From Breadbasket to Battlefield

The Impact of the Ukraine War on the level of food prices in the EU

Delft University of Technology

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The Impact of the Ukraine War on the level of food prices in the EU

by

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Preface

In today's global landscape, the intersection of geopolitics, economics, and environmental sustainability has emerged as an area of concern, shaping the future of international relations and economic stability. The European Union (EU), as a significant actor in the global landscape, has found itself at the nexus of these forces, particularly in the aftermath of recent geopolitical events that have reshaped the global order and tested the resilience of its economies.

The invasion of Ukraine by Russia in 2022 marked a significant geopolitical upheaval and triggered a cascade of economic shocks affecting global commodity markets, supply chains, and inflationary pressures. These events have underscored the intricate linkages between geopolitics, market dynamics, and economic policies, calling a comprehensive analysis of grain, oil and gas prices' impact on the EU's inflationary indices.

This research paper aims to investigate the impact of the Ukraine war on the level of food prices in the EU. It focuses on key commodities such as wheat, corn, oil, and gas, which have been notably affected since the onset of the conflict and thus can be a reason of hight inflation. Ukraine and Russia play crucial roles as exporters of these commodities, making the disruptions of theris supply chains highly relevant to the EU's food security and economic stability.

By examining the shifts in commodity prices, supply chain disruptions, and the ensuing policy responses, this study seeks to provide insights into the resilience and adaptability of the EU's economies in the face of geopolitical tensions. The research question at hand is: ”What is the impact of the war in Ukraine on the level of food prices in the European Union?” To answer this question, the study will analyse the dependency level of the EU food industry on imported goods, the direct and indirect dependency on Ukrainian and/or Russian grain, fertilizers, and energy, and the significance of the relationships among commodities.

The research methodology involves the use of the Vector Error Correction Model (VECM) to analyse the short-term and long-term effects of fluctuations in commodity prices on the Consumer Price Index (CPI) and the Food Price Index (FPI) of EU countries. This model is chosen for its ability to capture the dynamic adjustment of indices towards a long-term equilibrium relationship with commodity prices while accounting for the immediate impacts of price fluctuations.

The findings of this research contribute to the broader discussion on the strategic actions for ensuring economic stability and sustainability in an increasingly interconnected and volatile world. It is our hope that this study will provide valuable insights for policymakers, economists, researchers and society in understanding the complex interplay between geopolitics, market dynamics, and the EU's level of inflation.

Delft, June 2024

Executive Summary

The European Union (EU) has faced substantial economic challenges, geopolitical conflicts and global market disruptions in recent years. This study investigates the impact of the Russia-Ukraine war on food prices within the EU. Focusing on key commodities such as wheat, maize, oil, gas, and fertilizers, the study aims to evaluate the effect of disruption caused by the war in Ukraine. Given the critical roles of Ukraine and Russia as major exporters of these commodities, the disruption caused by the conflict is expected to have implications for the EU's economic stability and food security.

The research revealed significant volatility in maize, wheat, energy, and fertilizer prices, especially around mid-2022, correlating with the major geopolitical event of the time - the war in Ukraine. The VECM analysis was applied to study both short-term and long-term dynamics, which are crucial for understanding the impact of commodity prices on the Food Price Index (FPI) as a measure of inflation and food security. While the VECM model captured market dynamics, the predictions were not significantly accurate for precise forecasting due to the impact of policies and income and substitution effects. The direct impact of commodity price fluctuations on the FPI appeared to be close to significant, indicating the need for further research and additional variables to be added to the predictive model.

Increased food prices lead to higher levels of food insecurity, particularly among low-income households, exacerbating poverty, malnutrition, and social inequality. Additionally, higher food prices contribute to overall inflation, straining household budgets and reducing disposable income, thus slowing down the economy. This situation underscores the importance of strategic measures to mitigate adverse outcomes and enhance resilience to disruptions in supply chains and food supply.

The study offers several recommendations for policymakers. Implementing subsidies for essential food items and considering temporary price controls helped stabilize markets and ensure affordability. The subsidies were designed as an emergency mechanism to lower the prices, but it appeared that the effect of such an action on the level of inflation was insignificant. Diversifying import sources and maintaining strategic reserves of essential commodities are crucial steps towards reducing vulnerability to geopolitical conflicts. This policy recommendation comes from the fact that over 50% dependency on Ukrainian grain and over 20% dependency on Russian gas puts the EU on the weaker side of the bargaining process. Diversification equalises all sides involved and leads to collaboration rather than price bargaining.

The study also underscores the importance of investments in alternative energy production and high-tech farming. The suggestion comes from the high dependency of the EU on the grain, energy and fertilisers imported from the countries involved in the war. Technologically advanced farming methods will thus decrease the reliance on imports and change the European economy's course towards sustainability.

In conclusion, this study contributes to the broader discussion on economic resilience in an interconnected world by comprehensively analysing the impact of the Russia-Ukraine conflict on food prices. The findings measure the European food industry's reliance on agricultural products imported from Ukraine and Russia. Additionally, the study measures the significance of the impact of price changes of agricultural goods imported from Ukraine and Russia on the level of inflation in the EU.

Contents

1 Introduction

1.1. The issue at stake

In the contemporary global landscape, the intersection of geopolitics, economics, and environmental sustainability has emerged as a pivotal area of concern, shaping the future of international relations and economic stability. The European Union (EU), a significant actor in the global landscape, has found itself at the nexus of these forces, particularly in the aftermath of recent geopolitical events that have reshaped the global order and tested the resilience of its economies. The invasion of Ukraine by Russia (2022) marked a significant geopolitical upheaval and triggered a cascade of economic shocks affecting global commodity markets, supply chains, and inflationary pressures. These events have underscored the intricate linkages between geopolitics, market dynamics, and economic policies, necessitating a comprehensive analysis of their implications on the EU's macroeconomic environment.

The availability of essential food products at affordable prices is a vital factor in ensuring economic progress. Food prices are necessary for living standards, wage levels and inflation. Productivity growth and strong international competition resulted in the long-term trend of decreasing food prices, positively affecting living standards in many economies. However, since 2020, food availability at affordable prices in the European economy has come under significant stress. The problems started with Brexit (The United Kingdom officially left the European Union on January 31, 2020) and became intensified following the COVID-19 pandemic (officially marked by WHO on March 11, 2020) and the full-scale invasion of Russia into Ukraine (February 24, 2022). These combined events disrupted economic activity and global supply chains, and international commodity markets[6, 37, 49] were particularly affected. The disturbance can be seen in figure 1.1, where the prices of wheat and maize are visualised. Over the past ten years, there has been an evident decrease in prices of wheat and maize since 2013, which was then substituted by the continuous growth of prices starting in late 2019/early 2020. The peak was reached in 2022, with a stable drop in prices afterwards.

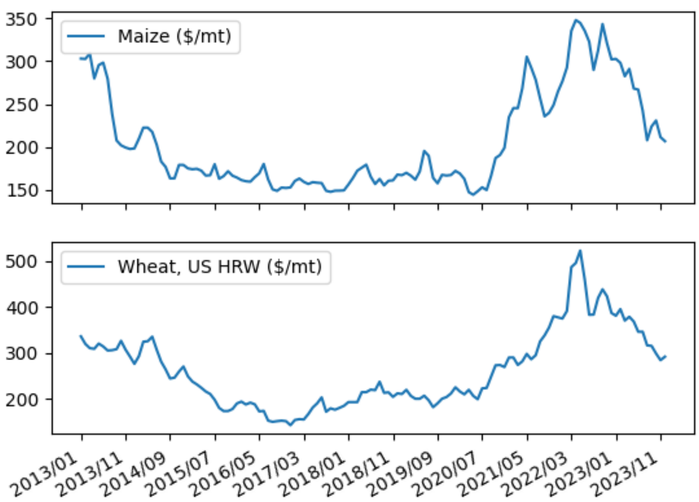


Figure 1.1: Prices of wheat and maize over the past ten years

The increase in the prices of energy and food, in turn, affected global stock markets[38]. Additionally, there is evidence that even though the war in Ukraine affected the world globally, the geographical proximity and level of efficiency of financial markets define the magnitude of the impact[31]. In effect, the economy of the EU was affected much more than the economies of the US or Japan, for example. The distortions of supply chains caused by COVID have been only worsened by sanctions imposed on Russia[49]. With Ukraine, Russia and Belarus being the key suppliers of agricultural and energy goods, the war shook the whole world[4, 48]. Research done by Forbes shows the dramatic growth of food prices during 2022-2023 (e.g. meat - 8.8%, eggs - 39.8%, milk - 17%)[14] providing evidence of global food crisis.

The increase in the aggregate price levels is called inflation[24]. In essence, high inflation means that money is losing its purchasing power (put simply, with high inflation, one can buy less with the same amount of money). In contrast, a drop in price levels is called deflation. Deflation increases the purchasing power of money. High inflation has an impact on the economy as a whole. With high inflation, one can buy fewer goods/services, given that the price of each now costs more. As a result, companies supplying those goods/services suffer from revenue losses due to decreased demand. The decrease in companies' revenue, in turn, leads to a reduction in economic growth[24].

The effects of the Russia-Ukraine conflict extend across commodities markets and energy markets. Wide-spread price increases affected global food security, and the Russia-Ukraine war strongly affected the countries of the European Union. Therefore, this thesis investigates the effects of the Russian-Ukrainian war on prices and inflation in the European Union. Out of the considerable scope of publicly traded commodities, grain, fertilisers, oil, and gas have been chosen due to their pivotal roles in the global supply chain and their significant influence on the economic stability and energy security of the European Union. Ukraine and Russia are the key exporters of wheat and corn[26, 27], Russia is a crucial European exporter of natural gas and crude oil[20], and Belarus and Russia are critical exporters of fertilisers essential for a wide variety of farming activities[3, 30].

The interconnectedness of commodity prices with the state of the global economy makes it evident that minor changes in exports of previously mentioned goods may cause relatively large disturbances [21, 11, 49]. Even though there are facts showing that the world managed to adjust to the chaos brought about by the invasion of Russia in Ukraine, experts evaluate the current state of the EU economy as fragile and unstable[22][1]. The average inflation rate in the European Union has shown a steady decrease since its peak in 2022 due to actions of Central Banks and restructuring, which leaves room for optimism. However, recent disturbances in the Middle East and Ukraine's highly volatile supply of agricultural goods continue to lead to high levels of uncertainty. The World Bank Group concludes by pointing out the effectiveness of monetary tightening done by countries worldwide, followed by high uncertainties regarding the future state of the world economy[17].

The main objective of this study is to empirically investigate the impact of fluctuations in oil, gas, grain and fertiliser prices, which have been notably affected since the onset of the Russian-Ukrainian conflict in early 2022, on the Consumer Price Index(CPI) and the Food Price Index of EU countries. This research is particularly relevant given Ukraine's status as a bread basket of Europe and Ukraine's and Russia's substantial share of world export of previously mentioned commodities. The changes in the global food market dynamics, accentuated by geopolitical tensions, have the potential to influence international trade and investment patterns significantly.

1.2. Research question and method

The research answers the following question: **"What is the impact of the war in Ukraine on the level of food prices in the European Union?"**. The completeness and robustness of the answer are ensured by the list of sub-questions used as the milestones throughout the research. The sub-questions are the following:

- "What is the dependency level of the EU food industry on imported goods?"
- "How significant is the direct dependency of the EU food industry on Ukrainian and/or Russian grain, fertilisers and energy?"

[1] Additionally, evidence of world adjustment to the war can be seen on Figure 3.2a. Source: `https://bit.ly/CMO_October_2023_FullReport`

- ”How much are the prices of commodities and the inflation indices of interest synchronised with each other?”
- ”What are the dependencies between the prices of commodities and inflationary indices?”

This research endeavours to dissect the multifaceted impact of the invasion on the EU, focusing on key areas such as food security, commodity dependency, and inflation. By examining the shifts in commodity prices, the study aims to provide insights into the resilience and adaptability of the EU’s economies in the face of geopolitical tensions. Additionally, it seeks to contribute to the broader discourse on the strategic imperatives for ensuring economic stability and sustainability in an increasingly interconnected and volatile world. To achieve that, the short-term and long-term effects on the aforementioned food price indices will be analysed using the Vector Error Correction Model (VECM). VECM is an appropriate choice for this research, given its ability to model the dynamic adjustment of indices towards a long-term equilibrium relationship with commodity prices while simultaneously accounting for the immediate impacts of price fluctuations[46]. The complex nature of the VECM analysis requires more in-depth analysis of the causal relationships present in the dataset and descriptive statistical analysis of the unprocessed data. These tests ensure extensive and reliable research and complete control over every relevant aspect of the studied data.

1.3. Relevance to MOT studies

The Management of Technologies (MOT) Master’s programme is designed to train engineers to navigate complex technology-based international businesses through unpredictable business environments. The master’s program combines courses in economics, finance, intra- and inter-corporate decision-making, people and innovation management. The thesis tackles the economic and financial aspects of corporate decision-making by suggesting the future state of the economy and assessing the effectiveness of already existing policies aimed to neutralise the negative impacts of war.

The research assesses the impact of changes in the prices of specific commodities on the level of inflation. The unexpected change in the inflation level affects all parts of the economy, and thus, inflationary studies are relevant to corporations as much as to policymakers and society in general. By analysing the import dependency of the EU on Ukraine and Russia and measuring the impact of the price fluctuations of the commodities on the inflationary indices, the research aims to estimate the long-term state of the level of inflation. For corporations, this knowledge leads to more accurate budget planning and more precise investment management. For policymakers, the report’s conclusions suggest areas for additional policies to stabilize the economy and ease the inflationary pressure on the citizens.

1.4. Structure of the report

Chapter 2 provides an extensive literature review on the research about food security and the impact of the war in Ukraine on it. The chapter outlines the knowledge gap and, thus, the study’s relevancy. Chapter 3 defines the scientific basis of the method used in the research, alongside the justification of the data used in the study. The chapter also outlines the plan of the research and provides the theoretical knowledge needed to be able to understand the test and the results. Chapter 4 explains the study process and all the findings. The chapter is split into four parts: (a) an investigation of the relationship between the prices of wheat and maize and the inflation indices, (b) an investigation of the relationship between the prices of wheat, maize, crude oil, natural gas and fertilisers relation and the inflation indices, (c) an analysis of the relationship between the prices of wheat, maize, energy and fertilisers and the inflation indices and (d) final prediction of the inflation rate based on the best-performing version of the model. Finally, chapter 5 summarises the results of all the steps made in the report by providing the conclusion. The chapter also discusses the limitations and potential reasons for the model inaccuracies alongside the derived recommendations for policymakers and corporations.

2
Literature review

This chapter shows the results of the existing studies about the impact of the war in Ukraine on the EU and the world. It aims to emphasise all the studied implications of Russia's invasion of Ukraine and define the scientific importance of research about food price level shifts carried out in this research paper. The chapter discusses the problem of food and energy security in the EU. In light of the war in Ukraine, the world and the EU, in particular, faced significant challenges to a stable food supply, thus calling for research as this.

2.1. Introduction

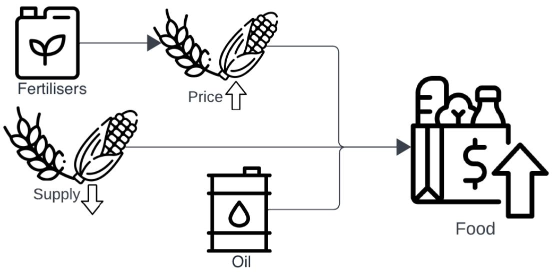
The war in Ukraine has triggered profound disruptions across global food markets[5, 36, 53, 55]. This chapter explores the multifaceted impact of the war in Ukraine on food security within the EU, emphasizing disparities in the alteration of global supply chains and the subsequent effects on food accessibility and affordability. Through a comprehensive review of the existing literature, this chapter aims to outline the current state of EU food security and highlight crucial knowledge gaps that persist in the face of ongoing geopolitical tensions.

The review addresses the question of food security. Thus, it is essential to define the concept. According to FAO, food security is defined as follows: 'when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life'. The definition plays an important role, given that the various dietary needs determine the response to the different fluctuations of the food market. Out of four main pillars of food security (Food availability, Food access, Food utilization, Food stability)[35] let us focus on food availability and food access. Food availability entails that one has adequate amounts of food at the time of need [13, 35]. Food access means that one has the physical and economic power to retrieve available food[35]. The ongoing war in Ukraine affected food access for low-income citizens, while food availability is not considered to be at risk[1, 8, 9, 36].

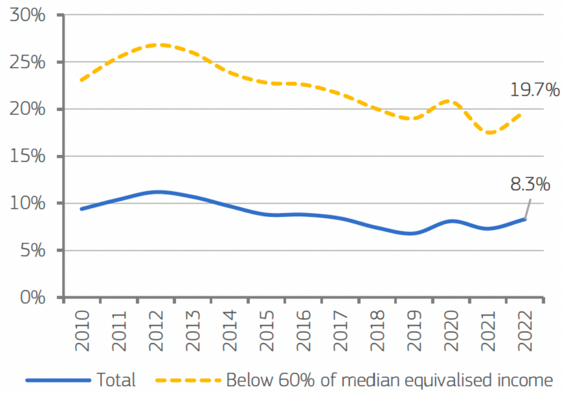
2.2. Food price and food affordability in the EU

Concerns regarding food affordability[1] comes from the complex nature of the food price process. An increase in food prices comes from three main areas: an increase in the price of fertilisers, which affects the cost of production of agricultural products[1, 9, 36, 53], an increase in crop prices[1, 5, 8, 9, 42, 41, 55], and an increase in oil prices[8, 36, 41, 53]. Figure 2.1a summarises the three main channels affecting the food prices.

[1]Based on the definitions, food access and food affordability are used interchangeably in the research. The author acknowledges that access implies the physical and financial ability to get food, while in the study, only the economic aspect is considered.



(a) Three factors affecting food prices



(b) Inability to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day [51]

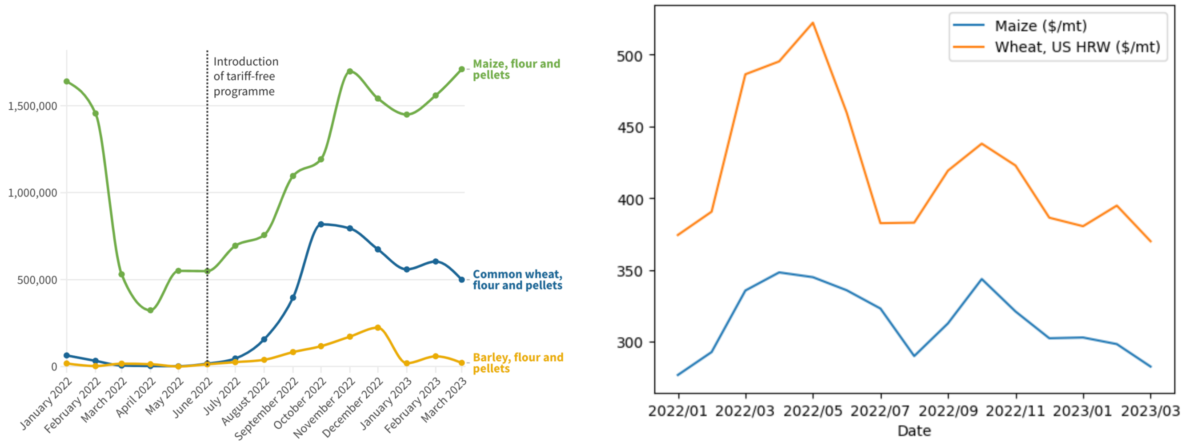
Figure 2.1: Relation between imports and food prices

Given the significant export share of grain products of Ukraine and Russia, the distribution of supply chains and shortage of supply evidently raise concerns about food affordability[1, 5, 8, 9, 41, 42, 55, 47]. Thus, the Russian invasion of Ukraine has the potential to worsen food security levels around the world, as both countries are significant exporters of grains and other agricultural products[36, 47]. Figure 2.1b shows the percentage of people unable to afford meat or fish products every second day, thus highlighting the issue of food affordability. The trend before 2020 was strongly declining. Then, the COVID-19 pandemic caused an increase in the number of those unable to afford fish and meat. The stress caused by the pandemic was then neutralised, given the decline visible in the graph. Since 2022 (invasion of Russia in Ukraine), the graph has changed direction upward. It can be seen that the number of people struggling to afford meat and fish for every second day started to increase. This fact emphasises the importance of research on food security in the EU. Additionally, food inflation (raise of food prices) is the main driver of food security[50, 51]. The higher the food prices are, the less people can afford it.

As was seen from the blockage of export routes of the Black Sea[18] and constant bombings of the farms[43], the unexpected drop in export amounts leads to an immediate increase in food prices[53]. This effect aligns with the basic understanding of the markets. The upward-sloping supply and downward-sloping demand curves usually describe the simple version of the market. The intersection of the two curves determines the equilibrium market price of the commodity (wheat, maize, sunflower oil, etc.). The shortage of supply forces the supply curve to shift to the left side, increasing the price of the commodity as a result. This principle explains the most evident connection between the price level of food and the disruption in the supply of wheat and maize. This type of market is called the spot market.

Figure 2.2 shows the explained above principle. Due to the Russian invasion of Ukraine, the supply of grain decreased. This caused prices to go up and, as a result, decreased demand. When the supply levels were restored, the demand was still low due to the high prices. EU representatives decided to impose a tariff-free program on the grain products imported from Ukraine[32]. This move resulted in a decrease in grain prices. The decrease in grain prices thus stimulated the demand and, as a result, boosted the amount of grain imported. Figure 2.2a shows the change in import amounts of maize, wheat and barley due to the tariff-off programme and figure 2.2b shows the reaction of the wheat and maize prices to this change. It can be seen that the programme proved to be an effective way of lowering prices. The EU members intend to keep the programme active while the war is active[32].

