Comparative Time Series Analysis and Forecasting of Wheat Prices in Germany and Belgium Amidst Global Challenges

Team Time Travelers

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1.0. Abstract

In this report, we undertake a detailed time series analysis to examine the fluctuations in wheat prices within Germany and Belgium, expressed in local currency units (LCU). Our investigation aims to decode the patterns of wheat pricing and assess their impact on food inflation in these European contexts. To this end, we have compiled data from the Food and Agriculture Organization of the United Nations (FAO) and employed a suite of time series models, such as Autoregression (AR), ARIMA, and Seasonal ARIMA (SARIMA).

Our methodological approach includes rigorous tests such as the Augmented Dickey-Fuller (ADF) test to ensure the stationarity of the time series data, which is a prerequisite for the reliability and validity of our models. Through analysis and comparison of the models, ARIMA stands out as the most effective in accurately capturing the market's complexities and offering steady predictions.

Our approach has been carefully structured to mitigate the constraints, aiming to deliver a profound understanding of the agricultural economic trends that shape future inflation rates.

By deploying the ARIMA model, which has been optimized for our specific datasets, we provide stakeholders with valuable insights and forecasts that can inform decision-making. This report elucidates the dynamic processes driving wheat prices and presents a thorough forecast that underlines the anticipated market movements in Germany and Belgium, contributing to a strategic outlook on agricultural economics and inflationary expectations.

2. Introduction

Wheat serves as a cornerstone in the agricultural framework of many countries, and its pricing directly impacts the global economy. Germany and Belgium are no exceptions, with Germany being one of the top wheat producers in the European Union, averaging annual production between 23 to 26 million tons (FAO - Crops and livestock products/QCL)[1] . Belgium, while producing significantly less—around 3 to 4 million tons—boasts some of the highest yields in Europe[2] . In this report, we dive into the multifaceted realm of wheat prices, exploring their historical trends and the factors influencing these dynamics, including the critical role of Local Currency Unit (LCU) prices for farmers and the broader implications of food inflation.

Recent global events, such as pandemics and geopolitical conflicts, have caused significant disruptions in wheat supply chains. These disruptions have led to volatile wheat prices, which, in turn, have had far-reaching consequences for people's livelihoods around the world, notably affecting the affordability of staple foods like bread.

Our analysis is grounded in a dataset sourced from the FAOSTAT database, focusing on producer prices within the "prices" category for Germany and Belgium, with a specific emphasis on wheat. Covering a period from 2010 to 2022, this dataset provides a window

[1] FAO - Crops and livestock products/QCL - https://www.fao.org/faostat/en/#data/QCL
[2] [ibid.]

into understanding the price trends and informing our forecasts.

