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Forecasting Inflation in Kenya Using ARIMA Model

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ABSTRACT

This study was to investigates the dynamics of inflation in Kenya through the application of advanced time series modeling techniques, specifically Autoregressive Integrated Moving Average (ARIMA) analysis. Inflation is a critical economic indicator that directly influences monetary policy, investment decisions, and overall economic stability. Given the dynamic of inflation in emerging economies such as Kenya, a fine understanding of its patterns and the ability to make accurate forecasts are imperative for policymakers, businesses, and investors. The ARIMA(2,2,2) model was employed to capture the underlying trend and seasonality in the inflation data, providing insights into the historical behavior of inflation in Kenya. In this study, we used R programming software and STATA to analyze and generate meaningful information from the data. The data was obtained from World Bank for a period from 1960 to 2022.
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1 Introduction

In the context of Kenyan Economy, inflation refers to the sustained increase in general prices level of goods and service over a period of time, typically measured by the Consumer-Price Index (CPI).

Inflation can be caused by various factors such as increase in demand, tax, supply shortage, rising production cost or increase in money supply. Types of inflation:

1) (Cost-push inflation) - is the result of an increase in prices working through the production of inputs.
2) (Demand–pull inflation)- it occurs when an increase in the supply of money and credits stimulates the overall demand for goods and services to economically increase more rapidly than production.
3) (Built inflation)- is related to the adaptive inflation that people expect current inflation rates to continue in the future.

Kenya has experienced strong economic growth for over nearly a decade. However, inflation, which was thought to be under control, has become a major challenge. High, and rapid change, inflation is a threat to good economic performance and has negative effects on many of the poor [16]. Economic growth took off in 2004 in Kenya, but alongside higher growth there has been rapid inflation. The rise of inflation in Kenya is not an isolated event; other African countries are facing the same problem (AFDB, 2011). Yet, there is no agreement on the causes of the rise in inflation. In Kenya, the inflation pressures, however, seems to be ticking up in the first half of 2014, pointing to the need for policy makers to keep close watch to ensure that price stability is maintained. A combination of factors notably, rising global crude oil prices, erratic weather patterns that adversely impacted agriculture, and weakening domestic currency as a result of impairment in current account deficits, underlie the evolving inflation developments. Forecasting inflation is specifically challenging on emerging markets given the changes in the underlying environment due to structural and institutional adjustments, and the high weight of change on food and energy in the consumer price index [7]. Modeling and forecasting inflation are generally desirable in an economy for sustaining price rises regardless of the source, leading to a fall in real wages and to a distribution of income in favor of profits and low paid workers not protected by trade unions tend to suffer most. To control and maintain inflation often has an adverse effect on balance of payment of a country's current and capital account and thereby aggravates the foreign exchange constraint on development [5]. The purpose of this study is to forecast inflation using univariate time series models, ARIMA models. Forecasts of inflation are important because they affect many economic decisions. Without knowing future inflation rates, it would be difficult for lenders to price loans, which would limit credit and investments in turn have a negative impact on the economy.

2 Literature Review

In general, there are two types of approaches for modeling the inflation: macro-economic based models and option pricing based models.

According to discovered that the positive relationship between inflation uncertainty and unemployment is dependent on three significant factors. First, the existence of a positive relationship between inflation and unemployment only begins to manifest in mid-1970s [13]. Second, the inflation uncertainty-unemployment relationship is not applicable in every single digit SIC firms. Thirdly, the relationship between inflation uncertainty and unemployment exists only on low-frequency components.

[2] further argued that the negative long-run relationship between inflation and growth found in the above literature is only present with high frequency data and with extreme inflation observations. [10]investigated the properties of monetary regimes that combine price-level and inflation targeting. They considered both, at an optimal control and a simple rule characterization of these regimes.
[6]compared the accuracy of survey respondents' inflation forecast relative to univariate time series modeling on the real interest rate. They observed that the interest rate model yields inflation forecast with a lower error variance than a univariate model, and that the interest rate model's forecast dominate those calculated from the Livingston survey.

[12] considered fractionally integrated moving Average (FIMA) models with conditional heteroscedasticity, which combined with popular generalized auto regressive conditional heteroscedasticity (GARCH) and (ARIMA) models. This is supported by Drost and Klaassen (1997) who argued that financial data set exhibit conditional heteroscedasticity and as a result GARCH – type model are often used to model this phenomenon.

[14] considered the autoregressive integrated moving average (ARIMA) for forecasting Irish inflation and justified that ARIMA models are surprisingly robust with respect to alternative (multivariate) model. [7] also used the Variable regression coefficient time lags as the source of randomness to find the relationships between economic time series. This was modelled here by means of variable regression coefficients. The model entails heteroscedastic residuals with a negative serial correlation and can be estimated by the Kalman filter.

Most studies on inflation in Kenya do not explicitly deal with the role of food prices for example; [17] focuses on the exchange rate and oil prices using a generalized Phillips curve. The study by (AFDB, 2011) also reports that monetary expansion is a key driver of inflation in Kenya, but it only accounts for 0.3 of the variation in the long run. In fact, the exchange rate seems to explain a large part of the variation according to its coefficient, but no details are provided.

The most recent study on Kenya is (IMF, 2012b) which reports results from work in progress on a small monetary model with Kenya-specific features. The parameters are calibrated, not estimated, which allows for a more complex model specification. The imported food price shocks and poor harvests explain some of the inflation dynamics, both in 2008 and 2011.

