FORECASTING THE AVERAGE PRICE OF SOME SELECTED FOOD ITEMS IN NIGERIA USING TIME SERIES ANALYSIS

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CERTIFICATION

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DEDICATION

This project was dedicated to Almighty Allah for his almost blessing and sustainer throughout this journey.

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ABSTRACT

The fluctuation in food prices highlights the urgent need for ongoing monitoring. Rising costs disproportionately impact vulnerable households, worsening poverty and restricting access to proper nutrition. Ensuring consistent access to safe and nutritious food is important for food security. This research focuses on the time series analysis of the average price of some selected food items in Nigeria which includes Rice, Beans, Gari, and Yam tuber using 8 years of 87 months from January 2017 to December 2023 extracted from the National Bureau of Statistics Website.

The data showed an upward trend in the series and the results of both the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) suggested that the series is not stationary at original level but later stationary at the second difference. The ARIMA (3,2,0), ARIMA (0,2,1), ARIMA (0,2,1), and SARIMA (1,2,2)(1,0,0)[12] was chosen for Rice, Beans, Gari, and Yam tuber respectively as the best-fit model using the selected criterions for optimal model selection which are Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) and were used to make future forecasts.

It was concluded that ARIMA (3,2,0), ARIMA (0,2,1), ARIMA (0,2,1), and SARIMA (1,2,2)(1,0,0)[12] are the best models that fit the average price of selected food items in Nigeria (Rice, Beans, Gari, and Yam tuber respectively), the forecast made for two(2) years from January 2024 to December 2025 using the fitted model showed that the average price of selected food items in Nigeria (Rice, Beans, Gari, and Yam tuber) will continue to steadily increase for the time forecasted so the trend points to potential inflationary pressures on food commodities in Nigeria, which may exacerbate food insecurity, particularly for low-income households, if necessary steps are not taking either by the individual or government at large.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

The food prices have increased continuously over the years (Gombkötő, 2019). There is a consensus that the rising food inflation in low-income countries is a pointer to the high degree of uncertainty in the food market (Edamisan *et al.*, 2021). The high food prices have serious implications for food and nutrition security, macroeconomic stability, and the political security of any nation. Except for clothing and shelter as the necessities of life, food remains the most vital item in the hierarchy of needs because of its centrality to human existence (Elijah, 2014). The challenge of feeding the growing world population, which is expected to reach 9 billion people in 2050 requires new strategies and new multicultural and multi-sectorial rethinking capable of generating new forms of dialogue, at different specialist levels, toward a more sustainable use of the available natural and human resources, to ensure food and nutrition security especially through agricultural commodity processing (Ogbonna, 2020).

The price behavior of staple food was initially caused by people living in poverty. They spend most of their income on food due to increased staple food prices (Naylor *et al.*, 2010). According to Food and Agriculture Organization of the United Nations (FAO), during the food crises, not only did the price of food increase but also undernourished people (0.1% in Asia and 8% in Africa). The price of staple foods depends on the supply and demand in the market. The supply side is the ability and willingness to produce food. The demand side of staple food is mainly driven by income growth. For instance, an increasing demand for staple food, including cereals up to a certain level of income, after which further increases in income levels result in a natural decline in cereal demand (Regmi *et al.*, 2013).

According to Ismail *et al.,* (2018), the rise in global food prices has impacted macroeconomic policy decisions, leading to inflation, high lending rates, and fluctuating exchange rates. High interest rates on loans for agricultural production have raised production costs. Importing agrochemicals has made procurement challenging and has contributed to cost increases due to the depreciation of the Naira exchange rate. This has resulted in a low level of investment in agriculture by the private sector due to the increasing cost of farm input and low profitability in Farm Enterprises in Nigeria. Olanike (2007) found that the prices of staple foods like millet, maize, and sorghum have risen by 100 to 200% since 2007, leading to increased malnutrition, poverty, and instability in many countries. According to Brinkman (2009) state that those most affected by high food prices are individuals who spend a large portion of their income on food, purchase more food than they sell (net buyers), and have limited coping mechanisms. These groups include the urban poor, rural landless individuals, pastoralists, and many small-scale farmers.

The increase in diesel and petrol prices will lead to higher prices for other commodities, particularly food items. High natural gas prices have also driven fertilizer prices, putting pressure on agricultural prices and food items. Furthermore, the soaring energy prices have also increased the cost of cooking gas in Nigeria, affecting household consumption and the income of food vendors, thereby leading to overall increases in food prices in Nigeria. The rising food prices affect the region where is located Grace (23). They discussed several methods used to detect price fluctuations in different markets in one of the states of Nigeria. These methods include the Laspeyres price index, Paasche's Price Index, and more. It was emphasized that the price of food items has increased rapidly.

Shehu *et al.,* (2023) examines the factors influencing the increase in food prices in Nigeria by comparing the impact of oil prices. It was found that rising oil prices have a significant effect on the cost of goods in Nigeria. Since food is a basic necessity, the various effects of price increases and high volatility underline the importance of ongoing monitoring of food prices over time. Rising food prices significantly impact food and nutrition security, as they can push the most vulnerable households further into poverty and weaken their ability to access adequate food (Gustafson, 2013). Food security refers to a situation in which all people have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and preferences for an active and healthy life at all times (FAO, 2002).

It is important to have access to food that is nutritionally balanced, safe, acceptable, and obtained without resorting to emergency supplies or similar coping strategies (Fred, 2012). According to Hyacinth *et al.*, (2015), an individual or household is considered food secure if they can sustainably acquire and consume nutritionally balanced, safe, and preferred food through socially acceptable means to ensure well-being. It has long been recognized that food availability and cultural factors play a major role in food selection and cultural influences lead to differences in the regular consumption of certain foods prepared differently (Lau *et al.*, 1984). Cultural factors can impact food prices in various ways. Dietary preferences and consumption patterns within a culture can drive demand for specific types of food, affecting their prices. Moreover, cultural practices may influence the types of crops grown or livestock raised, thereby affecting the overall supply and pricing of certain foods. Cultural preferences for specific cuisines or ingredients can also lead to price fluctuations based on the demand for those particular products. This study aims to measure the variability in the average price of some selected food items (Rice, Beans, Gari, and Yam tuber) across all regions in Nigeria.

1.2 Aim and Objectives

The study aims at predicting the average prices of some selected food items in Nigeria so as to study the pattern, trends, and forecast for future prices.

To achieve the above aim below are the objectives to;

- **i.** examine the patterns and trends of prices of food;
- **ii.** determine the stationarity of the price of food items;
- **iii.** determine the appropriate model;
- **iv.** forecast for the average prices of some selected food items;

1.3 Statement of the problem

According to (Adeola and Akinyemi, 2020; and Olabisi *et al.,* 2021) the price of food in Nigeria has been increasing and volatile influenced by various factors that involve inflation, exchange rates, and so on. The changes affect the consumers, policymakers, and business owners which have an impact on food security, economic planning, and cost of living.

Therefore, this study employs a time series analysis of some selected food prices in Nigeria in order to understand the pattern and determine the best predictive models for reliable forecasts.

1.4 Justification for the study

Food price prediction is essential for both economic policy and food security in Nigeria. Accurately predicting price trends would allow policymakers, agricultural producers, and consumers to make informed decisions. For farmers, reliable forecasts can guide planting decisions and marketing strategies. For consumers, such forecasts help in budgeting household expenses. In addition, policy makers can design interventions to stabilize prices or implement safety nets to protect vulnerable populations from food price shocks.

Considering the challenges posed by food price volatility, particularly for low-income households, this study is essential in providing a systematic approach to predicting price fluctuations and aiding in the country’s economic planning.

1.5 Source of the Data

The data used in this study are secondary data extracted from the National Bureau of Statistics Website selected food items from January 2017 to December 2023.

CHAPTER TWO

LITERATURE REVIEW AND METHODOLOGY

2.1 Literature review

It is essential to understand the dynamics of food prices when trying to comprehend the broader economic landscape. This review aims to explore existing literature on the prices of some selected food items, with a focus on Rice, Beans, Garri, and Yam tuber. By synthesizing findings from various studies, we aim to identify patterns and trends in the average price variations of these food items. Additionally, we will use time series analysis to determine the stability and predict the prices of these common food items.

In recent decades, research on food prices has progressed significantly, with many studies providing valuable insights. Early researchers such as Gilbert (2010) established the initial framework for understanding food prices. Subsequent studies, including (Lau *et al.*, 1984), explored the psychological factors that influence consumers' food price choices.

In the field of research, Francis (2014) built upon earlier findings and introduced a new methodology to enhance our understanding of Multivariate analysis techniques, specifically principal component analysis (PCA), which is used for data reduction. Seglah identified major dimensions to evaluate price levels of various food items, aiming to identify specific markets where items are either high-priced or low-priced. In a study conducted by (Monika *et al.*, 2020), the researchers investigated the relationship between crude oil and food prices. They found evidence of long-term connections between crude oil and selected food prices.

Another study by Ekine and Okidm (2003) analyzed the effects of fuel subsidy removal on selected food prices in River State (2001-2002). The study aimed to examine the impact of subsidy removal on prices of specific food items, compare prices before and after subsidy removal, and determine if subsidy removal caused inflation. The study concluded that fuel subsidy removal indirectly increases fuel prices and affects food prices. Furthermore Akpan *et al.,* (2009) investigated the variations in consumer prices of selected food items among markets in Cross River. Their study concluded that consumer prices did not significantly differ for the selected food items in the zone. They utilized the analysis of variance (ANOVA) technique to test the null hypothesis and the complete block design (CRD) method to estimate F.

The study examines the impact of unexpected increases in non-seasonal food prices on household food security, with a focus on both domestic and imported rice as key components of the Nigerian diet. The research found that higher prices of imported rice have negative effects on dietary diversity and the proportion of household consumption expenditure spent on food, while the effects of domestic rice price volatility are unclear. The impact of rice price increases varies based on household wealth, with poorer households experiencing a greater increase in the proportion of consumption expenditure spent on food and richer households experiencing a greater decrease in dietary diversity (Khadijat *et al.,* 2021). In the Ika North East Local Government Area of Delta State, the average monthly income of the household head was N52, 000, and the average household expenditure on staple foods was N16,915.78 in the study area (Mercy *et al.,* 2016).

Studying these prices is important because they directly impact the cost of living, poverty levels, and overall economic stability. High volatility in food prices can lead to increased hunger and malnutrition, especially among vulnerable populations (Akpan, 2012). For example, (Adebiyi *et al.*, 2014) have used ARIMA models to forecast rice prices in Nigeria, demonstrating their effectiveness in capturing price dynamics. (Festus *et al.*, 2012) utilized VAR models to analyze the impact of macroeconomic policies on food prices in Nigeria, showing the interplay between policy decisions and price movements. Similarly, studies such as those by (Oladipo *et* *al.*, 2011) have applied GARCH models to understand the volatility of maize prices, highlighting significant fluctuations within the market.

In a study by Adejumo *et al.,* (2018), time series analysis was used to evaluate the trend and seasonality of food prices in Nigeria. The study analyzed monthly price data for eight food items from January 2010 to December 2016. The time series analysis showed that the prices of food items were characterized by seasonal patterns and upward trends. Similarly, Oladejo *et al.,* (2020) conducted a study on the price volatility of selected food items in Nigeria using time series analysis. The study analyzed monthly price data for seven food items from January 2014 to December 2018. The results revealed that the prices of rice, beans, yam, and wheat were highly volatile, while the prices of semolina, Garri, and maize were relatively stable.

The research conducted by Apata (2013) on the cointegration between food prices and inflation in Nigeria highlights the long-term connections and short-term adjustments in the market. Numerous studies have consistently found that food prices in Nigeria show strong seasonal patterns, which are influenced by harvest cycles, climatic conditions, and agricultural practices. For example, Akinleye *et al.,* (2007) identified significant seasonal variations in the prices of yam and maize. Exchange rate fluctuations and inflation are important factors affecting food prices. Akpan (2012) demonstrated that exchange rate volatility directly impacts the prices of imported food items, contributing to overall price instability in the market.