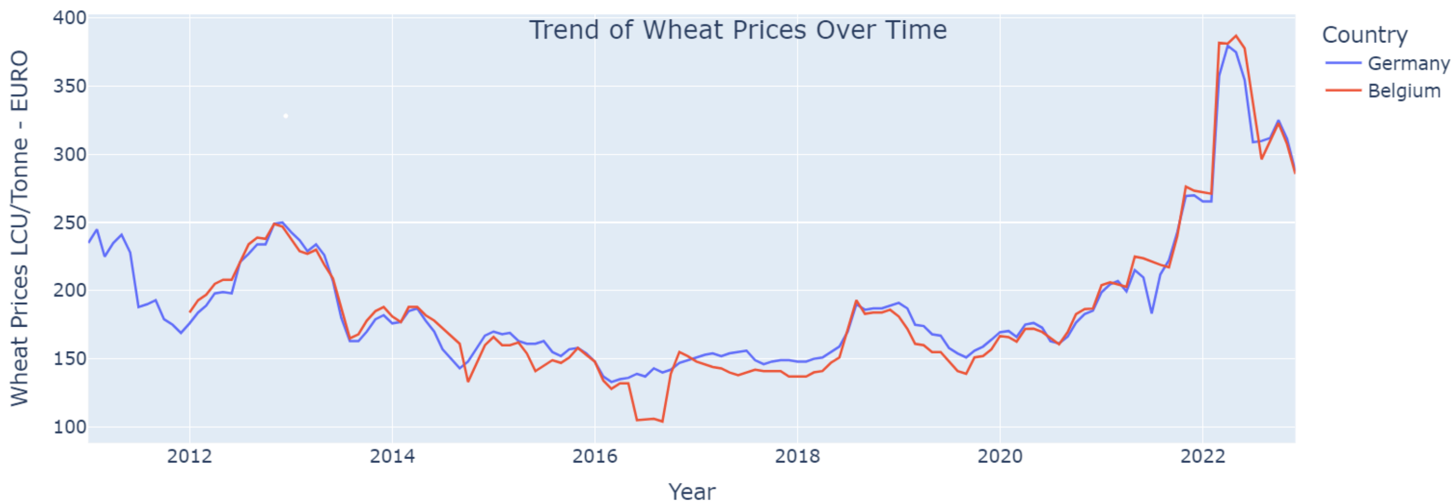


Figure 1. - Trend of wheat prices over time in Belgium and Germany

Disparities in data collection methods and the inherent limitations of the data, such as its annual granularity, pose challenges to our analysis. Nonetheless, by employing time series analysis methods—including Autoregression, ARIMA, and Seasonal ARIMA—we have constructed a steady framework to interpret past behaviors and predict wheat prices future trends.

3. Data Analysis

Raw Data:

Our analysis utilizes comprehensive datasets obtained from the Food and Agriculture Organization of the United Nations (FAO), encompassing producer price indices and marketing year averages. Here are some details about this raw data.

1. The dataset covers producer price indices and year averages for over 100 agricultural commodities across 230 countries and territories from 1961 to the latest year.
2. It provides a detailed picture of agricultural price trends globally at the producer level, enabling analysis of commodity price volatility and farmer incomes over long time periods.
3. With indices expressed in both national currency units as well as US dollars, the data facilitates international comparisons and understanding factors impacting trade competitiveness.

3.1. Comparative Analysis of Wheat Prices: 2018-2023

Over the past five years, wheat prices in Europe have consistently trended upwards, with Germany and Belgium serving as prime examples. In Germany, the price of wheat escalated from 148.0 LCU in January 2018 to a significant high of 379.7 LCU in April 2022, before witnessing a decline. Despite this reduction in price, the rates remained significantly elevated compared to the start of the period. In Belgium, wheat prices started at 137.0 LCU in January 2018 and similarly rose over time, reaching a peak of 276.4 LCU in November 2021. After peaking, prices fell but continued to stay above the levels seen in 2018.

3.2. Food Inflation Trends and Peak in Germany and Belgium

In terms of food inflation, Germany and Belgium have experienced notable shifts alongside these wheat price changes. Germany saw its food inflation rate surge in 2022, hitting a high of 21.198% in March 2023, before experiencing a downward trend towards September 2023. Belgium's food inflation has generally increased over the same five years, with the highest rate recorded at 18.024% in March 2023. Despite intermittent periods of deflation in 2021, Belgium witnessed a rapid upswing in inflation in the subsequent years, reflecting the ongoing volatility and upward pressure on food prices in the broader European context.[3]

