food and nonfood CPI is stationary after differencing.

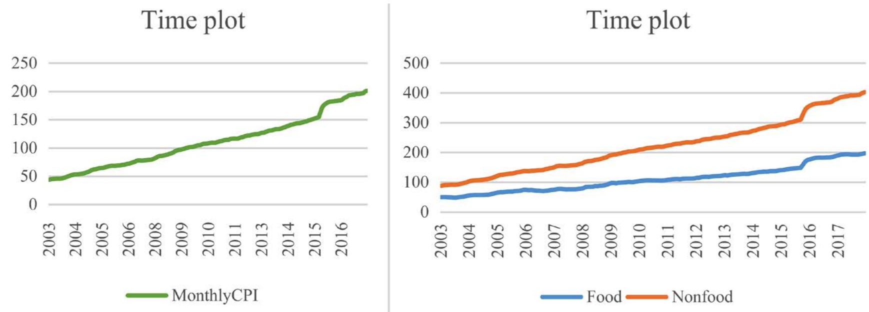

Figure 1. Time plots for monthly CPI, food and nonfood.

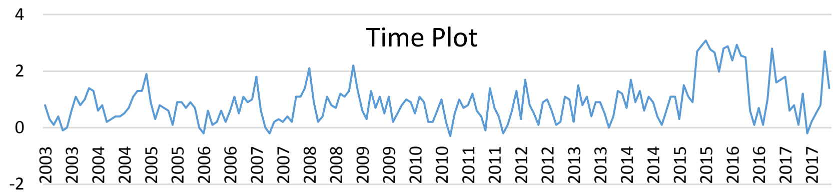

Figure 2. Time plot of the differenced data ($d = 1$).

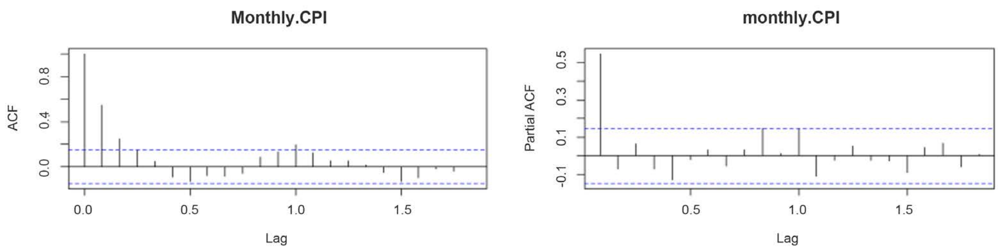

Figure 3. ACF (left) and PACF (right) for $d = 1$

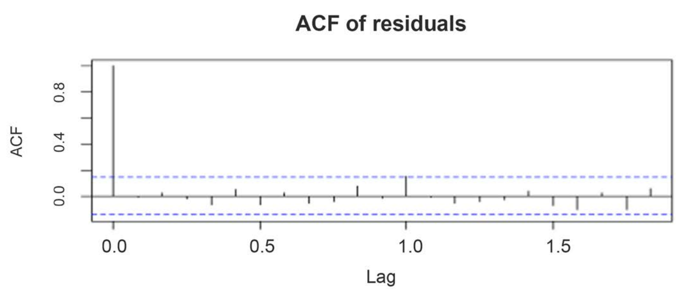

Figure 4. ACF of residuals plot.

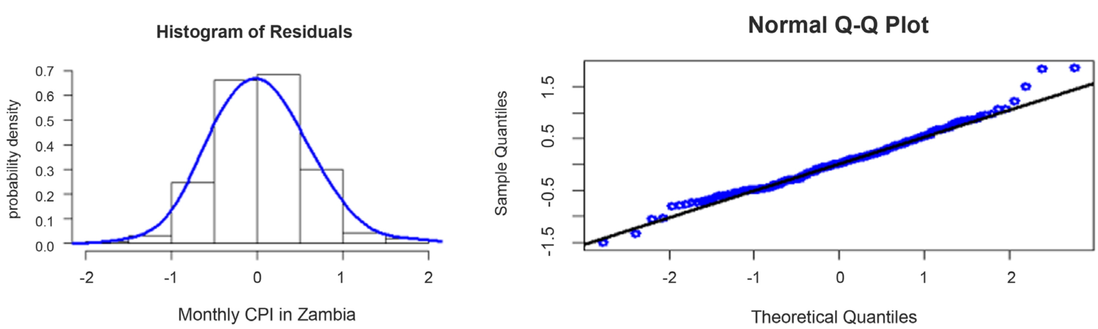

Figure 5. Histogram and q-q plot of residuals.