Nowadays, another type of market participates in the price-setting process. This type of market is called the future market. The marker has future contracts, the idea of which is that one can buy a certain commodity at a preset price on the preset date[39]. The market has three main areas: food, energy and metals. The market allows for hedging (the supplier can partially fixate on demand for a commodity while the consumer can partially fixate on the supply), which, as a result, works as a defence mechanism against unexpected price decreases/increases[39]. Overall, the presence of future markets partially safeguards consumers from uncontrolled price increases and provides suppliers with minimum



(a) Monthly EU imports from Ukraine [32]

(b) Wheat and maize prices 01/2022-03/2023

Figure 2.2: Relation between imports and food prices

constant demand.

Overall, high uncertainty around food prices and inconsistent import amounts of grain from Ukraine and Russia raise a lot of concerns. Russia and Ukraine are key exporters of grain to the EU[12], and figure 2.2 showed that the EU possesses tools to lower the prices in case of pressing need. The diversification of imports can be one of the viable solutions, as well as the increase in domestic production.

2.2.1. The case of price spike in May 2022

The decrease in supply causes the price of the commodity to increase. The case of dramatic price spike of the wheat and maize illustrated in Figure 2.3 outlines another significant factor in price setting. Ukraine and Russia together are responsible for roughly 30% of grain world export[52, 12]. Since the beginning of the invasion, dated 24th of February 2022, there has been a steep increase in the price of both commodities. The panic which originated in the countries of North Africa played a significant role in the price change[18]. The fear of starvation and uncertainty about future export amounts of Ukrainian grain stimulated North African countries to increase purchasing quantities, thus increasing the demand for the previously mentioned commodities. The steep decrease in prices after May of 2022 is motivated by Grain Initiative[52] and increased production of agricultural products by other countries[36]. The case emphasises the effects of a decrease in the supply of agricultural products caused by the war in Ukraine. In the imaginary case of the absence of future markets, the war could have caused even more significant damage.

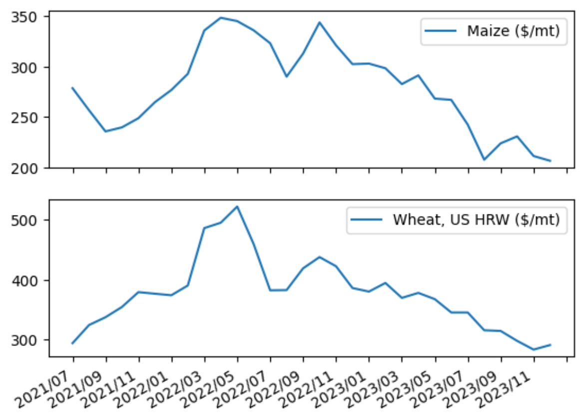


Figure 2.3: Price of wheat and maize 2020-2024

2.3. Fertilisers and energy

The effect of war in Ukraine is having a significant impact not only on the export amounts of grain products but also on the export amounts and prices of fertilisers[1, 8, 53]. Fertilisers are crucial for the analysis of the food markets, given the need for such for farming activities. The increase in fertiliser prices directly increases the production cost of any crop. Cost of production is defined as 'all of the direct and indirect costs businesses face from manufacturing a product or providing a service'[25]. Businesses get profit as the difference between the selling price and the cost of production. When the cost of production increases (in this case, due to the rise in the price of fertilizers), the profit of crop-selling companies decreases. The decrease in profit thus stimulates companies to increase the prices of crops. This relationship was observed since the beginning of the war in Ukraine[36, 53]. The cost of production can be decreased by improving the mechanisation of the agricultural sector[5]. Advanced mechanisation of the farm output is expected to increase efficiency in the field[5]. However, dependency on Ukrainian and Russian fertilizers and/or liquid gas (which is required for the production of fertilisers[53]) make efficiency levels of the sector highly dependent on imported fertilizers and gas from Ukraine, Belarus and Russia[1]. The dependency of the agriculture industry on fertilisers is immense. In June of 2022, fertilisers accounted for ∼20% of all production costs in agriculture, while wheat and maize share was 35%and 36% respectively[2]. To reduce the impact of dependency on Ukraine's and Russia's fertilizers, the EU has implemented various measures to safeguard supply[9].

Given that Russia is a considerable energy supplier[20], the effect of sanctions towards oil and gas cannot be omitted. Sanctions, and thus the decrease in supply quantities of crude oil, oil products and natural gas, impact the prices of food[36, 8, 41]. The effect of energy products on the food industry is indirect, given that the changes affect transportation costs and prices of fertilisers (as discussed earlier)[1, 41, 47]. Sanctions imposed on Russia stimulated European countries to diversify the oil and gas suppliers and invest in domestic production of gas[41]. The actions taken by the EU members resulted in an increase in the cost of energy and, as a result, a rise in food prices.

The report made by the World Bank Group outlines that as of April 2024, the commodity price indices have returned or, in some cases, became lower than the reference value of January 2022[16]. Figure 2.4 shows the findings of the research. Evidently, it can be seen that the shock caused by the invasion of Russia in Ukraine in 2022 and major supply chain disruptions have been neutralised over the past two years. The diversification of imports and the recreation of disrupted supply routes can explain the stabilisation of the commodity indices. This sets the stage for the research about the presence of long-term equilibrium in commodity prices and, thus, in commodity index value. Short-term fluctuations caused by an external shock lead to an increase in the price level; however, the increase does not last long. These facts encourage research on the nature of the long-term and short-term relationship between the level of food prices and the prices of oil, gas, wheat, corn and fertilisers.

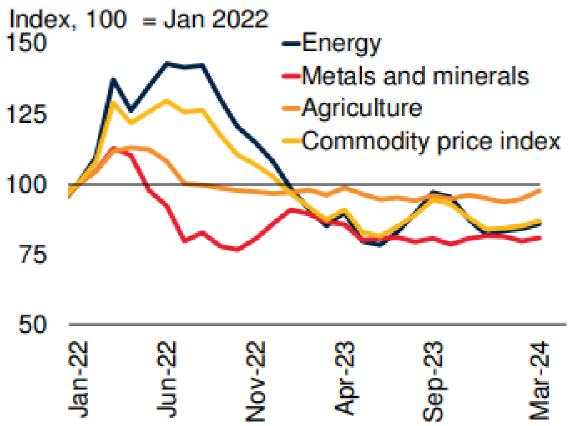


Figure 2.4: Commodity indices

2.4. Conclusion

To summarise, the literature review emphasised the importance of research on food price levels, as food prices are the driver of inflation[50, 51]. Since the invasion of Russia in Ukraine in 2022, the world has been hit by an increase in food prices, which has caused serious concerns regarding food and energy security given that Ukraine and Russia are key exporters of agricultural products and Russia is a key exporter of oil and gas to the EU. Food affordability became a big issue as a result of the war, thus increasing the number of families who are unable to afford a meal with meat or fish every second day. It can be concluded that the food prices are the most important reason for this effect and the prices are the central object of the research.

The literature review revealed multiple channels affecting the level of prices measured by the Consumer Price Index (CPI). The channels are summarised in the figure 2.5. The figure shows that the level of food prices, energy prices and transportation costs affect the general level of prices. It can be seen that the level of food prices is affected by maize and wheat (the primary crops imported from Ukraine and Russia) prices and energy costs. The transportation costs affect the price of crops, thus indirectly affecting the level of food prices. Oil and gas prices are at the very bottom of things. Gas affects

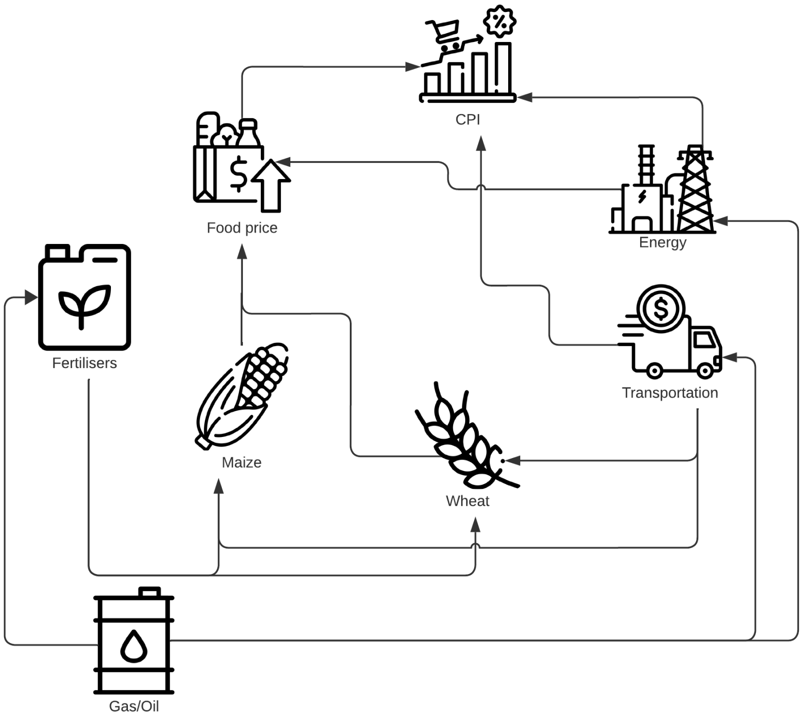


Figure 2.5: The summarised version of the relationship between commodities and indices

the price of fertilisers, which, in turn, affects the price of crops. Gas and oil affect transportation and energy prices, which are affecting the level of food prices. The figure shows the complex nature of the relationship between goods imported from Ukraine and Russia and the level of inflation (level of growth of prices).

By means of econometric research, the thesis aims to study the impact of the war in Ukraine on the level of inflation in the EU. The research aims to study the relationship between wheat, maize, oil, gas, fertilisers, and inflationary indices. The data used for such research and the models used to perform the relationship study are explained in the next chapter. The literature review outlines the significance of the problem of food affordability and shows scientific evidence of the significant impact of wheat and maize imported from Ukraine and Russia on the state of food security in the EU in particular.

3

Data and methods

This chapter explores the methods and data used to study the impact of geopolitical conflicts on the European Union's inflation level, focusing on the recent conflict between Russia and Ukraine (2022-Present time). The data's origins and relevance for the econometric study of the EU food market are explained in detail in this chapter. The data includes a variety of economic indices and commodity prices collected from trusted global and European sources. Studying wheat, corn, oil, and gas to assess the Ukraine war's impact on the price level of food in the EU is pivotal due to the high dependency of the European economy on imports of these products from Ukraine and Russia. Ukraine is a major global supplier of wheat and corn, and disruptions in its supply can significantly influence global market prices and food security within the EU. Similarly, Ukraine's geopolitical position as a critical transit route for Russian natural gas highlights the importance of oil and gas in this context, as any supply disruptions can profoundly affect energy prices, cost of living, energy security and economic stability in the EU. These commodities, therefore, provide us with a comprehensive view of the potential economic repercussions of the conflict.

This chapter also explains the statistical methods used to analyse these data, including time-series analysis and econometric modelling. These methods help pinpoint the economic effects of external shocks and contribute to discussions on how economies can remain resilient and how long it takes to overcome the shock's negative effects. This chapter provides a clear foundation for our study, detailing the mechanisms and data used to examine how the Russian-Ukrainian conflict has influenced the European Union's economic stability and growth.

3.1. Data

The research aims to study the relationship between corn, wheat, oil, gas and fertilisers prices and the Consumer price index (CPI) and Food price index (FPI) values in the scope of the European Union (EU)[1]. CPI is a weighted average of prices for a basket of goods and services representative of aggregate consumer spending[23]. The CPI is considered one of the most common ways to measure inflation. To calculate the inflation based on the value of CPI, the following formula is used:

$$\text{Inflation Rate} = \frac{\text{New CPI} - \text{Prior CPI}}{\text{Prior CPI}} \times 100 \tag{3.1}$$

The formula shows that the inflation rate is entirely dependent on the value of CPI. CPI contains multiple categories: food, energy, housing, travelling, etc. So, it can be stated that CPI covers all possible areas of spending. Food prices are measured independently by the Food and Agriculture Organisation of the United Nations (FAO) using FPI. FPI measures monthly changes in the international prices of a set of globally traded food commodities. Thus, FPI is used to cover precisely the effect of the war in Ukraine

[1]The research defines EU as a set of following countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden.

on the food markets, while CPI tracks the global state of price levels and the impact of the war in Ukraine on it. Given the nature of CPI, it can be safely assumed that FPI is a part of CPI. Figure 3.1 illustrates the vector of the research and visually defines the relationships being studied. The research tests the impact of the corn and wheat prices on the CPI and FPI, considering side forces like oil/gas and fertiliser prices. The study takes data from EU members, as it is of significant interest to analyse countries in immediate proximity to the ongoing war.

The research uses monthly wheat, corn, crude oil and natural gas prices.[2] Monthly data are selected given the reduced amount of 'daily or weekly noise'[3] which is considered irrelevant for the analysis which is carried out in this research. To get an understanding of the effect of fertilizers' price adjustment, the fertilizers price index is used[4] (the index represents the cumulative price of all fertilizers used in agriculture). The use of the index is pivotal, given that countries involved in conflict export fertilisers as well as required ingredients for producing fertilisers. The index is capable of capturing the effect of price shifts. The study takes publicly available data on prices from the 1st of January 2013 to the 31st of December 2023[5] and studies past events to define the impact of those on the food market to allow a comprehensive analysis of the effects of the war in Ukraine on the state of commodity prices. The relation between commodities majorly exported from the parties involved in the war and the general price levels of food is studied using the CPI and FPI of EU countries.

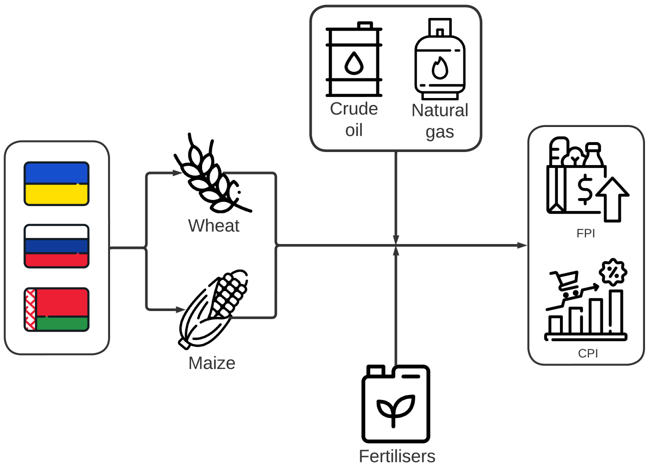


Figure 3.1: Commodity dependency diagram

Grain

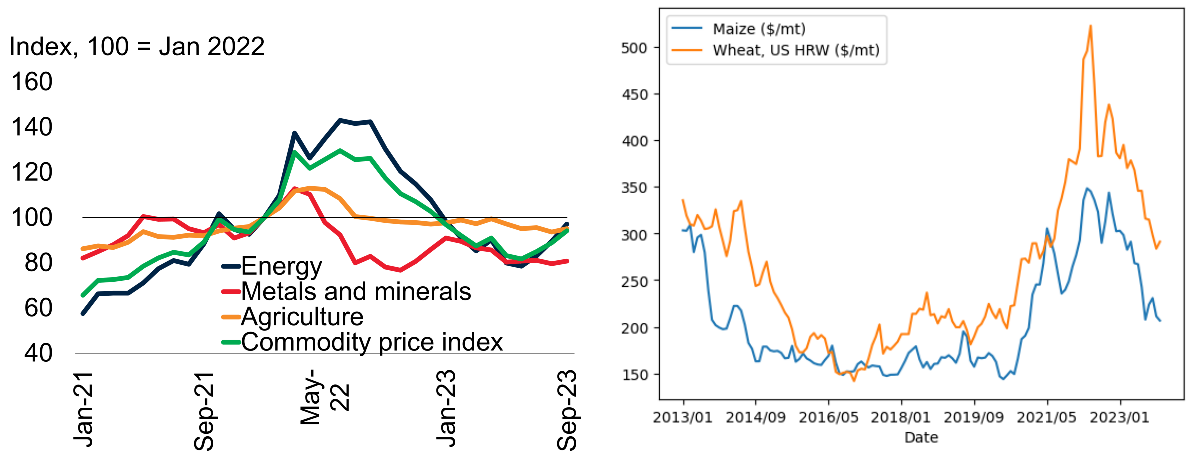
This section presents the data used to research the influence of grain prices on the price level in the European Union (EU). The data presented in Table 3.1 provide a yearly breakdown of the EU's dependency on maize and soft wheat imports from Ukraine and Russia over a span of four crop years, ranging from 2020/21 to 2023/24. The table reveals a significant reliance on Ukrainian grain imports, particularly for maize, including processed products, with import dependency percentages consistently above 45%. This figure peaks in the 2023/24 crop year, indicating a dependency of 59%. In comparison, the EU's reliance on Russian maize remains marginal throughout the period. Similarly, the import dependency on Ukrainian soft wheat, including flour and groats, is also substantial, showing a notable increase from 31% in 2020/21 to a high of 65% by 2023/24. The dependence on Russian soft wheat displays more variation, with a decrease in the most recent year observed (the decrease comes from the active sanctions on Russian exports to the EU). The assumed dependence of the inflation level, measured by CPI and FPI, on grain prices and the significant dependency of the EU on Ukrainian and Russian grain thus provide a solid base for the research.

[2]Resources which were used for further research https://www.worldbank.org/en/research/commodity-markets
[3]By 'noise' author means random fluctuations of data which are irrelevant for the analysis
[4]https://www.worldbank.org/en/research/commodity-markets
[5]This time interval results into N=132 data points

Table 3.1: Import dependency of EU on Ukraine and Russia (Grain)

Year	Commodity	From Ukraine	From Russia
2020/21	Maize (Incl. processed products)	45%	2%
	Soft wheat (incl. flour and groats)	31%	12%
2021/22	Maize (Incl. processed products)	49%	2%
	Soft wheat (incl. flour and groats)	12%	16%
2022/23	Maize (Incl. processed products)	57%	1%
	Soft wheat (incl. flour and groats)	63%	2%
2023/24	Maize (Incl. processed products)	59%	1%
	Soft wheat (incl. flour and groats)	65%	4%

Since the beginning of the Ukraine war, the world noticed a considerable price increase in food, given that Ukraine and Russia have accounted for 40% of the world's wheat exports. The expected response to the shortage of this significance was the emergence of new leaders in wheat exports like India, China, Canada and others[33]. The data confirm that the short-term spike of wheat and maize prices was further neutralized over time[16, 17] as can be seen in figure 3.2b. The figure shows a considerable drop in wheat and maize prices in 2013-2020. Table 3.1 shows that since the beginning of the war, Russia drastically reduced the export quantities of wheat, while Ukraine increased the levels of grain export. The effect of the reduction can be observed in the massive increase in wheat price during 2022 (Figure 3.2b). The price of wheat further shows a stable decline, which leads to the conclusion that the grain shortage was ameliorated. The long-term effects of actions taken to fix supply issues of agricultural products are yet unknown, but dropping grain prices suggest that the shock is neutralised at the time of the writing. It is evident that active war has dramatically damaged Ukrainian black soil and will take considerable time before Ukraine can export before-war wheat amounts [19]. Additionally, there is evidence that the impact of the war in Ukraine on agriculture and, thus, on the whole food industry is much more significant than the impact on the energy sector, which suffered colossal damages[29].



(a) Commodity market outlook

(b) Wheat and maize prices 2013-2023

Figure 3.2: Grain market data

Figure 3.2a outlines the state of the commodity price index (average price of all traded commodities) worldwide[17]. It can be clearly seen that a general increase in the index itself is mainly led by the energy price increase (the dark blue line spikes dramatically in the period of the COVID-19 outbreak, slightly goes down and returns to the high value around the time of the Russian invasion in Ukraine). However, the price difference between COVID/post-COVID times and prices after the invasion do not differ much. On the other hand, the price of agricultural goods has slowly, yet steadily, increased since the pandemic and reached its peak during the post-invasion period. Since the outbreak of the war and at the time of this writing, it can be seen that regardless of the fact that Ukraine and Russia are unable to supply the exact quantities of grain as before the Ukraine war, the world has managed to adjust.

Oil and natural gas

One of the most evident implications of the war in Ukraine is the shortage of energy products in the EU. Given that Russia generates 25% of global natural gas exports and 11% of global crude oil exports[15], sanctions applied to Russia alongside damages caused to the supply chains due to the war in Ukraine significantly affect the price levels of energy products. Evidence shows that a shortage of energy products due to a decrease in supply forces countries to implement energy rationing, which, in turn, slows down economic development[56]. As a result, the slowing of the European economy causes political and societal instability. The stock shocks caused by the COVID-19 pandemic, followed by the war in Ukraine, become the reason for long-term economic problems[49].

Following the data shown in Table 3.2, the dependency of the EU countries on oil and gas products from Ukraine and Russia can be analysed. The table shows that Ukraine does not export any oil and gas products to the EU, while Russia's exports of gas and oil products are significant. Since 2020, the export amounts of crude oil and oil products have decreased significantly, while liquid natural gas amounts have increased.

Table 3.2: Import dependency of EU on Ukraine and Russia (Oil and gas)

Year	Product	From Russia	From Ukraine
2020	Oil and petroleum products	21%	0%
	Crude oil	24%	0%
	Natural gas liquids	14%	0%
2021	Oil and petroleum products	22%	0%
	Crude oil	24%	0%
	Natural gas liquids	18%	0%
2022	Oil and petroleum products	17%	0%
	Crude oil	19%	0%
	Natural gas liquids	26%	0%
2023	Oil and petroleum products	4%	0%
	Crude oil	4%	0%
	Natural gas liquids	17%	0%
2024	Oil and petroleum products	5%	0%
	Crude oil	5%	0%
	Natural gas liquids	27%	0%

The sabotage of the Nord Stream pipelines (the 26th of September 2022) had significant implications for the natural gas and crude oil markets in Europe. Although the pipelines were not operational at the time due to previous geopolitical tensions and sanctions[40], the event led to heightened security concerns and speculation about future energy supply stability. The Nord Stream 1 and 2 were used to supply natural gas from Russia directly to Germany[7, 40]. These facts make oil and natural gas essential commodities and thus are included in this research.