The pricing of food is influenced by a complex interplay of factors, including climatic conditions, global market trends, and domestic policies. Future research should concentrate on integrated models that capture these multifaceted interactions (Apata, 2013). Using advancements in machine learning and big data analytics can enhance the accuracy and robustness of time series models. Integrating these technologies with traditional statistical methods can offer deeper insights into food price dynamics (Adebiyi *et al., 2014*). It's crucial to ensure that insights from time series analysis are effectively integrated into policy frameworks. Collaborative efforts between researchers, policymakers, and stakeholders can bridge the gap between analysis and implementation (Festus *et al.,* 2012).

Research studies by (Nwafor, *et al.*, 2011) emphasize the influence of agricultural policies on food production and prices, advocating for more stable and supportive policy frameworks. Global food price shocks and trends also impact domestic prices. Ajetomobi and Binuomote (2006) examined the transmission of global cereal prices to the Nigerian market, showing significant spillover effects. Adewumi *et al.,* (2014) used ARIMA models to predict rice prices, revealing the significant impact of domestic production and import policies on price stability. They concluded that improving local rice production could alleviate the effects of international price fluctuations. Oladipo *et al.*, (2011) used GARCH models to analyze maize price volatility, finding that external shocks such as global oil prices and climatic conditions significantly affect maize prices, highlighting the necessity for robust agricultural policies to manage these external forces.

A study by Akinbamowo *et al.,* (2019) examined the factors affecting the prices of key food items in Nigeria through a time series analysis. The research assessed monthly price data for seven food items spanning from January 2007 to December 2016. It revealed that the exchange rate, inflation rate, and oil price had substantial influences on the prices of food items in Nigeria. In addition, Bamidele *et al.,* (2019) conducted a study where they analyzed monthly price data for five selected food items in Nigeria using time series analysis. The research investigated the trends and seasonal patterns of food prices from January 2008 to December 2017. The study revealed that the prices of maize, rice, and yam exhibited seasonal variations, whereas the prices of Garri and beans remained relatively stable.

Richard *et al.,* (2023) investigate how changes in petroleum product prices affect the prices of food items in the Nigerian economy. They use annual time series data from 1991 to 2021 and employ the ARDL approach to determine the long-run and short-run relationship between the price of premium motor spirits and the price of food items in Nigeria. The unit root test reveals a combination of 1(0) and 1(1) order of integration. Based on these results, the ARDL approach is deemed more appropriate. The findings indicate that the price of premium motor spirits has a positive and significant impact on food items in the short run. However, in the long run, the prices of premium motor spirits have a positive but insignificant impact on the food items in Nigeria.

The study conducted by Edamisan *et al.,* (2021) finds that there are welfare implications on both food price and transport cast volatilities on household welfare in Nigeria. Where they constitute an average of 12% and 13% on welfare costs of volatilities of rural food and transport costs. The study shows a general increase in the price of food items, clothing, and building materials. This shows that the price of food items has increased between 13.93 and 84.04%, except custard which was reduced by 15%, the price of clothes increased between 11.2 and 100%, except Ankara which was reduced by less than 8%, and also the price of building materials as also increase between 5.9 and 69.7% (Ayoola 2015). This indicates that not only does the price of food increase the price of commodities also has been increasing over the years.

The ARIMA Model was suggested to use for the model Nigerian consumer price index. Where there is a rising trend in the consumer price index inflation of the food sector in Nigeria. The three candidate models are the least square equation, non-seasonal ARIMA (1, 2, 0), and seasonal ARIMA (1, 2, 0)*(1, 0, 0)12. The seasonal ARIMA (1, 2, 0)*(1, 0, 0) 12 is closer than the Non-seasonal ARIMA (1, 2, 0) and linear trend equation. Also, the seasonal ARIMA (1, 2, 0)*(1, 0, 0)12 is most suitable for forecasting the consumer price index as a measure of inflation in the Nigerian Food Sector (Olatunji *et al.,* 2019). There is a contribution of up to 70% to the world output of yam, Nigeria is the largest country that produces yam as the second most commonly harvested tuber crop. Results indicated that variables were not stationary but they became stationary at the first differencing. At a 5% significance level, in the long run, the price of yam was determined by annual production (coef.=-0.8095), GDP (coef.=-3.009), and annual money supply (coef.=0.829). Which indicates the price of yam increased (Ajibade *et al.,* 2018).

The highly significant factors that influence the food expenditure were the household size, per capita income, dependency ratio, and age. 76% of the households were food-secured, while 24% were food insecure. It was also observed that households that spend more on food have higher incomes and therefore tend to be more food secure (Babatunde *et al.,* 2019). La'ah *et al.,* (2022) state that the result of VECM revealed that in the long run, the coefficient of rice price (0.000533) was statistically significant at 1%, the coefficient of maize price (1115.509) was positive and statistically significant at 1% while the coefficient of wheat price (4.728131) was positive and statistically significant at 1%. The study shows that prices of rice, maize, and wheat have a positive and significant influence on the production or output of rice, maize, and wheat in Nigeria in the long run. Hence, there is an increase in prices of rice, maize, and wheat increasing the quantities that are being produced by the farmers in Nigeria.

The study by Shehu *et al.,* (2023) uses the linear autoregressive distributive lag model to analyze inflation dynamics and food prices in Nigeria. The study specifically focuses on identifying the fundamental factors contributing to the increase in food prices. By analyzing annual data from 1990 to 2021, the study explores the relationships between oil prices, exchange rates, money supply, and government expenditure, and their long- and short-term effects on inflation and food prices in Nigeria. The prices of most food items experienced a significant increase between the periods 2000-2006 and 2007-2012, with the price of rice nearly tripling (Jerumeh, 2022).

Recent research, including studies by Marks (2024) examined gaps in understanding by using descriptive statistics to assess how regional price differences impact the risk of food insecurity. However, it is important to conduct a comprehensive review of existing literature to identify any emerging trends and unresolved issues.

2.2 Methodology

This study aims at predicting the average price of some selected food items (Rice, Beans, Gari, and Yam tuber) in Nigeria for 8 years (87 months) from January 2017 to December 2023, using either AMRA, ARIMA, or SARIMA models. One of the major assumptions of the Box-Jenkins' time series model is stationarity and this was examined using the Augmented Dickey-Fuller (ADF) which was implemented in Econometric.

2.2.1 Time series

A time series is a series of data points indexed listed or graphed in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Most measurements in the social sciences are made at regular intervals giving rise to discrete time series data. Examples of time series are heights of ocean tides, counts of sunspots, and the daily closing value of the Dow Jones Industrial Average. Time series are very frequently plotted via line charts. Time series are used in statistics, signal processing, pattern recognition, econometrics, mathematical finance, weather forecasting, intelligent transport and trajectory forecasting, earthquake prediction, control engineering, astronomy, communications engineering, and largely in any domain of applied science and engineering that involves temporal measurements.

2.2.1.1 Component of time series

There are four components of time series namely, trend, seasonal variation, cyclical variation, and irregular variation.

i. Trend (T_t): It is a long-term change. A trend is also known as a secular trend it is the overall long-term direction of a time series. It is the general tendency of a time series to increase, decrease, or stagnate over a long period. A trend can be positive if the series exhibits a long-term upward movement or negative if it exhibits a long-term downward movement, if a time series does not show an upward or downward pattern, then the series is stationary in the mean.

ii. Seasonal variation (S_t): Many of the time series data exhibit a seasonal variation which is an annual period, seasonality occurs in the series when the time series exhibits regular fluctuations during the same month (or months) every year, or during the same quarter every year.

iii. Cyclical variation (C_t): The cyclical component is the fluctuation above and below the long-term trend line. They are sizable fluctuations unfolding over more than one year in time above and below the secular trend. The cyclical variation is periodic and repeats itself like a business cycle, which has four phases (i) Peak (ii) Recession (iii) Trough/Depression (iv) Expansion.

iv. Irregular variation (I_t): This component is unpredictable. Every time series has some unpredictable component that makes it a random variable. For example a rise in the prices of steel due to strikes in the factory, accidents due to failure of break, floods, earthquakes, war, etc.

2.2.2 Time series model

There are two types of model in time series namely the Additive time series model and the Multiplicative Time Series Model

i. Additive Time Series Model: The additive time series model is expressed as;

$$Y_t = T_t + S_t + C_t + I_t \tag{2.1}$$

The additive model is based on the assumption that all four components of the time series operate independently of each other so that none of these components has any effect on the remaining three components However, this assumption is not true in most of the economic and business, social and physical science time series where the four components of the time series are not independent

ii. Multiplicative Time Series Model: The multiplicative time series model is expressed as;

$$Y_t = T_t . S_t . C_t . I_t \tag{2.2}$$

This model is based on the assumption that the four components of the time series are due to different causes and not necessarily independent since they can affect each other.

2.2.3 Stationarity

Time series may be stationary or non-stationary. Stationary series are characterized by a kind of statistical equilibrium around a constant mean level as well as a constant dispersion around that mean level (Box and Jenkins; 1976). Stationarity is a necessary condition for building a time series model that is useful for future forecasting. A series is said to be weakly or second-order stationary if it has a fixed mean and a constant variance. covariance structure. When a series possesses this covariance stationarity, the covariance structure is stable over time (Diebold, 1998). That is to say, the autocovariance remains the same regardless of the point of temperate reference. Under these circumstances, autocovariance depends only on the number of periods between the two points of temporal reference (Mills: 1993). If a series is stationary, the magnitude of the autocorrelation attenuates fairly rapidly, whereas if the series in non-stationary or integrated, the autocorrelation diminishes gradually overtime. If, however, these equally spaced observations are deemed realizations of multivariate normal distributions, the series is considered to be strictly stationary. Many macroeconomic series are integrated or no stationary.

If the series has a stochastic trend, then the level with an element of randomness is a function of time. There are certain test used to inspect if a series is stationary or not.

2.2.3.1 Test for Stationarity

There are two different approaches: the unit root test such as the Augmented Dickey-Fuller test (ADF test) and the stationarity test such as the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test).

2.2.3.1.1 Augmented Dickey-Fuller test

In statistics and econometrics, an Augmented Dickey-Fuller test [ADF] tests the null hypothesis of a unit root present in a time series sample. The alternative hypothesis is different depending on which version of the test is used but is usually stationary or trend-stationarity. It is an augmented version of the Dickey-Fuller test for a larger and more complicated set of time series models. The Augmented Dickey-Fuller [ADF] statistic used in the test, is a negative number. The more negative it is, the stronger the rejection of the null hypothesis that there is a unit root at some level of confidence.

2.2.3.1.2 Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test)

This test sets its null hypothesis that the series is stationary. Many econometric and financial data sets take the form of a time series of curves, or functions. The best-known and most extensively studied data of this form are yield curves. Even though they are observed at discrete maturities, in financial theory they are viewed as continuous functions, one function per month or per day. The yield curves can thus be viewed as a time series of curves, a functional time series. Other examples include intraday price, volatility, or volume curves. Intraday price curves are smooth, volatility and volume curves are noisy and must be smoothed before they can effectively treated as curves. As with scalar and vector-valued time series, it is important to describe the random structure of a functional time series A fundamental question, which has received a great deal of attention in econometric research, is whether the time series has a random walk, or unit root, component.

The work of Kwiatkowski et al. (1992) was motivated by the fact that unit root tests developed by Dickey and Fuller (1981), and Said and Dickey (1984) indicated that most aggregate economic series had a unit root. In these tests, the null hypothesis is that the series has a unit root. Since such tests have low power in samples of sizes occurring in many applications, Kwiatkowski et al (1992) proposed that trend stationarity should be considered as the null hypothesis, and the unit root should be the alternative. Rejection of the null of trend stationarity could then be viewed as a convincing evidence in favor of a unit root. It was soon realized that the KPSS test of Kwiatkowski et al. (1992) has a much broader utility. For example, Lee and Schmidt (1996) and Giraitis et al. (2003) used it to detect long memory, with short memory as the null hypothesis.

