CHAPTER 2

COVID-19 AND FOOD INFLATION: A CASE STUDY OF ARIMA MODELING IN TURKEY

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ABSTRACT

The COVID-19 pandemic, which affected the world in 2020, significantly impacted the food and agriculture sectors. Production in the agricultural industry has been negatively affected, and food supply chains have been disrupted. Examining the consequences of the pandemic on the food and agriculture industries has become a major area of study for these reasons. Since prices are one of the most significant economic indicators, this book chapter examined the impact of the pandemic on the food and agriculture sector using price data. The primary objective of the book chapter is to assess the effects of COVID-19 on food prices in Turkey and to choose the most appropriate model for future price forecasting. Turkey's consumer price index for food and soft drinks and producer price index for food were used as data to evaluate the effect. The Box-Jenkins approach was utilized to forecast future periods of food inflation. Following the methodology mentioned above, the data period began before the pandemic. While the 2017m07-2021m08 period was determined as the estimation sample, the 2021m09-2021m11 period was determined as the forecast sample. The findings indicate that the ARIMA (0,1,1) model is Turkey's most accurate predictor of food inflation. According to the results, it is anticipated that food prices in Turkey will continue to rise.

Keywords: COVID-19, Food Inflation, ARIMA Modeling, Forecast

1. Introduction

In 2020, the world experienced an unprecedented pandemic, COVID-19. The pandemic has severely impacted the food and agriculture industries, as so have all industries. The pandemic is viewed as both a health and food safety problem. The agricultural sector is critical in providing food which is a fundamental human need, and guaranteeing food security. Food security can be ensured by making the food readily available and accessible. While dietary preferences are assumed to be the origin of the pandemic, the pandemic has a fatal effect on those with chronic conditions that are directly connected to poor diet. The vulnerability of the global food system has been proven by this pandemic period. The belief that poor eating habits damage the immune system and worsen the effects of the pandemic reveals a direct association between COVID-19 and the food industry (STM thinktech, 2020). In the light of this knowledge, it is essential to investigate COVID-19's effects on the agriculture and food sector, along with possible precautions.

Prices are the most fundamental drivers that shape the economies by the signals they provide to producers and consumers in market economies, commonly known as "price mechanisms." As a result, when prices are appropriately collected and recorded, they are considered the most reliable data on which market analyzes can be established. In recent years, price increases and volatility in agricultural and food products have been among the crucial topics on the global agenda (Yavuz, 2021).

The COVID-19 pandemic has seriously affected both the agricultural sector and food security. Problems were experienced in food supplies' production, distribution, and accessibility (STM thinktech, 2020). Adequate nutrition and food security have risen to the top of individuals' concerns. The agricultural supply chain has been disrupted, which has caused supply interruptions (Aydın & Güner, 2020). With the pandemic, the food supply chain has been unable to function correctly. This negative situation led to an increase in the marketing margin, and the producer's share in the value chain decreased (Yavuz, 2021).

The pandemic and the efforts adopted to combat it has unexpectedly impacted every area, from individuals' lives to global trade. The health precautions imposed have lowered agricultural and industrial food production, and difficulties with raw material availability have made production more difficult (STM thinktech, 2020). It has also impacted foreign trade since some nations have implemented trade barriers (TGDF, 2020). Countries that aim to ensure sufficient nourishment for their citizens have imposed trade restrictions on food products in response to disruptions in the food supply chain (Aydın & Güner, 2020).

Restrictions and regulations made due to the pandemic, changes in the trade structure, quarantine, and closure periods have impacted the countries' food supply chains, causing significant price fluctuations (TGDF, 2020). Due to limitations and travel bans, perishable food products could only be utilized as animal feed, and temporary agricultural workers could not work in the fields throughout the period, resulting in a decline in the agricultural labor supply (STM thinktech, 2020).

Food price inflation, which arose due to the 2008-2009 economic crisis and later the COVID-19 pandemic, has been one of the leading interests of producers and society, particularly low-income consumers, policymakers, politicians, and economists. The low-price elasticity of supply and demand for agricultural and food products is the primary cause of their prices' quick rises and fluctuations. Because of this characteristic of agricultural and food products, prices fluctuate quickly in response to changes in supply and demand. Food inflation resulting from the rapid increase in agricultural and food product prices adversely affects the food security of consumers, especially those with low and middle income. Food inflation also leads to an increase in general inflation, which has a detrimental impact on the performance of economies. In the most general sense, the factors that cause inflation in economies are also the reason for food inflation. The decrease in food supply, sudden and periodic increases in food demand, deterioration in the food supply chain, rising world prices, speculative activities, and crises induced by different reasons lead to an increase in food prices. Some of these factors can contribute to food inflation by triggering one another. Four factors primarily cause food inflation. These factors include aggregate demand exceeding aggregate supply, increases in production costs due to natural disasters and epidemics, increases in the prices of primary inputs, stockpiling, demanding high wages of consumers and producers as a result of the expectations that prices will continue to rise in the future, increases in the money supply.

Other factors include climate change, logistics and production costs, widespread use of corn in biofuel production, increases in meat consumption over time, increased credit opportunities in agricultural production, changes in consumer preferences, and troubles in the food supply chain. The food inflation seen in 2020 was caused mainly by the adverse effects of COVID-19 on food supply, demand, and supply chain, as well as the increase in global prices and the drought seen in the fourth quarter of 2020. Although the primary indicator of food inflation is consumer prices, producer and input prices also have substantial effects on food inflation since they affect costs. Food inflation, which occurs when the producer price index of agricultural products (PPI) rises faster than the general PPI or the food consumer price index (CPI) rises faster than the general CPI, has become a hot topic in the last decade.

Increases in agriculture and food prices do not directly result in a profit for the producer but mainly cause higher marketing margins. Price fluctuations also adversely affect producers who cannot benefit from increased prices. In developed countries, food inflation is less damaging. However, in developing and underdeveloped countries, food inflation is more damaging to the economy since the share of foodstuffs in the consumer basket is higher than in developed ones (Yavuz, 2021).

The Turkish economy also relies heavily on the food and soft drinks industry. There are around 43,000 firms in this industry in Turkey, and their employees account for 10 to 12 percent of the country's workforce. This information illustrates the relevance of this sector (STM thinktech, 2020). The first COVID-19 case in Turkey was officially announced on 10 March 2020. Until the normalization period in May, various restrictions were implemented, such as the temporary closure of schools, restaurants, and cafes, bans on entrances and exits to cities, and lockdowns. During the lockdown, people's access to vital goods and services was severely restricted. Out-of-home food consumption has stopped until the normalization (TGDF, 2020).