Fertilizers

The production of fertilizers, which are essential for agricultural productivity, has similarly been impacted. Ukraine, Russia and Belarus are key suppliers of fertilizers to the global market[3, 30, 44][6]. The conflict in Ukraine has restricted fertilizer supply, increased prices, and introduced food production challenges to the EU and globally. Fertilizer prices, already rising before the start of the war, were further pushed up by the conflict, leading to higher agricultural production costs with possible consequences for harvests in the coming years. Table 3.3 shows that since the beginning of the war in Ukraine, the import amounts of fertilizers decreased, and the effect of supply change assumingly affects the general price levels of food, thus setting the stage for the research.

[6] The resources suggest that Belarus is a key player in the fertilisers market and not in grain and energy markets. That is the reason why Belarus is only included here and not in all the other commodity overviews.

Table 3.3: Import dependency of EU on Ukraine, Belarus and Russia (Fertilizers)

Year	Product Group	from Ukraine(%)	from Russia(%)	from Belarus(%)
2020	Ammonia	14	8	0
	Animal or vegetable fertiliser	3	10	0
	Mixed fertilisers	0	0	26
	Nitrogenous fertilisers	11	6	7
	Potassic fertilisers	3	0	28
2021	Ammonia	0	62	0
	Animal or vegetable fertiliser	0	1	2
	Mixed fertilisers	0	0	11
	Nitrogenous fertilisers	26	0	4
	Phosphates	0	22	0
	Potassic fertilisers	0	5	5
2022	Ammonia	0	8	0
	Animal or vegetable fertiliser	2	10	0
	Nitrogenous fertilisers	3	1	0
	Potassic fertilisers	0	32	13
2023	Ammonia	0	6	0
	Animal or vegetable fertiliser	0	6	1
	Mixed fertilisers	0	20	0
	Potassic fertilisers	0	6	0
2024	Animal or vegetable fertiliser	2	0	0
	Mixed fertilisers	0	35	0
	Nitrogenous fertilisers	5	2	0
	Phosphates	0	11	0
	Potassic fertilisers	0	7	0

3.2. Methodology

The present study examines the effect of the price change of corn, wheat, oil, gas and fertilisers on the Consumer Price Index (CPI) and Food Price Index (FPI). The relation between the two sets of variables shows the level of dependency of the European food market on agricultural products produced by Ukraine and Russia. The direct connection between any change in the price of wheat and maize and the War in Ukraine is explained by the quantity of commodities of interest imported from the countries mentioned above by the EU members.

The CPI and FPI are dependent variables representing the aggregate consumer price level in the EU. Thus, a change in the cost of wheat/corn as an essential crop for the food industry is expected to significantly affect the aggregate consumer price level. Wheat, corn, crude oil, natural gas and fertilizers affect the markets on several levels, while the final result is the degree of change in the two price indices of interest. Figure 3.3 illustrates the basic understanding of the connection between inflationary indices and wheat and corn prices.[7] The figure shows the following process. If the prices of wheat and corn increase, the food prices will increase. Wheat and corn are essential crops for the food industry, so any food item that uses wheat or corn will increase in price. Given that inflation is an increase in aggregate price levels, an increase in food prices will indeed drive the overall price level up. With rising inflation, employees tend to ask for higher wages to preserve their purchasing power. To satisfy employees' requests, corporations pump up the prices of their products to increase revenue and thus be able to pay higher wages. The price increase from the companies' side contributes to the rise in general price levels, driving inflation even more up. The inflation rises prices of food and the cycle ends.

[7] In the scope of this research, the part mentioned in red is acknowledged; however, the simplified linear relation is assumed. Thus, the study focuses on the examination of the dependency between the initial independent variable (wheat and corn prices) and dependent variable (inflationary indices) without any loops

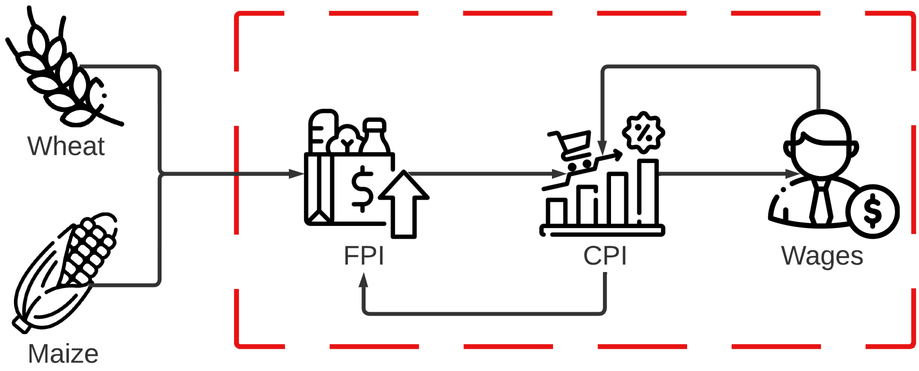


Figure 3.3: Crop price and indices dependency

The study uses the Vector Error Correlation Model (VECM) as a primary model to study the relationship between dependent and independent variables regarding long-term and short-term effects. The model considers the secondary variables (crude oil, natural gas and fertilizer price increase). In the modern research community, many statistical models for econometric research exist. Many statistical models are used for economic and/or financial studies; however, each has limitations and purpose. After thorough consideration, the VECM was chosen given that the model estimates the long-run relationship first and then the short-run relationships for each of the variables[46]. The process of implementing VECM assumes cointegration and stationarity checking, causality research between the variables of interest, and long-term/short-term quantitative analysis of the existing relationships, if any are found.

The research uses time-series data, meaning that data points are being collected over some time (in this research, the data have been collected monthly for the past ten years). The time-series data have the following properties[46]:

- **Auto-regressive character of time series**: time series data unravel the development of a variable over time. Autoregressive character assumes that a present value determines the future value, and this assumption allows the predictive nature of the model.
- **Stationary and non-stationary series**: when data are considered to be stationary, it means that any short-term fluctuations do not affect the mean of the series (so the data have constant mean, variance, etc.). There is no static mean over the data series when data are non-stationary.
- **Trend, cycle and seasonality in time series data**: a trend indicates a long-term sustained movement, while cycles represent short-term fluctuations within specific periods, such as months or quarters. Trends are inherently non-stationary as they do not revert to a long-term mean, unlike cycles that can be either stationary or non-stationary. Seasonality refers to patterns observed in data collected at high frequencies and is exemplified by predictable variations like increased sales during specific festivals or seasons.

Now, a detailed description of every step before the application of VECM will be discussed. Firstly, the rationale behind cointegration analysis will be discussed. Cointegration analysis is the Johansen cointegration test as the reliable way of cointegration checking. Afterwards, the stationarity checking procedure is discussed. The stationarity is checked using two tests: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The idea and the need for two tests are explained and discussed. Next, the Granger causality test is described. The test description defines the mathematical formula of the test along with the explanation of the expected results. Finally, the Vector-Error Correlation Model (VECM) is defined and explained. The metric system for the outputs of the model is defined.

3.2.1. Cointegration analysis: Theory

To use the VECM, a preliminary check must be made for the data's cointegration. Cointegration, in simple terms, means that the analysed variables share a long-term equilibrium relationship despite short-term fluctuations. This characteristic is crucial for understanding the nature of the relationships depicted by these models. The correlation highlighted in figure 3.4, where concurrent price spikes, suggest a potential relationship, thus serving as visual evidence of the desired interdependencies. Proven cointegration among variables is an essential requirement for the use of VECM.

The Johansen cointegration test will be used to test data for cointegration. The Johansen cointegration test provides two types of statistics as the result of running the test: trace statistics and eigenvalue statistics. Trace is a term from linear algebra that refers to the sum of all elements of the matrix's main diagonal (from the upper left to the lower right) of the matrix[54]. The trace is used to show that similar matrices would share the trace.

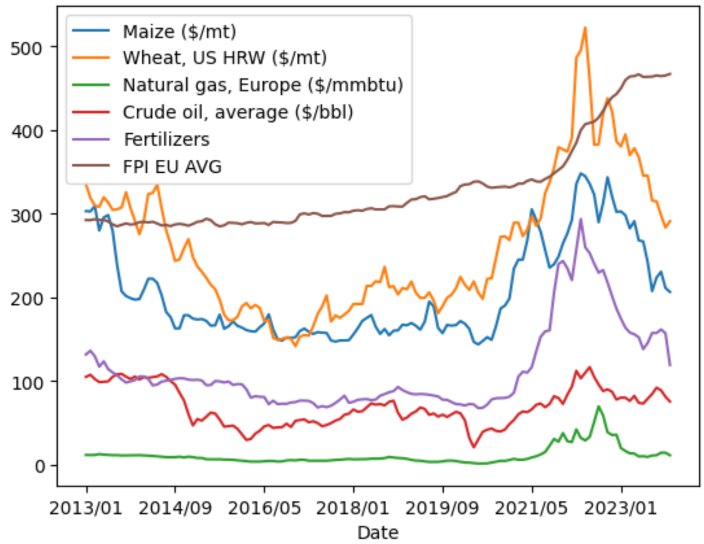


Figure 3.4: Prices of variables of interest over the past ten years

Eigenvalue statistics uses eigenvalue, which is also a term used in linear algebra. The eigenvalue is a scalar characteristic value or characteristic root of a matrix. The eigenvector approach is used when a certain number of cointegrating relationships is assumed, while the trace method is used to discover the number of relationships in the dataset. That is why the trace statistics will be used in the research.

Johansen's cointegration test also uses a parameter called deterministic order. Deterministic order categorises the analysed data into one of the predefined categories. There are three possible deterministic orders for the test: -1,0,1.

- -1 stands for cointegration with no long-term mean and trend. The value of -1 is generally used when data are assumed to be chaotic.
- 0 stands for cointegration with constant mean but no generic trend. The value of 0 is generally used when data are assumed to be seasonal.
- 1 stands for cointegration with constant mean and trend. This type of cointegration is used for the data, where the long-term equilibrium is assumed despite the short-term fluctuations.

To conclude, the study uses deterministic order = 1, given that it assumes data has stable long-run equilibrium while the spikes in commodity prices and values of indices of interest are temporary.

3.2.2. Stationarity analysis: Theory

Stationarity means that data have the same statistical properties over time, and thus that data have a unit root[45]. The Dickey-Fuller test was the first statistical test developed to test the null hypothesis that a unit root is present in an autoregressive model of a given time series and that the data are thus not stationary. The original test treats the case of a simple lag-1 AR model[45].

More tests were built based on Dickey-Fuller. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) are the examples and tests used in this thesis. Both tests have the null hypothesis of a non-stationary data series. The presence of a unit root defines data as non-stationary. The presence of the root or data being non-stationary implies that any shock done to the system has a permanent effect.

For VECM to be applied correctly, the data must be (a) cointegrated and (b) non-stationary. This implies that even though the shock has a permanent effect, it has a permanent effect on all the variables studied. As a result, the series move together in such a way that any deviation from their shared equilibrium is temporary.

The ADF test is the most generally used test, which is the reason for the usage of this test here. The Phillips-Perron test was made to perform a cross-check of ADF results. Sometimes, statistical tests tend to give false negative results, and in case the results do not match the value expected from the visual inspection of the data/graph, the PP test is run to cross-check the result. In the research, there are a couple of places where the reason for the usage of PP cross-check was explained, and the PP test was applied. By default, it is safe to assume that ADF provides reliable results.

The output of the stationarity tests (Augmented Dickey-Fuller (ADF) or Phillips-Perron (PP)) are visualised in the table in the research. The table has columns for test statistics, p-values and critical values. **The variable** column defines the name of the variable being tested for non-stationarity. **Test statistics** (can be ADF statistics or PP statistics) shows the outcome of the test. The value stored in this column shall be smaller than the critical value of the desired significance level. **P-value** shows the significance level. If p=0.05, then we have a significance level of 5%. **Critical values** determine the reference values for the focus variable and the significance level. In all the tests, a p-value smaller or equal to 0.05 results in the conclusion that the data is stationary.

3.2.3. Granger causality: Theory

This research's primary focus is to establish the effect of the price change of wheat, maize, crude oil, natural gas and fertilisers on the CPI and FPI indices as indicators of inflation. Thus, the dependency between the variables of choice is studied for causality. VECM studies the long-term return to the equilibrium, if such can be found. To ensure that the price change of the variables of choice indeed results in a change in FPI and CPI, causality research shall be done before applying VECM. Using the Granger Causality test, the predictive power of a variable can be tested. In the scope of the Granger Test, the causality is defined as follows:

> If $\sigma^2(X_t \mid U) < \sigma^2(X_t \mid \overline{U - Y_t})$, we say that Y_t is causing X_t, denoted by $Y_t \implies X_t$. We say that Y_t is causing X_t if we are **able to more accurately predict** X_t, using all available information than if the information excluding Y_t had been used.[10]

Let us discuss the definition and notations used. We want to prove that $Y_t \implies X_t$ (Y_t predicts/causes X_t). X and Y are sets of past values available for the test. The Granger causality test uses the least-squares approximation method to make a prediction. Let us denote an optimal prediction of X given Y as $P(X \mid Y)$. The least-squares approach assumes the predictive error (the difference between the prediction and the actual value) noted as $\epsilon_t(X \mid Y)$. $\sigma^2(X_t \mid U)$ denotes the variance of the predictive errors $\epsilon_t(X \mid Y)$. Based on those notations, the main inequality of causality $\sigma^2(X_t \mid U) < \sigma^2(X_t \mid \overline{U - Y_t})$ is interpreted as follows:

> The variance of errors $\sigma^2(X_t \mid U)$ when U (notation for the universe) predicts X is smaller than the variance of errors $\sigma^2(X_t \mid \overline{U - Y_t})$ when $U - Y$ predicts X. Meaning that any information without set Y predicts X less accurate than when Y is included in the predictive set defines causality between Y and X ($Y_t \implies X_t$).

The Granger causality test provides two types of statistical output: SSR F statistics and Chi2 statistics. It is known that Chi2 tests are applicable for categorical types of data (gender, marital status, blood type, etc.). The SSR F statistics are used for the rest of the data types. For every statistic outputted by the test, p-value and statistical values are given. The smaller the p-value is, the bigger the predictive strength of the variable with a given lag. Let us now define the purpose and outcomes of F statistics and explain the process in greater detail.

SSR F statistics

SSR stands for the Sum of Squares Residuals. This term refers to the total sum of the squared differences between observed values and the values predicted by a model. As mentioned before, the Granger causality test used the least-squares model for the analysis; thus, the sum of the squared differences is used to obtain F statistics. In the general version of the test, two statistics are provided as the outcome: chi-squared and F statistics. The core difference between the two is that chi statistics assumes categorical data while F statistics is used for time-series data for regression analysis, which measures the added predictive benefit of the previous data point. This is precisely what is needed for the research. The F value is calculated as follows[8]:

$$F = \frac{(\text{SSR}_R - \text{SSR}_U)/p}{\text{SSR}_U/(N-p-1)} \tag{3.2}$$

- SSR_R: Sum of Squared Residuals for the Restricted model. This is the simpler model, which does not include the additional predictors whose influence you're testing.
- SSR_U: Sum of Squared Residuals for the Unrestricted model. This model includes the additional predictors.
- p: The number of additional predictors in the unrestricted model that are not in the restricted model.
- N: The total number of observations in your dataset.
- N - p - 1: The degrees of freedom for the unrestricted model. The "-1" adjusts for the estimation of the intercept.

3.2.4. VECM definition

Assuming the cointegration, non-stationarity and significant Granger-causal relations of commodity prices, the last preparation step for applying VECM is the determination of the optimal lag length. This can be done using the Bayesian Information Criterion (BIC)[9]. With the optimal lag length defined, the VECM model can be built. The VECM provides insights into the long-term effect (expected equilibrium) of positive/negative shock on the market.

As a statistical model, VECM defines the presence and value of the long-term equilibrium alongside the analysis of shock impact. The model is able to predict the future state of the market/index/commodity and provide a range where the price can be due to unforeseen circumstances.

The VECM can be written as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + C x_t + \epsilon_t \tag{3.3}$$

Where:

- Δy_t is the vector of first differences of y_t.
- Π is the long-term impact matrix, defined as $\Pi = \alpha\beta'$, where α represents the speed of adjustment coefficients and β contains the cointegration vectors.
- Γ_i are the short-term dynamic coefficient matrices.
- C is the matrix of coefficients for the exogenous variables x_t.
- ϵ_t is the vector of error terms, assumed to be white noise with zero mean and constant variance.

The prediction of the VECM is further tested against predictions made by the simpler model - Vector Autoregression (VAR) model. The comparison allows for validation of the long-term equilibrium's presence and the prediction's accuracy.

The prediction done by the model will be measured for accuracy by Bias, MAE, MSE and RMSE. The closer every value is to 0, the more accurate a prediction is. The meaning of each of the error indicators is explained as follows:

- **Bias** measures the average difference between the predicted and actual values. A bias close to zero indicates that the model's predictions are unbiased.
- **MAE** represents the average magnitude of errors in the predictions without considering their direction (positive or negative).

[8] Found at https://stats.stackexchange.com/questions/557565/granger-causality-and-f-statistic
[9] BIC determines the number of lags in commodity price difference

- **MSE** measures the average of the squared differences between predicted and actual values. It is more sensitive to large errors due to the squaring of the differences.
- **RMSE** is the square root of MSE and provides an error metric in the same units as the original data.

3.2.5. Conclusion

The outlined steps of the research will be implemented and described in the chapter 4. The plan is designed to ensure all required checks are done before VECM is applied and prediction is made. In the research, in every section before section 4.5, the data will be split into two sets: train (122 records) and test (10 records) data. This is done with the purpose of running validation tests. The VECM/VAR model will be trained on train data, and prediction will be compared with test data. This allows us not only to compare VECM output with VAR output, but also to compare the absolute accuracy of the model against the actual state of things. This step will allow estimating the accuracy of the model and, thus, treat the final prediction (made in chapter 4.5) accordingly.

4 Results

4.1. Introduction

This chapter presents the findings of the empirical investigation into the economic repercussions of the Russia-Ukraine war on the European Union (EU). Utilizing the Vector Error Correction Model (VECM), the analysis focuses on the impact of fluctuations in key commodity prices—namely oil, gas, wheat, maize, and fertilizers—on the Consumer Price Index (CPI) and the Food Price Index (FPI) within the EU. The chapter is structured to provide a comprehensive overview of the results, beginning with a detailed examination of the data series for wheat, corn, CPI, and FPI.

The analysis is segmented into four key sections. The first section studies the impact of wheat and maize on inflationary indices in isolation from the other variables of interest. The section implements a full analysis of the data set, starting with cointegration analysis, followed by stationarity research, causality test and application of VECM for the prediction analysis as was outlined in chapter 3.2. The results of the VECM are then tested against the VAR model to assess the accuracy and reliability of the prediction.

The second section adds oil, gas, and fertiliser prices to the research scope to perform an impact analysis of changes in commodity prices on the inflationary indices of interest. The second section follows the exact steps as the first section to ensure the rigidity of the final outcome.

The third section studies the relationship between wheat and maize prices, energy and fertiliser price indices, and inflationary indices. Substituting gas and oil prices for the energy index assumes to cover the influence of energy prices as a whole, rather than the impact of oil and gas in isolation. The new variables are tested using the same methodology as the previous two sections, and thus, all the results can be compared with each other.

The fourth section shows the final predictions made by the models outside the dataset (meaning the actual forecasting, which cannot be validated). The section is using verified data, given that one of the models defined in the previous sections will be used.

4.2. Examining the wheat, corn, CPI, FPI data series

This section embarks on a comprehensive analysis of the influence of wheat and maize prices on inflationary indices. By isolating these two key agricultural commodities from other variables, the study aims to rigorously assess their individual impacts on inflation measured by the Consumer Price Index (CPI) and Food Price Index (FPI). The analysis begins with a thorough visual examination of the dataset, followed by a cointegration analysis to determine the long-term equilibrium relationships between the prices of wheat, maize, and inflationary indices of interest.

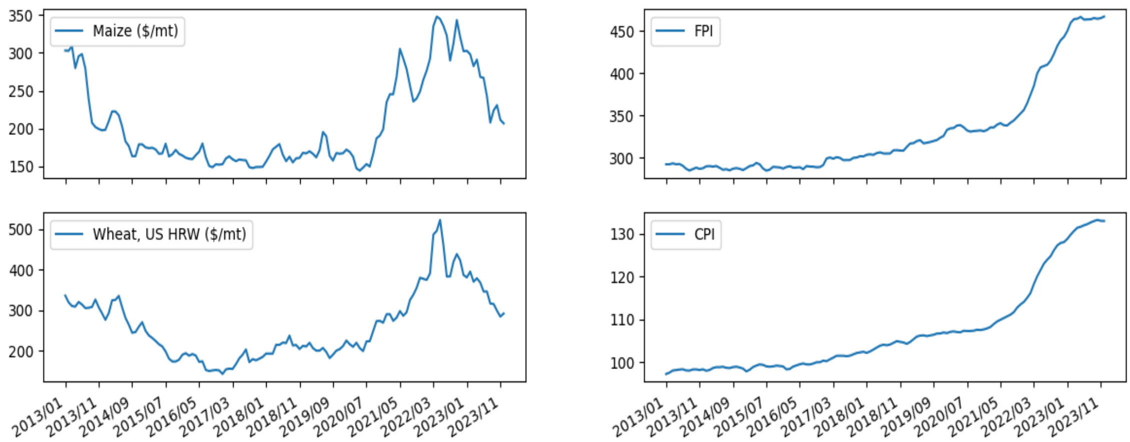
Following this, stationarity tests are conducted to ensure the data meets the prerequisites for further econometric modelling. The next step involves causality testing, which helps in understanding the directionality of the relationships between the variables. To forecast and understand the dynamic interplay between wheat and maize prices and inflation, the Vector Error Correction Model (VECM) is employed. This model not only allows for the prediction of short-term adjustments but also incorporates long-term equilibrium relations identified during the cointegration analysis.