2.2.4 Autocorrelation and Partial Autocorrelation function (ACF and PACF)

These statistical measures describe how the observations in a time series are related to each other. To determine a proper model for a given time series data, it is necessary to carry out the ACF and PACF analysis. For modeling and forecasting purposes it is often useful to plot the ACF and PACF against consecutive time lags. These plots help in determining the order of the Autoregressive (AR) and Moving average (MA) terms.

2.2.5 Differencing

The idea of making a non-stationary series to become a stationary one is called the differencing of the time series.

$$d_1 = Y_t - Y_{t-1} \tag{2.3}$$

Where Y, is the current observation Y_t., is the previous observation, and d, is referred to as the first differenced series of Y_{t-1}.

In some scientific fields, a time series Y_t may contain multiple unit roots and needs to be differenced multiple times to become stationary.

2.2.6 Models in time series

In time series forecasting, past observations are collected and analyzed to develop a suitable mathematical model that captures the underlying data-generating process for the series.

The future events are then predicted using the model. This approach is particularly useful when there is not much knowledge about the statistical pattern followed by successive observations or when there is a lack of a satisfactory explanatory model. Time series forecasting has important applications in various fields. Often valuable strategic decisions and precautionary measures are taken based on the forecast result.

Thus making a good forecast, ie fitting an adequate model to a time series is very important. Over the past several decades many efforts have been made by researchers for the development and improvement of suitable time series forecasting models. While building a proper time series model we have to consider the principle of parsimony. According to this principle, always the model with smallest possible number of parameters are to be selected so as to provide an adequate representation of the underlying time series data. Out of many suitable models. One should consider the simplest one, still maintaining an accurate description of the inherent properties of the time series. The idea of model parsimony is similar to the famous Occam's razor principle. As discussed by Hipel and McLeod, one aspect of this principle is that when faced with several competing and adequate explanations, pick the simplest one. The Occam's razor provides considerable inherent information when applied to logical analysis.

Moreover, the more complicated the model, the more possibilities will arise for departure from the actual model assumptions. With the increase of model parameters, the risk of over-fitting also subsequently increases. An overfitted time series model may describe the training data very well, but it may not be suitable for future forecasting. As potential overfitting affects the ability of a model to forecast well, parsimony is often used as a guiding principle to overcome this issue. Thus in summary it can be said that, while making time series forecasts, genuine attention should be given to selecting the most parsimonious model among all other possibilities.

The selection of a proper model is extremely important as it reflects the underlying structure of the series and this fitted model in turn is used for future forecasting. A time series model is said to be linear or non-linear depending on whether the current value of the series is a linear or non-linear function of past observations. In general models for time series data can have many forms and represent different stochastic processes. There are two widely used linear time series models in the literature, viz.

Autoregressive (AR) and Moving Average (MA) models. Combining these two, the Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models have been proposed in the literature. The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model generalizes ARMA and ARIMA models. For seasonal time series forecasting, a variation of ARIMA, viz. the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is used.

ARIMA model and its different variations are based on the famous Box-Jenkins principle and so these are also broadly known as the Box-Jenkins models.

Linear models have drawn much attention due to their relative simplicity in understanding and implementation. However, many practical time series show non-linear patterns. For example, non-linear models are appropriate for predicting volatility changes in economic and financial time series. Considering these facts, various nonlinear models have been suggested in the literature. Some of them are the famous Autoregressive Conditional Heteroscedasticity

(ARCH) model and its variations like Generalized ARCH (GARCH), Exponential Generalized ARCH (EGARCH), etc., the Threshold Autoregressive (TAR) model, the Non-linear Autoregressive (NAR) model, the Nonlinear Moving Average (NMA) model, etc.

i) The Autoregressive Moving Average (ARMA) Models

An ARMA (p. q) model is a combination of AR (p) and MA (q) models and is suitable for univariate time series modeling. In an AR (p) model the future value of a variable is assumed to be a linear combination of p past observations and a random error together with a constant term. To identify the appropriate order of the ARMA model, the ACF and PACF plots were used and four tentative ARMA models were identified.

For ARMA (1, 0, 1): p=1, d=0, q=1,

$$(1 - \emptyset_1\beta)X\_t \ = (1 - \ \theta_1\beta)\varepsilon_t \qquad (2.4)$$

ii) Autoregressive Integrated Moving Average (ARIMA) Models

The ARIMA models, described above can only be used for stationary time series data. However, in practice, many time series such as those related to socio-economic and business show non-stationary behavior. Time series, which contain trend and seasonal patterns, are also non-stationary. Thus from an application viewpoint, ARIMA models are inadequate to properly describe non-stationary time series, which are frequently encountered in practice. For this reason, the ARIMA model is proposed, which is a generalization of an ARMA model to include the case of non-stationarity as well.

In ARIMA models a non-stationary time series is made stationary by applying finite differencing of the data points. The mathematical formulation of the ARIMA (p.d.q) model... Where, p. d and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively.

The Model:

$$\emptyset_p(1-B)^d Z_t = \theta_q(B)a_t \tag{2.5}$$

iii) Seasonal Autoregressive Integrated Moving Average (SARIMA) Models

SARIMA models are an adjustment of Autoregressive Integrated Moving Average (ARIMA) models that accurately model seasonal time series data. Seasonality is defined in time series as a systematic pattern of repeated fluctuations over a given time, given that h is the periodicity of the series [27]. For example, data observed quarterly has h being 4. This behavior, which is frequent in most time series data, renders the Autoregressive Integrated Moving Average model ineffective when applied to the series. Seasonal AR and MA terms in an ARIMA forecast X_t based on previous observations and residual errors with lags multiples of S. (the seasonality duration of the series). The ARIMA models (non-seasonal) are widely referred to as ARIMA (p, d, q), given p is the order for the AR model denoting the set of time lag(s), d gives the differencing order, and q the MA order of the model [28]. The seasonal ARIMA model, on the other hand, combines non-seasonal and seasonal components represented as ARIMA (p,d,q) (P, D, Q)h [29].

Let B^S represent the operator then we have,

$$B^s X_t = (X_t - X_{t-s}) \tag{2.6}$$

2.7 Some Nonlinear Time Series Models

Linear time series models have been discussed so far. As mentioned by Cartier, nonlinear models should also be considered for better time series analysis and forecasting. Campbell and McKinley (1997) made important contributions towards this direction. According to them, almost all non-linear time series can be divided into two branches: one includes models nonlinear in mean and the other includes models non-linear in variance (heteroskedastic). As an illustrative example, there are two nonlinear time series:

i. Nonlinear Moving Average (NMA) Model: This model is non-linear in mean but not in variance.

ii. Eagle's (1982) ARCH Model: This model is heteroskedastic, i.e. nonlinear in variance, but linear in mean. This model has several other variations, like GARCH, EGARCH, etc.

2.2.8 Model selection

When selecting a model that best fits a time series from a finite number of models the information criterion has been the most widely used in time series analysis to determine the appropriate order of a model. Below are the most commonly used criteria

2.2.8.1 Akaike information criterion (AIC)

The Akaike information criterion (AIC) is an estimator of the relative quality of statistical models for a given set of data. It is defined as;

$$AIC = 2k - 2\ln(L) \tag{2.7}$$

Where, L is the maximized value of the maximum likelihood function of the model, L = (YU) is the parameter that maximizes the function, Y_t is the observation, n is the number of observations, k is the number of parameters

2.2.8.2 Bayesian information criterion (BIC)

The Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC) although it is stricter in penalizing loss of degree of freedom.

The Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred, It is defined as;

$$BIC = In(n)k - 2\ In \tag{2.8}$$

Where, L is the maximized value of the maximum likelihood function of the model, L = (Yt/), O is the parameter that maximizes the function, Y_t is the observation, n is the number of observations, k is the number of parameters.

CHAPTER THREE

3.0 DATA ANALYSIS AND INTERPRETATION

This chapter consists of the analysis of the data and its interpretations. The data collected is informed of time series data of average price of some selected food items in Nigeria from January 2017 to December 2023. The analysis was done using R-language software.

3.1 Time plot of the data

In other to understand the pattern of the data, there is a need to examine its pattern.

3.1.1 Time plot for the average price of rice in Nigeria

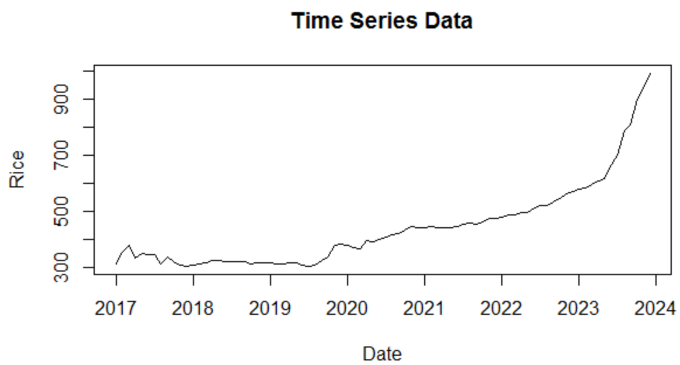

Figure 3.1: Time plot at original level for the average price of rice from 2017 January to 2023 December.

Comment: The time plot above shows that there is an upward trend in the average price of rice in Nigeria. It also shows that the data is not stationary at its original level which means the price is not stable over time.

3.1.2 Time plot for the average price of beans in Nigeria

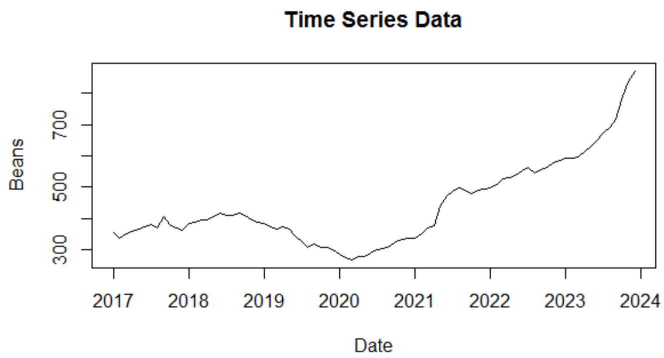

Figure 3.2: Time plot at original level for the average price of beans from 2017 January to 2023 December.

Comment: The time plot above shows that there is an upward trend in the average price of beans in Nigeria. It also shows that the data is not stationary at its original level which means the price is not stable over time.

3.1.3 Time plot for the price of Garri in Nigeria

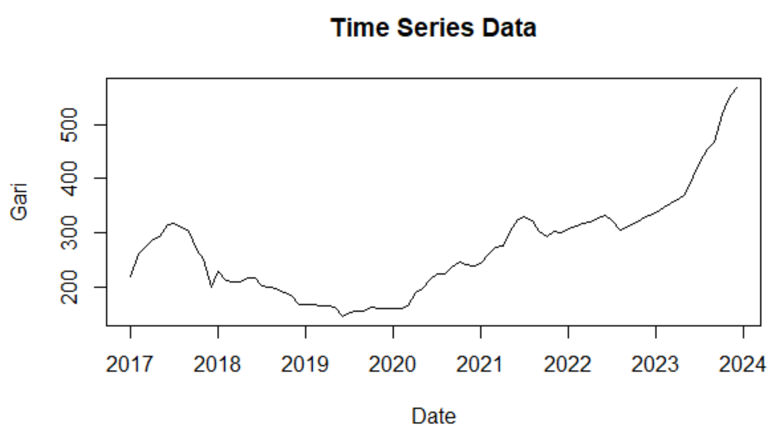

Figure 3.3: Time plot at original level for the average price of garri from 2017 January to 2023 December.

Comment: The time plot above shows that there is an upward trend in the average price of garri in Nigeria. It also shows that the data is not stationary at its original level which means the price is not stable over time.