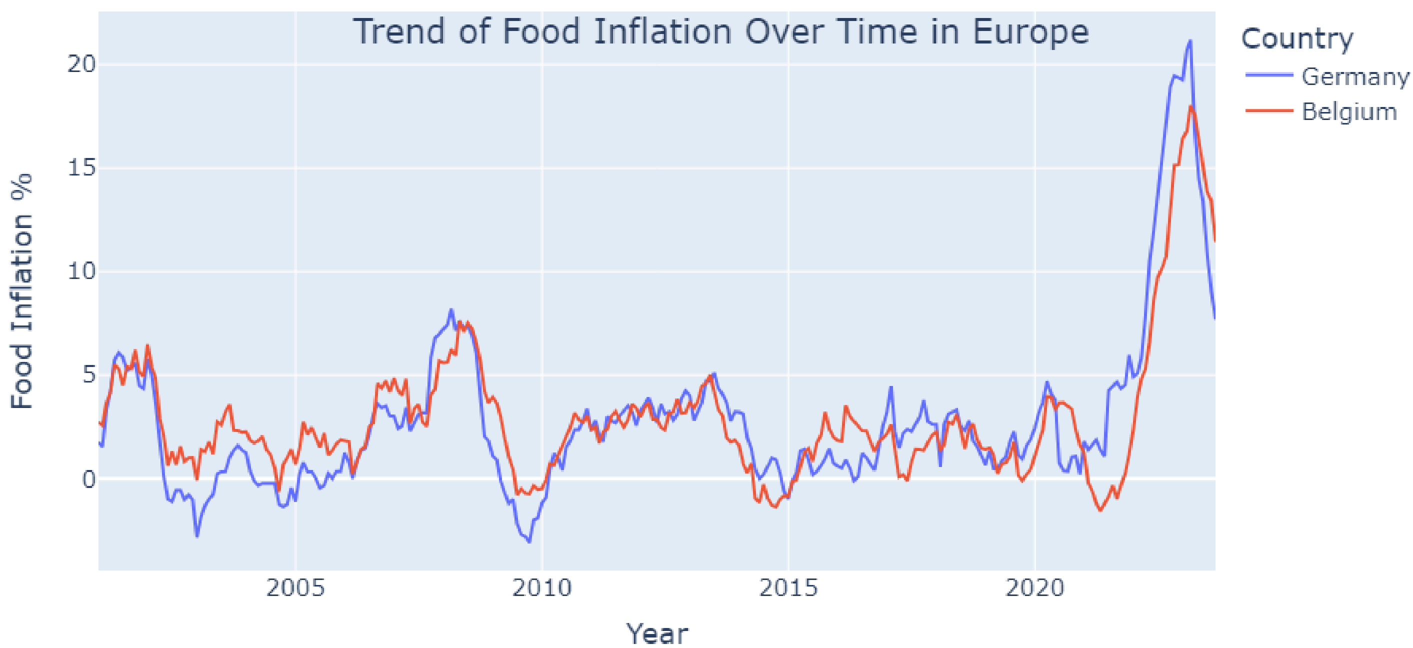


Figure 2. - Trend of Inflation over time in Belgium and Germany

3.3. Correlation of Wheat Prices and Inflation

Based on the historical data, there appears to be a tangible correlation between wheat prices and food inflation in Germany and Belgium. As wheat prices have surged, with Germany seeing a peak of 379.7 LCU in April 2022 and Belgium reaching 276.4 LCU in November 2021,

[3] Food Price Inflation - https://www.fao.org/faostat/en/#data/CP

food inflation rates have also climbed to significant highs in both countries around March 2023. This synchronicity suggests that the fluctuations in wheat prices have been a contributing factor to the broader inflationary trends in these economies, underlining the sensitivity of food prices to agricultural commodities in the European context.

The upward trend in wheat prices and the corresponding rise in food inflation rates in Germany and Belgium are indicative of a correlation that may be further influenced by external factors such as the Ukraine conflict with Russia, which has had widespread impacts on global grain markets.

4. Methodology

4.1. Overview of Time Series Analysis

In the upcoming sections of our report, we will focus on applying time series analysis to forecast wheat prices in Germany and Belgium and the corresponding inflation rates. Time series analysis is a critical approach for understanding and predicting future values based on previously observed values, and it is particularly well-suited for financial and economic datasets like the ones we are examining.

The models we intend to use for our time series forecasting of wheat prices and inflation include:

4.2. Forecasting Models

- **Autoregression (AR)**:

This model will help us understand and predict future values based on a time-delayed series of past data points.

- **ARIMA (Autoregressive Integrated Moving Average):**

Ideal for non-stationary series like wheat prices, which might have trends or other forms of non-stationarity.

- **Seasonal ARIMA (SARIMA):**

This extends ARIMA to account for seasonality patterns in the time series data, which are common in agricultural data due to planting and harvest cycles.