Finally, to validate the predictive model's robustness and accuracy, the VECM results are compared with those obtained from a Vector Autoregression (VAR) model. This comparison will help ascertain the findings' reliability and provide insights into the VECM's predictive power relative to the VAR model.

Through this structured and methodical approach, the section examines the standalone effects of wheat and maize prices on inflationary indices, setting a solid foundation for the subsequent sections incorporating additional variables.

4.2.1. Data set visualisation

The first thing that comes to attention is the presence or absence of cointegration. The correlation highlighted in figure 4.1a, where concurrent price spikes in two crops suggest a potential relationship, serves as empirical evidence of such interdependencies. Recognizing cointegration among variables informs the specification of the model and aids in the interpretation of its results, ensuring that the analysis accurately reflects the underlying economic realities. Additionally, it can be seen that CPI and 'FPI show clear signs of stationarity, given that shock has a permanent effect on both of them. The two variables increased their values dramatically at the time of invasion and remained on that level till the time of this writing. The stationarity of wheat and maize is not evident and thus will be analysed based on the stationarity tests in the later stages. Overall, it can be stated that all four variables move together, displaying some underlying economic dependency.



(a) Price change of Wheat and Corn

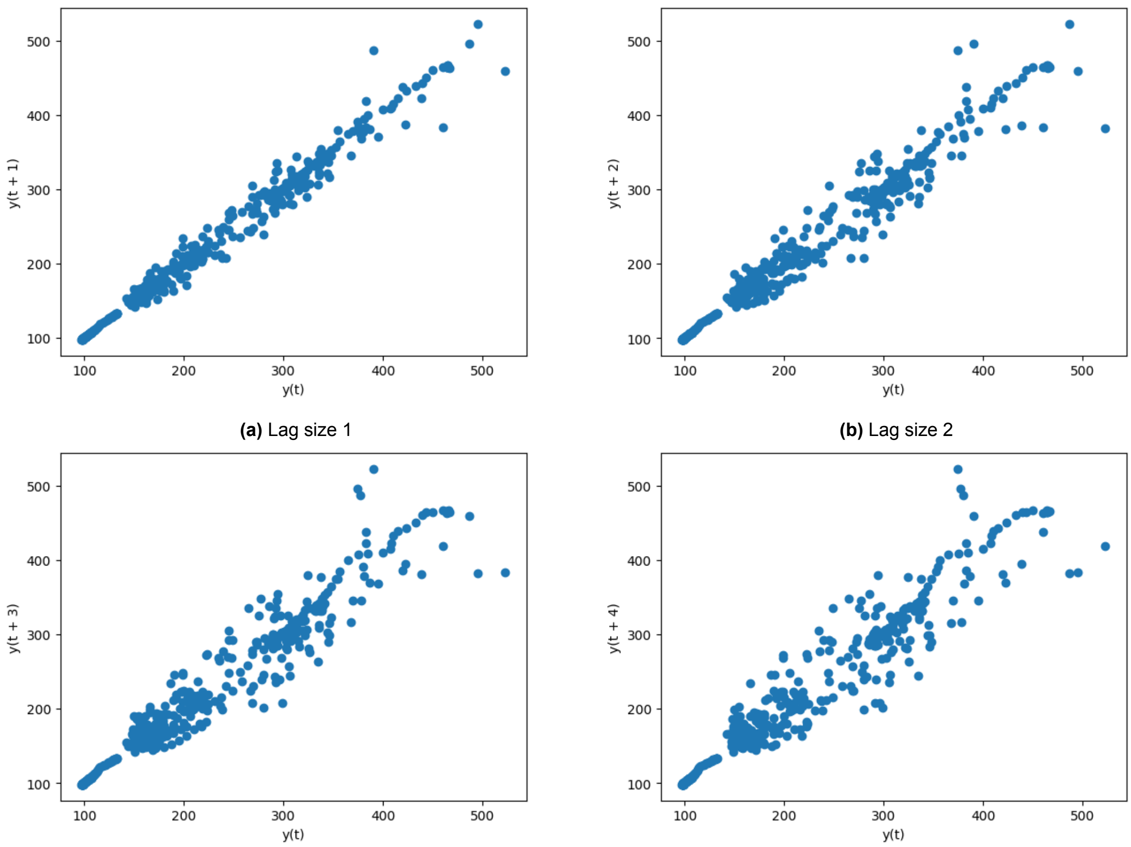
(b) CPI and FPI values

Figure 4.1: Historical data of variables of interest (01/2013-05/2023)

4.2.2. Cointegration analysis: Theory

Cointegration, in simple terms, means that the analysed variables share a long-term equilibrium relationship despite short-term fluctuations. This characteristic is crucial for understanding the nature of the relationships depicted by these models. The cointegration was defined and discussed in the chapter 3.2.1, while this section aims to visualise the cointegrating relation in great detail on the concrete example. This explanation will be done only once here and will be used further.

Figure 4.2 visualizes the lag plots for all four variables of interest (wheat, maize, CPI and FPI) with different lags (The lag can be seen by the Y-axis where y(t+1) indicates lag 1). The figure shows four lag sizes, starting with lag size 1 in the top left corner. To generate the plot, all variables were merged into one to demonstrate that all four of them show some sort of pattern and so provide intuitive evidence for the research. In all four cases, the points form an upward line, which means that the data correlate with their previous value, suggesting a trend or cyclical behaviour. It is also evident that the higher the lag value, the weaker the correlation, given that with a bigger lag, data points tend to drift away from an aligned state to a more chaotic one. A clear upward line on a lag plot means that there is a



(a) Lag size 1

(b) Lag size 2

(c) Lag size 3

(d) Lag size 4

Figure 4.2: Lag plot data of wheat, maize, CPI and FPI for lag sizes 1,2,3,4

positive correlation between y(t) and y(t+a) $a \in \{1, 2, 3, 4\}$. This information, coupled with the visual similarity of the data, suggests that the data are cointegrated. Formation of the line suggests that all the points, despite short-term disturbance or momentarily misalignment, move together in the long run. The relatively small number of misalignments and the clear visibility of the trend are the advantages of monthly data usage.

4.2.3. Cointegration analysis

Table 4.1a suggests the presence of four cointegration relationships among the variables (wheat, maize, CPI, and FPI). The results indicate a strong cointegrating relationship with more than a 95% confidence interval. The test suggests the presence of the maximum amount of cointegrating relationships and sets the stage for the highly effective usage of the VECM.

Table 4.1b also suggests the presence of four cointegrating relationships among the variables (wheat, maize, CPI, and FPI), which is the maximum number tested (because we are including four variables). The critical values displayed in the table represent values of the 95% confidence interval. Thus, the resulting test value located in the column Statistics shall be higher than the critical values for the relation to be significant. These relationships imply that although the variables may experience short-term fluctuations, they move together to maintain equilibrium in the long run. Such a finding is significant for understanding the dynamics and interconnectedness of the variables in the econometric analysis.

Table 4.1a and table 4.1b show two different libraries (one uses the inbuilt Johansen cointegration test in the VECM python library, while the other uses a stand-alone Johansen cointegration test) used for the cointegration test. Still, both of them come to the same conclusions. The same conclusion from both approaches suggests that VECM is the perfect choice for the analysis of the given dataset. However, only cointegration is not enough. Now, the data must be checked for non-stationarity.

Table 4.1: Cointegration results

(a) Johansen Cointegration Test Results

Hypotheses	95%	99%	Value
At most 0	55.2459	62.5202	65.8036***
At most 1	35.0116	41.0815	42.3700***
At most 2	18.3985	23.1485	21.3856**
At most 3	3.8415	6.6349	9.4274***

(b) Johansen Cointegration Test Results (Trace Test)

r_0	r_1	Statistic	Critical Value
0	4	65.80	55.25
1	4	42.37	35.01
2	4	21.39	18.40
3	4	9.427	3.841

4.2.4. Stationarity analysis

The ADF test is a required step for the VECM analysis. VECM assumes that the data being tested should be cointegrated (proven in table 4.1a and table 4.1b) and non-stationary (derived from ADF Test). For data that have proven to have a trend (the result of the cointegration test), non-stationarity is assumed.

Table 4.2: Results of the Augmented Dickey-Fuller Test

Variable	ADF Statistic	p-value	Critical Values	
			1%	5%
Maize	-2.666280	0.250348	-4.037	-3.448
Wheat	-1.770704	0.718710	-4.036	-3.448
CPI EU AVG	0.172828	0.995616	-4.045	-3.452
FPI EU AVG	2.073272	1.000000	-4.036	-3.448

The ADF test results shown in table 4.2 indicate that none of the studied series can reject the null hypothesis of having a unit root, suggesting that all these series are non-stationary. Specifically, the maize prices have an ADF statistic of -2.666280 with a p-value of 0.250348, which is greater than the critical values at both the 1% and 5% significance levels, indicating non-stationarity. Similarly, wheat prices are also non-stationary, with an ADF statistic of -1.770704 and a p-value of 0.718710. The EU's Consumer Price Index (CPI) has an ADF statistic of 0.172828 and a p-value of 0.995616, further confirming non-stationarity. Finally, the EU's Food Price Index (FPI), with an ADF statistic of 2.073272 and a p-value of 1.000000, also cannot reject the null hypothesis of a unit root, indicating non-stationarity. This is precisely the outcome needed to justify the use of the VECM for further analysis, as VECM requires the data to be non-stationary but cointegrated.

The table indicates that none of the studied series can reject the null hypothesis of having a unit root. This suggests that all these series—maize, Wheat, CPI EU AVG, and FPI EU AVG—are non-stationary. This is precisely the outcome needed to justify the use of the VECM for further analysis.

4.2.5. Change in growth rates

The important data modification shall be made before coming to the next logical step in VECM analysis - Granger causality research. The causality research is explained further in chapter 4.2.8, but the approach requires data to be stationary. It was proven that our data are non-stationary, so a preparation step must be made purely to conduct Granger causality research. The following steps are made:

Making a log transformation: this step allows us to move from absolute change in data to proportional. This action already moves the data closer to being stationary, given that the logarithmic transformation normalizes variance by moving from absolute values, which differ from asset to asset.

Differentiating the log-transformed data: Differentiation commonly reduces the complexity of the input data by bringing it closer to linearity. The step allows the predictive models (those used for Granger causality analysis) to have higher accuracy.

Log diff transformation changes the data from prices to growth rate. This change does not affect the goal or reliability of the study due to the fact that (a) all variables are transformed in the same way and (b) the research studies the relations between those variables. All in all, the modification of data from monthly prices to monthly growth rates does affect the hypotheses that are tested and the accuracy of the study.

The result of the log differencing of the data transformation can be seen in figure 4.3. It can be seen that the data, which previously had very broad variance and different ranges per commodity, now seems to be centred around 0 value. The modification made essentially transformed the present dataset into a dataset of relative growth rates. The stationarity effect of such transformation can be seen in table 4.3. The transformation of data made Wheat and Maize data stationary and, as a result, already useful for the Granger causality test. The CPI and FPI values did not change significantly, and the data still appears non-stationary. This result highlights the complexity of the data and calls for additional checks.

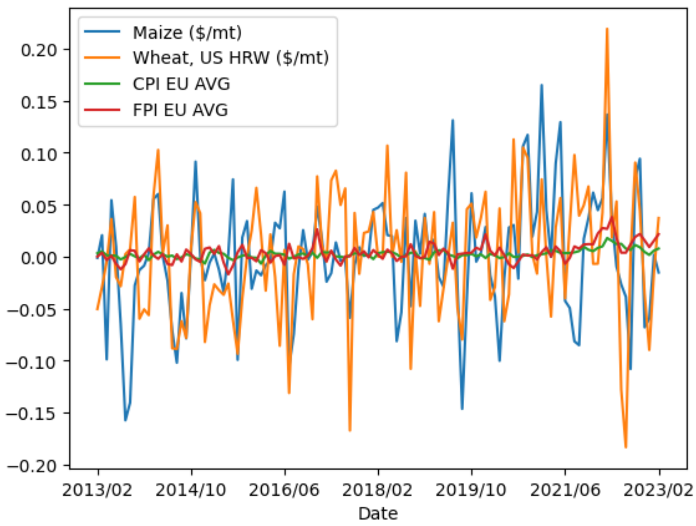
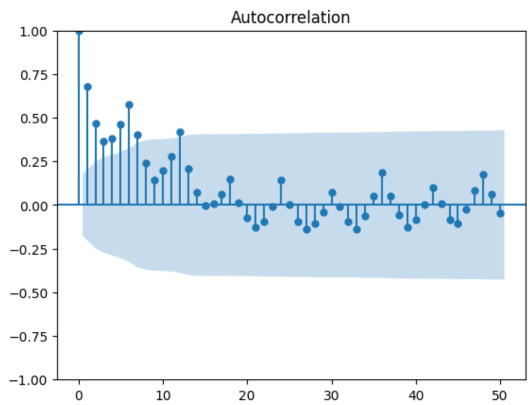
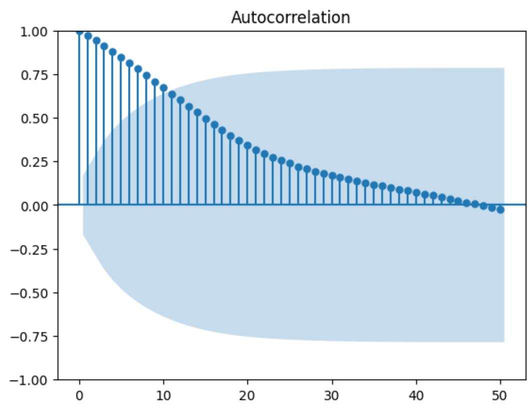


Figure 4.3: Log diff adjusted data

The Phillips-Perron test was made to perform a cross-check of ADF results and ensure that CPI non-stationarity is not a false negative. There are two main reasons why the possibility of false negative exists: a) due to visual similarities of graphs for CPI and FPI (figure 4.1b) and b) due to clear constant variance visible in the figure 4.3. figure 4.4a also confirms the expectation of data being non-stationary after the differentiation procedure was executed. The graph shows a quick drop from 1 to roughly 0.5, further declining to almost 0. On the right side of the graph, all data points are located strongly near 0, thus suggesting the stationarity of the data. The distinct difference can be seen if compared against auto-correlation analysis done to the data before the log difference (figure 4.4b). Performing analysis on clearly non-stationary data (CPI before any mutation of the data) showed a smooth, gradual decline of the auto-correlation indicator. This very thing is obviously absent in the data after the modification. The same outcome is derived from the Phillips-Perron test, which is summarised in the table 4.3. With all p-values being almost equal to 0, the conclusion of data being stationary was made. Those facts bring the conclusion that the data are stationary after the transformation and can be used for further causality research.



(a) CPI log-diff auto-correlation



(b) CPI auto-correlation

Figure 4.4: CPI auto-correlation analysis

Table 4.3: Results of the Augmented Dickey-Fuller Test and Phillips-Perron Test

Variable	ADF Stat	p-value	Critical Values		PP stat	p-value	Critical Values	
			1%	5%			1%	5%
Maize	-8.128203	0.000000***	-4.037	-3.448	-8.093	0.000	-4.04	-3.45
Wheat	-9.396255	0.000000***	-4.036	-3.448	-9.404	0.000	-4.04	-3.45
CPI EU AVG	-1.733904	0.735724	-4.045	-3.452	-5.795	0.000	-4.04	-3.45
FPI EU AVG	-6.857160	0.000000***	-4.036	-3.448	-6.921	0.000	-4.04	-3.45

4.2.6. Granger causality research: FPI and CPI

This section focuses on establishing the effect of the price change of wheat and maize on the CPI and FPI indices as indicators of inflation. Thus, the dependency between the variables of choice is studied for causality. VECM studies the long-term return to equilibrium, if such can be found. To ensure that the price change of wheat/maize indeed results in a change in FPI and CPI, we shall study the causality among them.

Table 4.4: Granger Causality Test result: FPI causing CPI

Lags	F-statistics	p-value
1	7.4694	0.0073
2	6.5779	0.0020
3	5.4567	0.0015
4	6.9609	0.0001
5	5.7807	0.0001
6	5.6708	0.0000
7	6.1808	0.0000
8	5.1488	0.0000
9	6.3548	0.0000
10	6.6153	0.0000

Using the Granger causality test, it was decided first to check if FPI can predict CPI, given that FPI is part of CPI, and thus, the causal relationship should be significant. The test results can be seen in table 4.4 and in figure 4.5. The figure and the table show p-values depending on the lag size, while the table gives an extended view using the F statistics. It can be seen that the p-values for all lags are below conventional significance levels (e.g., 0.05, 0.01), indicating strong predictive power The graph represents p-values depending on the lag size. Lag size can be explained as the ordinal number of the data point used for the prediction. The lag of size 1 shows that the immediate predecessor of the predicted value is used for the prediction. For every lag, the p-value determines the strength of the predictive power of the lag. The smaller the p-value is, the bigger the predictive strength of the lag is. For more details about this test, please refer to the chapter 3.2.3.

Table 4.4 uses the F-statistics to evaluate the significance of the Granger-causal relationship. The table and the graph allow us to conclude that FPI predicts CPI with high accuracy, and therefore, we can test the predictive power of wheat and maize on FPI and consequently conclude that by predicting FPI, we can predict CPI. This conclusion is pivotal for further research, as this outcome implies the model.

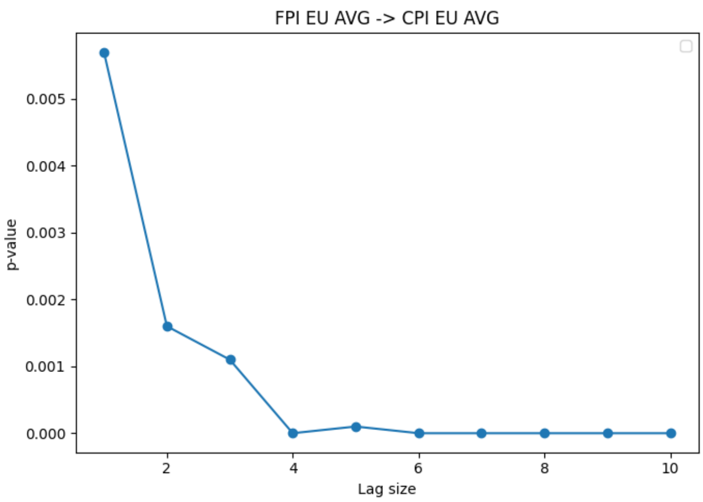


Figure 4.5: FPI causing CPI

Given the significantly strong causal relation, the factual prediction power of the FPI is further checked using VECM and VAR. This step allows evaluation of the predictive error and thus defines the significance of the prediction made using purely FPI data. The causality results alone leave very little room for failure; however, the test shall be done.

4.2.7. Intermezzo: Granger causality research: Wheat and Maize

To ensure full coverage of the predictive powers of all involved variables and to avoid double counting, it is essential to test the dependency level of wheat and maize prices on one another. Figure 4.6 summarises the results (y-axis shows the p-value) of the Granger causality test run for the following causalities:

1. The orange line shows the forecasting power of wheat prices while predicting maize prices. The graph clearly indicates that wheat cannot be considered a significant predictor for maize prices, given that p-values are considerably bigger than 0.05.
2. The blue line shows the forecasting power of the maize prices while predicting wheat prices. The graph clearly indicates that maize cannot be considered a significant predictor for wheat prices, given that p-values are considerably bigger than 0.05.

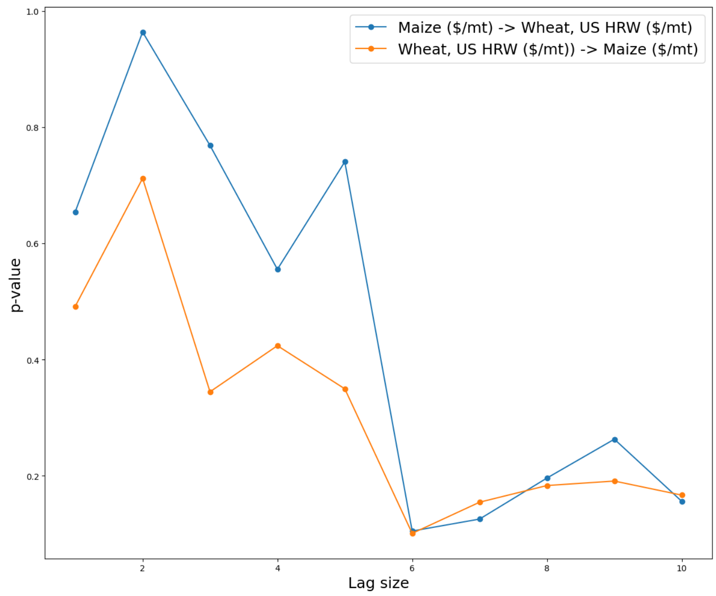


Figure 4.6: Predictive powers of wheat and maize

To conclude, wheat and maize do not have any causal dependency and thus have the potential to be great predictors for the FPI in further tests.