3.1.4 Time plot for the average price of yam tuber in Nigeria

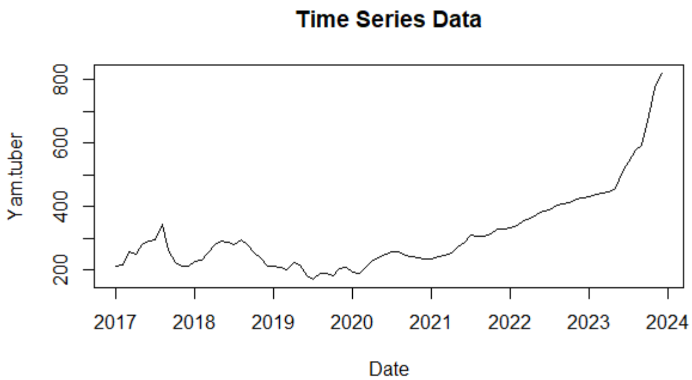

Figure 3.4: Time plot an original level for the average price of Yam tuber from 2017 January to 2023 December.

Comment: The time plot above shows that there is an upward trend in the average price of Yam tuber in Nigeria. It also shows that the data is not stationary at its original level which means the price is not stable over time.

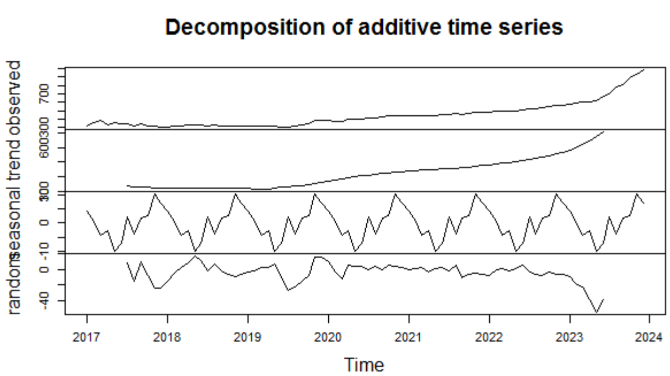

Figure 3.5: Decompose the time series plots at the original level of Rice from 2017 January to 2023 December.

Comment: The trend component represents the long-term movement in the data. It smooth out short-term fluctuations and highlights the overall direction upward in the data. The trend is increasing over time, it suggests a general upward movement in the time series.

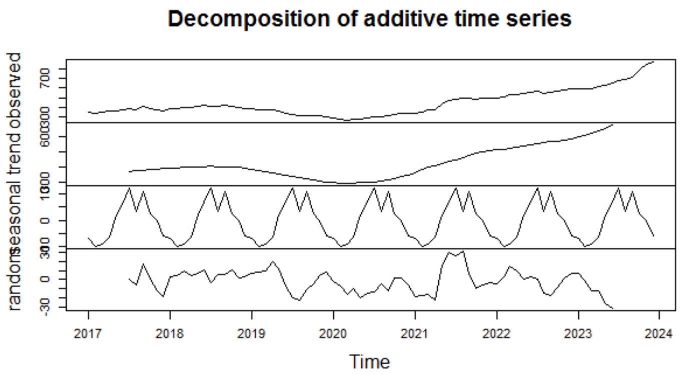

Figure 3.6: Decompose the time series plots at the original level of Beans from 2017 January to 2023 December.

Comment: The trend component represents the long-term movement in the data. It smooth out short-term fluctuations and highlights the overall direction upward in the data. The trend is increasing over time, it suggests a general upward movement in the time series.

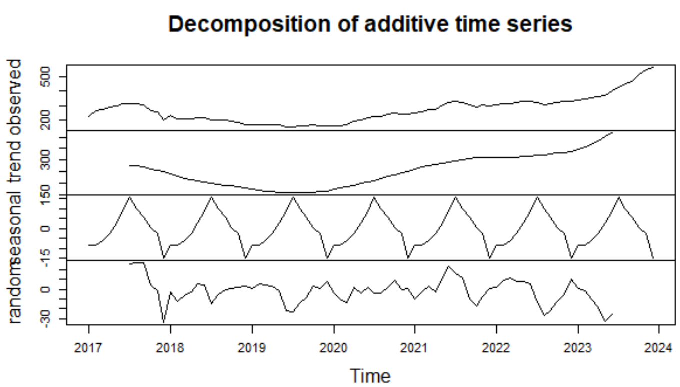

Figure 3.7: Decompose the time series plots at the original level of Garri from 2017 January to 2023 December.

Comment: The trend component represents the long-term movement in the data. It smooth out short-term fluctuations and highlights the overall direction upward in the data. The trend is increasing over time, it suggests a general upward movement in the time series.

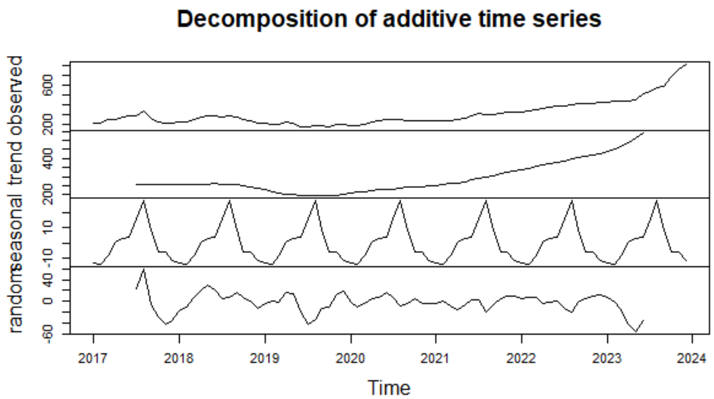

Figure 3.8: Decompose the time series plots at the original level of Yam tuber from 2017 January to 2023 December.

Comment: The trend component represents the long-term movement in the data. It smooth out short-term fluctuations and highlights the overall direction upward in the data. The trend is increasing over time, it suggests a general upward movement in the time series.

3.2 Test for the Stationary

3.2.1 Hypothesis

H_0: There is a unit root

H_1: There is no unit root

Table 3.1: Result for the Augmented Dickey-Fuller (ADF) test at the original Level of the average price of rice from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Rice	Value	0.9237	4
		p-value	0.99	

Interpretation: The result in the above table shows that a unit root is present in the series since p-value > 0.05, therefore the data is not stationary at the original level.

Table 3.2: Result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the original Level of the average price of rice from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Rice	Value	0.1667	1
		p-value	0.1	

Interpretation: The result in above table shows that the data is not stationary at the original level since the p-value < 0.05.

Table 3.3: Result for the Augmented Dickey-Fuller (ADF) test at the original Level of the average price of beans from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Beans	Value	0.2137	4
		p-value	0.99	

Interpretation: The result in the above table shows that a unit root is present in the series since p-value > 0.05, therefore the data is not stationary at the original level.

Table 3.4: Result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the original Level of the average price of beans from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Beans	Value	1.4399	3
		p-value	0.01	

Interpretation: The result in above table shows that the data is not stationary at the original level since the p-value < 0.05.

Table 3.5: Result for the Augmented Dickey-Fuller (ADF) test at the original Level of the average price of garri from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Garri	Value	-0.95549	4
		p-value	0.9397	

Interpretation: The result in the above table shows that a unit root is present in the series since p-value > 0.05, therefore the data is not stationary at the original level.

Table 3.6: Result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the original Level of the average price of gari from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Garri	Value	1.2945	3
		p-value	0.01	

Interpretation: The result in above table 3.6 shows that the data is not stationary at the original level since the p-value < 0.05.

Table 3.7: Result for the Augmented Dickey-Fuller (ADF) test at the original Level of the average price of yam tuber from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Yam tuber	Value	1.2299	4
		p-value	0.99	

Interpretation: The result in the above table shows that a unit root is present in the series since p-value > 0.05, therefore the data is not stationary at the original level.

Table 3.8: Result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the original Level of the average price of yam tuber from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Yam tuber	Value	1.4064	3
		p-value	0.01	

Interpretation: The result in the above table shows that the data is not stationary at the original level since the p-value < 0.05.

3.3 Time plot of the data at differencing Level.

3.3.1 Time plot of the average price of rice, Beans, Garri and Yam tuber at first-difference

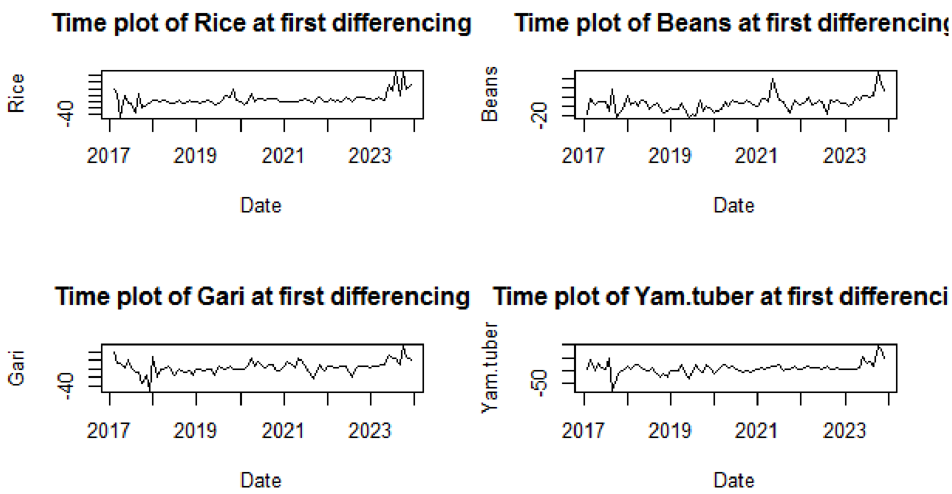

Figure 3.9: Time plot at the first difference for the price of Rice, Beans, Garri and Yam tuber from 2017 January to 2023 December.

Comment: The time plot above shows that the data is not stationary at the first difference as the trend exists in the series and it also indicates that the data is not stable over time.

Table 3.9: The result for the Augmented Dickey-Fuller (ADF) test at the first difference of the average price of rice from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Rice	Value	-2.1844	4
		p-value	0.5003	

Interpretation: The result in above table shows that a unit root is present in the series since p-value > 0.05, therefore the data is not stationary at the first difference.

Table 3.10: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the first difference of the average price of rice from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Rice	Value	0.8595	3
		p-value	0.01	

Interpretation: The result in above table shows that the data is not stationary at the first difference since the p-value < 0.05.

Table 3.11: The result for the Augmented Dickey-Fuller (ADF) test at the first difference of the average price of beans from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Beans	Value	-2.8383	4
		p-value	0.2322	

Interpretation: The result in above table shows that a unit root is present in the series since p-value > 0.05, therefore the data is stationary at the first difference.

Table 3.12: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the first difference of the average price of beans from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Beans	Value	0.6858	3
		p-value	0.01483	

Interpretation: The result in table above shows that the data is not stationary at the first difference since the p-value < 0.05.

Table 3.13: The result for the Augmented Dickey-Fuller (ADF) test at the first difference of the average price of garri from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Garri	Value	-3.957	4
		p-value	0.0157	

Interpretation: The result in above table shows that a unit root is not present in the series since p-value < 0.05, therefore the data is stationary at the first difference.

Table 3.14: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the first difference of the average price of garri from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Garri	Value	0.5695	3
		p-value	0.0260	

Interpretation: The result in above table shows that the data is not stationary at the first difference since the p-value > 0.05.

Table 3.15: The result for the Augmented Dickey-Fuller (ADF) test at the first difference of the average price of yam tuber from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	yam tuber	Value	-2.3905	4
		p-value	0.4158	

Interpretation: The result in above table shows that a unit root is present in the series since p-value > 0.05, therefore the data is not stationary at the first difference.

Table 3.16: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the first difference of the average price of yam tuber from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	yam tuber	Value	0.6858	3
		p-value	0.0148	

Interpretation: The result in above table shows that the data is not stationary at a first difference since the p-value < 0.05.

3.3.2 Time plot of the average price of rice at second-difference

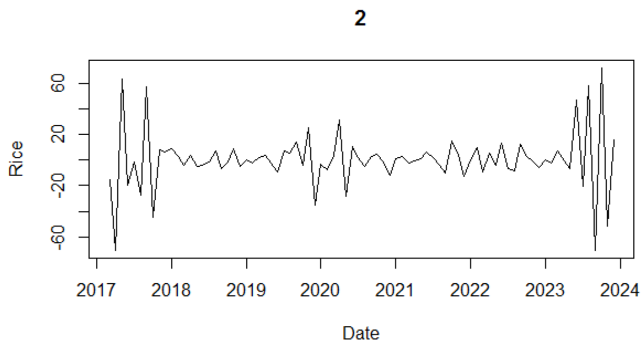

Figure 3.10: Time plot at the second difference for the price of Rice from 2017 January to 2023 December.