The prevailing view in mainstream economics is that inflation is caused by the interaction of the supply of money with output and interest rates [19]. A variety of models and empirical methods have been used in attempts to analyze inflation dynamics.

[6] compared the forecasting performance of different time series methods for forecasting cocoa bean prices at Bagan Datoh cocoa bean [1]. Four different types of univariate time series models were compared namely the exponential smoothing, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroscedasticity (GARCH) and the mixed ARIMA/ GARCH models.

[18]analyzed the relationship between inflation and inflation uncertainty in the United Kingdom from 1973 to 2003 with monthly and quarterly data [4]. Different types of GARCH Mean (M)-Level (L) models

that allow for simultaneous feedback between the conditional mean and variance of inflation were used to test the relationship.They found that there was a positive relationship between past inflation and uncertainty about future inflation, in line with [10] to which in their study of testing for rate of dependence and asymmetric in inflation uncertainty they concluded that there was a link between inflation rate and inflation uncertainty.

Monetary policy was more effective when it is forward looking [13]. Maintenance of price stability continued to be one of the main objectives of monetary policy for most countries in the world [15] and Kenya was not an exception. Achieving and maintaining price stability will be efficient and effective the better we understand the causes of inflation and the dynamics of how it evolves [17]. Therefore, inflation forecasting is not unimportant in light of both fiscal and monetary policy making. In Kenya, just like in any other country; inflation forecasts are envisioned to enable the CBK to possess some control over future inflation. In this study, we employ ARIMA(2,2,2) techniques to model and forecast inflation in Kenya.

3 Research Methods

From our data set, we have the following variables: Consumer Price Index (CPI), Inflation Rate,interest rate, Exchange Rate and GDP growth.

3.1 Model building and estimation procedures

3.1.1 Assumption of Data

1. **Stationarity:** The statistical properties of the time series, such as mean, variance, and autocorrelation, remain constant over time. This assumption ensures that patterns observed in the past will continue into the future.

2. **Autocorrelation:** The correlation between observations at different time points is known as autocorrelation. In a stationary time series, the autocorrelation depends only on the time lag between observations and not on the absolute time at which the observations are made.

3. **Homoscedasticity:** The variance of the errors (residuals) remains constant over time. It implies that the variability in the data is consistent across different time periods.

4. **Independence:** Observations in a time series should be independent of each other. This assumption ensures that the behavior of the time series at one point in time does not influence its behavior at another point in time.

5. **Linearity:** The relationship between variables is linear. While this assumption is often relaxed, especially in more advanced time series modeling, linear models are still widely used for their simplicity and interpretability.

6. **Normality:** The distribution of errors (residuals) should be normally distributed. This assumption is crucial for making statistical inferences and constructing confidence intervals.

3.1.2 The Moving Average (MA) model

Given:

$$CPI_t = a_0u_t + a_1u_{t-1} + ... + a_qu_{t-q} \tag{3.1}$$

Where u_t is a random process with mean zero and variance σ^2. We say that equation [1] is a Moving Average (MA) process of order q, commonly denoted as MA (q). CPI is the Consumer Price Index in Kenya at time t, $a_0 \ldots\ a_q$ are estimation parameters, u_t is the current error term while $u_{t-1} \ldots\ u_{t-q}$ are previous error terms. Hence:

$$CPI_t = a_0u_t + a_1u_{t-1} \tag{3.2}$$

is an MA process of order one, commonly denoted as MA (1). Owing to the fact that previous error terms are unobserved variables, we then scale them such that a_0=1. Since:
E(u_t)=0
for all t,it therefore; implies that:
E(CPI_t)=0
and

$$Var(CPI_t) = (\sum_{i=0}^{q} a_t^2)\sigma^2 \tag{3.3}$$

where u_t is independent with a common varience σ^2 . Hence, we can now re – specify general equation as follows:

$$CPI_t = u_t + a_1u_{t-1} + ... + a_qu_{t-q} \tag{3.4}$$

3.1.3 The Autoregressive (AR) model

Given:

$$CPI_t = \beta_1 CPI_{t-1} + ... + \beta_p CPI_{t-p} + u_t \tag{3.5}$$

Where $\beta_1 \ldots\ \beta_p$ are estimation parameters, $CPI_{t-1} \ldots\ CPI_{t-p}$ are previous period values of the CPI series and u_t is as previously defined. We say that equation is an Autoregressive (AR)process of order p, and is commonly denoted as AR (p); and can also be written as:

$$CPI_t = \sum_{i=1}^{p} \beta_{t-i} CPI_{t-i} + u_t \tag{3.6}$$

3.1.4 The Autoregressive Moving Average (ARMA) model

As initially propounded by Box and Jenkins (1970), an ARMA (p, q) process is simply a combination of AR (p) and MA (q) processes. Therefore, combining the general equations of MA(q) and AR(p); an ARMA (p, q) can be specified as follows:

$$CPI_t = \beta_1 CPI_{t-1} + ... + \beta_p CPI_{t-p} + u_t + a_1 u_{t-1} + ... + a_q u_{t-q} \tag{3.7}$$

or as;

$$CPI_t = \sum_{i=1}^{p} \beta_{t-i} CPI_{t-i} + \sum_{i=1}^{q} a_i u_{t-i} + u_t \tag{3.8}$$

A this juncture, it is quite essential to note that the ARMA (p, q) model, just like the AR (p) and the MA (q) models; can only be employed for stationary time series data; and yet in real life, many time series are non – stationary. For this simple reason, ARMA models are not for describing non – stationary time series.