Table 2. Augmented dickey-fuller test.

Column1	Test statistic	*p* value	conclusion
Monthly CPI	−0.20479	0.99	Has a unit root (not stationary)
Monthly CPI (difference of order 1)	−4.5328	0.01	Has no unit root (stationary)

Table 3. The error measures for ARIMA model selection.

Criteria	Formula	Criteria	Formula
MPE	$\frac{1}{n}\sum_{i=1}^{n}100\times\frac{\varepsilon_i}{y_i}$	RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\varepsilon_i^2}$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert\varepsilon_i\rvert$	MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{\varepsilon_i}{x_i}\right\rvert\times 100$
MASE	$\left\lvert\frac{\varepsilon_i}{\frac{1}{n-1}\sum_{i=1}^{n}\lvert Y_t - Y_{i-1}\rvert}\right\rvert$	AIC	$n+n\log(2\pi+n)\log\left(\frac{\text{RSS}}{n}\right)+2(p+1)$

Table 4. Error measures of tentative ARIMA models.

Tentative model	AIC	ME	RMSE	MAE	MASE
ARIMA (0, 1, 1)	324.15	0.00848	0.5927	0.45957	0.9061
ARIMA (0, 1, 2)	319.68	0.01039	0.58143	0.45173	0.89066
ARIMA (0, 1, 3)	317.59	0.01729	0.5743	0.44758	0.88246
ARIMA (0,1,4)	317.3	0.02732	0.57025	0.44855	0.88438
ARIMA (1, 1, 0)	331.77	0.0067	0.60575	0.47846	0.94335
ARIMA (1, 1, 1)	311.95	0.03747	0.56773	0.44612	0.8796
ARIMA (1, 1, 2)	312.33	0.0415	0.56504	0.44441	0.87622
ARIMA (1, 1, 3)	314.33	0.04153	0.56504	0.44439	0.87618
ARIMA (1, 1, 4)	315.88	0.04107	0.56433	0.44334	0.87411
ARIMA (2, 1, 0)	327.95	0.00746	0.59581	0.46693	0.92061
ARIMA (2, 1, 1)	312.45	0.04106	0.56525	0.44489	0.87716
ARIMA (2, 1, 2)	314.33	0.04151	0.56504	0.4444	0.8762
ARIMA (2, 1, 3)	316.23	0.04046	0.5649	0.44435	0.87609
ARIMA (2, 1, 4)	317.41	0.03786	0.56362	0.44161	0.8707
ARIMA (3, 1, 0)	327.92	0.00768	0.59236	0.46087	0.90866
ARIMA (3, 1, 1)	314.24	0.04168	0.5649	0.44402	0.87544
ARIMA (3, 1, 2)	316.23	0.04163	0.56489	0.44408	0.87555
ARIMA (3, 1, 3)	303.78	0.03879	0.53502	0.41461	0.81746

Table 5. Estimated parameters of ARIMA (3, 1, 3).

Coefficient	Estimates	Standard error	*t*-value	*p*-value
ar1	−0.7215	0.1009	−2.1031	2.20E−16
ar2	−0.9744	0.0803	−3.5156	2.20E−16
ar3	−0.5657	0.0954	−3.652	2.13E−15

Continued

ma1	−0.2672	0.0868	−3.0783	2.20E−16
ma2	0.1162	0.1009	1.1516	2.20E−16
ma3	0.1561	0.1024	1.5244	2.20E−16

Table 6. Box-Ljung test of residuals.