Through these models, we will attempt to capture the trends, seasonality, and other patterns in the historical wheat price data to make informed predictions about future prices. We will also estimate future inflation rates and analyze their potential impact on these price forecasts. Understanding the relationship between wheat prices and inflation will be key to providing actionable insights for policymakers and stakeholders in the agricultural sector. This analytical effort will shed light on how past events have shaped present trends and how these trends could evolve, influencing the decisions of farmers, investors, and governments.

4.3. Time Series Forecasting of Wheat Prices and Inflation Rates

4.3.1. Assessing Stationarity and Time Series Model Efficacy for Commodity Pricing

To ensure the reliability of our AR, ARIMA, and SARIMA forecasting models, we first need to confirm that our time series data—wheat prices —are stationary. Stationarity implies that the time series' statistical properties like mean, variance, and autocorrelation remain constant over time. This is essential because time series models predict future values based on these consistent properties. We use the Augmented Dickey-Fuller (ADF) test to check for stationarity, with a p-value below 0.05 indicating a rejection of the null hypothesis that the series is non-stationary.

The time series stationarity is conclusively demonstrated in the two tables below, which present the ADF test p-values for wheat prices and food inflation, both indicating results well below the critical threshold of 0.05.

Country	Non Stationary p-value	ADF Test p-value (Wheat Prices)
Germany	0.9372	1.085555×10^{-5}
Belgium	0.6922	3.70810×10^{-17}

Table 1. Augmented Dickey-Fuller (ADF) Test p-values for Stationarity of Wheat Prices in Germany and Belgium.

Country	Non Stationary p-value	ADF Test p-value (Food Inflation)
Germany	0.07821	5.7762×10^{-5}
Belgium	0.2224	1.7363×10^{-17}

Table 2. Augmented Dickey-Fuller (ADF) Test p-values for Stationarity of Food Inflation in Germany and Belgium.

Based on the provided p-values, both the wheat prices and food inflation data for Germany and Belgium have p-values significantly below the 0.05 threshold after differencing, indicating that the data have achieved stationarity. This suggests that the time series data for each country are now suitable for analysis using time series forecasting models.

4.3.2. Optimizing ARIMA Model Parameters for Accurate Market Predictions

The next step is to determine the appropriate parameters for our models by examining the Partial Autocorrelation Function (PACF) and the Autocorrelation Function (ACF). PACF aids in identifying the autoregressive (AR) order, while ACF pinpoints the moving average (MA) order. Correctly specifying these parameters is vital in capturing the intrinsic patterns within the data, thus enabling our models to forecast future values accurately.

4.4. ARIMA Model's Performance and Wheat Price Forecast Analysis for Germany and Belgium

After evaluating various models, including ARIMA, Seasonal ARIMA (SARIMA), and autoregressive models, the ARIMA model demonstrated the best results for forecasting Germany's wheat prices. Therefore, we will concentrate on the ARIMA model methodology in this section to elucidate the process and rationale behind its selection and usage.

In our time series analysis of Germany's wheat prices, we have utilized the ARIMA model, which has proven to yield superior predictive performance compared to other methods. We have included the performance metrics of the ARIMA model later in this report.

4.4.1. Hyperparameters

The hyperparameters in an ARIMA model are critical settings that define the model's structure and influence its behavior. They include the number of autoregressive terms (p), the number of differences to achieve stationarity (d), and the number of moving average terms (q). For seasonal data, these parameters are expanded to include the seasonal aspects of the ARIMA model, represented by P, D, and Q, along with the length of the seasonal cycle (m). After careful consideration and testing, we have determined the optimal set of hyperparameters for our model, which are presented in the table below.

Additionally, the data was split into training and test sets to validate the model's performance. The training set is used to fit the model, and the test set is used to evaluate its forecasting accuracy. This approach ensures that the model can generalize well to new, unseen data.