3.1.5 The Autoregressive Integrated Moving Average (ARIMA) model

ARIMA models are a set of models that describe the process (for example, CPI_t) as a function of its own lags and white noise process (Box and Jenkins, 1974). Making predicting in time series using univariate approach is best done by employing the ARIMA models (Alnaa and Ahiakpor, 2011). A stochastic process CPI_t is referred to as an Autoregressive Integrated Moving Average (ARIMA) [p, d, q] process if it is integrated of order "d" [I (d)] and the "d" times differenced process has an ARMA (p, q) representation. If the sequence $\triangle^d CPI_t$ satisfies and ARMA (p, q) process; then the sequence of CPI_t also satisfies the ARIMA (p, d, q) process such that:

$$\triangle^d CPI_t = \sum_{i=1}^{p} \beta_{t-i} \triangle^d CPI_{t-i} + \sum_{i=1}^{q} a_i u_{t-i} + u_t \tag{3.9}$$

where $\triangle$ is the difference operator.

3.2 Model Selection Criteria:

The parameters p,d and q can be obtained through:

1. parameter p will obtained in AR by looking at Autocorrelation Function (ACF) plot and choosing the lag where it crosses the significance threshold.
2. parameter d will be obtained by determining the number of differences needed to achieve the stationary.
3. parameter q will be obtained by looking at Partial Autocorrelation Function (PACF) plot and choosing the lag where it crosses the significance threshold.

The final model was selected using a penalty function statistics such as Akaike Information Criterion (AIC or AICc) or Bayesian Information Criterion (BIC). (Sakamoto, Ishinguro, and Kitagawa, 1986);(Akaike, 1974) and (Schwarz, 1978). The AIC, AICc and BIC are a measure of the goodness of fit of an estimated statistical model. Given a data set, several competing models may be ranked according to their AIC, AICc or BIC with the one having the lowest information criterion value being the best. These information criterion judges a model by how close its fitted values tend to be to the true values, in terms of a certain expected value. The criterion attempts to find the model that best explains the data with a minimum of free parameters but also includes a penalty that is an increasing function of the number of estimated parameters. Also some forecast accuracy test between the competing models can also help in making a decision on which model is the best. Minimum of free parameters but also includes a penalty that is an increasing function of the number of estimated parameters. This penalty discourages over fitting. In the general case, the AIC, AICc and BIC take the form as shown below:

$$AIC=2k - n\log(\frac{RSS}{n})$$

$$AICc=AIC + \frac{2k(k+1)}{n-k-1}$$

$$BIC=\log(\sigma_e^2) + \frac{k}{n}\log(n)$$

Where
k: is the number of parameters in the statistical model

RSS: is the Residual Sum Squares for the estimated model

n : is the number of observations

σ_e^2: is the error variance

3.3 The Box – Jenkins Methods

The first step towards model selection was to difference the series in order to achieve stationarity. Once the process was over,we then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It was 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 was 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 followed. Diagnostic checking usually done by generating the set of residuals and testing whether they satisfy the characteristics of awhite 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

4 Results

In this chapter, we unveiled the findings of our efforts to forecast inflation in Kenya using the ARIMA (2,2,2) model. Through meticulous analysis and rigorous experimentation, we presented the outcomes of our predictive endeavor. By delving into the complexities of the data and assessing the model's performance, we revealed valuable insights into the dynamics of inflation within the Kenyan economy. These findings not only highlighted the effectiveness of our forecasting approach but also offered significant implications for policymakers, economists, and stakeholders seeking a deeper understanding of inflationary trends. This chapter served as a comprehensive account of our empirical findings, laying the groundwork for insightful discussions and informed decision-making in subsequent sections of our project.

4.1 Data collection

Authors such as Chatfield (1996) and Meyler et al (1998) argued that more than 50 observations are recommended in order to build a reliable ARIMA model. This study was based on 63 observations of annual Consumer Price Index (CPI) in Kenya.All the data used in this study was gathered from the World Bank.

4.2 Descriptive Statistics

Descriptive	Statistic
Mean	47.50192
Standard deviation	65.03363
variance	4229.374
Skewness	1.37257
Kurtosis	3.602954
Max	228.7383
Min	0.741244

As shown in table above, the mean is positive. The large difference between the maximum and the minimum confirms the existence of an upward trend in the CPI time series. The skewness was 1.37357 and the most striking feature was positive, implied that the CPI series had a long right tailed and was non – symmetric. The rule of thumb for kurtosis was that it should be around 3 for normally distributed variables and in this analysis, kurtosis was found to be 3.602954 Therefore, the CPI series implied that it is normally distributed.

4.3 Diagnostic Tests and Model Evaluation

Stationarity Tests: Graphical Analysis
We examined whether a series was stationary or not by analyzing the time plot of Consumer Price Index

(CPI)against year. In that regard, a time plot of the CPI series is shown below:
The graph below shows that CPI is not stationary since it is trending upwards over the period under study. The implication is that the mean of CPI is changing over time and hence we can safely conclude that the variance of CPI is not constant over time.