Food inflation that started with the 2008 economic crisis, climate changes, and biofuel production increases became visible in Turkey in the first quarter of 2019 and gained momentum with COVID-19 (Yavuz, 2021). While food prices worldwide fell in the early stages of the pandemic, import quotas were imposed by important producer countries such as Russia, and the deterioration of the food supply chain caused food prices to rise over time. In Turkey, there has been a significant increase in food prices. One of the causes of the increase in food prices is the implementation of export restrictions on food trade after COVID-19 (STM thinktech, 2020). With the COVID-19 pandemic, a decline in tourists and outdoor eating and drinking activities, a decrease in demand for agricultural products, and government initiatives to improve agricultural production led to the expectation of a decrease in agricultural product prices. Food prices in Turkey have risen due to the prominence of the self-sufficiency policy in food, a sudden increase in demand of food exported from Turkey due to global export restrictions, the expectation of rising prices in the future, panic expenditures, and stockpiling made with uncertainty. Stockpiling has increased the food demand and supply chain interruptions have lowered food supply. Food demand and supply changes have caused food prices to rise (Yavuz, 2021). Food expenditures are one of the most real expenditures for individuals, and therefore changes in food prices have a direct impact on people from all segments of society. As a result, countries have to monitor changes in food inflation throughout the pandemic, analyze its results, forecast future inflation rates, and adopt the required policies and measures. According to the Food and Agriculture Organization of the United Nations (FAO) (2021), some of the precautions that can be adopted in the sector of agriculture and food are as follows: shortening the agricultural supply chain by expanding urban farming activities, reducing nutrition-related diseases by promoting healthy eating, managing and reducing food waste, enhancing green spaces, re-establishing linkages between urban and rural regions, and developing a healthier food system.

The interaction between COVID-19 and the food industry has been studied nationally and internationally. Some of these studies are summarized in this section. According to Adewopo et al. (2021), the COVID-19 pandemic and related measures have caused severe disruptions in food systems. Labor constraints, interruptions in transportation, and restrictions in the distribution of inputs caused unexpected fluctuations in food prices. On the other hand, rising food prices have led to concerns that poverty and food insecurity will increase (Hirvonen et al., 2021). Meyer et al. (2021) state that those who are most concerned about COVID-19 may also be those most affected by price increases in the countries. According to Haqiqi and Bahalou Horeh (2021), the agricultural sector and its producers are also affected by COVID-19. This study states that COVID-19 has increased price volatility for farmers worldwide, making it more difficult for them to profit from their products. Some farmers have suffered high production costs due to the pandemic's labor limitations. Due to higher trade and warehousing margins, some were able to generate lower sales revenues.

According to Demir (2021), consumers have switched to healthy eating, increased their local food consumption, improved their culinary abilities, and displayed panic buying behaviors due to the COVID-19 pandemic. There have been changes in individual food purchasing preferences, and food waste rates have also increased. People's access to safe food has grown more challenging, and nations have had to establish new policies to deal with the situation. Online food purchases were in high demand during the pandemic. As a result of this situation, numerous supermarkets have developed online ordering systems.

According to a study conducted by Cariappa et al. (2021) for India, some food prices rose rapidly due to deteriorating food supply following the early stages of the lockdown. However, in time food prices fell because the food demand decreased due to the closure of restaurants, cafes, and hotels, the prohibition of celebrations and ceremonies, and decreasing food demand from other countries. According to a study, the pandemic is said to have caused a severe increase in food prices and unprecedented panic purchasing. However, the impacts are considered modest due to the resilience of Indian agriculture. During the pandemic, the producers' profits decreased, the consumers paid more, and retailers made the most significant profit. While retail food prices skyrocketed, producers suffered losses due to a shortage of workers, transportation problems, and lower prices. Moreover, they observed that the price gap between wholesale and retail widened after the quarantine.

Although sales in other sectors declined in the March-April-May 2020 period, sales in the food sector climbed, panic purchasing was observed, and demand for frozen food increased, according to a study by Coluccia et al. (2021) made for Italy. The food consumer price index increased substantially during the early stages of the infection's spread. Food prices have changed over time in response to changes in domestic demand, foreign trade restrictions, and whether the food is storable. According to Sperling et al. (2022), the trade restrictions implemented at the start of the pandemic did not last very long. Furthermore, even though the global food price index fell at the start of the pandemic, it began to rise in June 2020 and reached its highest level since 2011 in November 2021. According to Hillen (2020), the pandemic has resulted in significant growth in online grocery sales, and if the pandemic has a winner, it is online retailers. Musa et al. (2020) have not observed any long-term relationship between the world food price index and COVID-19. However, they identified a negative relationship in the short run utilizing ARDL and Vector Error Correction methods for 20 January–31 March 2021.

This book chapter aims to provide information on post-COVID-19 agricultural and food price inflation and determine which ARIMA model better explains the Turkish food and soft drink inflation from 2017m07 to 2021m11. The rest of the paper proceeds as follows. The influence of COVID-19 on food prices in Turkey and throughout the globe was interpreted, and food inflation was discussed in the second section with the help of the food price index data. The ARIMA model, which can best forecast Turkey's food and soft drinks consumer price index (CPI of F&SD) during the COVID-19 period, was determined in Chapter 3 using the Box-Jenkins methodology. The conclusion section summarized the book chapter, provided the ARIMA model's results, and gave recommendations to policymakers on how to reduce/prevent food inflation, which has become a serious concern of the modern period.

2. Food Inflation in Turkey and Across the World During The Covid-19 Period

This subsection incorporates data from the Turkish Federation of Food and & Drink Industry Association of Turkey, the Food and Agricultural Organization of the United Nations (FAO), and the Turkish Statistical Institute. Consumer price index (CPI) and producer price index (PPI) are defined. The contents of these indices created for Turkey are explained. The

FAO food price index was used to compare Turkish data with the World food price index. Food inflation in Turkey and worldwide was analyzed using graphs spanning the COVID-19 period. The effect of COVID-19 on the Turkish food industry was examined, and food inflation was investigated using food and soft drinks CPI and domestic food PPI data. It has been discussed whether global and Turkish food price fluctuations occurred in the same direction during the COVID-19 period. According to CPI data prepared by the Federation of Food & Drink Industry Association of Turkey (2021), during the period between December 2020 and December 2021, when the effects of COVID-19 were significantly felt, there were decreases in the prices of some food products. However, these decreases remained lower than rising in other food prices. In Turkey, the prices of baking goods, potatoes, and margarine have risen by more than 100%. In addition, after these three foods, according to the price increase rate, the foods can be listed as Eggplant, dried apricots, chicken meat, wheat flour, coffee, sunflower oil, and yogurt. Some food prices declined at the same time. Garlic, cauliflower, and green beans are the top three goods whose prices have decreased the most. The top ten food products with the highest price increases/decreases and the increase/decrease rates are shown in Table 1.