4.2.8. Granger causality research: Wheat and Maize predict FPI

Figure 4.7 visually summarises the results of the Granger causality tests run to determine the influence of the wheat price on the value of FPI and maize price on the value of FPI[1]. The figure shows that Maize is a much more significant predictor. This conclusion is drawn from the fact that Maize has p-values lower than 0.05 (suggesting a strong causal relationship), while wheat has a minimum p-value around 0.2 with all consequent values higher (suggesting an even less significant relation).

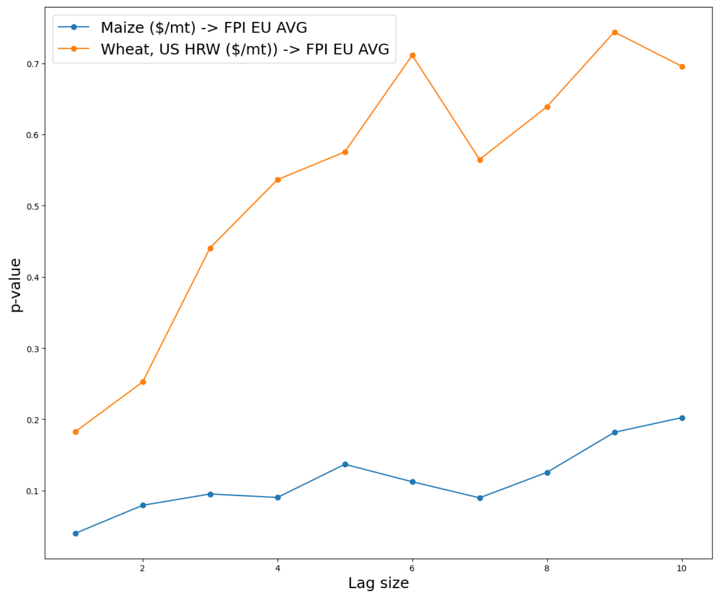


Figure 4.7: Relation between Wheat/Maize and FPI

Given that a causal relationship is present (even though wheat is a relatively insignificant predictor), the VECM model can give significant results given that prediction is not done in isolation. It means that wheat and maize will be used together to make a prediction.

In view of the discussion above (concerning the list of mandatory tests that are defined in chapter 3.2), all required tests are completed, so the VECM can be applied. The model is designed to analyse the nature of the long-term equilibrium

[1] Values are taken from the table B.1

present in data and the effect of the short-term stress on the stability of the system. The initial dataset shall be split into training (122 records) and test (10 records) data to apply the model. The training data is used to define the long-term equilibrium (if one is present), which further is used to predict the future behaviour of the system. The prediction made by the model is then compared with the test data to evaluate the accuracy of the model. Further, a detailed explanation of the VECM results is presented.

4.2.9. CPI-FPI relationship: VECM analysis

To finalise the conclusion about the relationship between FPI and CPI, the relationship shall be tested using VECM. Figure 4.8 summarises the predictions of the FPI made using VECM based on the CPI train data and different lag sizes. The resulting predictions are then compared with the actual test data. The figure shows the visual difference between values in the test dataset (visualised in blue) and the prediction made based only on the values of CPI (visualised in orange and green). It can be seen that the prediction vaguely represents the trend present in the actual data. Given that FPI shows a relatively constant value over that prediction period (suggesting very minor growth), the VECM results indicate that the value shall grow more drastically. The graph alone suggests that the predictions are imprecise due to obvious deviation from the actual values and thus cannot be considered trustworthy. Such a conclusion from the visual inspection can be confirmed by the quantitative analysis of the accuracy of the predictions made. Table 4.5 shows accuracy analysis results of the prediction of the FPI by CPI. The closer the values shown in the table are to zero, the more accurate the model is[2]. The values shown in the table suggest that CPI predicts FPI with relatively low accuracy.

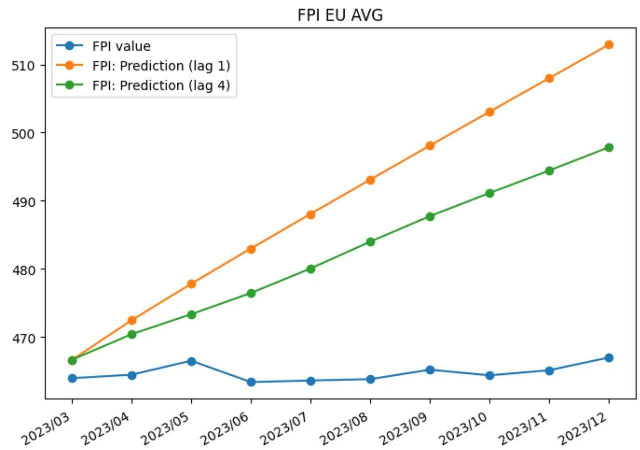


Figure 4.8: Predictions of FPI by CPI

The suggested lag difference by the Bayesian Information Criterion (BIC) is 1. BIC is a common way of determining the preferred lag difference for VECM and VAR analysis. However, figure 4.5 suggested that any lag after 3 gives a better fit. Thus, it was decided to compare the two options (lag 1 and lag 4) for the scientific rigidity of this study. The higher lag in our case showed higher accuracy of the model; however, given that data might contain some trend that is unclear right now and was picked up after running the BIC test, for further analysis, lag 1 will be used. The table also suggests that FPI is a much more significant predictor for CPI than CPI is for FPI. This comes hand in hand with the conclusion of the Granger-causality test, which defined FPI as a significant and accurate predictor for the CPI.

Table 4.5: Model Performance Metrics

	Bias	MAE	MSE	RMSE
CPI predicts FPI (lag 1)	-25.572513	25.572513	856.855240	29.272090
CPI predicts FPI (lag 4)	-17.468668	17.468668	397.598139	19.939863
FPI predicts CPI (lag 1)	-2.626038	2.626038	9.560307	3.091975
FPI predicts CPI (lag 4)	-1.761460	1.761460	4.283755	2.069724

Previously, figure 4.5 and table 4.5 showed that FPI is a significant predictor for CPI. The p-values for Granger-causality tests were approximately 0, signalling the strong presence of a causal relationship. This relationship is now tested by applying the VECM analysis of the two variables in isolation, with FPI as a predictor.

[2]Please refer to section 3.2.4 for a detailed explanation of each metric in the table

As was done for the prediction of FPI, it is of interest to the research to check the predictive strength of FPI for two different lag sizes (lag 1 and lag 4). Consistently, the larger lag size yielded higher accuracy of the model (figure 4.9 and table 4.5 provide visual and analytical confirmation). The difference between lag sizes is present but not significant. The outcome of the VECM analysis proved that FPI is a significant predictor of CPI. As a result, the use of FPI as a sole indicator of inflation is determined.

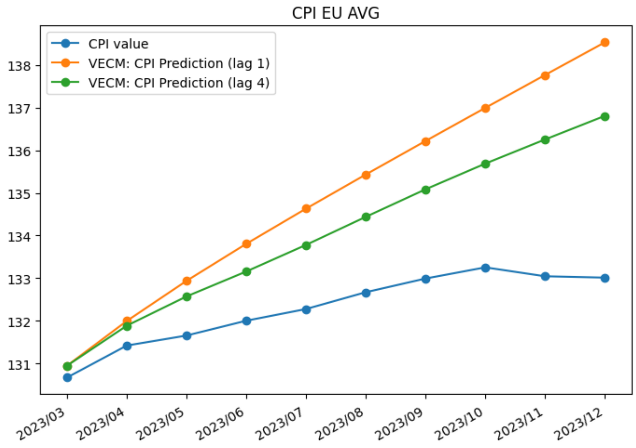


Figure 4.9: Predictions of CPI by FPI

Following the same logic as the previous predictions, the lag size suggested by BIC is used for a final prediction. This decision is made because BIC provides an analytically backed conclusion about the optional lag size. The visual inspection allows the development of an intuition rather than a final decision, so it cannot be blindly trusted.

The table 4.6 compares VECM's predictions with VAR's predictions. The VAR model is used to cross-check the prediction made by the VECM. The table shows predictive errors for the models which use the lag size suggested by BIC. It is evident that FPI is a much more significant predictor for CPI than CPI is for FPI.

Table 4.6: Comparison of VECM and VAR Prediction Errors for CPI and FPI

Model	Bias	MAE	MSE	RMSE
VECM prediction of CPI	-2.626038	2.626038	9.560307	3.091975
VAR prediction of CPI	-1.781498	1.781498	4.202524	2.050006
VECM prediction of FPI	-25.572513	25.572513	856.855240	29.272090
VAR prediction of FPI	-20.198821	20.198821	507.651848	22.531131

4.2.10. Intermediate conclusion

To conclude the research so far, there is a strong relationship between FPI and CPI that makes FPI a significant predictor of CPI. This statement is coherent with the outcomes of the Granger-causality tests, suggesting that the CPI can be excluded from the predictive model. All variables of interest will be used to predict FPI (as a sole measure of inflation). The FPI values can be further used to predict CPI, and the results yielded will be accurate, assuming that FPI was accurately predicted. Additionally, given that FPI is a part of CPI, FPI alone can be considered a good measure of inflation for the level of food prices, which is central to the research.

4.2.11. Wheat and Maize predicting FPI: VECM analysis

Based on the conclusion made concerning the relationship between FPI and CPI, wheat and maize prices will be used to predict the value of FPI. This is the final step of the section, as the conclusion will be made regarding the predictive power of wheat and maize monthly prices. To do so, the VECM model is used. The accuracy of the results will be tested to estimate the precision of the model and will be compared against the prediction of the VAR model (simplified counterpart of the VECM).

Figure 4.10 summarises all predictions made by the VECM. Previously, the causality study was made about the predictive power of wheat and maize (please refer to figure 4.7 and figure 4.6), which suggested that wheat and maize in isolation are weak predictors of FPI and of each other. The combination of two insignificant predictors should not result in a strong and reliable prediction, and figure 4.10 proves this point.

Figure 4.10 shows 20 last records of the test data (marked with the solid line and labelled 'Observed') and 10 more which were predicted (marked with the dashed line and labelled 'Forecast'). The figure also estimates the range of the forecasting error. The wider the range is, the less accurate the model is. An evident wide error range can be seen in the areas with wheat and maize predictions. This suggests that FPI and maize prices are poor predictors of wheat prices, and FPI and wheat prices are weak predictors of maize prices. This outcome was expected, and VECM analysis met the assumed expectations.

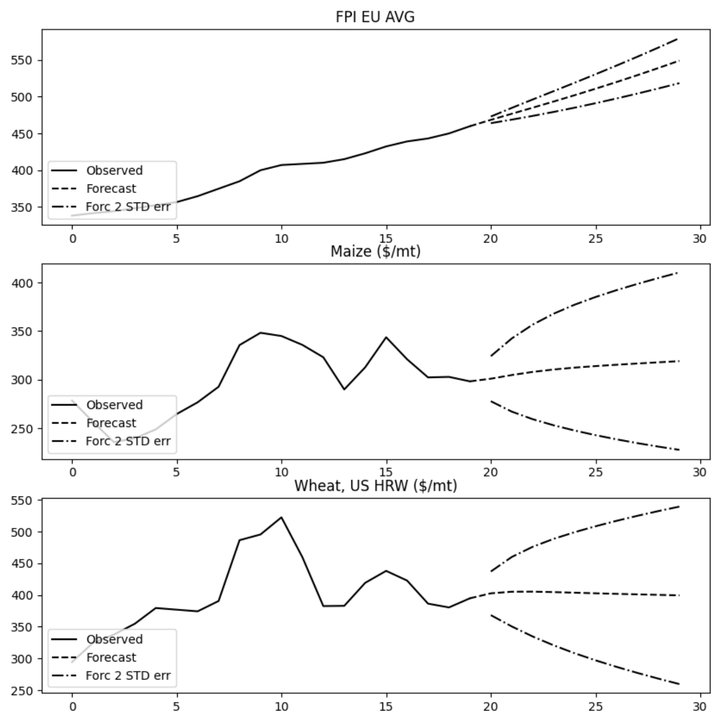


Figure 4.10: Wheat, Maize, FPI: VECM prediction results

The prediction of the FPI seems much more accurate than the prediction of wheat and maize prices. However, the accuracy results of the prediction summarised in table 4.7 in column VECM state otherwise. It is evident that all the numbers are nowhere close to 0, suggesting a high level of inaccuracy in the predictions. The result, as such, emphasises that wheat and maize do not significantly affect the value of FPI, thus suggesting the presence of other factors impacting the level of inflation measured by FPI. More parameters will be used in the coming tests to study the factors affecting inflation.

VAR validation

VAR is considered to be a simplified version of VECM. The major difference between VECM and VAR is that VAR assumes data stationarity, while VECM assumes non-stationarity. Luckily, the log-differentiated data is already available for this part of the research (please refer to the chapter 4.2.5). VAR will use the log-differentiated data to cross-check the VECM predictions.

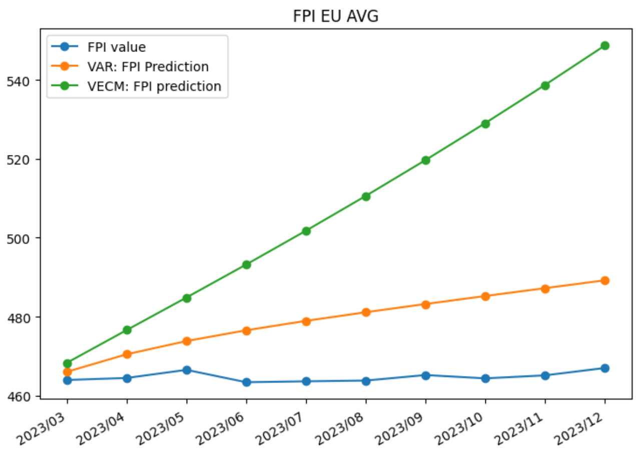


Figure 4.11: FPI prediction: VAR vs VECM comparison

Figure 4.11 showcases the prediction of the FPI value using wheat and maize monthly prices. The figure visualizes the comparison of the predictions made by VECM and VAR with the actual values. This is done to perform cross-validation of the VECM as the main predictive model. The blue line defines the actual (observed) values of the FPI index, while the orange shows the prediction made by the VAR model. It can be seen that the prediction trend of the VAR model aligns with the one determined by VECM (visualised in green) and figure 4.10. The comparison of the predictions made by the two models shows that the VAR model proved to be more accurate. However, both predictions follow an identical upward trend and seem relatively far off the observed values.

Table 4.7 compares the accuracy of both statistical models. The table shows that each error measuring parameter is better in the VAR model, suggesting that the VAR model is a better fit for the given dataset. This entails that the cointegration level of the data with FPI is insignificant for the VECM to be precise. A result like this also suggests that the given data set cannot comprehensively analyse the long-term equilibrium and can only determine the short-term relationship.

Table 4.7: FPI prediction: VECM vs VAR accuracy

Metric	VECM	VAR
Bias	-42.407437	-14.435286
MAE	42.407437	14.435286
MSE	2428.215134	254.251400
RMSE	49.276923	15.945263

4.2.12. Conclusion

To conclude, the simplified version of the model studied in this thesis shows a lack of accuracy while providing the ground for extensive research carried out further on. It was proven that wheat and maize prices are not significant predictors for the inflation level measured by FPI. It was concluded that FPI is a very strong predictor for CPI (a worldwide accepted variable to measure inflation). As a result of further statistical analysis, it was decided to use only FPI as a predicted variable. The next section adds crude oil prices, natural gas prices and fertiliser prices to increase the accuracy of the prediction and estimate the long-run value of the FPI.

4.3. Examining the wheat prices, corn prices, crude oil prices, natural gas prices, fertiliser index and FPI values data series

This section tests the hypothesis that wheat, maize, oil and gas, and fertiliser prices cause the increased inflation measured by CPI and FPI. Previously, it was proven that FPI accurately predicts CPI (given that FPI is a component of the CPI) and thus, the hypothesis was simplified to the form: wheat, maize, oil and gas, and fertiliser prices cause the increased inflation measured by FPI. Additionally, it was shown that wheat and maize prices are not significant predictors of FPI, and thus, despite the fact the war in Ukraine had a tremendous effect on those, wheat and maize alone cannot be used for accurate forecasting of the FPI.

This section aims to test the impact of crude oil, natural gas, and fertiliser prices, together with the prices of wheat and corn, on the value of FPI. It is assumed that combining all values would create a much more accurate model than before. The section will briefly discuss the cointegration, ADF and Granger causality test results as preparation steps before applying the VECM with the VAR as a cross-test model.

4.3.1. Data set visualisation

The usage of the VECM model implies that initial data is checked for cointegration (using the Johansen cointegration test), stationarity (using ADF test (in case of doubt previously, Philips-Perron test was used)) and Granger causality (using the Granger causality test). Before applying any of the tests, the data shall be visually inspected to spot obvious signs of cointegration, absence of stationarity and potential causal relationships. Figure 4.12 shows all five variables over the time period selected for the research (01/01/2013–31/12/2023). It is important to state that for fertiliser prices a cumulative index provided by the World Bank was taken. This decision was made due to the high variance of fertilisers and the complexity of their usage in the agriculture industry. The index is calculated as the average price of all fertilisers present on the market.

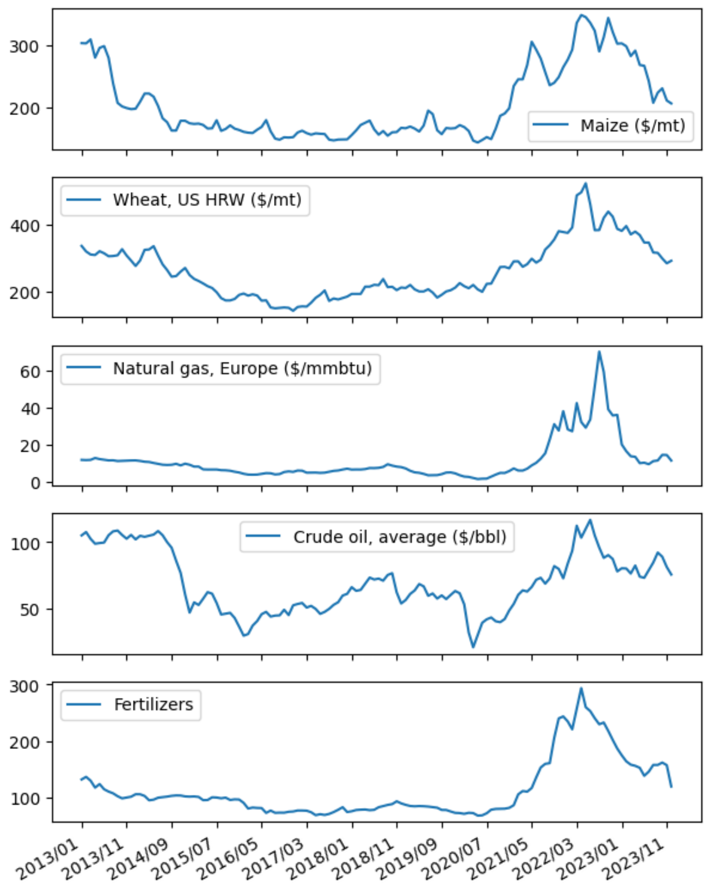


Figure 4.12: Wheat, Maize, Crude Oil, Natural Gas, Fertilisers prices

The graph clearly shows that all five variables experienced dramatic increases in prices in February and March 2022 (the time of Russia's invasion of Ukraine) and roughly returned to their previous values as of December 2023. The alignment of visible spikes of all the variables of interest suggests the presence of a causal relationship between all variables, and so sets the stage for more detailed research. The presence of synchronised change in value also suggests that data are cointegrated and non-stationary, given the high rate of fluctuation. The conclusions drawn from the visual inspection of raw data suggest the appropriateness of VECM analysis and thus lead to the first step: cointegration analysis.

4.3.2. Cointegration analysis

This section explores the long-term relationships between the variables using the Johansen cointegration test. The aim is to determine if there are any stable, long-term connections between variables. Understanding these relationships is crucial before applying the Vector Error Correction Model (VECM), as the presence of cointegration fundamentally influences the model's structure and interpretation.

Table 4.8: Cointegration results

(a) Johansen Cointegration Test Results

Hypotheses	95%	99%	Value
At most 0	107.3429	116.9829	158.3726***
At most 1	79.3422	87.7748	86.7267**
At most 2	55.2459	62.5202	55.7792**
At most 3	35.0116	41.0815	30.7021
At most 4	18.3985	23.1485	16.8097*
At most 5	3.8415	6.6349	4.6535**

(b) Johansen Cointegration Test Results (Trace Test)

r_0	r_1	Statistic	Critical Value
0	6	158.4	107.3
1	6	86.73	79.34
2	6	55.78	55.25
3	6	30.70	35.01

Table 4.8a and table 4.8b show the result of the Johansen cointegration test run using two different Python libraries. Table 4.8a uses a dedicated package for the Johansen cointegration tests and concludes the presence of 3 cointegrating relationships with a confidence interval of 95%. The hypothesis column defines the null hypothesis. It is important to mention that after the failure to reject the null hypothesis, any significant values for higher number of relationships do not matter. This comes from the straightforward logic: the test checks for the presence of at most n ≤ N cointegrating relationships (for n- current index and N - total number of variables). If the model believes that there are at most four relationships, it is imperative that it won't be able to find five. Thus, the fact that the null hypothesis for the presence of three cointegrating relationships is accepted makes the rejection of the null hypothesis for six cointegrating relationships irrelevant.

The same result is obtained from running the VECM package cointegration test, the results of which are summarised in table 4.8b. The critical value of 95% confidence interval is displayed, given that this is the confidence interval used for the cointegration test. As explained above, the test uses the same setup for null and alternative hypotheses. That is the reason why, after accepting the null hypothesis for the presence of at most 3 relationships, no other statistics are visualised. Both tests use trace statistics instead of Eigenvector statistics, following the same reasons shown in 3.2.1.