Comment: The time plot above shows that the data is stationary at the second difference as the trend no longer exists in the series and it also indicates that the data is now stable over time.

3.3.3 Time plot of the average price of beans at second-difference

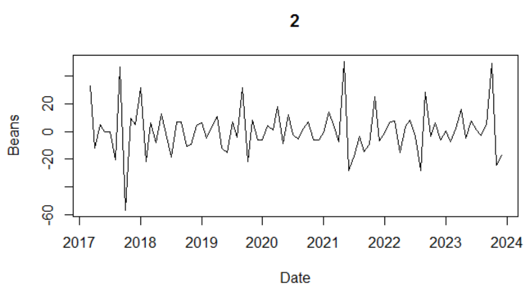

Figure 3.11: Time plot at the second difference for the price of Beans from 2017 January to 2023 December.

Comment: The time plot above shows that the data is stationary at the second difference as the trend no longer exists in the series and it also indicates that the data is now stable over time.

3.3.4 Time plot of the average price of garri at second-difference

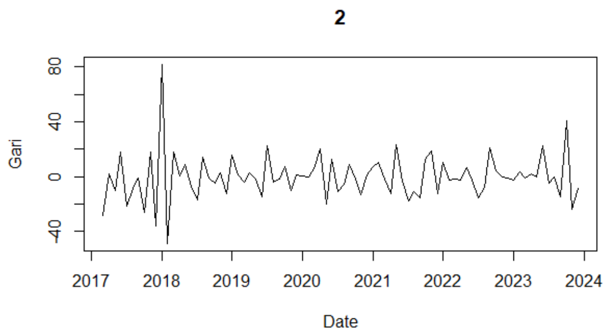

Figure 3.12: Time plot at the second difference for the price of Garri from 2017 January to 2023 December.

Comment: The time plot above shows that the data is stationary at the second difference as the trend no longer exists in the series and it also indicates that the data is now stable over time.

3.3.5 Time plot of the average price of yam tuber at second-difference

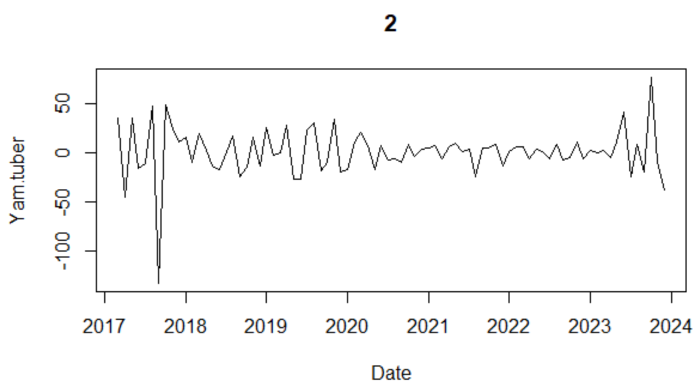

Figure 3.13: Time plot at the second difference for the price of Yam tuber from 2017 January to 2023 December.

Comment: The time plot above shows that the data is stationary at the second difference as the trend no longer exists in the series and it also indicates that the data is now stable over time.

Table 3.17: The result for the Augmented Dickey-Fuller (ADF) test at the second difference of the average price of rice from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Rice	Value	-4.5326	4
		p-value	0.01	

Interpretation: The result in above table shows that a unit root is not present in the series since p-value < 0.05, therefore the data is stationary at the second difference.

Table 3.18: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the second difference of the average price of rice from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Rice	Value	0.2137	3
		p-value	0.1	

Interpretation: The result in above table shows that the data is stationary at the second difference since the p-value > 0.05.

Table 3.19: The result for the Augmented Dickey-Fuller (ADF) test at the second difference of the average price of beans from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Beans	Value	-6.1841	4
		p-value	0.01	

Interpretation: The result in above table shows that a unit root is not present in the series since p-value < 0.05, therefore the data is stationary at the second difference.

Table 3.20: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the second difference of the average price of beans from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Beans	Value	0.0359	3
		p-value	0.1	

Interpretation: The result in above table shows that the data is stationary at the second difference since the p-value > 0.05.

Table 3.21: The result for the Augmented Dickey-Fuller (ADF) test at the second difference of the average price of garri from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	Garri	Value	-4.6841	4
		p-value	0.01	

Interpretation: The result in above table shows that a unit root is not present in the series since p-value < 0.05, therefore the data is stationary at the second difference.

Table 3.22: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the second difference of the average price of garri from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	Garri	Value	0.14401	3
		p-value	0.1	

Interpretation: The result in above table shows that the data is stationary at the second difference since the p-value > 0.05.

Table 3.23: The result for the Augmented Dickey-Fuller (ADF) test at the second difference of the average price of yam tuber from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without constant	Lag-order
Original	yam tuber	Value	-4.4368	4
		p-value	0.01	

Interpretation: The result in above table shows that a unit root is not present in the series since p-value < 0.05, therefore the data is stationary at the second difference.

Table 3.24: The result for the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test) at the second difference of the average price of yam tuber from 2017 January to 2023 December.

Variable Status	Variable Name	Statistics	Without trend	Lag parameter
Original	yam tuber	Value	1.6711	3
		p-value	0.1	

Interpretation: The result in above table 10 shows that the data is stationary at a second difference since the p-value > 0.05.

3.4 Model Identification

This is done using the autocorrelation and partial autocorrelation plots called Correlogram. The correlogram of each series is made and the appropriate model to fit the series is identified.

3.4.1 Correlogram for Rice

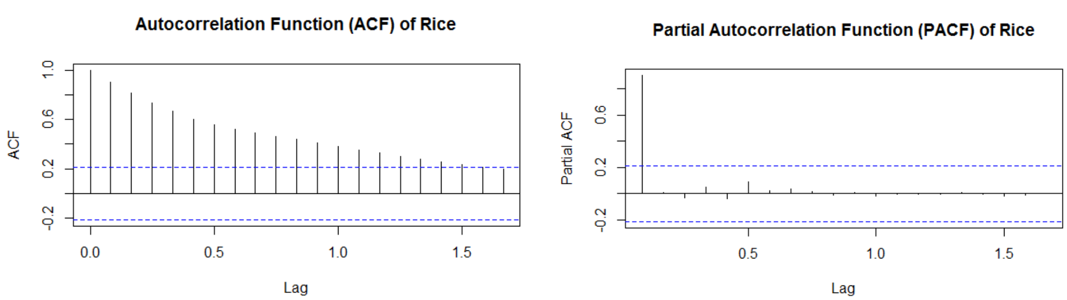

Figure 3.13: The Correlogram plot of Rice

Comments: The autocorrelation function decay and partial autocorrelation function cut off at lag1

3.4.2 Correlogram for Beans

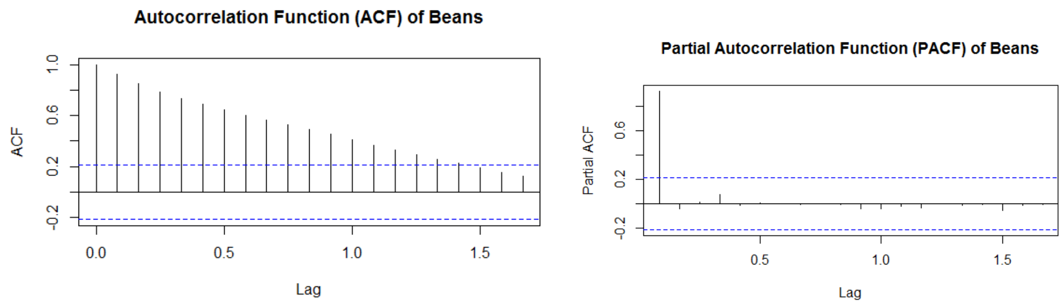

Figure 3.14: The Correlogram plot of Beans

Comments: The autocorrelation function decay and partial autocorrelation function cut off at lag1

3.4.3 Correlogram for Garri

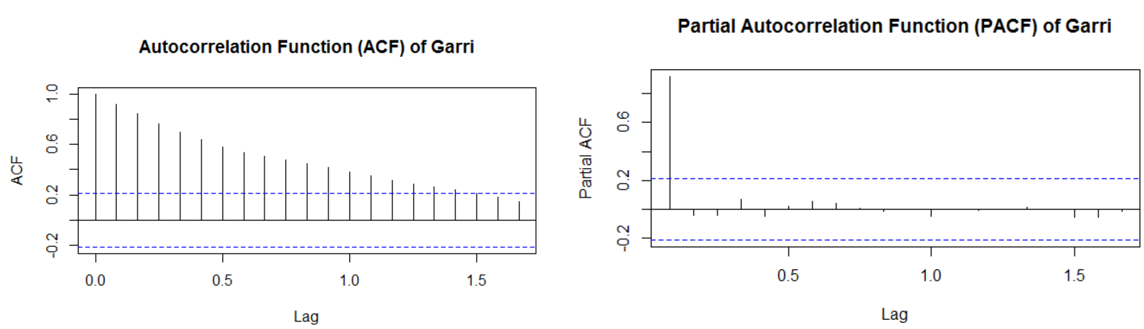

Figure 3.15: The Correlogram plot of Garri

Comments: The autocorrelation function decay and partial autocorrelation function cut off at lag1

3.4.4 Correlogram for Yam tuber

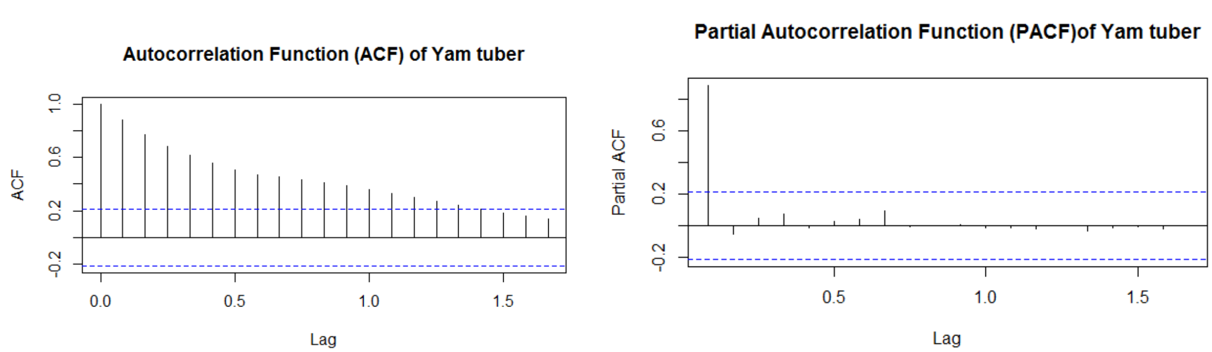

Figure 3.16: The Correlogram plot of Yam tuber

Comments: The autocorrelation function decay and partial autocorrelation function cut off at lag 1

3.5 Model selection for the average price of Rice

Table 3.25: Result of the Model selection ARIMA (p, d, q).

S/N	Model	Akaike Criterion	Bayesian Criterion	sigma^2	log-likelihood
1.	ARIMA (3,2,0)	691.53	701.15	250.3	-341.76

Model Estimation

Table 3.26: Result of the estimated parameter of ARIMA (3, 2, 0)

	Coefficients	std. error
Phi 1	-0.8857	0.1197
Phi 2	-0.4825	0.1619
Phi 3	-0.3212	0.1377

The selected ARIMA model equation is given thus**:**

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \emptyset_3 Y_{t-3} + e_t \quad 3.1$$

$$Y_t = -0.8857Y_{t-1} - 0.4825Y_{t-2} - 0.3212Y_{t-3} + e_t \quad 3.2$$

Interpretation: The results in above table show the test of various ARIMA models to determine the best ARIMA model to use for the data using the selected criterions, Akaike Criterion, and Bayesian Criterion. It is seen that ARIMA (3, 2, 0) has the lowest figure for the Akaike Criterion, and Bayesian Criterion. The best model is ARIMA (3, 2, 0) since it satisfies two out of the three criterions considered.