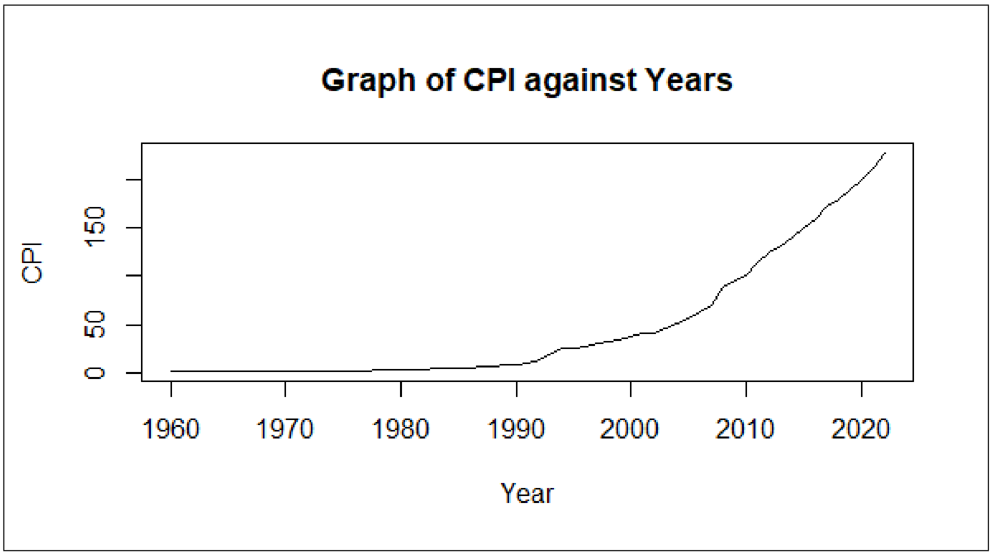

Figure 1:

The Correlogram

Autocorrelation Function (ACF) The ACF measures the correlation between a series and its lagged values. For non-stationary data, you may observe a gradual decline in the ACF plot, indicating that past values are still correlated with the current values but the correlation decreases as the lag increases. This suggested a lack of stationarity in the data, as the relationship between observations changed over time.

Partial Autocorrelation Function (PACF) The PACF shows the correlation between two variables while controlling for the effects of other variables in between. In non-stationary data, the PACF may exhibit spikes at the initial lags, indicating strong correlations that decay rapidly. This suggests that each observation may have a strong direct influence on subsequent observations, which is characteristic of non-stationary processes.
As shown in figure 2 below, these patterns indicates the persistence of correlations over time and the lack of stable relationships between observations, both of which are indicative of non-stationarity.
Thus, the need for further analysis or data transformation techniques to address the non-stationarity before modeling or forecasting.

The ADF Test

The Augmented Dickey Fuller (ADF test) was used to check the stationarity of the CPI series. The general ADF test is done by running the following regression equation:

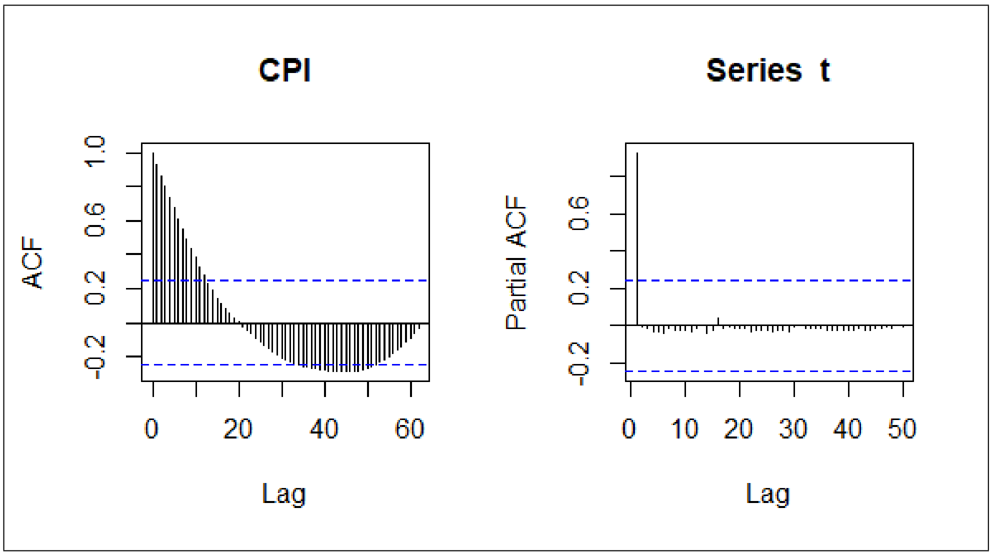

Figure 2:

$$CPI_t = \sum_{i=1}^{p} \beta_{t-i} CPI_{t-i} + \sum_{i=1}^{q} a_i u_{t-i} + u_t \tag{4.1}$$

The Augmented Dickey-Fuller (ADF) test was conducted to assess the stationarity of the data. The test statistic was found to be 1.6716, which exceeds the critical values at the 5% significance level. Additionally, the p-value associated with the test was 0.99, which is greater than 0.05. Therefore, we failed to reject the null hypothesis of non-stationarity, indicating that the data was non-stationary.
The table below indicates that the CPI series is not stationary at levels. Hence the need to check stationarity at first difference.