X-squared	Degrees of freedom	Critical value	*p*-value
0.13422	1	3.84	0.7141

Table 7. Augmented dickey-fuller test.

Augmented Dickey-Fuller Test before differencing				
Variable	**Test statistic**	**Critical value**	***p*-value**	**Conclusion**
Food	−0.82261	−3.44	0.9579	Fail to reject H0
Non-food	−0.48382	−3.44	0.9816	Fail to reject H0
Augmented Dickey-Fuller Test after differencing				
Column1	**Test statistic**	**Critical value**	***p*-value**	**Conclusion**
Food	−5.3269	−3.44	0.01	Reject H0
Non-food	−5.8307	−3.44	0.01	Reject H0

Figure 6 shows time plots for Food CPI and Non Food CPI after differencing respectively and both time plots exhibit an upward trend.

2) Johansen Cointegration Test

The results from the ADF test showed that both variables (food and non-food) become stationary at first difference. We then used the Johansen cointegration test whose results yielded test statistic of 62.539 which was compared to the critical value of 8.18 at 5% significance level. This shows that there is sufficient evidence to conclude that the two variables are cointegrated.

3) Estimation of the Error Correction Model

Having identified that both food and nonfood variables where stationary at first difference, the Error Correction Model was developed as shown below.

$$\text{food} = \text{food.l1} + \text{nonfood.l1} + \text{food.l2} + \text{nonfood.l2} + \text{const}$$

$$\text{nonfood} = \text{food.l1} + \text{nonfood.l1} + \text{food.l2} + \text{nonfood.l2} + \text{const}$$

Next, parameters of the Error Correction Model were estimated.

Table 8 shows the estimated parameters for food and non-food.

4) Diagnostic Checking

We carried out an empirical fluctuation process and we found that our observations where dynamic which implied that the lagged observations where included in our model in order to increase the accuracy of the model. Further an ARCH Engle's test for residual heteroscedasticity was carried out and we observed from our results that our model was significant for this research.

Results in Figure 7 show that the residuals are approximately normally

Table 8. Estimated parameters for food and non-food.

Estimated parameters of the equation for food					
Food	**food.l1**	**nonfood.I1**	**food.I2**	**nonfood.I2**	**constant**
	1.366035	0.442402	−0.402701	−0.407893	0.2817133
Estimated parameters of the equation for non-food					
Non-food	**food.l1**	**nonfood.I1**	**food.I2**	**nonfood.I2**	**constant**
	0.169389	1.116053	−0.168156	−0.114312	0.3545374

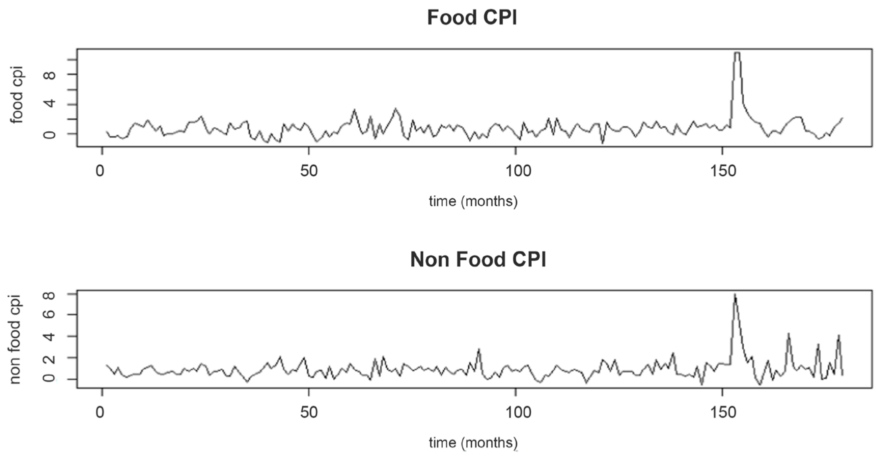

Figure 6. Time plot for Food CPI and Non Food CPI after first differencing.