3.4.2 Model Identification for the average price of beans

Table 3.27: Result of the Model selection ARIMA (p, d, q).

S/N	Model	Akaike Criterion	Bayesian Criterion	sigma^2	log-likelihood
1.	ARIMA (0,2,1)	671.99	676.81	202.9	-334

Model Estimation

Table 3.28: Result of the estimated parameter of ARIMA (0, 2, 1)

	coefficient	std. error
theta_1	-0.688	0.091

The selected ARIMA model equation is given thus**:**

$$Y_t = \theta_1 e_{t-1} + e_t \quad 3.3$$

$$Y_t = -0.688\, e_{t-1} + e_t \quad 3.4$$

Interpretation: The results in above show the test of various ARIMA models to determine the best ARIMA model to use for the data using the selected criterions, Akaike Criterion, and Bayesian Criterion. It is seen that ARIMA (0, 2, 1) has the lowest figure for the Akaike Criterion, and Bayesian Criterion. The best model is ARIMA (0, 2, 1) since satisfies two out of the three criterions considered.

3.4.3 Model Identification for the average price of garri

Table 3.29: Result of the Model selection ARIMA (p, d, q).

S/N	Model	Akaike Criterion	Bayesian Criterion	sigma^2	log-likelihood
1.	ARIMA (0,2,1)	666.99	671.8	191.1	-331.49

Model Estimation

Table 3.30: Result of the estimated parameter of ARIMA (0, 2, 1)

	coefficient	std. error
theta_1	-0.6604	0.0954

The selected ARIMA model equation is given thus**:**

$$Y_t = \theta_1 e_{t-1} + e_t. \tag{3.5}$$

$$Y_t = -0.6604\, e_{t-1} + e_t. \tag{3.6}$$

Interpretation: The results in above shows the test of various ARIMA models to determine the best ARIMA model to use for the data using the selected criterions, Akaike Criterion, and Bayesian Criterion. It is seen that ARIMA (0, 2, 1) has the lowest figure for the Akaike Criterion, and Bayesian Criterion. The appropriate model is ARIMA (0, 2, 1) since it satisfies two out of the three criterions considered.

3.4.4 Model selection for the average price of yam tuber

Table 3.31: Result of the Model Identification SARIMA (p, d, q).

S/N	Model	Akaike Criterion	Bayesian Criterion	sigma^2	log-likelihood
1.	SARIMA (1, 2,2)(1,0,0)	731.32	743.35	191.1	-331.49

Model Estimation

Table 3.32: Result of the estimated parameter of SARIMA (1, 2, 2) (1, 0, 0) [12]

	coefficient	std. error
Phi_1	-0.8227	0.0812
theta_1	0.2549	0.1086
theta_2	-0.7164	0.0965
Gamma_1	0.3373	0.1655

The selected SARIMA model equation is given thus**:**

$$Y_t = \emptyset_1 y_{t-1} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \delta_1 Y_t + e_t \quad 3.7$$

$$Y_t = -0.8227\, y_{t-1} + 0.2549\, e_{t-1} + -0.7164\, e_{t-2} + 0.3373 Y_t + e_t \quad 3.8$$

Interpretation: The results in table above shows the test of various SARIMA models to determine the appropriate SARIMA model to use for the data using the selected criterions, Akaike Criterion, and Bayesian Criterion. It is seen that SARIMA (1, 2, 2) (1, 0, 0) [12] has the least figure for the Akaike Criterion, and Bayesian Criterion. The appropriate model is SARIMA (1, 2, 2) (1, 0, 0) [12] since it satisfies two out of the three criterions considered and suggests that yam prices exhibit both non-seasonal patterns and seasonal patterns.

3.5 Model diagnostic checking

The following tests are applied to the residual; Test for Auto correlation to check the model adequacy.

Table 3.33: Result for residual autocorrelation function of Rice

LAG	ACF	Q-stat	df	P-value
17	0.0785	6.2902	14	0.9586

Interpretation: Result in above table shows that the Q-stat and the p-value in the table were greater than the exact p-value (0.05) which indicates that from lag there is no serial correlation which makes the model considered adequate.

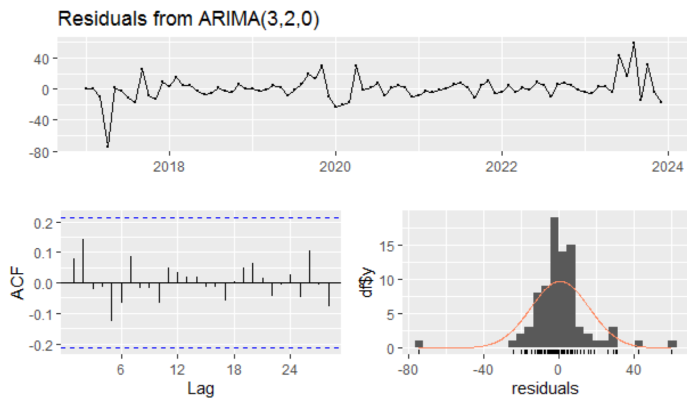

Figure 3.17: Residual ACF plot of the best ARIMA model for Rice

Comment: From the residual ACF, the report indicated that the errors are normally distributed and their values hover around zero line this made the model valid and adequate.

Table 3.34: Result for residual autocorrelation function of Beans

LAG	ACF	Q-stat	df	P-value
17	0.0382	12.198	16	0.7303

Interpretation: Result in table above shows that the Q-stat and the p-value in the table were greater than the exact p-value (0.05) which indicates that from lag there is no serial correlation which makes the model considered adequate.

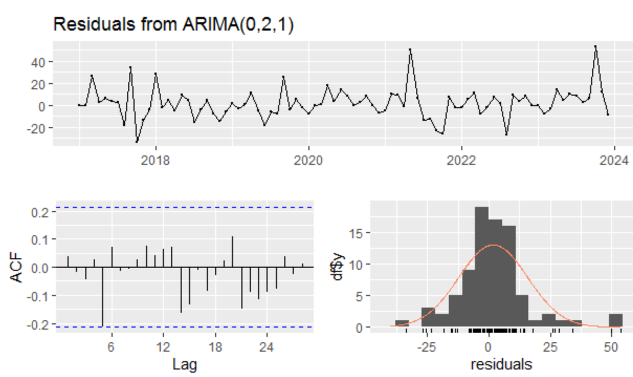

Figure 3.18: Residual ACF plot of the appropriate ARIMA model for Beans

Comment: From the residual ACF, the report indicated that the errors are normally distributed and their values hover around zero line this made the model valid and adequate.

Table 3.35: Result for residual autocorrelation function of Garri

LAG	ACF	Q-stat	df	P-value
17	-0.0305	9.0246	16	0.9124

Interpretation: Result in table 3.27 above shows that the Q-stat and the p-value in the table were greater than the exact p-value (0.05) which indicates that from lag there is no serial correlation which makes the model considered adequate.

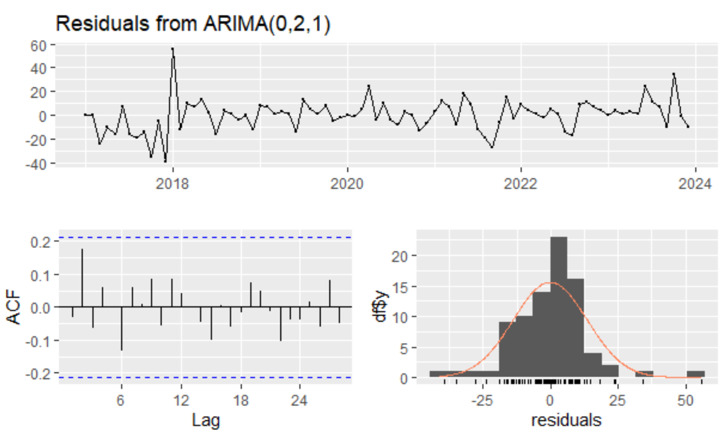

Figure 3.19: Residual ACF plot of the best ARIMA model for Garri

Comment: From the residual ACF, the report indicated that the errors are normally distributed and their values hover around zero line this made the model valid and adequate.

Table 3.36: Result for residual autocorrelation function of Yam tuber

LAG	ACF	Q-stat	df	P-value
17	-0.0312	6.1472	13	0.9406

Interpretation: Result in table above shows that the Q-stat and the p-value in the table were greater than the exact p-value (0.05) which indicates that from lag there is no serial correlation which makes the model considered adequate.

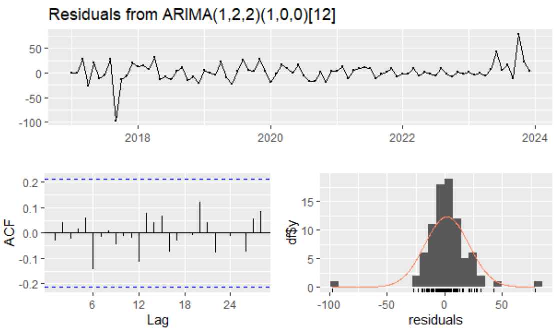

Figure 3.20: Residual ACF plot of the best SARIMA model for Yam tuber

Comment: From the residual ACF, the report indicated that the errors are normally distributed and their values hover around zero line this made the model valid and adequate.

3.6 Forecasting

Subjecting the equations to ARIMA Model after the model diagnosis testing an out sample forecast for the next 2 years was made.

Table 3.37: Result for the forecast of the average price of rice using ARIMA (3, 2, 0) for the next 2 years.

Time	Point. Forecast	80% Lower confident limit	80% Highest Confident Limit	95% Lower confident limit	95% Highest Confident Limit
Jan-24	1033.58	1013.305	1053.856	1002.571	1064.589
Feb-24	1095.892	1065.536	1126.249	1049.466	1142.319

Mar-24	1141.444	1098.031	1184.856	1075.05	1207.838
Apr-24	1196.242	1139.716	1252.769	1109.792	1282.693
May-24	1244.573	1171.006	1318.141	1132.062	1357.085
Jun-24	1299.555	1209.166	1389.944	1161.317	1437.793
Jul-24	1348.796	1239.71	1457.883	1181.963	1515.629
Aug-24	1401.991	1273.628	1530.353	1205.677	1598.304
Sep-24	1452.317	1303.027	1601.606	1223.998	1680.636
Oct-24	1505.12	1334.316	1675.924	1243.898	1766.342
Nov-24	1555.843	1362.299	1749.388	1259.843	1851.844
Dec-24	1608.135	1391.119	1825.151	1276.238	1940.032
Jan-25	1659.246	1417.696	1900.795	1289.828	2028.663
Feb-25	1711.314	1444.505	1978.122	1303.265	2119.362
Mar-25	1762.6	1469.609	2055.591	1314.509	2210.691
Apr-25	1814.496	1494.588	2134.404	1325.239	2303.753
May-25	1865.921	1518.259	2213.583	1334.218	2397.625
Jun-25	1917.72	1541.589	2293.852	1342.477	2492.964
Jul-25	1969.22	1563.847	2374.592	1349.255	2589.184
Aug-25	2020.955	1585.645	2456.266	1355.206	2686.705
Sep-25	2072.506	1606.535	2538.478	1359.865	2785.148
Oct-25	2124.203	1626.898	2621.509	1363.64	2884.766
Nov-25	2175.784	1646.46	2705.108	1366.253	2985.316
Dec-25	2227.457	1665.463	2789.45	1367.962	3086.951

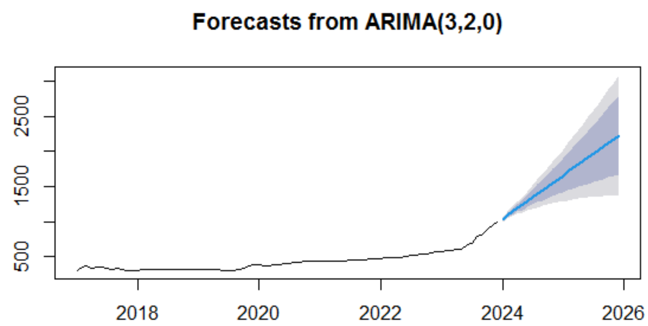

Figure 3.21: Graph of the forecast of the average Price of rice for the next two years.