Varibale	ADF statistics	Probability	Critical value		Decision
CPI	1.6716	0.99	@1%	-3.563	Non-stationary
			@5%	-2.920	Non-stationary
			@10%	-2.595	Non-stationary

Table 1: ADF table of Levels- intercept

1^{st} **Differencing**

Graphic Analysis of 1^{st} Differencing

The graph below shows that CPI is not stationary since it is trending downwards over the period under study. The implication is that the mean of CPI is changing over time and hence we can safely conclude that the variance of CPI is not constant over time.

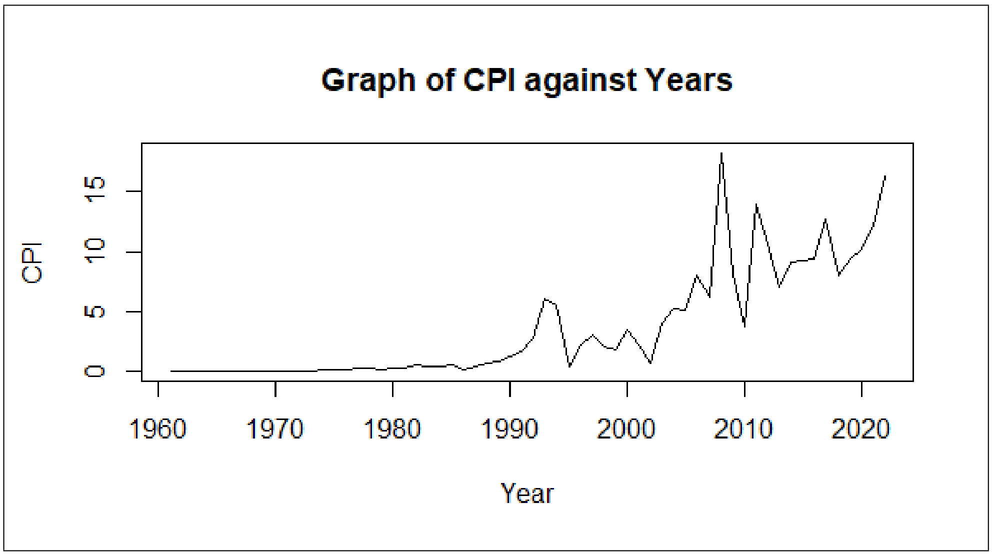

Figure 3:

The Correlogram (at First Differences)

ADF test
The Augmented Dickey-Fuller (ADF) test was conducted to assess the stationarity of the data. The test statistic was found to be -1.8651, which exceeds the critical values at the 5% significance level. Additionally, the p-value associated with the test was 0.6295, which is less than 0.05. Therefore, we failed to reject the null hypothesis of non-stationarity, indicating that the data is non-stationary.
The below test indicate that the CPI series is not stationary at levels. Hence the need to check stationarity at second differences.

Varibale	ADF statistics	Probability	Critical value		Decision
CPI	-1.8651	0.6295	@1%	-3.565	Non-stationary
			@5%	-2.921	Non-stationary
			@10%	-2.596	Non-stationary

Table 2: ADF table in 1^{st} Difference

2^{nd} Difference
The graph below shows a stationary series of CPI values after applying second differencing. Stationarity is evident from the absence of a clear trend or pattern over time. Fluctuations appear to be random around a constant mean level. **Graphical Analysis**
The stationary nature of the CPI series after second differencing indicates that the data is now suitable

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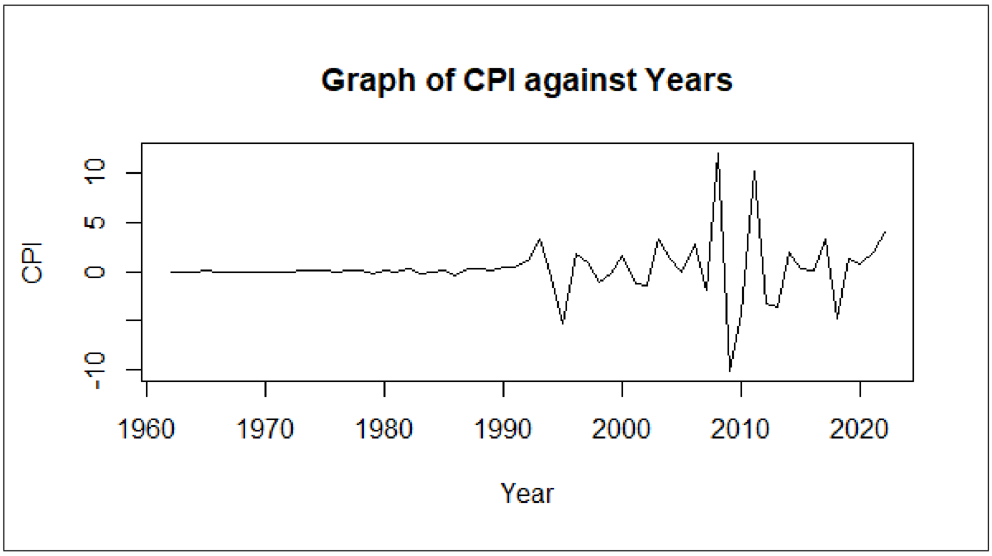

Figure 4:

for time series analysis, such as forecasting or modeling. The absence of a trend suggests that inflationary or deflationary pressures may have stabilized during the period under consideration.