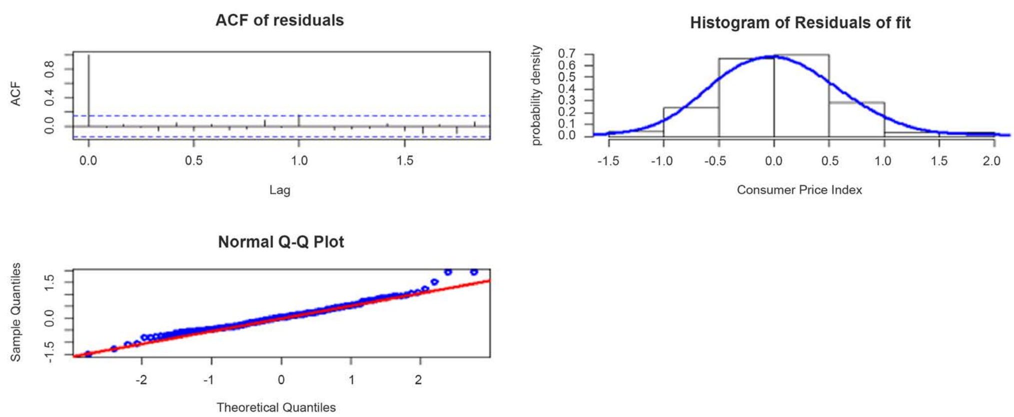

Figure 7. The ACF, Histogram and q-q plot of residuals for Error Correction Model.

distributed, and there is no correlation in the residuals implying Error Correction Model was successfully selected as the tentative model to be used for Forecasting.

5) Model Comparison

Finally, we compare the ARIMA and ECM prediction accuracy, the model with the smallest errors is selected as the better forecasting model.

Table 9 shows the comparison of the two models. The ECM model shows the smallest errors as compared to the ARIMA (3, 1, 3) model. Thus, ECM is the better forecasting model.

Table 10 shows the forecast for food from the ECM for January 2018 to December 2019. The average growth rate for food CPI is at 6.63%.

Table 11 shows the forecast for nonfood of the ECM for January 2018 to December 2019. The average growth rate for nonfood CPI is at 7.41%.

Table 9. Comparison between ARIMA and ECM.

Variable	ECM	ARIMA (3, 1, 3)
ME	0.0266	0.0388
RMSE	1.1224	0.5350
MAE	0.7420	0.4146
MPE	0.5509	−inf
MAPE	0.0266	inf
MASE	0.0220	0.8175

Table 10. Forecast for food from the ECM model.

	Year	Month	Forecast	Lower	Upper	C.I
1	2018	Jan	198.9561	196.7313	201.1809	2.224798
2	2018	Feb	200.0927	196.0107	204.1748	4.08203
3	2018	Mar	201.2004	195.4457	206.9551	5.75468
4	2018	Apr	202.2981	195.0866	209.5096	7.211504
5	2018	May	203.3956	194.9274	211.8639	8.468219
6	2018	Jun	204.4986	194.9452	214.052	9.553391
7	2018	Jul	205.6099	195.114	216.1058	10.495897
8	2018	Aug	206.7311	195.4101	218.0521	11.320995
9	2018	Sep	207.8631	195.8135	219.9126	12.049577
10	2018	Oct	209.0059	196.3074	221.7045	12.698527
11	2018	Nov	210.1597	196.8783	223.4411	13.281385
12	2018	Dec	211.3243	197.5153	225.1333	13.809007
13	2019	Jan	212.4994	198.2092	226.7895	14.290133
14	2019	Feb	213.6847	198.9529	228.4166	14.731846
15	2019	Mar	214.8801	199.7402	230.02	15.139931
16	2019	Apr	216.0852	200.5661	231.6044	15.529146
17	2019	May	217.2999	201.4264	233.1733	15.873442
18	2019	Jun	218.5237	202.3176	234.7298	16.206118
19	2019	Jul	219.7566	203.2366	236.2765	16.519952
20	2019	Aug	220.9982	204.1809	237.8155	16.817298
21	2019	Sep	222.2485	205.1483	239.3486	17.100163
22	2019	Oct	223.5071	206.1368	240.8773	17.370265
23	2019	Nov	224.7739	207.1448	242.4029	17.629085
24	2019	Dec	226.0487	208.1708	243.9266	17.877904

Table 11. Forecast for nonfood from the ECM model.