Comment: The graph above shows that the average price of the rice will continue to rise for the Period forecasted.

Table 3.38: Result for the forecast of the average price of beans using ARIMA (0, 2, 1) for the next 2 years.

Time	Point. Forecast	80% Lower confident limit	80% Highest Confident Limit	95% Lower confident limit	95% Highest Confident Limit
Jan-24	908.228	889.9721	926.4839	880.308	936.148
Feb-24	945.7861	915.6697	975.9024	899.7271	991.845
Mar-24	983.3441	941.0824	1025.606	918.7104	1047.978
Apr-24	1020.902	965.8082	1075.996	936.6432	1105.161
May-24	1058.46	989.7596	1127.161	953.3917	1163.529
Jun-24	1096.018	1012.926	1179.11	968.9403	1223.096
Jul-24	1133.576	1035.323	1231.829	983.3113	1283.841
Aug-24	1171.134	1056.973	1285.296	996.5391	1345.729

Sep-24	1208.692	1077.899	1339.485	1008.661	1408.723
Oct-24	1246.25	1098.127	1394.374	1019.715	1472.785
Nov-24	1283.808	1117.68	1449.937	1029.737	1537.88
Dec-24	1321.366	1136.579	1506.153	1038.759	1603.974
Jan-25	1358.924	1154.846	1563.003	1046.813	1671.036
Feb-25	1396.482	1172.497	1620.467	1053.927	1739.038
Mar-25	1434.04	1189.552	1678.529	1060.128	1807.953
Apr-25	1471.599	1206.026	1737.171	1065.44	1877.757
May-25	1509.157	1221.933	1796.38	1069.887	1948.427
Jun-25	1546.715	1237.289	1856.14	1073.489	2019.94
Jul-25	1584.273	1252.105	1916.44	1076.267	2092.279
Aug-25	1621.831	1266.395	1977.266	1078.239	2165.423
Sep-25	1659.389	1280.169	2038.608	1079.422	2239.355
Oct-25	1696.947	1293.438	2100.455	1079.834	2314.059
Nov-25	1734.505	1306.213	2162.796	1079.489	2389.52
Dec-25	1772.063	1318.503	2225.623	1078.402	2465.723

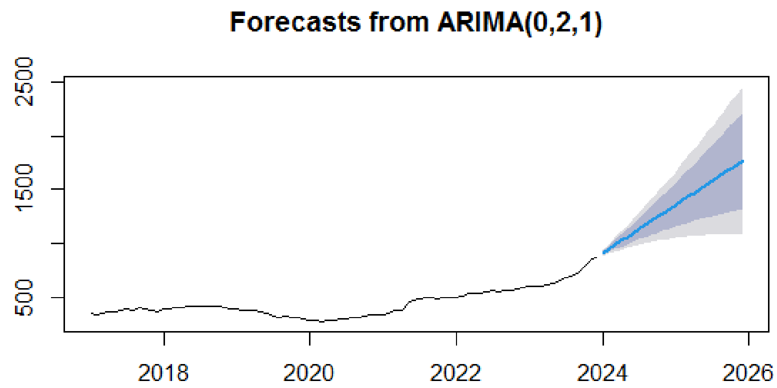

Figure 3.22: Graph of the forecast of the average Price of beans for the next two years.

Comment: The graph above shows that the average price of the beans will continue to rise for the Period forecasted.

Table 3.39: Result for the forecast of the average price of garri using ARIMA (0, 2, 1) for the next 2 years.

Time	Point Forecast	80% Lower confident limit	80% Highest Confident Limit	95% Lower confident limit	95% Highest Confident Limit
Jan-24	594.9241	577.2094	612.6388	567.8318	622.0165
Feb-24	621.1282	591.5152	650.7412	575.8391	666.4174
Mar-24	647.3323	605.3595	689.3052	583.1404	711.5243
Apr-24	673.5364	618.3952	728.6777	589.2052	757.8677
May-24	699.7406	630.5611	768.9201	593.9396	805.5415
Jun-24	725.9447	641.8624	810.027	597.3519	854.5375
Jul-24	752.1488	652.3239	851.9737	599.4798	904.8178

Aug-24	778.3529	661.9754	894.7304	600.3689	956.3369
Sep-24	804.557	670.8472	938.2668	600.0656	1009.048
Oct-24	830.7611	678.968	982.5542	598.6136	1062.909
Nov-24	856.9652	686.3645	1027.566	596.0539	1117.877
Dec-24	883.1693	693.0613	1073.277	592.4241	1173.915
Jan-25	909.3735	699.081	1119.666	587.7589	1230.988
Feb-25	935.5776	704.4445	1166.711	582.0901	1289.065
Mar-25	961.7817	709.171	1214.392	575.447	1348.116
Apr-25	987.9858	713.2781	1262.693	567.8567	1408.115
May-25	1014.19	716.7823	1311.598	559.3442	1469.036
Jun-25	1040.394	719.6987	1361.089	549.9329	1530.855
Jul-25	1066.598	722.0415	1411.155	539.6443	1593.552
Aug-25	1092.802	723.824	1461.781	528.4987	1657.106
Sep-25	1119.006	725.0584	1512.954	516.5149	1721.498
Oct-25	1145.21	725.7564	1564.665	503.7108	1786.71
Nov-25	1171.415	725.9289	1616.9	490.103	1852.726
Dec-25	1197.619	725.5861	1669.651	475.7072	1919.53

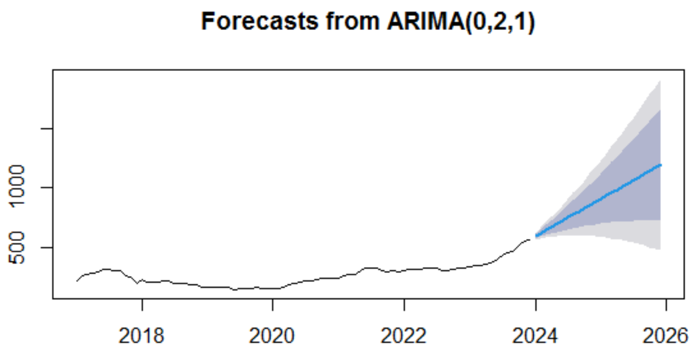

Figure 3.23: Graph of the forecast of the average Price of garri for the next two years.

Comment: The graph above shows that the average price of the garri will continue to rise for the Period forecasted.

Table 3.40: Result for the forecast of the average price of yam tuber using SARIMA (1, 2, 2) (1, 0, 0) [12] for the next 2 years.

Time	Point Forecast	80% Lower confident limit	80% Highest Confident Limit	95% Lower confident limit	95% Highest Confident Limit
Jan-24	880.0036	854.5557	905.4515	841.0844	918.9228
Feb-24	926.3049	881.8735	970.7363	858.353	994.2569
Mar-24	985.0631	924.5436	1045.583	892.5066	1077.62
Apr-24	1032.34	953.2314	1111.449	911.3538	1153.326
May-24	1091.365	994.1306	1188.599	942.6581	1240.071
Jun-24	1157.56	1040.247	1274.874	978.1456	1336.975
Jul-24	1220.83	1083.265	1358.395	1010.442	1431.218
Aug-24	1282.417	1123.063	1441.771	1038.706	1526.128
Sep-24	1341.112	1159.524	1522.7	1063.397	1618.826
Oct-24	1422.535	1217.456	1627.614	1108.893	1736.176
Nov-24	1503.489	1274.345	1732.633	1153.043	1853.935
Dec-24	1569.285	1315.006	1823.564	1180.399	1958.171
Jan-25	1641.795	1358.044	1925.545	1207.836	2075.754
Feb-25	1707.925	1392.628	2023.223	1225.719	2190.132

Mar-25	1779.404	1431.823	2126.985	1247.824	2310.983
Apr-25	1846.067	1464.528	2227.606	1262.553	2429.58
May-25	1917.468	1501.155	2333.78	1280.773	2554.163
Jun-25	1990.649	1538.154	2443.144	1298.617	2682.68
Jul-25	2063.368	1573.837	2552.899	1314.695	2812.042
Aug-25	2135.088	1607.293	2662.883	1327.895	2942.281
Sep-25	2206.188	1639.264	2773.112	1339.152	3073.224
Oct-25	2284.661	1677.507	2891.814	1356.099	3213.222
Nov-25	2363.216	1714.973	3011.459	1371.814	3354.619
Dec-25	2436.461	1746.121	3126.802	1380.677	3492.246

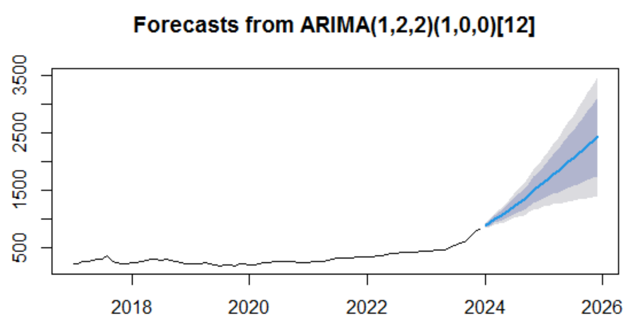

Figure 3.24: Graph of the forecast of the average price of Yam tuber for the next two years.

Comment: The graph above shows that the average price of the yam tuber will continue to rise for the Period forecasted.

CHAPTER FOUR

This chapter presents the summary, conclusion, and recommendations of the study

4.1 Summary

The purpose of this analysis is to examine the time series analysis of the average price of some selected food items in Nigeria (Rice, Beans, Gari, and Yam tuber) using Autoregressive Integrated Moving Average. The average prices of the selected food items were shown to be non-stationary in nature at their original level and they also have an upward trend from the time plot. There was a differencing of order two to transform the series from non-stationary to a stationary series and this was found to be enough to make the series stationary as reported from the time plot, results provided by both the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Philips-Schmidt-Shin Test (KPSS test). The ARIMA (3,2,0), ARIMA (0,2,1), ARIMA (0,2,1), and SARIMA (1,2,2)(1,0,0)[12] was chosen for Rice, Beans, Garri, and Yam tuber respectively as the best-fit model using the selected criterions for optimal model selection which are Akaike Information Criterion, and Bayesian Information Criterion. The selected model was also diagnosed and they were confirmed to be the best model for the data since their residual error was found to be normally distributed and ACF lags hovered around the zero line. The average price of some selected food items in Nigeria (Rice, Beans, Gari, and Yam tuber) was forecasted at 80% and 90% confidence intervals for five years using the fitted ARIMA model from January 2024 to December 2025.

4.2 Conclusion

From the study, it was concluded that the average price of rice is in a series with an upward trend. The study also concludes the ARIMA (3, 2, 0) model is the best model that fits the average price of rice. It was concluded that the average price of rice forecast made for two (2) years from January 2024 to December 2025 using the fitted model showed that the average of price of rice will continue to increase for the time forecasted.

Also, it was concluded that the average price of beans is in a series with an upward trend. The study also concludes the ARIMA (0, 2, 1) model is the best model that fits the average price of beans. It was concluded that the average price of beans forecast made for two (2) years from January 2024 to December 2025 using the fitted model showed that the average price of beans will continue to increase for the time forecasted.

The average price of Garri is in a series with an upward trend. The study also concludes the ARIMA (0, 2, 1) model is the best model that fits the average price of Gari. It was concluded that the average price of Garri forecast made for two (2) years from January 2024 to December 2025 using the fitted model showed that the average price of Garri will continue to increase for the time forecasted.

For the last food item considered, it was noted that the average price of yam tuber was also in a series with upward trend. Which concludes the SARIMA (1, 2, 2) (1, 0, 0) [12] model is the best model that fits the average price of yam tuber. It was concluded that the average price forecast made for five (5) years from January 2024 to December 2025 using the fitted model showed that the average price of yam tuber will continue to increase for the time forecasted. The **S**ARIMA (1, 2, 2) (1, 0, 0) [12] model suggests that yam prices exhibit seasonal patterns.