Table 1. Ten Food Products with the Most Significant Increases/Decreases in Prices Between December 2020 and December 2021 in Turkey

***PRODUC*T**	**CHANGE IN PRICE (%)**	***PRODUCT***	**CHANGE IN PRICE (%)**
Baking Goods	8712%	***Garlic***	-39.79%
Potatoes	115.81%	***Cauliflower***	-34.11%
Margarine	113.79%	***Green Beans***	-30.47%
Eggplant	97.38%	***Cherry***	-8.30%
Dried Apricot	88.5%	***Grape***	-7.89%
Chicken Meat	86.26%	***Onion***	-6.61%
Wheat Flour	85.44%	***Peach***	-6.55%
Coffee	83.55%	***Spinach***	-6.13%
Sunflower Oil	75.78%	***Lemon***	-6.12%
Yogurt	74.26%	***Strawberry***	-4.5%

Source: Federation of Food & Drink Industry Association of Turkey. (2021). *ÜFE ve TÜFE verileri*. TGDF. Retrieved 7 January 2022, from https://www.tgdf.org.tr/ufe-ve-tufe-verileri/

The consumer price index (CPI) and the producer price index (PPI) are two widely used inflation indicators. The CPI is the most often recognized and followed one. Unlike the GDP deflator, the CPI is a fixed-weight index. The CPI is calculated using a bundle of goods created to represent the market basket purchased monthly by the urban consumer. CPI percentage changes are used to monitor inflation. The PPI is another widely used price index. This index measures the prices producers receive for products at the end of the production process and throughout the process. It is determined independently at each stage of the manufacturing process. A significant advantage of PPI was its ability to detect price increases early. It is, therefore, seen as a leading indicator of future consumer prices (Case et al., 2012). In Turkey, the Turkish Statistical Institute measures and publishes these two indicators. The primary objective of the CPI, which uses 2003 as its base year, is to measure inflation by tracking changes in the prices of goods and services subject to market consumption. All final domestic monetary consumption expenditures on goods and services by households, foreign visitors, and corporate population are included in the computation. Turkey's CPI has 415 items. The suitable baskets and weights are revised at the end of each year, and the series is maintained using the Laspeyres formula. Every year in December, new goods are included, or goods that lose their importance are removed (Turkish Statistical Institute, 2022). CPI of F&SD is one of the sub-main expenditure categories, comprising 133 products and accounting for 25.9 percent of total consumption expenditures (Yavuz, 2021). Another data used in this study is the domestic producer price index (domestic PPI). A price index measures price changes over time in a certain period by comparing the producer prices of goods produced and sold in a particular country. The index is calculated using 2003 as the base year. After each year, the product basket is refreshed, and the series is continued using the Laspeyres formula (Turkish Statistical Institute, 2022a). Another set of interpreted data is the FAO World Food Price Index, which is composed of the averages of five commodity group price indices (grain, vegetables, milk, meat, and sugar) weighted by the average export shares of each group for the period 2014-2016. The index includes 95 price offers representing international food commodity prices by FAO specialists (FAO, 2022). In 2021, Turkey's overall CPI increased by 36.08 percent, while the CPI of F&SD increased above the general CPI by 43.80%. After transportation, the food sector has been the leading expenditure group with the most significant yearly price increase. On the other hand, the domestic general PPI increased by 79.89% in 2021. Although the annual domestic PPI for the food sector increased by 64.84% in 2021, the increase remained below the annual domestic general PPI (Turkish Statistical Institute, 2022a). The PPI for agricultural products is another price indicator. Agricultural PPI is calculated monthly to monitor the proportional indicator of changes in the first-hand sales prices of the farmer's products. According to the index, which uses 2015 as the base year and is calculated using the Laspeyres formula, the PPI of agricultural products increased by 36.39% in 2021 (Turkish Statistical Institute, 2022b).

Figure 1. FAO Monthly World Food Price Index (2017-2021)

Data Source: Food and Agriculture Organization of the United Nations

Since price increases worldwide affect domestic prices to a greater or lesser extent depending on trade policies, they can cause domestic food inflation. According to Figure 1, the FAO food price index remained relatively stable between January 2017 and September 2019, with minor increases and decreases. Between September 2019 and January 2020, a modest increase is observed. Between January 2020 and June 2020, the first months of COVID-19, there was a drop in world food prices. According to Aydın and Güner (2020), the cause for the decline in food prices during the early stages of the pandemic and the subsequent decline to the lowest level in May 2020 can be attributed to the pandemic-induced contraction in food demand. However, a structural break is observed in the food price curve as of June 2020. The price line has changed from a stable view to an upward trend. Increase in the price level was maintained until June 2021. Even if minor drops occur beyond this date, one can generalize about the existence of a growing trend effect.

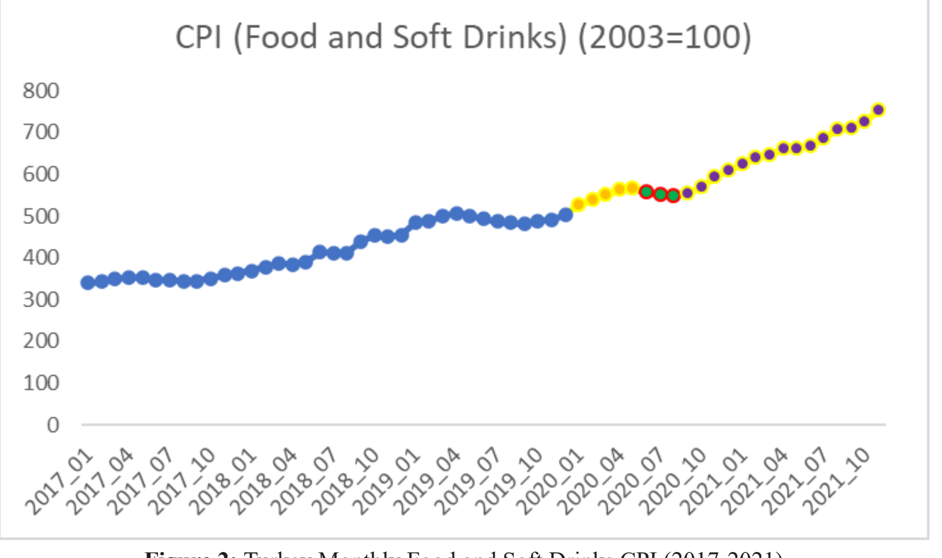

Figure 2: Turkey Monthly Food and Soft Drinks CPI (2017-2021)
Data Source: Turkish Statistical Institute