Here is a summary table of the hyperparameters employed in the ARIMA model for Germany and Belgium:

Parameter	Description	Germany	Belgium
p	Initial AR order to be tested	0	0
d	Differencing order	2	2
q	Initial MA order to be tested	0	0
P	Initial seasonal AR order to be tested	0	0
D	Seasonal differencing order	1	1
m	Number of periods in each season	12	12
max P	Maximum AR order to be considered	2	7
max Q	Maximum MA order to be considered	5	5
start P	Model start value for AR order	0	0
start Q	Model start value for MA order	0	0
seasonal	Whether to fit a seasonal ARIMA	true	true
trace	Whether to trace the evaluation of each model	true	true
stepwise	Whether to use stepwise search for model	true	true

Table 3. Hyperparameters of the ARIMA Model for Forecasting Germany and Belgium's Wheat Prices

This table outlines the specific hyperparameters chosen for the ARIMA model after a thorough process of evaluation and selection. These settings are tailored to capture the seasonal patterns and trends in the historical wheat price data for Germany and Belgium, enabling accurate and reliable forecasts.

For the forecast horizon, we set n_periods to 12 to project the future wheat prices for the next year. This approach aligns with the seasonal cycle of the data, allowing for a comprehensive annual forecast.

4.4.2. Performance

In evaluating the performance of our predictive models, we commonly employ metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE), which help us quantify the accuracy of our model predictions in relation to the observed actual values.

1. Root Mean Square Error (RMSE): RMSE quantifies the square root of the average squared differences between predicted values and actual observed values, offering a measure of the prediction accuracy of a model.

2. Mean Absolute Error (MAE): MAE calculates the average of the absolute errors between predicted values and observed data, providing a straightforward metric of average prediction error magnitude.

3. Mean Squared Error (MSE): MSE measures the average of the squares of the errors, essentially averaging the squared difference between the estimated values and the actual value, used to gauge the quality of an estimator.

Our ARIMA model showed good accuracy in forecasting Germany's wheat prices, with a Root Mean Squared Error (RMSE) of 0.08021, marginally better than the Auto Regressor's 0.0805. The additional metrics, a Mean Absolute Error (MAE) of 0.05492 and a Mean Squared Error

(MSE) of 0.00643, further affirm its reliable performance. A supporting graph will visually represent these findings, showcasing the 12-month forecast alongside actual prices for a clear comparison.

For the Belgian wheat price model, the performance metrics indicate a sound predictive accuracy with a Mean Absolute Error (MAE) of 0.06773, a Mean Squared Error (MSE) of 0.00858, and a Root Mean Squared Error (RMSE) of 0.09263. These figures suggest that the model has a moderately low level of prediction errors, signifying a reliable forecast that can be instrumental for stakeholders making informed decisions in the wheat market.