So the trend for the selected food items points to potential inflationary pressures on food commodities in Nigeria, which may exacerbate food insecurity, particularly for low-income households. Several factors including supply chain disruptions, climate change effects on agriculture, rising production costs, and macroeconomic instability likely drive the increase in food prices.

4.3 Recommendation

From the study's perspective, the ARIMA models are the best fit for analyzing and forecasting the prices of these food items in Nigeria. Policymakers can utilize these models for price forecasting to anticipate price movements and implement appropriate market interventions. The accuracy of these models in predicting future price trends suggests they could be useful in designing timely policies that stabilize prices and reduce the impact of inflation on essential food items.

Additionally, as indicated by these ARIMA models, prices are projected to keep rising. Therefore, the government and agricultural stakeholders should focus on strategies to control price increases. This can be accomplished by increasing agricultural productivity, enhancing supply chain infrastructure, and implementing climate-resilient farming techniques. With the guidance of the forecasts from these models, stakeholders can make better preparations for upcoming market conditions, ultimately leading to improved food security and reduced inflationary pressures on essential commodities.

For future researchers, the study highlights the importance of using ARIMA models in time series analysis of agricultural prices. Researchers working on similar topics can rely on ARIMA models for their robustness in dealing with non-stationary data and their ability to capture trends over time. It is recommended that ARIMA be considered as a standard approach when working with time-dependent agricultural or economic data due to its flexibility and effectiveness in forecasting future trends.

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Appendix 1

Date	Rice	Beans	Gari	Yam tuber
Jan-17	312.08	353.6	219.56	210.58
Feb-17	352.69	337.11	260.94	215.55
Mar-17	377.99	353.28	273.67	255.86
Apr-17	332.81	357.19	288.45	250.3
May-17	350.36	365.86	292.97	279.15
Jun-17	348.23	374.26	315.61	292.06
Jul-17	344.4	382.35	317.1	294.12
Aug-17	313.45	370.25	310.15	343.39
Sep-17	339.47	404.84	301.99	259.51
Oct-17	320.64	382.58	268.1	223.63
Nov-17	309.87	369.78	251.91	212.27
Dec-17	304.9	361.97	199.68	211.61
Jan-18	308.53	385.53	229.26	226.51
Feb-18	314.77	387.48	210.21	230.85
Mar-18	317.17	395.34	209.12	254.51
Apr-18	323.56	395.19	208.21	279.61
May-18	325.37	407.73	216.01	291.33
Jun-18	323.12	418.78	216.72	285.84
Jul-18	319.35	411.02	200.67	280.83
Aug-18	322.55	410.16	198.82	292.97
Sep-18	319.46	416.07	195.86	280.28

Oct-18	314.89	411.05	188.39	252.21
Nov-18	318.94	396.73	183.59	239.15
Dec-18	318	386.78	166.64	212.65
Jan-19	317.63	382.76	165.8	211.21
Feb-19	314.53	373.91	166.61	206.49
Mar-19	313.55	368.07	163.51	200.88
Apr-19	316.3	372.84	163.37	222.36
May-19	316.94	365.32	161.55	216.03
Jun-19	308.07	342.82	145.31	182.15
Jul-19	305.93	327.18	151.73	170.85
Aug-19	309.27	307.27	154.1	190.04
Sep-19	326.4	318.99	154.55	190.23
Oct-19	339.78	308.93	162.42	179.75
Nov-19	378.5	307.3	160.06	203.2
Dec-19	381.68	299.48	159.39	206.82
Jan-20	381.42	285.61	159.64	193.04
Feb-20	373.16	276.3	159.33	189.53
Mar-20	368.36	267.81	164.6	206.12
Apr-20	394.56	277.05	190.23	230.09
May-20	392.54	277.49	196.16	236.9
Jun-20	400.73	289.89	214.73	250.7
Jul-20	410.69	300.26	222.47	256.44
Aug-20	415.43	305.43	224.53	256.06

Sep-20	423.04	312.66	235.77	245.62
Oct-20	434.96	326.88	244.96	242.87
Nov-20	444.94	334.66	241.25	236.25
Dec-20	443.03	336.24	238.65	233.48
Jan-21	442.17	337.09	243.76	234.67
Feb-21	444.17	351.68	259.59	242.82
Mar-21	443.36	368.98	274.03	244.82
Apr-21	441.85	378.82	276.33	252.8
May-21	441.49	439.22	301.88	269.98
Jun-21	447.62	471.24	324.26	287.54
Jul-21	456	485.44	329.2	308.72
Aug-21	460.33	496.03	323.01	305.48
Sep-21	454.28	492.13	301.58	306.87
Oct-21	463.38	478.76	292.57	313.05
Nov-21	476.67	490.19	302.28	327.53
Dec-21	477.03	494.83	299.51	328.75
Jan-22	477.33	498.85	307.53	331.24
Feb-22	487.43	509.65	313.27	339.76
Mar-22	488.58	527.66	317.33	353.56
Apr-22	494.88	530.62	318.74	361.2
May-22	496.98	536.91	326.85	372.23
Jun-22	511.94	551.4	332.53	384.48
Jul-22	520.37	562.55	323.17	389.75

Aug-22	520.18	545.61	305.92	403.63
Sep-22	532.42	556.81	309.69	409.23
Oct-22	547.11	564.69	317.9	409.86
Nov-22	561.12	578.55	325.82	421.08
Dec-22	569.46	586.14	332.95	425.48
Jan-23	578.36	593.96	337.52	431.36
Feb-23	584.55	594.15	345.88	436.41
Mar-23	597.5	596.96	353.16	443.02
Apr-23	609.57	615.67	362.5	444.69
May-23	615.32	629.75	371.42	457.25
Jun-23	667.51	651.12	403.15	510.77
Jul-23	699.06	673.53	429.89	539.41
Aug-23	788.24	692.95	456.32	576.39
Sep-23	806.91	716.97	467.89	593.83
Oct-23	897.49	790.01	520.35	687.68
Nov-23	936.25	838.85	548.95	772.72
Dec-23	991.08	870.67	568.72	818.92

Appendix II

```
library(forecast)

library(tseries)

library(ggplot2)

data <- read.csv("SFICODE.csv")

data

#data1 = read.csv("SFI1N.txt")

#data1

head(data, 10)

# Convert the Date column to Date type

data$Date <- as.Date(data$Date, format = "%1/%1/%2017")

data$Date

head(data$Date)

head(data$Date, 10)

str(data$Date)

data$Date <- as.character(data$Date)

head(data$Date, 10)

data$Date <- trimws(data$Date)

data$Date

install.packages("anytime")

library(anytime)

head(data$Date, 10)

str(data$Date)
```

```
class(ts_dataR)  # Should return "ts"

is.numeric(ts_dataR)  # Should return TRUE

data <- read.csv("SFICODE.csv")

data

head(data$Date)

head(data$Date, 10)

ts_data <- ts(data,start = c(2017, 01), frequency= 12)

ts_data

# Convert to a time series object

ts_dataG <- ts(data$Gari, start = c(2017, 01), frequency = 12)

ts_dataG

ts_dataY <- ts(data$Yam.tuber, start = c(2017, 01), frequency = 12)

ts_dataY

ts_dataSP <- ts(data$Sweetpotato, start = c(2017, 01), frequency = 12)

ts_dataSP

# Replace YYYY with the start year and MM with the start month

# Plot the time series

plot(ts_dataG, main = "Time Series Data", ylab = "Gari", xlab = "Date")

plot(ts_dataY, main = "Time Series Data", ylab = "Yam.tuber", xlab = "Date")

plot(ts_dataSP, main = "Time Series Data", ylab = "Sweetpotato", xlab = "Date")

# Decompose the time series

decomposedG <- decompose(ts_dataG)

decomposedY <- decompose(ts_dataY)
```

```
decomposedSP <- decompose(ts_dataSP)

# Plot the decomposed components

plot(decomposedG)

plot(decomposedY)

plot(decomposedSP)

# ADF test for stationarity

adf_testG <- adf.test(ts_dataG)

adf_testY <- adf.test(ts_dataY)

adf_testSP <- adf.test(ts_dataSP)

# Print the test results

print(adf_testG)

print(adf_testY)

print(adf_testSP)

# Perform the KPSS test

kpss_testG <- kpss.test(ts_dataG)

kpss_testY <- kpss.test(ts_dataY)

kpss_testSP <- kpss.test(ts_dataSP)

# Print the results

print(kpss_testG)

print(kpss_testY)

print(kpss_testSP)

# Differencing the data

diff_tsG <- diff(ts_dataG)
```

```
diff_tsY <- diff(ts_dataY)

diff_tsSP <- diff(ts_dataSP)

# Plot the differenced series

plot(diff_tsG, main = "2", ylab = "Gari", xlab = "Date")

plot(diff_tsY, main = "2", ylab = "Yam.tuber", xlab = "Date")

plot(diff_tsSP, main = "2", ylab = "Sweetpotato", xlab = "Date")

# ADF test on differenced data

adf_test_diffG <- adf.test(diff_tsG)

print(adf_test_diffG)

adf_test_diffY <- adf.test(diff_tsY)

print(adf_test_diffY)

adf_test_diffSP <- adf.test(diff_tsSP)

print(adf_test_diffSP)

# Perform the KPSS test

kpss_test_diffG <- kpss.test(diff_tsG)

kpss_test_diffY <- kpss.test(diff_tsY)

kpss_test_diffSP <- kpss.test(ts_dataSP)

print(kpss_test_diffG)

print(kpss_test_diffY)

print(kpss_test_diffSP)

####Gari

diff_tsG2 <- diff(diff_tsG)

print(diff_tsG2)
```

```
plot(diff_tsG2, main = "2", ylab = "Gari", xlab = "Date")

# ADF test on SECOND differenced data

adf_test_diffG2 <- adf.test(diff_tsG2)

print(adf_test_diffG2)

kpss_test_diffG2 <- kpss.test(diff_tsG2)

print(kpss_test_diffG2)

####YAMTUBER

###SECOND DIFFERENCE

diff_tsY2 <- diff(diff_tsY)

print(diff_tsY2)

plot(diff_tsY2, main = "2", ylab = "Yam.tuber", xlab = "Date")

# ADF test on SECOND differenced data

adf_test_diff2 <- adf.test(diff_tsY2)

print(adf_test_diff2)

kpss_test_diffG2 <- kpss.test(diff_tsG2)

print(kpss_test_diffG2)

####Sweetpotato

###SECOND DIFFERENCE

diff_tsSP2 <- diff(diff_tsSP)

print(diff_tsSP2)

plot(diff_tsSP2, main = "2", ylab = "Sweetpotato", xlab = "Date")

# ADF test on SECOND differenced data

adf_test_diffSP2 <- adf.test(diff_tsSP2)
```

```
print(adf_test_diffSP2)

kpss_test_diffSP2 <- kpss.test(diff_tsSP2)

print(kpss_test_diffSP2)

# Fit an ARIMA model

fitG <- auto.arima(ts_dataG)

fitY <- auto.arima(ts_dataY)

fitSP <- auto.arima(ts_dataSP)

# Summary of the model

summary(fitG)

summary(fitY)

summary(fitSP)

# Plot the residuals to check for white noise

checkresiduals(fitG)

checkresiduals(fitY)

checkresiduals(fitSP)

# Forecast future values

forecastedG <- forecast(fitG, h = 60) # h = number of periods to forecast

forecastedY <- forecast(fitY, h = 60)

forecastedSP <- forecast(fitSP, h = 60)

# Plot the forecast

plot(forecastedG)

plot(forecastedY)

plot(forecastedSP)
```

```
# Print forecasted values

print(forecastedG)

print(forecastedY)

print(forecastedSP)

accuracy(forecastedG)

FG = write.csv(forecastedG, "forecasted_values.csv")

print(FG)

write.csv(forecastedY, "forecasted_values1.csv")

write.csv(forecastedSP, "forecasted_values2.csv")
```