The Correlogram (in 2^{nd} Differences)

Autocorrelation Function (ACF)

After second differencing, the ACF plot typically shows correlations close to zero for most lags, indicating no significant autocorrelation. Any remaining significant correlations may suggest higher-order dependence or other structural features in the data.

Assumption 1 has been meet.

Partial Autocorrelation Function (PACF)

Similarly, the PACF plot after second differencing also show correlations close to zero for most lags. Significant spikes in the PACF at certain lags may indicate direct correlations between observations at those lags, suggesting potential patterns or seasonality in the data. By examining both the ACF and PACF plots, analysts can gain insights into the autocorrelation structure of the stationary data after second differencing, helping to identify any remaining dependencies that may need to be accounted for in the analysis.

ADF test

The Augmented Dickey-Fuller (ADF) test was conducted to assess the stationarity of the data after second differencing. The test statistic was found to be -5.6099, which is more negative at the 5% significance level. Additionally, the p-value associated with the test was 0.01, which is less than 0.05. Therefore, reject the null hypothesis of non-stationarity, indicating that the data is stationary.

The below test indicate that the CPI series is stationary at levels.

The table above confirm that the CPI series became stationary after taking second differences. Assumption of stationarity has been meet.

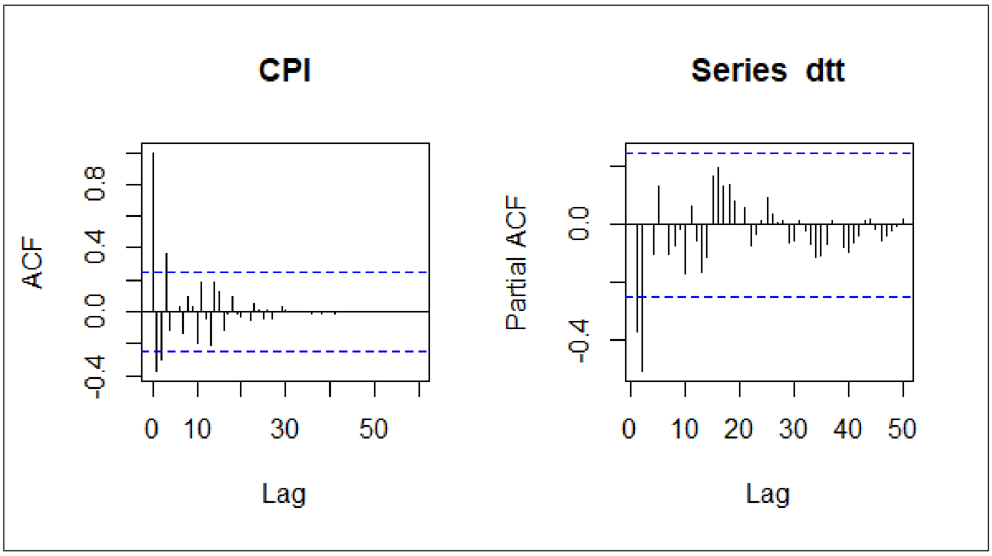

Figure 5:

Varibale	ADF statistics	Probability	Critical value		Decision
CPI	-5.6099	0.01	@1%	-3.566	Stationary
			@5%	-2.922	Stationary
			@10%	-2.596	Stationary

Table 3: ADF table of in 2^{st} Difference

4.4 Evaluation of various ARIMA models

In this study, we delve into evaluating various ARIMA(p,2,q) models for forecasting CPI. The ARIMA(p,2,q) model specification signifies a second-order differencing, capturing the changes in the CPI over time while considering autoregressive and moving average terms represented by p and q, respectively.
The evaluation of ARIMA(p,2,q) models for CPI forecasting involves utilizing statistical criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria help assess the trade-offs between model complexity and goodness of fit, aiding in the selection of the most suitable model for CPI forecasting.

By comparing AIC and BIC values across different ARIMA(p,2,q) models, we aim to identify the optimal combination of autoregressive and moving average terms that effectively capture the underlying inflation dynamics. Lower AIC and BIC values indicate better fitting models, with preference given to models that strike a balance between explanatory power and simplicity. As shown in the table above,

Model	AIC	BIC
ARIMA(1,2,0)	401.3122	407.5448
ARIMA(0,2,1)	363.7977	367.9528
ARIMA(0,2,0)	425.5811	429.7361
ARIMA(2,2,0)	358.8671	367.1773
ARIMA(3,2,0)	345.7627	356.1504
ARIMA(4,2,0)	329.0979	341.5631
ARIMA(5,2,0)	317.9323	332.4751
ARIMA(0,2,3)	296.5635	304.8736
ARIMA(0,2,4)	297.4662	307.8539
ARIMA(0,2,5)	292.8012	305.2664
ARIMA(2,2,2)	**283.338**	**296.8926**
ARIMA(3,2,3)	293.6945	308.2373
ARIMA(1,2,5)	293.7939	308.3367
ARIMA(2,2,1)	316.1163	326.504
ARIMA(3,2,1)	309.031	319.4187
ARIMA(4,2,1)	300.9981	315.5408
ARIMA(1,2,1)	347.5728	353.8054
ARIMA(1,2,2)	308.3114	316.6215
ARIMA(1,2,3)	316.7522	327.1399
ARIMA(1,2,4)	295.0148	307.4800

the ARIMA (2, 2, 2) model has the lowest AIC value and again it has the lowest BIC value making it to be the best model.