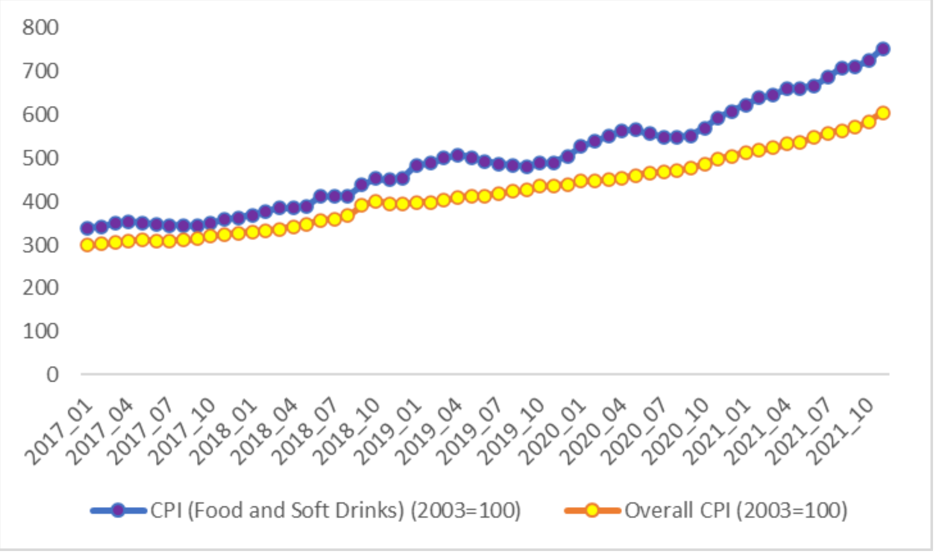

Figure 3: Turkey Monthly General CPI and Food and Soft Drinks CPI (2017-2021)
Data Source: Turkish Statistical Institute

According to Figure 2, the price index for food and soft drinks in Turkey fluctuated from 2017 until the end of 2019. Eventually, it increased slightly in terms of the graph's overall appearance. Turkey's food CPI continued to climb between January 2020 and May 2020, in contrast to world food prices. Although there is a slight decline in the summer of 2020, June-July-August, when there is normalization in Turkey, it has been observed that the trend effect has increased more rapidly since September 2020. According to the world food price index, global food prices are on the decline and are at their lowest level during the COVID-19 period (January-June 2020), when drastic measures are implemented. Although the FAO world food price index decreased, at the same time food CPI and PPI increased in Turkey. This situation may have occurred for a variety of reasons. According to Yavuz (2021), the sudden increase in demand for food products from Turkey due to the country's food self-sufficiency policies at the beginning of the pandemic and global export restrictions, as well as the expectation of future price increases, may have resulted in an increase in stocks and thus food prices. Additionally, during times of crisis, food demand increases due to vital food stockpiling for consumption and commercial uses. Also, food supply decreases due to disruptions in production or supply chain. This circumstance may have resulted in an increase in food prices on both the demand and supply sides. According to Demir (2021), panic buying behaviors and stockpiling at the start of the pandemic may have increased food demand and consequently increased food prices in Turkey. For these reasons, despite the decline in world food prices in the early stages of the pandemic, Turkey's food prices may have increased. In the later stages of the pandemic, both world food prices and Turkey's food prices have increased.

When examining Figure 3, it is clear that food and soft drinks CPI has been more significant than the general CPI since 2017. This situation demonstrates that Turkey had food inflation over the indicated period. Until April 2020, the difference between them widened and narrowed slightly until September 2020, and the difference continued to increase in the following months. Additionally, it is observed that the fluctuation and volatility of the CPI of food and soft drinks are greater than those of the general CPI. Considering these conditions, it is evident that Turkey suffered from food inflation throughout the pandemic period.

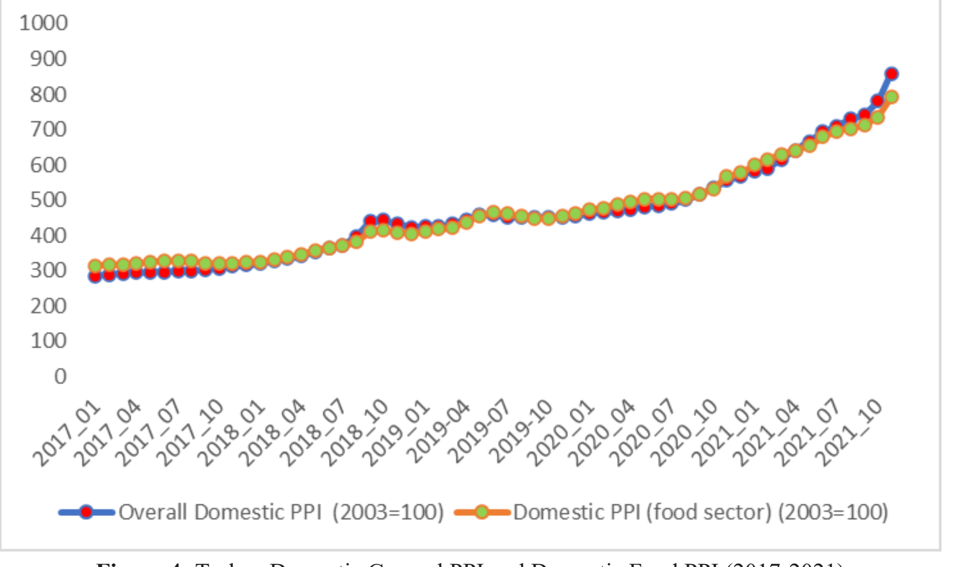

Figure 4: Turkey Domestic General PPI and Domestic Food PPI (2017-2021)
Data Source: Turkish Statistical Institute

According to Figure 4, food PPI is almost at the same level as the overall PPI in Turkey. The food PPI is sometimes higher than the overall PPI, sometimes the opposite. However, the food PPI is higher than the overall PPI beginning in the second quarter of 2021. It is well established that the PPI is a leading indicator of future CPI levels. The PPI of food climbed by 64.84% in 2021. On the other hand, the CPI of food and soft drinks climbed by 43.8% in 2021. This difference can indicate that the CPI for food and soft drinks will continue to increase in the upcoming periods.