Conclusion

The identification of cointegrating relationships is crucial for justifying the application of the Vector Error Correction Model (VECM). The VECM is designed to capture both the short-term dynamics and the long-term equilibrium relationships among the variables, making it an appropriate model for this dataset. The presence of cointegration suggests that individual variables share a stable, long-term equilibrium relationship. This means that the variables move together over time in a way that maintains their equilibrium, and any short-term deviations from this equilibrium are expected to be corrected over time.

Overall, the cointegration analysis shows that there are three significant long-term equilibrium relationships among the variables, providing a solid foundation for further modelling and analysis. This sets the stage for stationarity research to ensure the effective application of the VECM.

4.3.3. Stationarity research

This section focuses on the stationarity analysis of the dataset, which is a crucial step in time series analysis. Stationarity implies that the statistical properties of a time series, such as mean and variance, are constant over time. The Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test are employed to assess the stationarity of wheat, maize, gas, oil, fertilisers and FPI.

Table 4.9 presents the results of the ADF and PP tests for six different variables: Maize, Wheat, Natural Gas, Crude Oil, Fertilizers, and FPI EU AVG. These tests help determine whether the time series data for each variable contains a unit root, which would indicate non-stationarity. VECM analysis expects

Table 4.9: Results of the Augmented Dickey-Fuller Test

Variable	ADF Stat	p-value	Critical Values		PP stat	p-value	Critical Values	
			1%	5%			1%	5%
Maize	-2.666280	0.250348	-4.037	-3.448	-2.203	0.488	-4.04	-3.45
Wheat	-1.770704	0.718710	-4.036	-3.448	-1.514	0.824	-4.04	-3.45
Natural gas	-2.526852	0.314670	-4.045	-3.452	-2.449	0.354	-4.04	-3.4
Crude oil	-2.183919	0.498905	-4.036	-3.448	-1.812	0.699	-4.04	-3.45
Fertilizers	-3.732138	0.020326	-4.039	-3.449	-2.015	0.593	-4.04	-3.45
FPI EU AVG	2.073272	1.000000	-4.036	-3.448	3.243	1.000	-4.04	-3.45

data to be non-stationary, and from the visual inspection of the graph, the non-stationarity is assumed. Both ADF and PP tests define the absence of stationarity as the null hypothesis.

The left side of table 4.9 shows the results of the ADF test. It is evident that all variables show clear non-stationarity, except for Fertilizers. The graph of fertilizer prices does not significantly differ from the other presented in figure 4.12, and thus, the conclusion of the fertilizers variable being stationary calls for cross-checking using the PP test. The right side of table 4.9 shows the results of the PP test. The results align with the ADF results for all variables except for Fertilisers. The PP results indicate that Fertilizers show non-stationarity traits, which aligns with the initial intuition and visual representation of data.

Conclusion

The stationarity analysis using both the Augmented Dickey-Fuller and Phillips-Perron tests reveals that most of the variables in the dataset are non-stationary, except for fertilizers, which show signs of stationarity at the 5% level according to the ADF test but not according to the PP test. Using logical thinking and considering the complexity of the problem being solved in this study, the fertilizer prices will be considered non-stationary for further analysis. Stationarity results together with cointegration results suggest that the dataset is appropriate for the usage of VECM. The next step is log-differentiation as a preparation step for the Granger causality test.

4.3.4. Change in growth rates

The final check before applying the VECM is the Granger-causality analysis. A crucial factor in this test is ensuring that the data is stationary. The previous sections have demonstrated that the raw data is non-stationary. To address the requirement of stationarity, the data has been log-transformed and then differentiated. This transformation is necessary for stabilizing the variance and making the data suitable for further econometric analysis. For a detailed explanation of this transformation process, refer to chapter 4.2.5.

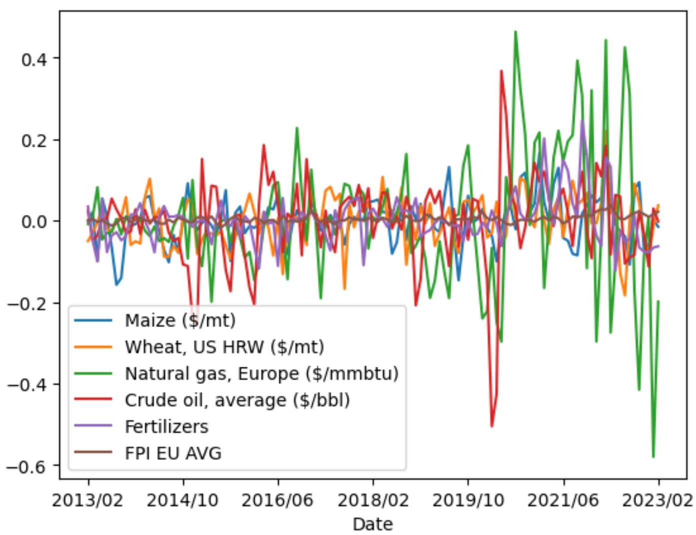


Figure 4.13: Log diff adjusted data

Figure 4.13 shows the logarithm application result and the differentiation of the initial dataset. It can be clearly seen that data transformed to the growth rate is much more stationary, given that all data points are clearly located around a value of 0. Natural gas seems to be the most volatile variable out of the whole mix, given that the growth rate fluctuation stands out in comparison to the rest of the variables present in figure 4.13. The data already shows traits of stationarity, so now ADF and PP test results will be discussed to validate the intuition based on the visual representation of the log-differentiated data.

The data is now tested using stationarity tests. The left side of Table 4.10 summarizes the results of the Augmented Dickey-Fuller (ADF) test applied to the transformed data. The results indicate that all variables, except for fertilizers, are stationary. Before transformation, fertilizers were identified as stationary. The visual inspection and statistical results align, except for fertilizers, where the visual inspection suggests stationarity despite statistical results indicating non-stationarity using ADF test. Thus, the Phillips-Perron (PP) test is applied to verify the conclusion of ADF test.

Table 4.10: Results of the Augmented Dickey-Fuller and Phillips-Perron Tests

Variable	ADF Stat	p-value	Critical Values		PP Stat	p-value	Critical Values	
			1%	5%			1%	5%
Maize	-8.128203	0.000000	-4.037	-3.448	-7.657	0.000	-4.04	-3.45
Wheat	-9.396255	0.000000	-4.036	-3.448	-9.323	0.000	-4.04	-3.45
Natural gas	-7.730767	0.000000	-4.036	-3.448	-7.786	0.000	-4.04	-3.45
Crude oil	-8.166505	0.000000	-4.037	-3.448	-7.325	0.000	-4.04	-3.45
Fertilizers	-1.706861	0.747848	-4.039	-3.449	-8.743	0.000	-4.04	-3.45
FPI EU AVG	-6.857160	0.000000	-4.036	-3.448	-6.993	0.000	-4.04	-3.45

The right side of Table 4.10 presents the results of the Phillips-Perron (PP) test. Consistent with the PP test results before transformation, the test confirms that all variables are stationary after the log transformation and differentiation. This alignment of visual shown in figure 4.13 and statistical evidence reinforces the reliability of the transformation.

Conclusion

In conclusion, these tests have demonstrated that the non-stationary raw data was successfully transformed into stationary data by applying log transformation and differencing. This transformation was validated by both visual inspection and statistical tests, namely the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The consistency of the vast majority of results confirms the reliability of the data preparation process.

The findings from the stationarity tests are crucial as they set the foundation for the next step in the analysis: testing for Granger causality. Establishing stationarity is a prerequisite for performing Granger causality tests, which will determine the directional relationships between the variables. The upcoming section will delve into the Granger causality tests, building on the stationary data prepared in this chapter, to explore and quantify these causal dynamics.

4.3.5. Granger-causality research

The Granger causality test is a pivotal analytical tool in econometric modelling, particularly for Vector Error Correction Models (VECM). This test examines whether one time series can predict another, establishing a directional relationship between the variables.

The data must be stationary for the Granger causality test to be valid. As established previously, the raw data underwent log transformation and differencing to achieve stationarity. This transformation ensures that the statistical properties of the series, such as mean and variance, remain constant over time, which is a fundamental requirement for reliable Granger causality testing. The details of the logic of the Granger causality test can be found in section 3.2.3.

Figure 4.14 presents the p-values from the Granger causality test for six variables of interest: Maize, Wheat, Natural Gas, Crude Oil, and Fertilizers, all in relation to the FPI EU AVG (detailed data visualised on the figure can be found in table 4.11). The x-axis represents the lag size, ranging from 1 to 10, while the y-axis indicates the p-values, marking the significance of the predictive power of the variable forecasting FPI. The closer the p-value to 0, the more significant the predictive power of the variable.

The analysis reveals that maize and fertilizer prices consistently exhibit low p-values across all lag sizes, indicating a significant Granger causality with the FPI EU AVG. Conversely, wheat and crude oil prices show decreasing predictive power with an increase in lag number, with p-values continuously rising over the significance threshold (p = 0.05). Natural gas prices display a fluctuating pattern, with some lags indicating relatively lower p-values, suggesting limited predictive power for FPI EU AVG.

Table 4.11: P-values of the Granger Causality Test for Variables Predicting FPI

Lag	Maize	Wheat	Natural gas	Crude oil	Fertilizers
1	0.0398	0.1825	0.0765	0.1621	0.2152
2	0.0792	0.2524	0.2256	0.0996	0.1053
3	0.0951	0.4406	0.1936	0.1627	0.0036
4	0.0902	0.5365	0.2861	0.2545	0.0081
5	0.1368	0.5755	0.3651	0.3611	0.0022
6	0.1123	0.7112	0.5480	0.4294	0.0024
7	0.0897	0.5649	0.3969	0.5705	0.0105
8	0.1255	0.6390	0.4749	0.6483	0.0077
9	0.1817	0.7439	0.1756	0.6918	0.0268
10	0.2023	0.6957	0.2127	0.7334	0.0496

The p-values obtained from the test show the complex nature of the relationships between variables, making the selection of appropriate lag sizes very complicated. The Bayesian Information Criterion (BIC) is used to ensure that the lag size is accurately selected. The BIC suggests a lag size of 1. Thus, the VECM further uses this lag size for forecasting research.

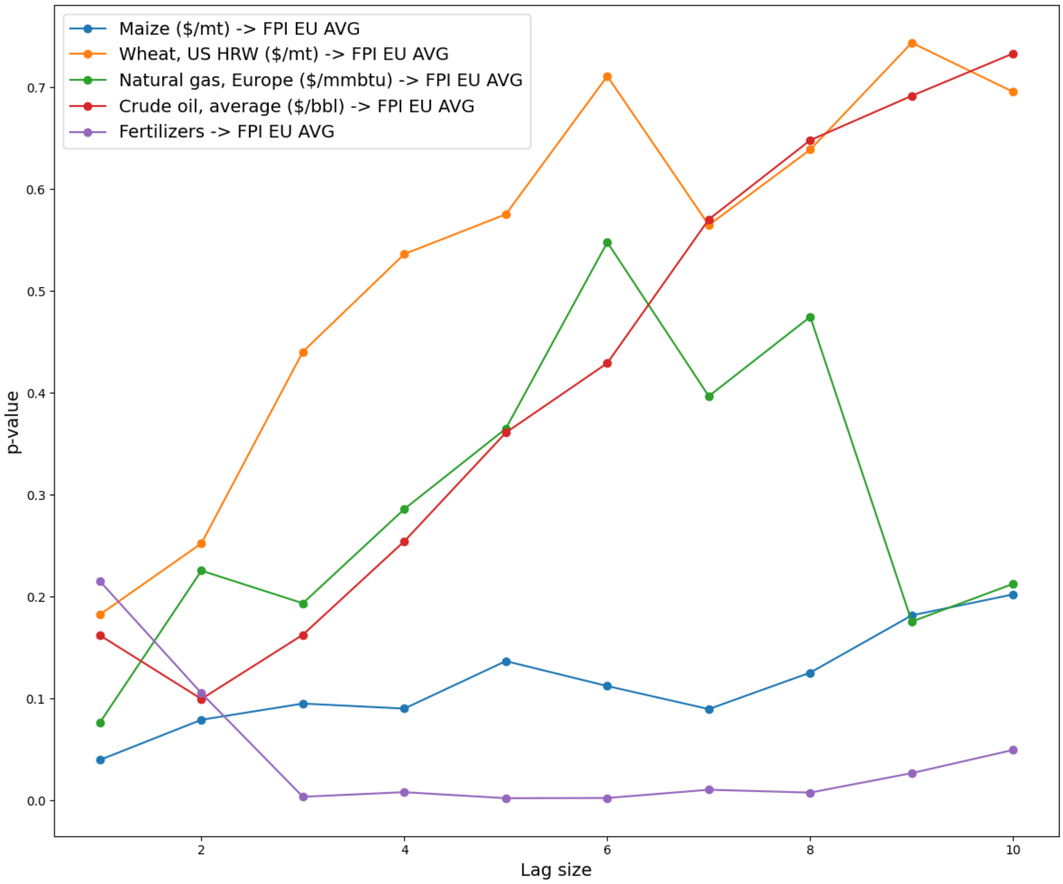


Figure 4.14: Granger causality results (p-value summary)

Conclusion

The results of the Granger causality test, as summarized in Table 4.11 and figure 4.14, provide insight into the predictive relationships between economic variables of interest and the Food Price Index (FPI) in the EU.

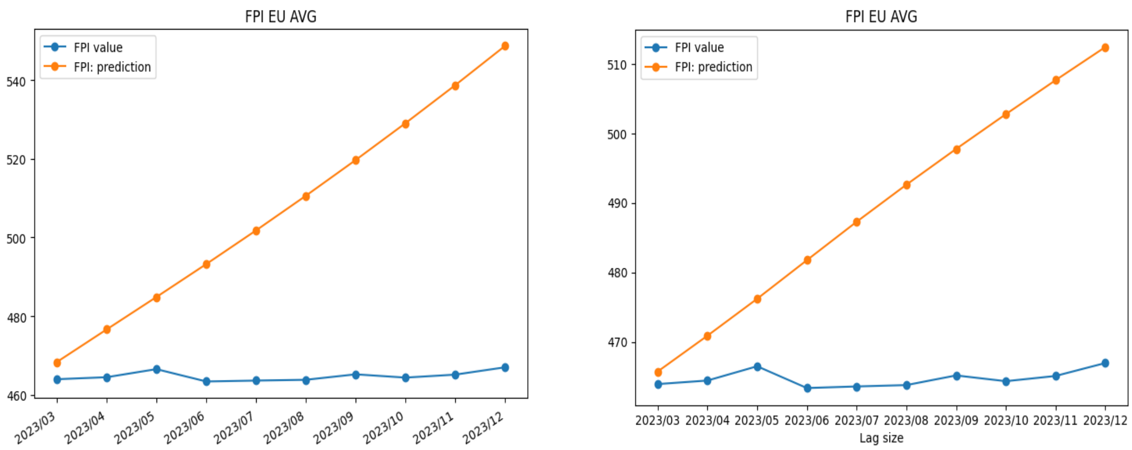
The analysis showed that maize prices and fertilizers, exhibit lower p-values at various lag lengths, suggesting that these variables have a strong predictive power for FPI. Other variables, such as wheat, natural gas and crude oil prices, show higher p-values, indicating weaker or no predictive relationships with the FPI.

The VECM will be applied in the next section to capture both the short-term dynamics and the long-term equilibrium relationships between the variables. The VECM is particularly suited for datasets where the variables are cointegrated and non-stationary, allowing for a more comprehensive understanding of the interdependencies and adjustments towards equilibrium.

4.3.6. Wheat, corn, crude oil, natural gas and fertilisers predicting FPI: VECM analysis

The VECM is particularly suitable for our dataset, as it allows for the modelling of both short-term dynamics and long-term equilibrium relationships among the variables. Unlike traditional Vector Autoregressive (VAR) models, which require all variables to be stationary, the VECM uses non-stationary data by incorporating error correction mechanisms. This feature makes the VECM ideal for datasets where variables exhibit long-term cointegration, as identified in our previous analyses.

In the subsequent analysis, the VECM will be used to estimate the short-term adjustments and long-term relationships between the variables. By application of the VECM, this study aims to produce accurate forecasts of the FPI, contributing to better-informed decisions and strategic planning.



(a) Wheat and Maize predict FPI

(b) Wheat, Maize, Gas, Oil, Fertilisers predict FPI

Figure 4.15: VECM: Predictions of FPI

Figure 4.15 and table 4.12 show the comparison between two versions of the VECMs measured based on the accuracy of the predicted value of FPI. The left figure (figure 4.15a) shows the resulting predictions of FPI based on wheat and maize prices. The prediction was previously considered inaccurate, thus suggesting more variables to be used in the VECM prediction. The figure on the right (figure 4.15b) shows the predictions made by the new VECM using wheat, maize, gas, oil and fertiliser prices (referenced as WMGOF in the table 4.12). The Y-axis of the graph on the right already suggests increased accuracy of the prediction (given that the maximum value of 510 is smaller than 540, the maximum of the graph on the left). The table confirms the increase in the predictive accuracy of the improved model. There, it can be seen that every indicator measuring the accuracy became closer to 0 (absolute accuracy). This fact confirms that added variables are relevant to the research and increase the accuracy of the predicted value of FPI, even though the accuracy still needs to be improved.

Table 4.12: FPI prediction: performance metrics

Metric	WM → FPI	WMGOF → FPI
Bias	-42.407437	-24.811952
MAE	42.407437	24.811952
MSE	2428.215134	829.980275
RMSE	49.276923	28.809378

VAR validation

This section focuses on validating the Vector Error Correction Model (VECM) by comparing it with the Vector Autoregression (VAR) model. Initially, the FPI (Food Price Index) was predicted using a model that included only wheat and maize prices, referred to as the WM model. Both VECM and VAR were applied to predict FPI, and the results were compared. Now, more input variables (wheat, maize, natural gas, crude oil, and fertilisers abbreviated as WMGOF) were added to predict FPI. The validation of the improved VECM is now performed using the VAR model.

Figure 4.16 shows the comparative analysis of the VECM and VAR models, plotting the FPI predictions against actual FPI values. The green line shows the VECM model's predictions. The line displays a dramatic increase in the value of FPI, while the actual values show relatively stable, close to zero growth. The lines representing the FPI value and VECM FPI prediction are moving in the same direction, suggesting that the VECM model captures the underlying trend effectively. This alignment demonstrates that the VECM model anticipates growth of the FPI value, but the magnitude of the growth is captured imprecisely. The orange line shows the predictions of FPI based on the VAR model. The resulting graph has a smaller deviation from the actual values while still overestimating the growth magnitude of the FPI value. This indicates that while both models are effective and determine the presence of the correct growth trend, the VAR model may offer more accurate predictions.

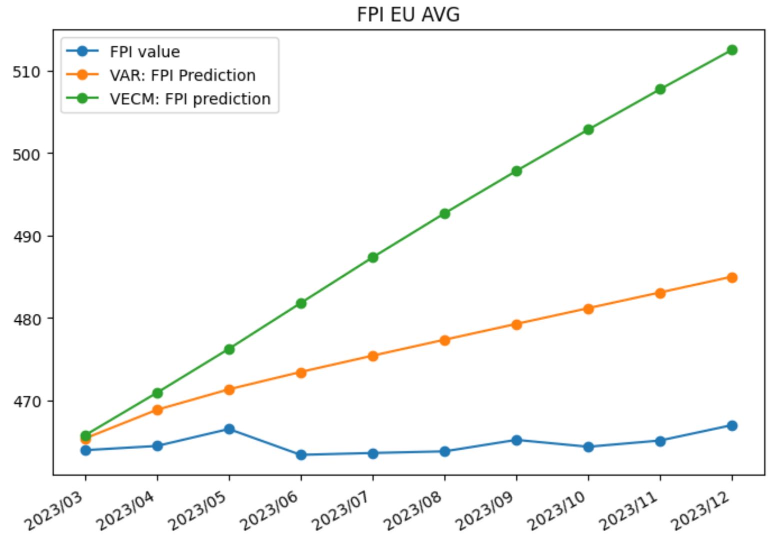


Figure 4.16: FPI prediction: VAR vs VECM comparison

Table 4.13: Performance Metrics for VAR and VECM Models

Metric	VAR: WMGOF	VAR: WM	VECM: WMGOF	VECM: WM
Bias	-11.282488	-14.435286	-24.811952	-42.407437
MAE	11.282488	14.435286	24.811952	42.407437
MSE	159.424670	254.251400	829.980275	2428.215134
RMSE	12.626348	15.945263	28.809378	49.276923

Table 4.13 summarizes key metrics such as Bias, MAE (Mean Absolute Error), MSE (Mean Squared Error), and RMSE (Root Mean Squared Error) for both the VECM and VAR models, including the previous WM models. These metrics are crucial for understanding the accuracy and reliability of the predictions. It is evident that VAR model using WMGOF dataset shows the most accurate prediction, with VECM applied for the same dataset taking the second place based on the accuracy of the prediction. This outcome proves that initial hypotheses were right, however the accuracy of those predictions still can be improved.

4.3.7. Conclusion

The results indicate that the improved VECM model (WMGOF) outperforms the previous WM model, as evidenced by lower Bias, MAE, MSE, and RMSE values. The resulting predictions and accuracy show that incorporating additional variables such as natural gas, crude oil, and fertilizers significantly enhances the predictive accuracy of FPI. Not significant causal relationships can be the explanation for the poor quality of the final predictions of FPI. Despite the reduced complexity of the model, it appears that the VAR model outperforms the more advanced VECM based on predictive accuracy. This fact suggests that the prediction of such a complex inflation indicator as FPI required more inputs than has been provided.