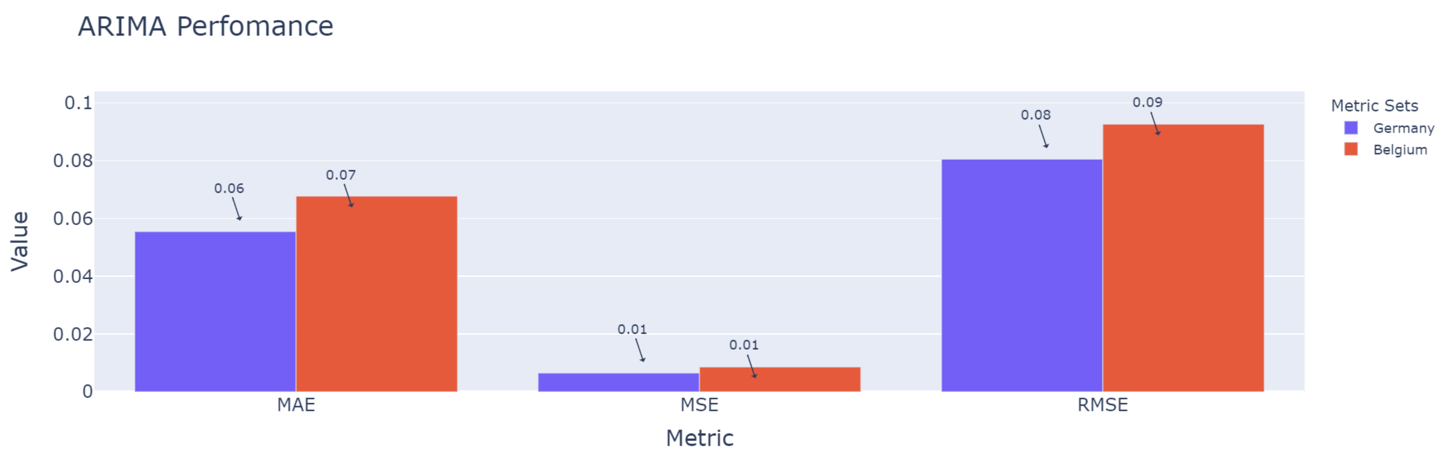


Figure- 3. Performance Metrics ARIMA model for Germany and Belgium Wheat Prices

4.5. Forecasting:

4.5.1. Germany Forecast

Our 2023 German wheat price forecast indicates a year of moderate price volatility within the market, as reflected by an average price of 190.834 LCU and a standard deviation of 50.847. The model predicts a gradual increase from 189.900 LCU in January to a peak of 191.489 LCU by March, followed by a subtle decline to 190.779 LCU in April. Mid-year predictions suggest a downward adjustment with May at 189.806 LCU and June at 188.734 LCU, leading to the year's lowest forecasted price of 186.287 LCU in July. A rebound is expected in August to 190.490 LCU, with minor fluctuations thereafter, peaking again at 191.164 LCU in October, before tapering off to 188.977 LCU by December end.

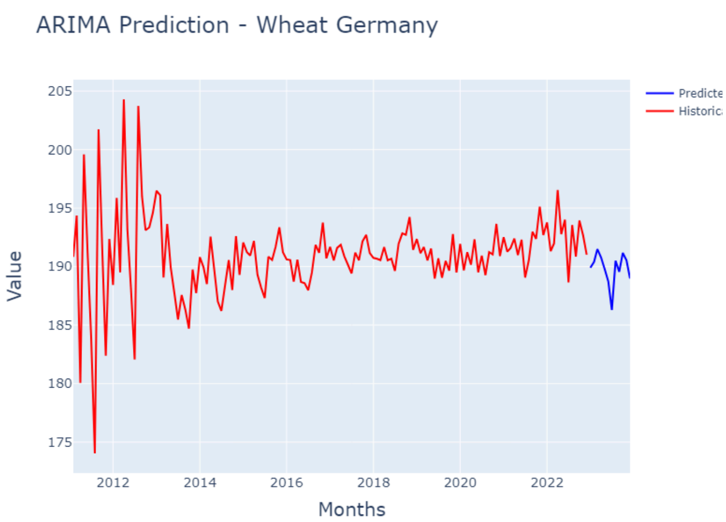
The consistency in the forecasted prices, staying within a relatively narrow band around the mean, indicates a stable market with no extreme volatility expected. The model's predictions, accompanied by small error margins, provide a credible tool for stakeholders in Germany's wheat market to plan with a degree of confidence throughout 2023.

4.5.2 Belgium Forecast

The Belgian wheat prices forecast for the year stretching from the end of 2022 to the end of 2023 shows a pattern of moderate fluctuations. The model predicts an initial value of 178.227 LCU on December 31, 2022, followed by a steady climb, reaching 182.503 LCU at the end of January 2023, and further ascending to 187.430 LCU by the end of February. A slight peak is observed in March with a price of 188.134 LCU, the highest forecasted for the period. Subsequently, there's a noticeable dip to 181.206 LCU by the end of April, stabilizing slightly above 180 LCU over May and June. The remainder of the year sees prices gently oscillating above 181 LCU, with a minor uptick to 183.589 LCU as we enter the closing month of November.

While recognizing that no predictive model is infallible, the relatively small error margins in our model are encouraging. They imply a certain robustness in the forecast, suggesting that the model can serve as a valuable asset for estimating future wheat prices in Germany and

Belgium. As such, it stands to offer guidance to farmers, buyers, and market investors, enabling more strategic decision-making grounded in the model's foresight.