3. Empirical Results from ARIMA Modeling for the Food and Soft Drinks Consumer Price Index in Turkey

3.1. Data

The primary purpose of this book chapter is to establish the ARIMA model that produces the best accurate forecasts for Turkey's Consumer Price Index of food and soft drinks data using the Box-Jenkins methodology. Consumer Price Index of food and soft drinks (CPI of F&SD), for which 2003 was taken as the base year, was obtained from the Turkish Statistical Institute. The study was conducted by taking sufficient observations to establish a time series forecast while not deviating too far from the COVID-19 period as the beginning date. Box et al. (2016) stated in their study that a time series forecast analysis should include at least fifty observations. This caution was considered while determining the sample size for this study. The data collection period began two years before March 2020, when the COVID-19 case was first publicized in Turkey, and included 53 months between 2017m07 and 2021m11, including the last month when it could be accessed. The estimation sample period is 2017m07 to 2021m08, and the forecast sample period is 2021m09 to 2021m11. Table 2 provides descriptive statistics of the data utilized.

Table 2. Descriptive Statistics of Food and Soft Drinks CPI of Turkey

Variable	Number of Observations	Mean	Standard Deviation	Min.	Max.	Jarque-Bera Skewness/ Kurtosis tests Joint Probability
CPI of F&SD	53	512.58	112.17	343.79	753.88	0.3415

When Table 2 is investigated, it is apparent that the CPI of F&SD has fluctuated between 343.79 and 753.88, averaging 512.58 through the 53 months. By examining the results of the Jarque-Bera test, in which the null hypothesis is that the series has a normal distribution, the probability value is found as 0.3415. Since the probability value is more than 0.05, the null hypothesis cannot be rejected, and the series is assumed to have followed a normal distribution with a 95% confidence interval.

3.2. ARIMA Methodology

The forecasting analysis of the series used in the study was conducted utilizing the Autoregressive Integrated Moving Average (ARIMA) methodology. The ARIMA approach, also referred to as the Box-Jenkins methodology, is a type of time series analysis used to forecast future values of specified variables and was developed by Box and Jenkins (1976).

ARIMA modeling is a technique for forecasting the future periods of a time series data using its current and past periods. These forecasting techniques assume that time series exhibit a recognized stochastic pattern. Forecast values are a linear function of the past and current periods of the series. ARMA models combine autoregressive (AR) and moving average (MA) models. The current value of a process in an AR model is the finite and linear aggregate of its previous values and the random shock. Formula (1) illustrates a stationary AR(p) process.

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \ldots + \phi_p z_{t-p} + a_t \tag{1}$$

The formula denotes the time series by z, and the period by t. θ values indicate the parameter coefficients of the past periods of the series. The value denoted by p indicates the number of periods over which the series can be explained using its historical values, and the AR process of order p expresses this process. The random shock of period t is denoted by a_t.

Suppose a time series is linearly dependent on a finite q number of past values of the random shock. This series is known as the MA process, and the formula (2) denotes the stationary MA process of order q.

$$z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q} \tag{2}$$

The q value indicates how many past random shocks the series can be explained by. θ values denote the parameter coefficients of random shocks. A stationary ARMA model incorporates AR and MA processes, as in formula (3).

$$z_t = \phi_1 z_{t-1} + \ldots + \phi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q} \tag{3}$$

Stationarity is crucial in time series analysis. Stationary models indicate that the series is in statistical equilibrium with time-invariant probabilistic properties, which are the values distributed around a constant mean and have a constant variance. In practice, many series appear as non-stationary series that do not distribute around a constant mean (Box et al., 2016). In order to consider a series as covariance stationary, it must possess three properties. These three properties can be listed as follows:

- the tendency of a series fluctuating around a constant mean to return to the long-term mean,
- having a finite time-invariant variance,
- having a decreasing correlogram as the lag length increases.

Without stationarity condition, none of the standard regression analysis results are valid in time series analysis. Regressions with non-stationary series are called spurious regressions.

Shocks temporarily influence a stationary time series; their effects fade with time, and the series returns to its long-term mean. Therefore, long-term estimates of the series will converge to its unconditional mean (Asteriou & Hall, 2021).

The difference in the series is taken to make it stationary. The value that indicates how many differences a series is become stationary by taking is represented by d. If d equals zero, the series is considered to be stationary. The process for identifying stationary and non-stationary time series is the ARIMA process of order (p, d, q), as shown in formula (4).

$$w_t = \phi_1 w_{t-1} + \ldots + \phi_p w_{t-p} + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q} \tag{4}$$

where $w_t = \nabla^d z_t$ (Box et al., 2016).

In substance, an ARIMA model is labeled and illustrated as (p, d, q). In this notation, p denotes the autoregressive order, d denotes the required difference order to stabilize the series, also known as integrated order, and q denotes the model's moving average order. It is critical for these models to be stationary in order to provide accurate findings (Fattah et al., 2018). Stationary models indicate that the series is in statistical equilibrium with time-invariant probabilistic properties, which are the values distributed around a constant mean and have constant variance (Box et al., 2016).

The Box-Jenkins technique is divided into three stages: identification, estimation, and diagnostic testing. After applying these processes sequentially, the forecasting stage can begin with the model selected during the stages. To provide an accurate forecast, it is critical to specify the model and parameter coefficients precisely (Box et al., 2016; Asteriou & Hall, 2021; Enders, 2015).

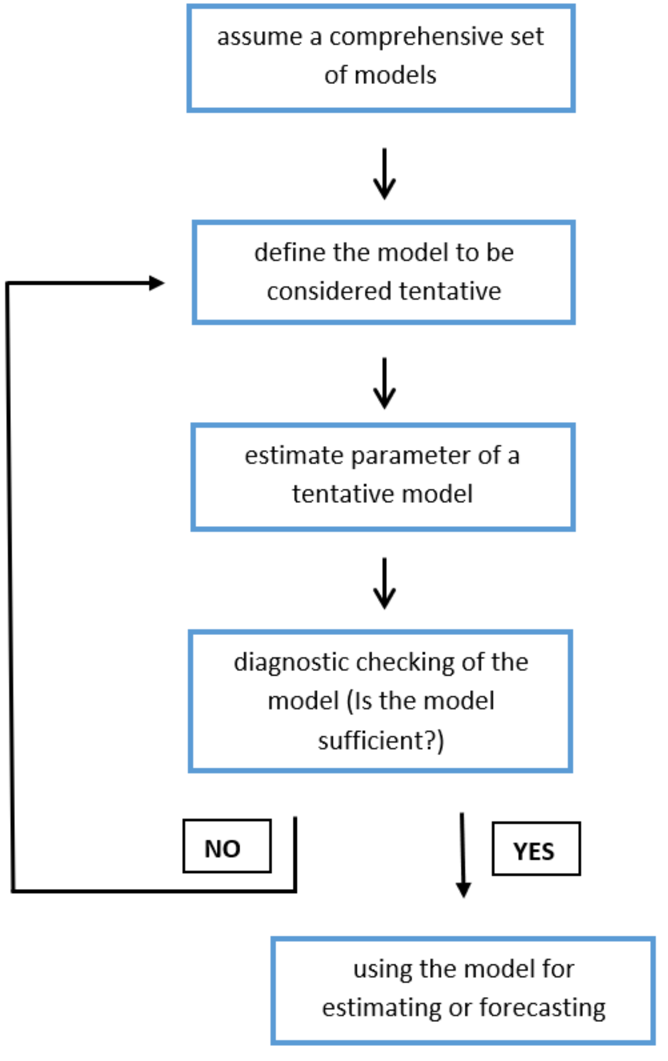

Figure 5. Stages for Iterative Methods for Model Building

Source: Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). *Time series analysis, forecasting, and control* (5th ed.). Wiley.