Overall, the initial hypotheses were correct and indeed wheat, maize, natural gas, crude oil and fertilisers do affect the level of food prices measured by FPI and as a result affect the general level of prices. However, the relationship proved not significant enough and shows that there are other variables which potentially can improve the predictive power of the model.

4.4. Intermezzo: wheat and maize prices, energy and fertiliser indices predict FPI

Given the complexity behind predicting the Food Price Index (FPI), it was decided to utilize an Energy indicator instead of the individual crude oil and natural gas prices. The assumption behind this decision is that the Energy Index provided by the World Bank would comprehensively capture the movements of oil, gas and oil/gas-based products, thereby providing a more holistic and integrated measure of the energy market's impact on food prices measured by FPI. This approach aims to simplify the modelling process while still accounting for the critical fluctuations in energy prices that can significantly affect the predictive accuracy of FPI. This section aims to briefly explain the results of such modelling and compare the results to the previous versions of the models used for predictions of FPI.

4.4.1. Data set visualisation

The graph presents a view of the time series data for: Maize, Wheat, Energy, Fertilizers, and the Food Price Index (FPI) for the EU Average, spanning from January 2013 to January 2023. This visualization aids in understanding the dynamics and interactions among these variables over the observed period.

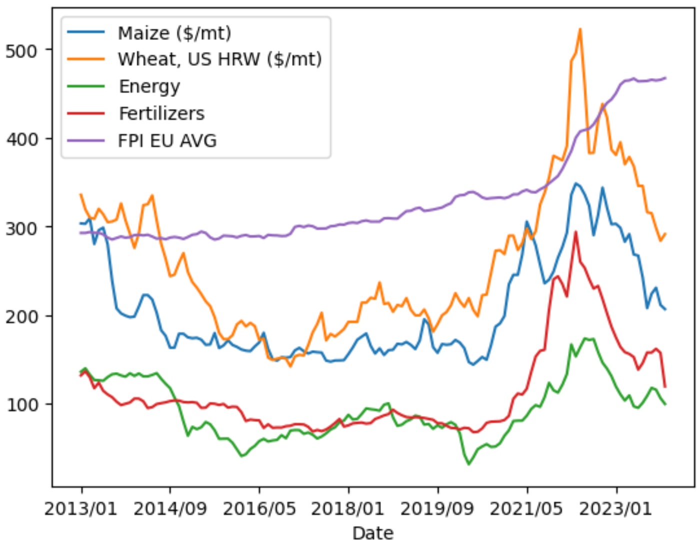


Figure 4.17: Wheat, Maize, Energy, Fertilisers, FPI

It is evident that all variables except FPI show clear pattern in price changes. Maize prices, wheat prices, energy index and fertiliser index all show significant spike in 2022 marking the invasion of Russia in Ukraine. Synchronised movement of all those variables calls for cointegration of the variables and non-stationarity. FPI shows steady growth till late 2022 where FPI value growths significantly, peaking in early 2023.

Overall, the graph illustrates the interconnectedness of these variables, particularly around the mid-2021-mid-2022 period, where a simultaneous rise in prices for maize, wheat, energy, and fertilizers is observed. This synchronization suggests common underlying factors driving these price movements. Additionally, the steady increase in the Food Price Index for the EU Average underscores the impact of these fluctuating input prices on overall food costs in the region. This visualization provides a valuable context for further analysis, including the application of econometric models like VECM to understand and predict food price movements.

4.4.2. Cointegration analysis

As was done for all the other versions of the predictive model, the very first step is to check the cointegration of the data. Table 4.14 summarises the results of the Johansen cointegration test. Given that, in this study, the target significance level is 95%, only the first null hypothesis can be rejected, suggesting that the dataset has only one cointegrating relationship. All the rest show significance in the 90% - 95% interval and thus cannot be considered significant.

Table 4.14: Johansen Cointegration Test Results

Hypotheses	90%	95%	99%	Value
At most 0	75.1027	79.3422	87.7748	93.1301***
At most 1	51.6492	55.2459	62.5202	53.3355*
At most 2	32.0645	35.0116	41.0815	33.4193*
At most 3	16.1619	18.3985	23.1485	17.3515*
At most 4	2.7055	3.8415	6.6349	4.2997**

Overall, the cointegration results suggest that only one cointegrating relationship is present in the data set.

4.4.3. Stationarity analysis

Table 4.15: Results of the Augmented Dickey-Fuller Test and Phillips-Perron Test

Variable	ADF Stat	p-value	Critical Values		PP stat	p-value	Critical Values	
			1%	5%			1%	5%
Maize	-2.666280	0.250348	-4.037	-3.448	-2.203	0.488	-4.04	-3.45
Wheat	-1.770704	0.718710	-4.036	-3.448	-1.514	0.824	-4.04	-3.45
Energy	-2.031013	0.584443	-4.036	-3.448	-1.887	0.661	-4.04	-3.45
Fertilizers	-3.732138	0.020326	-4.039	-3.449	-2.015	0.593	-4.04	-3.45
FPI EU AVG	2.073272	1.000000	-4.036	-3.448	3.243	1.000	-4.04	-3.45

The stationarity analysis was conducted using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test on: Maize, Wheat, Energy, Fertilizers, and the FPI EU AVG.

The ADF test results showed that Maize, Wheat, Energy, and FPI EU AVG are non-stationary. Their ADF statistics were higher than the critical values, and their p-values were greater than 0.05, meaning we could not reject the null hypothesis of presence of a unit root. The PP test results suggest that Maize, Wheat, Energy, and FPI EU AVG are non-stationary as well. The Fertilisers, like in the previous case, also shown to be stationary by ADF test and non-stationary by PP test. In the previous section (section 4.3.6) the logic behind belief in PP test results more than in ADF test results was explained. Here, the same approach is being used and as the result, fertilisers are considered to be non-stationary.

In summary, the stationarity analysis reveals that Maize, Wheat, Energy, Fertilisers, and FPI EU AVG are non-stationary according to PP test and rationale after inspection of the data plot. This implies the appropriateness of further causality research.

4.4.4. Causality research

From previous chapters, the causality studies were performed on wheat, maize and fertilisers. The outcome showed not significant causal relationship between those variables and FPI. This section shows only causal studies performed on the influence of Energy index on FPI. Figure 4.18 shows the resulting p-values after running the Granger causality test on two variables. The graph shows that the causal relationship weakens with the increase of the lag size, given that p-value increases in value after lag size 2. This suggests that small lags lead to higher accuracy of the prediction, as opposed to the bigger lag sizes. However, the minimum p-value of 0.1 emphasises that even the strongest causal relationship cannot be considered significant.

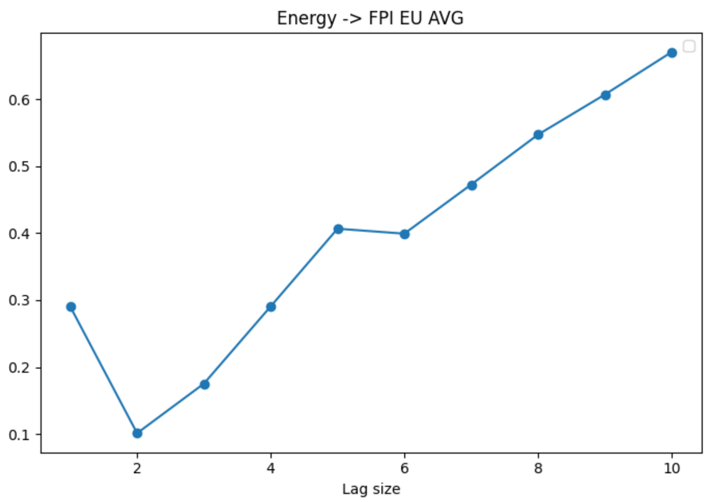


Figure 4.18: Energy Granger-causing FPI

This result, suggests that predictive power of this model will not be improved by this index. To verify this intuition, the VECM and VAR will be applied to the dataset.

4.4.5. Wheat, corn, energy and fertilisers predicting FPI: VECM analysis

Similarly to the previous chapters, the predictions done using VECM model are compared against the data in the test set and against VAR predictions. Figure 4.19 shows the forecast values obtained using VECM and VAR alongside with the values present in the test dataset. Consistently with all previous cases, VECM tends to exaggerate the magnitude of the change of the FPI while the trend matches the trend in the actual data. VAR output, overshoots as well, however closer to the actual value. The accuracy of the model shall be compared with the values obtained in the previous cases. The comparison will allow the best selection of the data for the final prediction.

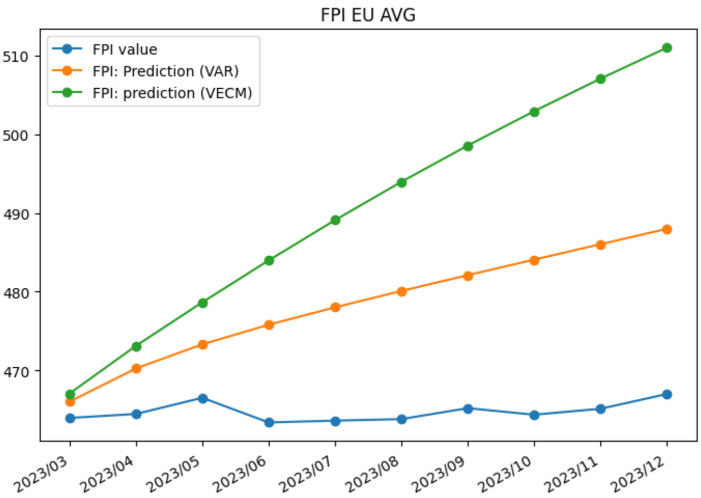


Figure 4.19: Forecasted FPI value: VECM vs VAR

Table 4.16 summarises the error metrics of all versions of the model run so far. WMGOF stands for the model which uses Wheat, Maize, Gas, Oil and Fertilisers for the prediction of FPI. WM uses Wheat and Maize and WMEF uses Wheat, Maize, Energy and Fertilisers. From the table, it can be seen that ultimately WMGOF proved to be the most accurate of all used models. Even though all the values are relatively far from 0, the model gives the most accurate results so far. WMEF gives comparable results but slightly less accurate. WM version gives the most inaccurate results of all versions tested.

Table 4.16: Performance Metrics for VAR and VECM Models

Metric	VAR: WMGOF	VECM: WMGOF	VAR: WM	VECM: WM	VECM: WMEF	VAR: WMEF
Bias	-11.282488	-24.811952	-14.435286	-42.407437	-25.811668	-13.630544
MAE	11.282488	24.811952	14.435286	42.407437	25.811668	13.630544
MSE	159.424670	829.980275	254.251400	2428.215134	851.766369	226.385813
RMSE	12.626348	28.809378	15.945263	49.276923	29.185037	15.046123

4.4.6. Conclusion

After all tests are run and everything is considered, the WMGOF version of the predictive model will be used for the final prediction in the next section. Substituting crude oil and natural gas prices for the energy index did not improve the accuracy of the prediction; however, the predictions were not far away from those obtained using oil and gas prices.

4.5. Final prediction

In this section, the data set will be used fully (without the split for test and train data) to make a prediction outside the dataset. Based on all the tests and predictions made previously, it was decided to use the following data: prices of wheat, maize, crude oil and natural gas and price index of fertilisers to predict the value of FPI. FPI is proven to be a reliable predictor of inflation, given its significant relationship with CPI and the predictive accuracy of the VECM and VAR based on FPI.

Please note: *The prediction is made for the period 01/2024–05/2024. Despite the fact that the data is in the past relative to the time of this writing, the dataset did not have the data for these months due to the complexity of CPI and FPI. The data is delayed by a few months and thus cannot be compared with the predictions.*

The data were already tested for all needed requirements (for more details, please check chapter 4.3.6) and so the VECM model can be applied directly. Additionally, given that there is no real data to compare the predicted values against, the prediction will be compared with the predictions made by VAR model.

Figure 4.20 shows the predictions made by both VECM (in orange) and VAR (in blue) models. From the previous chapters and test, both VECM and VAR have proven to exaggerate future events. The trend of both models matched the one present in the test data, so rising FPI in the coming month can be a trustworthy fact. The magnitude of growth cannot be estimated by VECM and/or VAR due to the relatively high error values derived from the previous tries. The war in Ukraine is obviously a shock, and it can be the case that only the unpredictability of this event alone impacts the model's predictive power. However, it also can be the case that the amount of gathered data is not enough to make statistically accurate predictions.

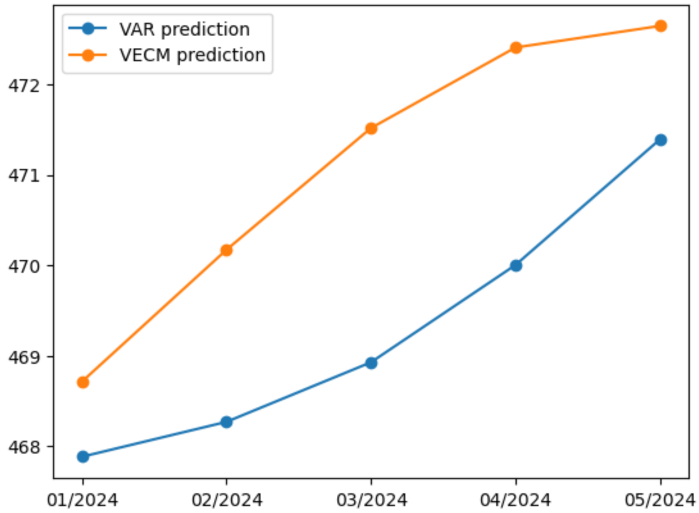


Figure 4.20: Forecasted FPI value: VECM vs VAR

5
Conclusion and discussion

This chapter summarises all the findings discovered in the thesis. The findings are then used to answer the sub-questions and the main research question defined in the chapter 1. Then, the chapter discusses the reasons for the predictive models' overfitting observed in all the research scenarios to suggest ways of fighting the inaccuracy and deriving more accurate predictions. The chapter then discusses the societal implications of the already applied policies, followed by actionable suggestions for policymakers and corporations.

5.1. Conclusion

The research conducted in this study has shed light on the impact of the war in Ukraine on the level of food prices in the European Union. The level of food prices is the driver of food security[50, 51]. Thus, studying the level of food prices contributes to the studies about the level of food security. The findings have highlighted the challenges faced by the EU in terms of food availability and affordability as a result of the invasion of Russia in Ukraine in 2022.

The increase in global commodity prices, particularly for wheat, maize, fertilizers, crude oil and natural gas, has caused significant stress to the European economic system. However, the direct impact on the EU's level of food prices was not significant to define those variables as the drivers of inflation. The dependency on imported goods, especially from Ukraine and Russia, has made the EU susceptible to supply disruptions and price fluctuations and forced the EU to make certain steps towards forceful price decreases (tariff-free programme discussed in chapter 2.2).

The research has shown a very strong causal relationship between the Food Price Index (FPI) and the Consumer Price Index (CPI). This discovery allowed for the simplification of causal relationships and more straightforward modelling. The significance of the predictive relationships between wheat, maize, gas, oil, fertilisers and FPI were close to significant. The predictive models built using those data were able to define future trends (upward or downward), but the predicted value proved to be exaggerated and thus needs to be adjusted by the overfitting factor to be accurate. The prediction made outside the dataset showed that FPI and, thus, CPI are expected to grow for at least five months (January to May 2024). This outcome suggests that despite the prices of commodities already going down, inflation does not react to these changes immediately.

In detail, the research answered the following questions:

- **"What is the dependency level of the EU food industry on imported goods?"** The EU economy (food sector) has a positive trade balance, suggesting a high level of independence, with 7.7% reliance on imported goods[34]. However, some sectors of industry, particularly cereals, are shown to be strongly dependent on imports[34]. The high dependency of the EU on cereals thus explains the negative effect of the war in Ukraine on the stability of the EU's food industry.
- **"How significant is the direct dependency of the EU food industry on Ukrainian and/or Russian grain, fertilisers and energy?"** Chapter 3 showed that the EU has more than 45% of

imported maize and over 31% of wheat coming from Ukraine. Thus making Ukraine an essential grain supplier to Europe. Russia imports relatively small amounts of wheat and maize to the EU while showing a considerable share of energy imports. Over 15% of natural gas liquids are imported from Russia. The share of oil imports from Russia, however, shrank from 21% to 5% over the past four years. Thus, these numbers show a significant dependency of the EU on commodities produced by Ukraine and Russia, even during active war.

- **"How much are the prices of commodities and the inflation indices of interest synchronised with each other?"** The cointegration and stationarity research suggested that all commodity prices and inflationary indices show cointegrating and non-stationary traits. The descriptive statistics and visual representation of data showed clearly synchronised movement. The thorough research on the price change pattern suggested that synchronisation exists; however, it is not statistically significant.
- **"What are the dependencies between the prices of commodities and inflationary indices?"** The visualisation of the prices of the commodities of interest to the research revealed visual synchronisation of those. It was observed that inflationary indices follow the same pattern with a delay (it was observed that some amount of time is needed for inflationary indices to react to the price shifts). The cointegration research also suggested that some of the variables move synchronously. However, the Granger-causality tests showed that shared tendencies are not enough to state the causal relationship between commodities and inflationary indices, thus suggesting a more complex relationship between commodities and inflationary indices. The research states that there is dependence between the commodities of interest, but it is insignificant.
- **"What is the impact of the war in Ukraine on the level of food prices in the European Union?"** Overall, the thesis showed that chronologically, the changes in commodity prices have changed significantly since the invasion of Russia in Ukraine in 2022. The response of the EU has resulted in the normalization of prices (return of commodity prices to the pre-war level). The negative inflationary impact of commodity prices has not been proven to be caused by products imported from Ukraine and Russia. However, the research showed that gas, wheat, maize, oil and fertilisers play essential roles in the process of inflation setting; however, they are not significant enough to make them primary inflation setters.

Furthermore, the research suggests that future studies should consider expanding the dataset to include a longer time period, from 1991 to 2024, to provide a more comprehensive analysis of the impact of geopolitical conflicts on the EU's food industry. This extended timeframe would allow for a deeper understanding of long-term trends and patterns in commodity prices and their effects on food security.

Additionally, it is recommended that future studies include sunflower oil in the analysis. Sunflower oil is a significant commodity in the EU, which is mainly imported from Ukraine, and its inclusion would provide a more holistic view of the impact of the war in Ukraine on the EU's food industry. By examining the fluctuations in sunflower oil prices and their relationship with other commodities, researchers can better understand the interconnectedness of different sectors within the food industry. This additional variable will holistically estimate the role of Ukraine and Russia in the EU's food market.

In conclusion, the war in Ukraine has stressed the European Union's food security. The research highlights the challenges faced by the EU in terms of food availability and affordability. The findings suggest that the policies implemented to neutralise the unexpected growth of food prices achieved the desired effect on commodities. However, food prices and, thus, inflation remain high and far from the desired level. The potential solution for hedging the risk of such singular dependence would be import diversification.

5.2. Potential reasons for model inaccuracies

It is fundamental to understand the reasons for the huge forecasting errors of the predictive models shown in the research. The models tested so far for the final prediction take the data without considering unmeasurable side factors like politics and consumer psychology. Thus, there are two possible explanations for why the forecasts are exaggerated. From the facts known to the author, the income/-substitution effects and government policy adjustments can explain the model's inaccuracies.

The income and substitution effects[28] play a crucial role in moderating the impact of higher input costs on the Food Price Index (FPI). Real wages decline when nominal wages rise less than the Consumer Price Index (CPI) and FPI, reducing consumers' purchasing power. This decrease in real income leads to reduced demand for food products. Additionally, consumers often respond to rising food prices by substituting more expensive items with cheaper alternatives. The quantities of the less expensive goods may not meet the customers' level of demand, thus causing price increases for those goods. These income and substitution effects are fundamental drivers of food prices, as they directly affect consumer behaviour and demand.

Government policies and subsidies also play a significant role in buffering the impact of rising input costs. Various government interventions, such as direct support for food prices (please recall the tariff-free program introduced by the EU in the chapter 2.2), can stabilize the market and prevent the full transmission of increased costs to consumers. These policies are designed to have significant effects in the relatively short term. The impact made by the tariff-off programme appears unexpectedly, thus making the future impact on FPI unclear to the statistical models used in the thesis. By mitigating the impact of cost increases, government interventions can lead to a smaller-than-expected rise in the FPI. These policies can substantially impact price dynamics and should be considered when modelling the FPI.

In summary, the model's overestimation of the FPI can be primarily attributed to the combined effects of reduced consumer demand due to lower real wages, substitution behaviour and stabilizing government policies. These mechanisms have a substantial impact on the state of prices and thus temporarily break the predictable behaviour of the system. Later, the system will adapt to the shock-neutralising actions of the governments and, as a result, the predictions made will be of higher accuracy.

5.3. Societal implications

The research showed that food security is a topic of huge importance, and the EU puts a lot of effort into stabilizing food price levels, which were increased due to the war in Ukraine. The war has raised concerns about food security in Europe. Despite the fact that even with the decreased amount exported whet, food acceptability did not become the topic of major unrest, the question of food affordability became. Poor countries of the EU received much more economic damage than the other members. The figure 5.1 visually represents the percentage of the population, per EU member, who cannot afford a fish/meat meal every second day. The figure shows that less developed countries in the immediate proximity of the war area suffer more than those far away.