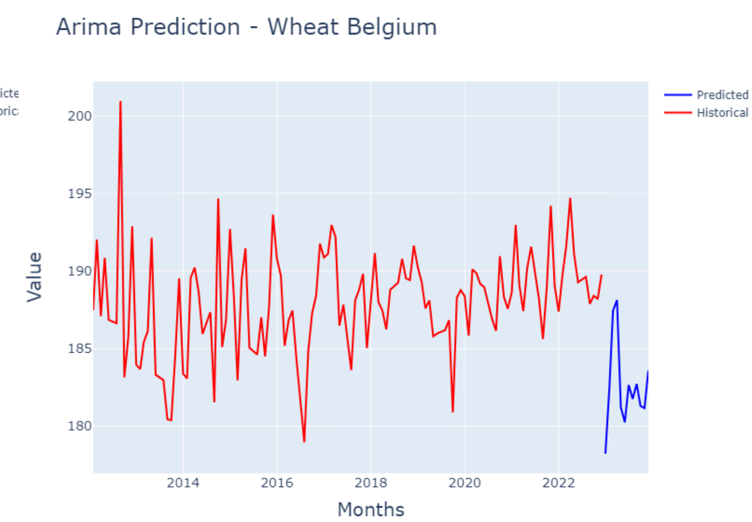


Figure- 4- and 5. ARIMA Predictions for Germany and Belgium

5. Hypothesis of the Wheat Price-Inflation Relationship through Forecasting

The correlation between wheat prices and inflation rates in Germany and Belgium, as evidenced by the data, demonstrates the sensitivity of food inflation to fluctuations in commodity prices. Forecasting models like ARIMA provide a quantitative lens through which this relationship can be examined. The predictive insights gained suggest that wheat prices can be a leading indicator of inflationary trends, given their pivotal role in the food supply chain.

The forecasts indicate a period of moderate volatility for wheat prices, which could imply a similar trend for food inflation, given their established correlation. The absence of extreme volatility in the wheat market suggests that while food inflation may not subside drastically, it may not spiral out of control either, at least in the short term covered by the models unless there are global factors that may influence these numbers.

6. Policy Implications

6.1. Policy Implications:

Stabilization Measures: With the forecast indicating moderate price volatility, policymakers should consider stabilization measures to mitigate any potential spikes in wheat prices, which could translate into inflationary pressures.

Strategic Reserves: Building or maintaining strategic wheat reserves could be a prudent step to cushion against unexpected supply shocks that could cause prices to surge.

Agricultural Policies: Encouraging local production through supportive agricultural policies could reduce reliance on imports, which can be subject to volatile international market prices and geopolitical risks.

7. Conclusion

The comparative analysis and forecasting of wheat prices and food inflation trends from 2018 to 2023 in Germany and Belgium underscore the interconnected nature of agricultural commodities and broader economic indicators. The use of time series analysis and ARIMA forecasting models has provided a window into future expectations for wheat prices, which bear direct relevance to food inflation rates. Policymakers and stakeholders are advised to use these predictive insights to inform decision-making, with an eye towards stabilizing the wheat market and mitigating the knock-on effects on inflation. By anticipating future trends, they can implement strategies that safeguard against potential volatility, ensuring economic stability and food security.

8. Recommendations:

Monitoring Systems: Implement robust monitoring systems for wheat prices and related food inflation, utilizing forecasting models to anticipate market movements.

Farmer Support: Provide support to farmers to ensure wheat production remains profitable, which in turn could contribute to stable market supply and prices.

Consumer Subsidies: Consider temporary subsidies or price controls for essential food items if forecasts indicate a substantial increase in wheat prices, to protect consumers from the immediate impact of inflation.

Futures Markets: Promote the use of futures markets for wheat, allowing farmers and buyers to hedge against price volatility.

9. References:

1. FAO - Crops and livestock products/QCL - https://www.fao.org/faostat/en/#data/QCL
2. Food Price Inflation - https://www.fao.org/faostat/en/#data/CP