	Year	Month	Forecast	Lower	Upper	C.I
1	2018	Jan	206.4711	204.7569	208.1853	1.714221
2	2018	Feb	207.7814	205.073	210.4899	2.708437
3	2018	Mar	209.0853	205.4959	212.6746	3.589368
4	2018	Apr	210.3871	206.0116	214.7626	4.375521
5	2018	May	211.6907	206.6093	216.7721	5.081361
6	2018	Jun	212.998	207.2778	218.7182	5.720199
7	2018	Jul	214.3104	208.0068	220.614	6.303619
8	2018	Aug	215.6283	208.7871	222.4696	6.841229
9	2018	Sep	216.9523	209.6115	224.2931	7.340802
10	2018	Oct	218.2824	210.4739	226.091	7.808557
11	2018	Nov	219.6188	211.3694	227.8683	8.249465
12	2018	Dec	220.9616	212.294	229.6291	8.667512
13	2019	Jan	222.3106	213.2447	231.3765	9.065914
14	2019	Feb	223.6659	214.2186	233.1132	9.44729
15	2019	Mar	225.0274	215.2137	234.8412	9.813787
16	2019	Apr	226.3953	216.2281	236.5624	10.167187
17	2019	May	227.7693	217.2603	238.2783	10.50898
18	2019	Jun	229.1495	218.3091	239.9899	10.840424
19	2019	Jul	230.5359	219.3733	241.6985	11.162587
20	2019	Aug	231.9285	220.4521	243.4049	11.476387
21	2019	Sep	233.3272	221.5446	245.1098	11.782619
22	2019	Oct	234.732	222.65	246.814	12.08197
23	2019	Nov	236.1429	223.7679	248.5179	12.375046
24	2019	Dec	237.5599	224.8975	250.2223	12.662377

5. Discussion

This paper aimed at comparing two-time series models, ARIMA and Multicointegration using the Zambia CPI data which is recorded monthly. This data was collected from January 2003 to December 2017. ARIMA (3, 1, 3) model was chosen from other ARIMA models as it exhibited the smallest Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Squared Error (MASE). A diagnostic checking was carried using q-q plot, ACF plot and the histogram of residuals. Results showed that the model was significant.

Multicointegration was also used as an appropriate approach to establish whether the two variables food and nonfood are cointegrated and if they can be used to model CPI. We established that both variables were stationary at first difference which enabled us to carry out a cointegration test as a special case. Results from the Johansen cointegration test showed that the variables where cointegrated and it was appropriate to estimate an ECM. An ECM was estimated successfully. To check if the model was significant, we further carried out an ARCH and STABILITY tests and the results showed that the model was significant.

The ECM was selected as the better model to forecast CPI as it showed smallest errors. The identified model was later used to forecast the CPI of Zambia using the relationship of the food CPI and the non-food CPI. The forecast showed an average growth rate for food CPI at 6.63% and an average growth rate for nonfood CPI at 7.41%.

6. Conclusion

The main objective of this research was to compare the forecasting ability of two time-series models using Zambia Monthly Consumer Price Index. Multicointegration was identified as the more accurate model for forecasting compared to the ARIMA (3, 1, 3). The ECM forecast showed an average growth rate for food CPI at 6.63% and an average growth rate for nonfood CPI at 7.41%. The consumer price index plays a very important role as an economic indicator because it is key in the measurement of the inflation rate. Having the ability to forecast CPI is an important factor for any economy because forecasting is essential in economic planning for the future. Forecasts need to be accurate to avoid future dilemmas such as underestimating or overestimating economic flow variables; hence identifying a more accurate model to produce forecasts is a major contribution to the development of Zambia.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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