4.5 Residual for ARIMA(2,2,2)

Residuals are the differences between the observed values of the time series and the values predicted by the ARIMA(2,2,2) model. A well-fitted model should produce residuals that are random, with mean zero and constant variance.
The residual data is normally distributed as shown in the residual plot and the assumption of normality has been meet.

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

Ensuring the stability of time series models is essential for reliable forecasting and analysis. In the context of the Autoregressive Integrated Moving Average (ARIMA) model, stability tests help validate the

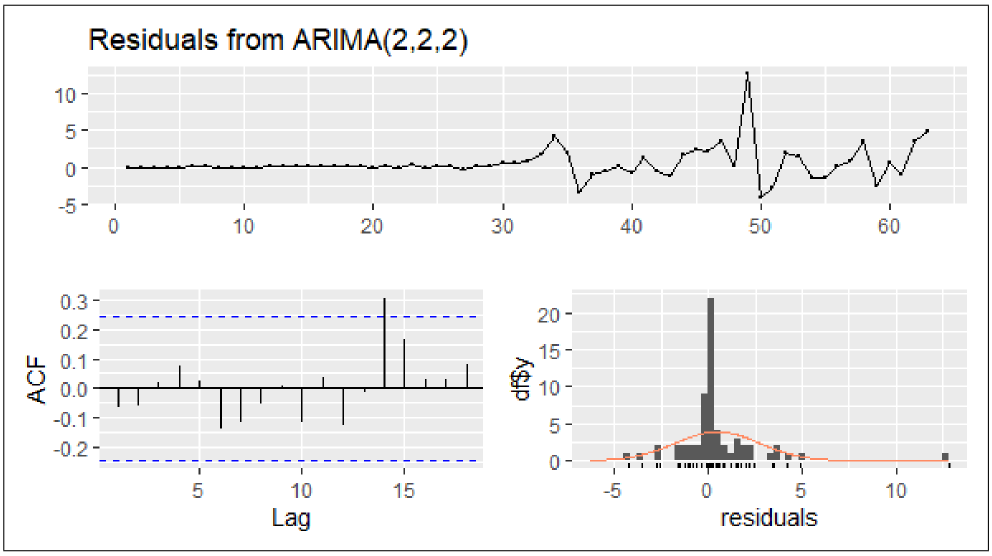

Figure 6:

suitability of the chosen parameters to accurately capture the underlying data dynamics. Specifically, the ARIMA (2, 2, 2) model, characterized by second-order autoregressive, differencing, and moving average terms, requires thorough stability assessment.

The figure above indicates that the ARIMA (2, 2, 2) model is also stable since the corresponding inverse root of the characteristic polynomial is in the unit circle.

4.7 Findings and Discussion

$$\nabla^2 CPI_t = -0.7637 CPI_{t-1} + 0.2004 CPI_{t-2} - 0.2678 \mu_{t-1} + 0.9998 \mu_{t-2} \tag{4.2}$$

Variable	Coefficient	Standard error	z	p¿(z)
AR(1) $[\beta_1]$	-0.7637	0.2340	-6.91	0.0000
AR(2) $[\beta_2]$	-0.4219	0.1753	-9.09	0.0000
MA(1) $[\alpha_1]$	0.2004	0.2532	-14.02	0.0000
MA(2) $[\alpha_2]$	-0.2678	0.2331	6.09	0.0000

4.7.1 Interpretation & Discussion of Findings

ARIMA (2, 2, 2) model

Both β_1 and β_2 (the AR components) are negative and statistically significant at 1% level of significance. Again both and α_2 (the MA component) is also negative and statistically insignificant. The AR components are closer to 1 (since they are well above 0.5), implying that the series returns to its mean relatively

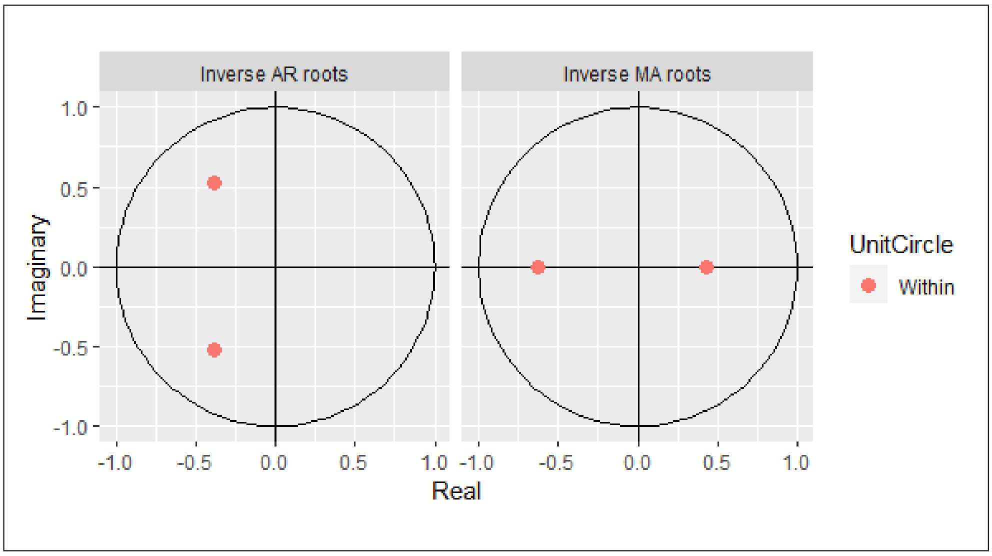

Figure 7:

slowly. The significance of the MA component indicates that previous period shocks to inflation in Kenya do not adequately explain current inflation levels.