The iterative process for selecting a time series model is illustrated in Figure 5. The identification stage is when rough estimations of model parameters are obtained. The estimation stage adapts temporarily selected models to the data and obtains parameter estimations. At this stage, the model parameters are estimated using more advanced iterative methods such as the maximum likelihood method and nonlinear least squares. The diagnostic checking stage is performed to verify the presence of any possible lack of fit problems. If the model fits appropriately, it is ready for use. If any inadequacy is present, the iterative cycle is repeated until the appropriate pattern is found (Box et al., 2016).

When the stages of the Box-Jenkins methodology are followed sequentially, the first stage is identification. At this stage, it is determined primarily whether the series is stationary. The raw series' graph, autocorrelation function (ACF), and partial autocorrelation function (PACF) are constructed to determine stationarity condition. Additionally, unit root tests can be used to verify the stationarity of the series. The Augmented Dickey-Fuller and Phillips-Perron unit root tests are the most often utilized unit root tests in the literature. If the unit root test results indicate that the series is not stationary at level, the series is made stationary by taking the difference. By performing unit root tests on the differenced series again, the integrated order 'd' value can be derived. The integrated order is calculated by combining the results of the Augmented Dickey-Fuller unit root test, the Phillips-Perron unit root test, the ACF, and the PACF. After establishing the standing order of series, appropriate p and q values for the ARIMA model are identified by analyzing the ACF and PACF outcomes of the stationary series. ACF and PACF are used to estimate the form of the model and the approximate values of the parameters. Once the model achieves stationarity, taking a further difference, namely over differencing, should be avoided. The ACF is used to determine the q value, the PACF is used to determine the p value, and potential models are created. Parsimony is another factor to consider while establishing the model. Including more explanatory variables in a regression increases the goodness of fit (R^2), but the degree of freedom decreases. It is stated that parsimonious models generate more accurate forecasts than parametrized models. It is desirable to select the model with the fewest parameters possible. In this circumstance, our primary objective should be to obtain adequate but parsimonious models (Box et al., 2016; Asteriou & Hall, 2021; Enders, 2015).

Following the establishment of tentative models, the second step is the estimation stage. The ϕ and θ parameter coefficients of the tentative models are estimated using appropriate methods in this stage. The statistical significance of the coefficients for each estimated parameter in the models is evaluated. To select the most appropriate model, the most parsimonious one with the lowest Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC), and Hannan-Quinn (H-Q) Information Criteria values and the highest explanatory power is searched among the alternatives. The model selected by the SIC criteria will never have more parameters than the model selected by the AIC according to their selection rules. Therefore it is appropriate to choose a model based on the SIC criteria. Given the objective of selecting a parsimonious model, information criteria are more suitable indicators for model selection than the adjusted R^2 value.

The third stage is diagnostic checking. Following the model estimation stage, it is required to determine whether the residuals are white noise and whether they fulfill the criteria such as constant variance and no serial autocorrelation, which is checked by diagnostic tests. If the model's residuals satisfy the diagnostic assumptions, it can be utilized for forecasting. Otherwise, modifying the series or re-building the model will be necessary to meet the assumptions (Box et al., 2016; Enders, 2015).

Following the completion of these stages, forecasting, the primary purpose of the study, is initiated. If no model has been chosen as the best model in previous stages, it is assessed which model forecasts the series best using accuracy measures such as root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The model with the lowest accuracy measures is the best forecasting model (Enders, 2015; Pillay, 2020; Edward & Manoj, 2016).

3.3. Empirical Results

The most appropriate ARIMA model for forecasting the CPI of F&SD data has been established in this section using the Box-Jenkins methodology. The period 2017m07-2021m08 has been chosen as the analysis's estimation sample range, and the period 2021m09-2021m11 has been determined as the forecast sample range of the analysis. The forecast performance of the models was compared by applying the out-of-sample forecasting method.

3.3.1. Identification Stage

The data were initially evaluated graphically; Figure 6 depicts the graph of the change in the data over the sample period.

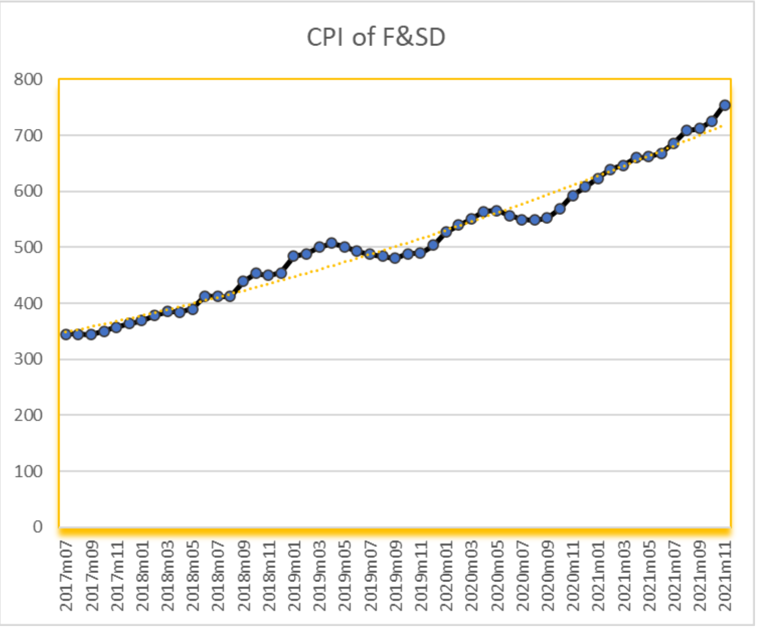

Figure 6: CPI of F&SD Graph over 2017m07 - 2121m11

The time-varying graph of the series demonstrates that the data does not exhibit seasonality. Additionally, seasonality was evaluated using dummy variables, and there was no seasonal effect observed in the series. It is seen that the series has a rising trend over time. As indicated by the graph, the series is not stationary. The series' stationarity was also investigated using the ACF and PACF plots and unit root tests. After examining the ACF and PACF graphs of the series depicted in Figure 7, it is concluded that the series is not stationary.

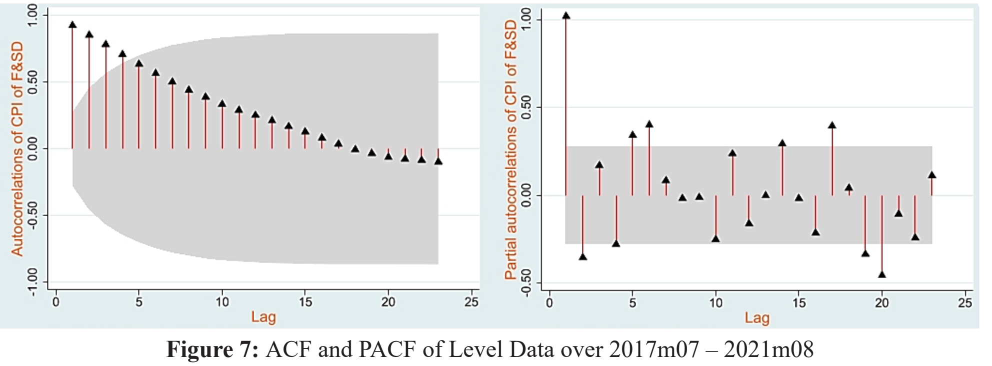

Figure 7: ACF and PACF of Level Data over 2017m07 – 2021m08
Grey areas indicate the 95% confidence, bands

Table 3. Unit Root Test Results				
	LEVEL		FIRST DIFFERENCE	
	Augmented Dickey-Fuller	**Phillips-Perron**	**Augmented Dickey-Fuller**	**Phillips-Perron**
t-statistics	1.2218	0.8326	-3.9858	-4.4671
Prob.	0.9978	0.9937	0.0034	0.0008

Finally, unit root tests were conducted on the level and first differenced series of estimation sample, and whether the series became stationary at first difference was determined. The test results are given in Table 3. The Augmented Dickey-Fuller and Phillips Perron unit root tests indicate that the series is not stationary at the level but stationary when the first difference is taken. In this case, ARIMA modeling should be performed using the series' first difference, and the d value was determined as one.

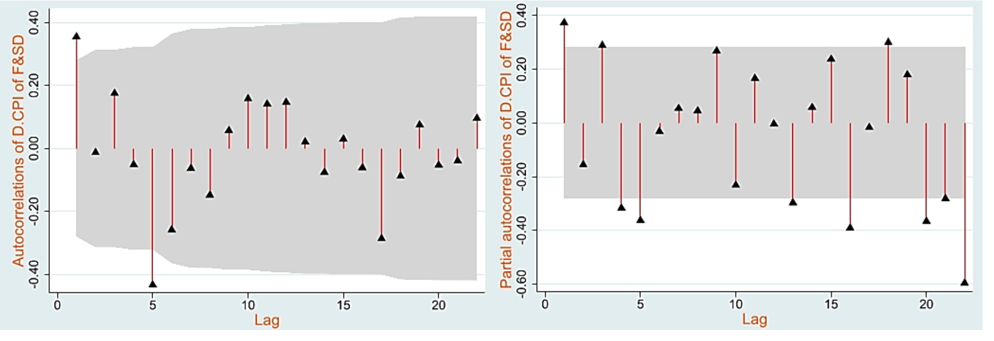

Figure 8: ACF and PACF of Differenced Data over 2017m07 – 2021m08
grey areas indicate the 95% confidence, bands

The ACF and PACF graphs of the first differenced series in Figure 8 were used to identify the p and q values of the tentative ARIMA models. Numerous models were evaluated in the study, and the best-suited models were chosen by considering the parsimony rule. ARIMA (0,1,1), ARIMA (0,1,3), ARIMA (1,1,0), ARIMA (1,1,2), ARIMA (3,1,2) and ARIMA (1,1,5) models were chosen as tentative models and further investigations were conducted in subsequent stages.

3.3.2. Estimation Stage

In this stage, parameter estimates for the tentative models were generated using the ARMA Conditional Least Squares method, which Box et al. (2016) refer to as one of the ARIMA modeling methods. Table 4 displays the information criteria, adjusted R^2value, parameter coefficients of ϕ's and θ's, and significance of the parameters for each tentative model. Three information criteria are utilized to determine which model best fits the time path of the series.

Table 4. Estimation Results of Tentative Models

	ARIMA (0,1,1)	**ARIMA (0,1,3)**	**ARIMA (1,1,0)**	**ARIMA (1,1,2)**	**ARIMA (3,1,2)**	**ARIMA (1,1,5)**
Constant	7.5129 0.0003*	7.8444 0.0023*	7.8566 0.0005*	7.5247 0.0000*	8.0115 0.0009*	7.2922 0.0000*
ϕ_1			0.3728 0.0104*	0.8134 0.0000*	-0.3894 0.0119*	0.5400 0.0016*
ϕ_2					-0.5726 0.0001*	
ϕ_3					0.3957 0.0119*	
ϕ_4	0.5786 0.0000*	0.4187 0.0027*		-0.3409 0.0136*	1.0655 0.0000*	-0.3099 0.0009*
ϕ_5		0.04470 0.7662		-0.5950 0.0000*	0.9406 0.0000*	0.0154 0.8534
ϕ_6		0.5454 0.0002*				-0.0201 0.8229
ϕ_7						0.2978 0.0003*
ϕ_8						-0.8609 0.0000*
Adjusted R-Squared	0.1872	0.2152	0.1155	0.1914	0.3466	0.3373
Schwarz criteria	**7.2680**	7.3482	7.3595	7.3866	7.3244	7.3590
Akaike criteria	7.1907	7.1938	7.2815	7.2307	**7.0858**	7.0861
Hannan-Quinn criteria	7.2200	7.2524	7.3110	7.2896	**7.1752**	7.1892

*indicates $p<0.05$, which is the 95% confidence interval significance

Bold red colors indicate the minimum value of selected criteria among all models.

After Table 4 is analyzed, it has been revealed that the ARIMA (3,1,2) model has the highest adjusted R^2 value and was picked by Akaike and Hannan-Quinn's information criteria. On the other hand, Schwarz criteria which chose more parsimonious models picked the ARIMA (0,1,1) model. All parameter coefficients of both models are statistically significant. Diagnostic tests were run on the ARIMA (1,1,5) model's residuals, which have the second-lowest value according to Akaike and Hannan-Quinn information criteria, along with the residuals from the selected models, which are ARIMA (3,1,2) and ARIMA (0,1,1) to determine if they show the characteristics of white noise.

3.3.3. Diagnostic Checking Stage

In this stage, the models will be evaluated to determine whether they satisfy the white noise requirements of constant variance, the absence of serial correlation, and parameter stability. Table 5 gives the results of the diagnostic tests.