4.7.2 Forecast Graphs

The graphs below with a forecast range of 5 years, that is; 2022 – 2027) indicate that Consumer Price Index in Kenya is likely to progress in an upward trend, implying that inflation is likely to continue rising sharply in Kenya. The most striking characteristic of the figures 7 is that they strongly concur in their forecasts; that inflation in Kenya is indeed expected to go up, of course; as long as no appropriate counter – cyclical policy measures are taken.

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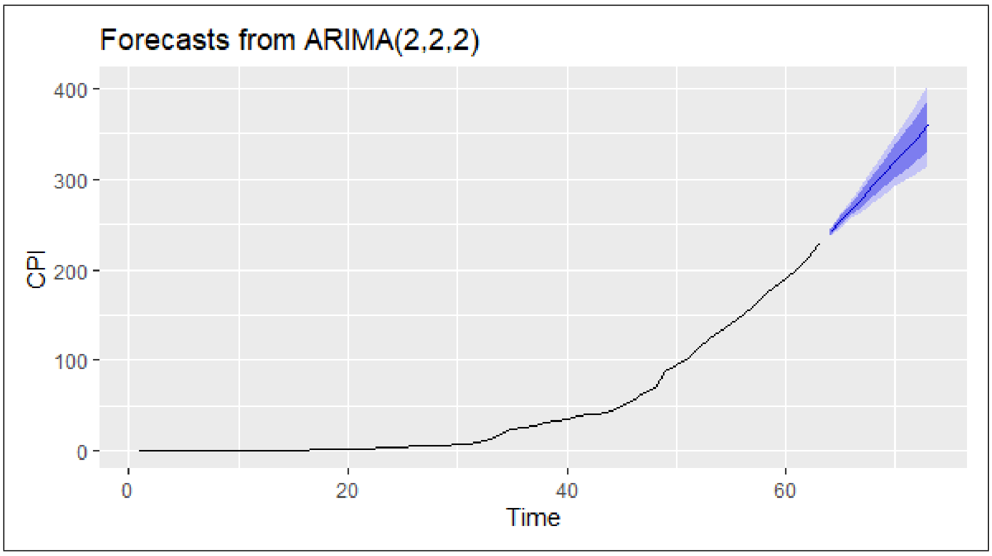

Figure 8:

5 Conclusion and Recommendation

5.1 Conclusion

The forecast indicating an upward trend in the Consumer Price Index (CPI) in Kenya suggests potential shifts in inflationary pressures, which necessitates careful consideration and strategic planning. The ARIMA (2, 2, 2) model has provided valuable insights into the future trajectory of CPI, capturing the underlying dynamics and trends in the data. This model, with its autoregressive, differencing, and moving average components, has demonstrated its efficacy in forecasting CPI, contributing to a better understanding of inflationary patterns in the Kenyan economy.

The ARIMA(2,2,2) model analysis of Kenya's CPI data provides valuable insights into inflationary trends and dynamics, offering policymakers and stakeholders a robust framework for decision-making, policy formulation, and risk management in the context of economic stability and growth. Continued research and analysis are essential to refine and improve inflation forecasting models and strengthen their relevance and effectiveness in addressing real-world challenges.

Monetary policy is more effective when it is forward looking. Maintenance of price stability continues to be one of the main objectives of monetary policy for most countries in the world today and Kenya is not an exception. Achieving and maintaining price stability will be efficient and effective the better we understand the causes of inflation and the dynamics of how it evolves. Therefore, inflation forecasting is not unimportant in light of both fiscal and monetary policy making. In Kenya, just like in any other country; inflation forecasts are envisioned to enable the CBK to possess some control over future inflation. In this study, we employ ARIMA techniques in order to model and forecast inflation in Kenya.

5.2 Recommendation

The study prescribes the following recommendation:

i) **Monitor Economic Indicators** Given the forecasted upward trend in CPI, it is essential for policymakers, businesses, and individuals to closely monitor other economic indicators such as GDP growth, unemployment rates, and monetary policy decisions. Understanding the broader economic context can help in devising appropriate strategies to mitigate the impact of rising inflation.

ii) **Adjust Budgets and Financial Plans** Individuals and businesses should review and adjust their budgets and financial plans to accommodate potential increases in prices. This may involve reassessing expenditure priorities, exploring cost-saving measures, and considering alternative investment strategies to hedge against inflationary pressures.

iii) **Enhance Data Collection and Analysis** Continuous refinement and enhancement of data collection and analysis processes are crucial for improving the accuracy and reliability of inflation forecasts. Investing in advanced statistical techniques and data analytics capabilities can provide deeper insights into inflation dynamics and support more informed decision-making.

iv) The researchers may employ the use of both ARIMA and GARCH models for forecasting the inflation in order to come up with more insight of future inflation rate.

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