Table 5. Diagnostic Tests Results of the Selected Models

	ARIMA (0,1,1)	**ARIMA (3,1,2)**	**ARIMA (1,1,5)**
ARCH Heteroscedasticity Test	F: 1.4385 p-value: 0.2365	F: 0.4407 p-value: 0.5103	F: 0.9708 p-value: 0.3298
Breusch-Godfrey Serial Correlation LM Test	F: 0.3310 p-value: 0.7199	F: 0.3550 p-value: 0.7035	F: 0.9097 p-value: 0.4110
Ljung-Box Q-statistics	Q-statistics of all lags are insignificant	Some of the Q-statistics are significant	Q-statistics of all lags are insignificant
Are all roots inside the unit circle?	Yes	Yes	Yes
Stability	no stability problem	no stability problem	no stability problem

All p-values were more significant than 0.05, indicating that the null hypotheses of the White test and

LM test could not reject. There is neither heteroscedasticity nor serial correlation problem in these models.

The diagnostic test findings indicate that the residuals of ARIMA (0,1,1) and ARIMA (1,1,5) models exhibit white noise characteristics. These models showed no evidence of heteroscedasticity, ARCH effect, serial autocorrelation, or instability. All roots of all models are inside the unit circle, and this finding establishes the parameters' stability. According to the outcomes of the Breusch-Godfrey Serial Correlation LM Test with two lags, the ARIMA (3,1,2) model does not exhibit serial correlation. The Ljung-Box Q-statistics, on the other hand, did not support the LM test result for this model only. When the Q-statistics, which has the null hypothesis that there is no serial correlation in the model, were examined, the null hypothesis was rejected for certain lags of the ARIMA (3,1,2) model. Therefore, it was deemed appropriate to make predictions with ARIMA (0,1,1) and ARIMA (1,1,5) models and to determine the best model by evaluating their forecasting performance.

3.3.4. Out-of-sample Forecasting

In this stage, out-of-sample forecasting has been conducted by selecting the period 2021m09-2021m11 as the forecasting sample. After comparing the ARIMA (0,1,1) and ARIMA (1,1,5) models' forecast performance, the best forecasting model, CPI F&SD series, was decided. Figure 9 displays the changes over time in the forecast values of both models and the observed data values from 2021m09 to 2021m11. Table 6 summarizes the accuracy measures for both models' predictions.

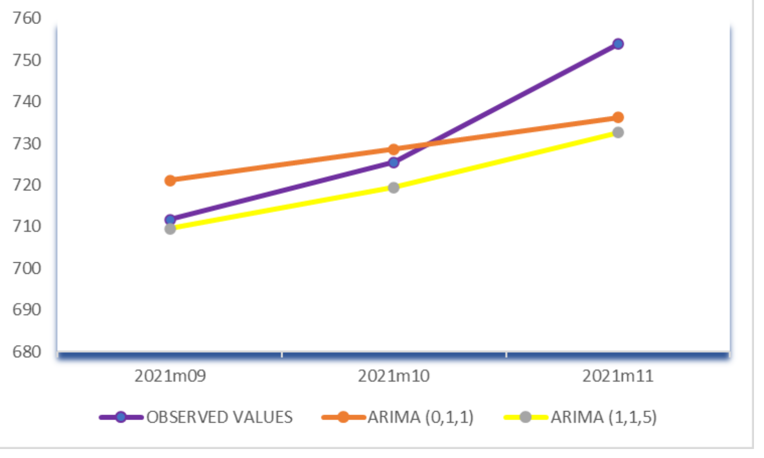

Figure 9: Graph of Out-of-Sample Forecasted Values and Observed Values over 2021m09 - 2021m11

Table 6. Accuracy Measures of ARIMA (0,1,1) and ARIMA (1,1,3) Forecasts

	ARIMA (0,1,1)	**ARIMA (1,1,5)**
RMSE	11.7142*	12.8391
MAE	10.1111	9.8570*
MAPE	1.3715	1.3238*
Theil Inequality Coefficient	0.0080*	0.0088
*indicates the minimum value		

When the accuracy measures listed in Table 6 for both models are examined, it is visible that the RMSE and Theil Inequality Coefficient prefer ARIMA (0,1,1), whereas MAE and MAPE prefer ARIMA (1,1,5). Under the parsimony principle, the ARIMA (0,1,1) model is the most appropriate one for forecasting the CPI of F&SD in Turkey.

4. Conclusion

COVID-19 has profoundly affected every area of the global economy and the food and agricultural sectors, which provide one of the most basic human requirements, nutrition. For economic analysis, the most reliable data are properly obtained price data. While the pandemic caused inflation in almost every sector worldwide, the food sector was a significant source of this inflation. As a result, it was determined that an investigation of the impacts of COVID-19 on the food sector was essential. The impacts of COVID-19 on the food sector in Turkey were analyzed in this book chapter using data from the CPI for food and soft drinks and the producer price index for food. After COVID-19, severe increases are observed in both indices, which are expected to remain for a while. After conducting an ARIMA analysis of the CPI F&SD using the period 2017m07-2021m08 as the estimated sample and the period 2021m08-2021m11 as the forecast sample, it was determined that the ARIMA (0,1,1) model is the most appropriate model for explaining future food inflation in Turkey.

It is vital to consider various factors contributing to food inflation when developing policies and implementing measures to combat it. The importance of ensuring food supply continuity has increased during the pandemic, and sustainability and flexible policies have gained importance against unpredictable crises. The sustainability of food supply should be ensured, and precautions should be taken to prevent such crises in the future. To maintain food supply continuity, governments should encourage producers and regulate the legal infrastructure of production under emerging conditions.

Additionally, more transparent communication with customers regarding food safety should be created. By examining the data, it is clear that food inflation increased significantly during and after the COVID-19 period. Inflation has reached dangerously high levels, affecting both producers and consumers. Thus, governments should provide financial assistance to producers to facilitate their payments. To ensure consumers' access to food is not disrupted, it is critical to implement precautions against food inflation, assure food price stability, and regulate individuals' purchasing power concerning inflation. It is necessary to improve the technological infrastructure of food supply chains and adapt them to the modern era and possible crises. Minimizing idle capacity in agriculture and the food sector, enhancing production efficiency, tracking technology advancements, and applying them to sectors are also essential to avoid future crises.

Additionally, decreasing food waste and redistributing surplus food to those in need will be a sustainable implementation. Eliminating unnecessary intermediaries in the supply chain that contribute to excessive price increases and shortening the chain from producer to customer can help reduce food inflation. Moreover, if states prohibit exorbitant prices and impose penalties on the opportunists who cause it, food inflation can be mitigated.

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