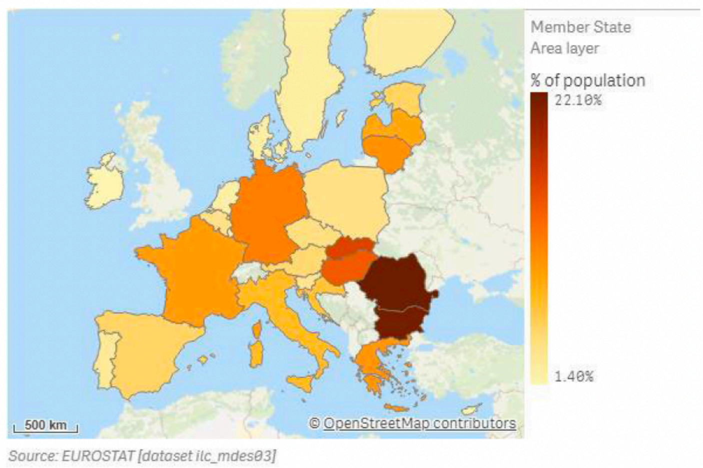


Figure 5.1: Inability to afford fish/meat meal every second day 2022 [51]

In chapter 2.2, the effectiveness of the policies targeted to reduce food prices immediately is discussed. The policies have proven to be effective and led to price decreases for all goods studied in this thesis. However, the long-term effect of these policies and the effect of price decreases on the level of inflation are yet unknown. The policies became an external shock to the system, thus damaging the models' predictability while achieving the goal of partial market control.

The research done in the thesis confirmed that the policies contribute greatly to the population's purchasing power by forceful reduction of prices. It was seen that, indeed, commodities of interest returned to the pre/war price level while FPI stayed in the shock state (remained much higher than during pre-war time), emphasising that the general price level remains inflated. The predictions made suggest that inflation will remain high for the time being. This fact shows that FPI developed some inertia and price reduction is not enough to demolish the harmful impact of the war on the economic well-being of European citizens. This suggests that more policies must be implemented to lower high inflation.

5.4. Actionable suggestions

This section aims to give concrete steps for corporations and policymakers to prevent similar disruptions in the future. The action items are suggested based on the knowledge gathered during the research explained in this thesis. The section has two main blocks: corporations and policymakers. Each block focuses on concrete actions for the concrete group to ensure the suggestions are the most applicable.

5.4.1. Corporations

Even though inflation affects all sectors of the economy, the suggestions will be given only to corporations related to the studied commodities and not to the corporations as a generic term.

Firstly, the research highlighted the importance of diversifying imports (from the perspective of the country of operation). The panic that emerged with Russia's invasion led to an immediate spike in the prices of all goods imported from Ukraine and Russia. Supply chain disruptions and the blockage of the Black Sea were the drivers of supply uncertainty. The immense panic, thus, suggested a high level of dependency on one supply channel and called for a more diversified import structure.

Secondly, food corporations shall invest in high-tech farming and alternative energy. Investing in those sectors will lead to a more predictable and controllable supply of agricultural and energy products. High-tech agriculture has the potential to eliminate factors like extreme weather conditions and alternative energy decouples the dependency on limited natural materials like gas and oil.

These two steps would lead to a more technologically enhanced food industry, which would make it more predictable in the long run. However, these changes take time, given that considerable research is still needed.

5.4.2. Policymakers

The first and obvious step towards solving the food crisis studied in the research would be to stop the war. The invasion of Ukraine in 2022 started disrupting supply chains and decreasing the supply of agricultural products. So far, the European Union has made specific steps towards stabilisation of the European economy, but war, as a central stress factor, still remains in the active phase.

Additionally, policymakers can boost corporations' interest in high-tech farming and alternative energy by providing subsidies for research and development (R&D). This policy adjustment would increase companies' willingness to contribute to alternative food and energy production methods, thus decoupling the supply chains of countries involved in the war.

Finally, the research showed the effectiveness of EU policies. The thesis highlighted the positive effects of the tariff-off programme on grain imported from Ukraine. However, the research outlined the complexity of the relationships between commodity prices and inflationary indices, thus suggesting additional policies explicitly targeted at reducing the level of inflation rather than the affected underlying commodities.

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A

Import data

Country Code	Commodity	Importer	Year	Tonnes imported
LT	Maize (Incl. processed products)	Ukraine	2014/15	84300.900
			2015/16	54376.832
			2016/17	35495.128
			2017/18	50523.540
			2018/19	340161.934
			2019/20	274221.432
			2020/21	69833.820
			2021/22	40972.305
			2022/23	106905.483
			2023/24	32446.148
	Soft wheat (incl. flour and groats)		2014/15	20512.532
			2015/16	0.000
			2016/17	27.422
			2017/18	0.000
			2018/19	10492.520
			2019/20	1009.635
			2020/21	20.000
			2021/22	0.000
			2022/23	52059.968
			2023/24	14845.675
	Maize (Incl. processed products)	Russia	2014/15	0.000
			2015/16	16993.635
			2016/17	8737.150
			2017/18	27218.552
			2018/19	42366.850
			2019/20	42958.800
			2020/21	63519.580
			2021/22	63296.690
			2022/23	30189.730
			2023/24	51.150
	Soft wheat (incl. flour and groats)		2014/15	420.000
			2015/16	20.000
			2016/17	0.000
			2017/18	2948.519
			2018/19	22871.677

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Country Code	Commodity	Importer	Year	Tonnes imported
			2019/20	7261.154
			2020/21	444.644
			2021/22	21.440
			2022/23	7339.010
			2023/24	0.000
PL	Maize (Incl. processed products)	Ukraine	2014/15	3422.728
			2015/16	309868.920
			2016/17	103289.024
			2017/18	102804.041
			2018/19	219631.333
			2019/20	7137.130
			2020/21	1787.196
			2021/22	642417.535
			2022/23	1803994.039
			2023/24	2592.223
	Soft wheat (incl. flour and groats)		2014/15	2581.167
			2015/16	3720.738
			2016/17	3669.445
			2017/18	1606.750
			2018/19	8753.892
			2019/20	2454.720
			2020/21	2474.175
			2021/22	6324.269
			2022/23	865021.111
			2023/24	6186.920
	Maize (Incl. processed products)	Russia	2014/15	0.176
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	2123.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	822.514
			2015/16	0.343
			2016/17	60.000
			2017/18	50.270
			2018/19	0.000
			2019/20	995.212
			2020/21	251.921
			2021/22	302.701
			2022/23	0.000
			2023/24	0.000
HU	Maize (Incl. processed products)	Ukraine	2014/15	0.000
			2015/16	471.305
			2016/17	2130.501
			2017/18	33973.103
			2018/19	21223.072
			2019/20	15299.648
			2020/21	19137.557
			2021/22	216993.337

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Country Code	Commodity	Importer	Year	Tonnes imported
			2022/23	1564548.707
			2023/24	9620.795
	Soft wheat (incl. flour and groats)		2014/15	424.050
			2015/16	148.200
			2016/17	591.168
			2017/18	1446.450
			2018/19	384.965
			2019/20	0.000
			2020/21	0.431
			2021/22	1543.150
			2022/23	248572.375
			2023/24	2326.972
	Maize (Incl. processed products)	Russia	2014/15	0.086
			2015/16	24.380
			2016/17	21.492
			2017/18	57.914
			2018/19	16.520
			2019/20	91.409
			2020/21	0.240
			2021/22	115.441
			2022/23	20.728
			2023/24	59.945
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	10.500
			2020/21	0.556
			2021/22	0.000
			2022/23	0.000
			2023/24	0.000
SI	Maize (Incl. processed products)	Ukraine	2014/15	42.546
			2015/16	61.272
			2016/17	33518.351
			2017/18	18982.325
			2018/19	16176.770
			2019/20	22612.307
			2020/21	33.090
			2021/22	88274.480
			2022/23	522566.320
			2023/24	568687.142
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	61098.865
			2023/24	54322.374
	Maize (Incl. processed products)	Russia	2014/15	0.000

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Country Code	Commodity	Importer	Year	Tonnes imported
			2015/16	0.000
			2016/17	9200.900
			2017/18	4000.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	3098.880
			2016/17	0.000
			2017/18	0.000
			2018/19	0.048
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	0.000
IE	Maize (Incl. processed products)	Ukraine	2014/15	170712.876
			2015/16	275909.411
			2016/17	201408.335
			2017/18	185702.148
			2018/19	404527.643
			2019/20	476394.518
			2020/21	184116.018
			2021/22	163500
			2022/23	40564.041
			2023/24	24444.501
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	6.000
			2021/22	5.000
			2022/23	0.000
			2023/24	21116.231
	Maize (Incl. processed products)	Russia	2014/15	11000.000
			2015/16	0.000
			2016/17	83671.905
			2017/18	0.031
			2018/19	31792.090
			2019/20	0.000
			2020/21	0.000
			2021/22	0.001
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.450
			2017/18	0.000

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Country Code	Commodity	Importer	Year	Tonnes imported
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.001
			2022/23	0.000
			2023/24	0.000
EL	Maize (Incl. processed products)	Ukraine	2014/15	2147.940
			2015/16	23053.344
			2016/17	108124.541
			2017/18	24721.916
			2018/19	32970.558
			2019/20	3.007
			2020/21	0.000
			2021/22	20352.004
			2022/23	191416.401
			2023/24	110135.511
	Soft wheat (incl. flour and groats)		2014/15	82785.375
			2015/16	72909.846
			2016/17	32886.267
			2017/18	38156.702
			2018/19	14291.380
			2019/20	18216.781
			2020/21	90998.347
			2021/22	33972.152
			2022/23	306007.264
			2023/24	231310.687
	Maize (Incl. processed products)	Russia	2014/15	30567.993
			2015/16	172670.771
			2016/17	178369.228
			2017/18	57445.152
			2018/19	23533.521
			2019/20	9302.466
			2020/21	94098.930
			2021/22	99748.844
			2022/23	83500.747
			2023/24	38566.473
	Soft wheat (incl. flour and groats)		2014/15	138952.744
			2015/16	244207.317
			2016/17	80020.202
			2017/18	146714.728
			2018/19	302785.162
			2019/20	145669.093
			2020/21	181507.906
			2021/22	202781.824
			2022/23	119784.491
			2023/24	127530.138
PT	Maize (Incl. processed products)	Ukraine	2014/15	456512.142
			2015/16	828358.271
			2016/17	846985.499
			2017/18	639966.861
			2018/19	921518.912
			2019/20	813227.829
			2020/21	765554.953

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Country Code	Commodity	Importer	Year	Tonnes imported
			2021/22	425443.333
			2022/23	681109.382
			2023/24	309047.164
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	30766.775
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	63222.361
			2023/24	124995.172
	Maize (Incl. processed products)	Russia	2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	17539.680
			2021/22	59868.990
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	28291.220
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	0.000
BE	Maize (Incl. processed products)	Ukraine	2014/15	95416.685
			2015/16	414986.835
			2016/17	443877.575
			2017/18	514158.185
			2018/19	688982.050
			2019/20	604161.019
			2020/21	474055.815
			2021/22	520100.725
			2022/23	384750.140
			2023/24	132743.999
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.088
			2021/22	0.011
			2022/23	286.290
			2023/24	196.614

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Country Code	Commodity	Importer	Year	Tonnes imported
	Maize (Incl. processed products)	Russia	2014/15	0.000
			2015/16	0.005
			2016/17	0.000
			2017/18	0.004
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	5500.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.001
			2017/18	0.000
			2018/19	32820.002
			2019/20	0.004
			2020/21	0.000
			2021/22	0.039
			2022/23	0.000
			2023/24	0.000
FR	Maize (Incl. processed products)	Ukraine	2014/15	2240.121
			2015/16	20.591
			2016/17	1997.719
			2017/18	4255.252
			2018/19	112899.812
			2019/20	511.089
			2020/21	69.324
			2021/22	924.188
			2022/23	12425.571
			2023/24	7752.895
	Soft wheat (incl. flour and groats)		2014/15	572.420
			2015/16	30.150
			2016/17	0.001
			2017/18	2230.096
			2018/19	4849.161
			2019/20	2461.489
			2020/21	0.000
			2021/22	2.988
			2022/23	735.660
			2023/24	4650.887
	Maize (Incl. processed products)	Russia	2014/15	0.016
			2015/16	3.906
			2016/17	276.273
			2017/18	21.355
			2018/19	42.445
			2019/20	0.326
			2020/21	19.318
			2021/22	98.822
			2022/23	21.096
			2023/24	0.194
	Soft wheat (incl. flour and groats)		2014/15	415.867
			2015/16	4.929
			2016/17	0.000

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Country Code	Commodity	Importer	Year	Tonnes imported
			2017/18	0.137
			2018/19	22.959
			2019/20	0.054
			2020/21	0.000
			2021/22	26.068
			2022/23	0.007
			2023/24	0.007
FI	Maize (Incl. processed products)	Ukraine	2014/15	1182.130
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	27261.832
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	5.918
	Maize (Incl. processed products)	Russia	2014/15	804.131
			2015/16	1180.000
			2016/17	492.000
			2017/18	237.170
			2018/19	15320.826
			2019/20	10770.315
			2020/21	9660.762
			2021/22	9907.809
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.411
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	3159.000
			2019/20	0.000
			2020/21	0.001
			2021/22	249.641
			2022/23	0.000
			2023/24	0.000
SE	Maize (Incl. processed products)	Ukraine	2014/15	0.000
			2015/16	1.728
			2016/17	3157.560
			2017/18	4248.288
			2018/19	0.008
			2019/20	13772.322

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Country Code	Commodity	Importer	Year	Tonnes imported
			2020/21	0.000
			2021/22	22.000
			2022/23	34.425
			2023/24	22.160
	Soft wheat (incl. flour and groats)		2014/15	0.021
			2015/16	2.467
			2016/17	0.000
			2017/18	0.041
			2018/19	0.033
			2019/20	0.033
			2020/21	0.888
			2021/22	0.000
			2022/23	801.243
			2023/24	1242.755
	Maize (Incl. processed products)	Russia	2014/15	3484.118
			2015/16	16815.330
			2016/17	7557.994
			2017/18	10536.555
			2018/19	35000.174
			2019/20	4971.012
			2020/21	0.955
			2021/22	1029.312
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.009
			2016/17	3844.374
			2017/18	0.023
			2018/19	37392.900
			2019/20	0.003
			2020/21	1.202
			2021/22	0.412
			2022/23	0.000
			2023/24	0.000
DE	Maize (Incl. processed products)	Ukraine	2014/15	265517.122
			2015/16	434364.620
			2016/17	11246.055
			2017/18	340022.703
			2018/19	1600333.259
			2019/20	697791.465
			2020/21	277399.954
			2021/22	105463.921
			2022/23	462976.267
			2023/24	426674.271
	Soft wheat (incl. flour and groats)		2014/15	14520.961
			2015/16	13509.879
			2016/17	13338.276
			2017/18	7807.111
			2018/19	4621.539
			2019/20	2667.262
			2020/21	5033.747
			2021/22	4726.378
			2022/23	97234.957

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Country Code	Commodity	Importer	Year	Tonnes imported
			2023/24	57611.693
	Maize (Incl. processed products)	Russia	2014/15	5875.593
			2015/16	102469.808
			2016/17	53133.850
			2017/18	43233.048
			2018/19	17595.203
			2019/20	25231.351
			2020/21	6242.322
			2021/22	21.865
			2022/23	25.624
			2023/24	11.245
	Soft wheat (incl. flour and groats)		2014/15	54.944
			2015/16	3017.863
			2016/17	4416.256
			2017/18	38381.718
			2018/19	19887.519
			2019/20	275.892
			2020/21	71.755
			2021/22	44.105
			2022/23	54.633
			2023/24	24.578
AT	Maize (Incl. processed products)	Ukraine	2014/15	2947.477
			2015/16	15897.983
			2016/17	5692.861
			2017/18	1027.443
			2018/19	3863.537
			2019/20	3128.362
			2020/21	72.648
			2021/22	10643.165
			2022/23	163454.994
			2023/24	20380.089
	Soft wheat (incl. flour and groats)		2014/15	2283.840
			2015/16	7105.218
			2016/17	9650.930
			2017/18	12958.068
			2018/19	0.000
			2019/20	40.000
			2020/21	245.850
			2021/22	0.000
			2022/23	6260.911
			2023/24	118.640
	Maize (Incl. processed products)	Russia	2014/15	0.240
			2015/16	30.496
			2016/17	17.365
			2017/18	0.240
			2018/19	16.534
			2019/20	218.117
			2020/21	24.418
			2021/22	110.292
			2022/23	23.608
			2023/24	60.343
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000

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Country Code	Commodity	Importer	Year	Tonnes imported
			2016/17	0.000
			2017/18	0.000
			2018/19	0.548
			2019/20	4.610
			2020/21	1.223
			2021/22	1.092
			2022/23	27.377
			2023/24	0.000
HR	Maize (Incl. processed products)	Ukraine	2014/15	0.000
			2015/16	26.838
			2016/17	4.795
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	47.688
			2021/22	9989.290
			2022/23	99487.364
			2023/24	48106.136
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	20278.268
			2023/24	8050.125
RO	Maize (Incl. processed products)		2014/15	41.599
			2015/16	36.995
			2016/17	156.651
			2017/18	489.466
			2018/19	316.457
			2019/20	536.807
			2020/21	337.079
			2021/22	103853.214
			2022/23	1230053.851
			2023/24	8044.072
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	258.035
			2019/20	56.817
			2020/21	0.432
			2021/22	2223.925
			2022/23	717427.593
			2023/24	1335.990
	Maize (Incl. processed products)	Russia	2014/15	0.056
			2015/16	227.619
			2016/17	795.890
			2017/18	58.865
			2018/19	0.000

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Country Code	Commodity	Importer	Year	Tonnes imported
			2019/20	140.052
			2020/21	0.000
			2021/22	158.729
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	2.400
			2016/17	2880.810
			2017/18	0.000
			2018/19	0.000
			2019/20	3299.170
			2020/21	0.000
			2021/22	0.004
			2022/23	0.000
			2023/24	0.000
NL	Maize (Incl. processed products)	Ukraine	2014/15	1255231.358
			2015/16	1692924.865
			2016/17	2169182.304
			2017/18	2336854.762
			2018/19	4142968.949
			2019/20	3663658.330
			2020/21	2131799.859
			2021/22	1874419.771
			2022/23	1605600.049
			2023/24	1053240.982
	Soft wheat (incl. flour and groats)		2014/15	59181.222
			2015/16	133729.477
			2016/17	40655.993
			2017/18	9777.540
			2018/19	130794.527
			2019/20	25157.217
			2020/21	20142.567
			2021/22	47694.099
			2022/23	32808.105
			2023/24	70245.206
	Maize (Incl. processed products)	Russia	2014/15	85913.882
			2015/16	473292.298
			2016/17	255479.148
			2017/18	31846.602
			2018/19	12911.960
			2019/20	14084.621
			2020/21	32511.233
			2021/22	486.837
			2022/23	7572.257
			2023/24	0.472
	Soft wheat (incl. flour and groats)		2014/15	0.137
			2015/16	44893.021
			2016/17	78488.210
			2017/18	25920.096
			2018/19	116965.599
			2019/20	4439.776
			2020/21	0.351
			2021/22	3295.712

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Country Code	Commodity	Importer	Year	Tonnes imported
			2022/23	0.131
			2023/24	0.784
ES	Maize (Incl. processed products)	Ukraine	2014/15	2353030.236
			2015/16	2811369.775
			2016/17	2428814.978
			2017/18	1759824.555
			2018/19	3997555.334
			2019/20	3760694.385
			2020/21	1885408.549
			2021/22	2902547.506
			2022/23	3415115.848
			2023/24	2677740.051
	Soft wheat (incl. flour and groats)		2014/15	734270.937
			2015/16	1119177.109
			2016/17	429345.147
			2017/18	1121176.407
			2018/19	311803.717
			2019/20	315900.077
			2020/21	346800.756
			2021/22	140278.121
			2022/23	2881071.318
			2023/24	2786706.912
	Maize (Incl. processed products)	Russia	2014/15	0.000
			2015/16	44698.563
			2016/17	156110.493
			2017/18	1327.481
			2018/19	0.000
			2019/20	0.000
			2020/21	31368.880
			2021/22	0.002
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	64250.307
			2015/16	82624.966
			2016/17	70276.675
			2017/18	117651.760
			2018/19	91502.957
			2019/20	18279.325
			2020/21	13977.710
			2021/22	116763.383
			2022/23	47227.960
			2023/24	75572.318
SK	Maize (Incl. processed products)	Ukraine	2014/15	0.000
			2015/16	0.010
			2016/17	2.150
			2017/18	1.023
			2018/19	3419.400
			2019/20	3548.900
			2020/21	0.000
			2021/22	66452.570
			2022/23	608308.939
			2023/24	478.572
	Soft wheat (incl. flour and groats)		2014/15	18.764

Continued on next page

Country Code	Commodity	Importer	Year	Tonnes imported
			2015/16	2.748
			2016/17	0.274
			2017/18	17.892
			2018/19	0.137
			2019/20	28.545
			2020/21	36.852
			2021/22	1435.090
			2022/23	98291.092
			2023/24	2356.338
	Maize (Incl. processed products)	Russia	2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	57.397
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	21.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.003
			2019/20	0.001
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	0.000
BG	Maize (Incl. processed products)	Ukraine	2014/15	22.020
			2015/16	2.100
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	187.000
			2020/21	127.312
			2021/22	2354.807
			2022/23	17606.664
			2023/24	273.281
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	4259.904
			2019/20	0.000
			2020/21	0.000
			2021/22	6005.140
			2022/23	14110.724
			2023/24	10974.954
	Maize (Incl. processed products)	Russia	2014/15	0.580
			2015/16	0.000
			2016/17	0.000
			2017/18	61.100

Continued on next page

Country Code	Commodity	Importer	Year	Tonnes imported
			2018/19	40.824
			2019/20	0.000
			2020/21	746.299
			2021/22	3.096
			2022/23	3.588
			2023/24	2.745
	Soft wheat (incl. flour and groats)		2014/15	5.178
			2015/16	4.420
			2016/17	5.887
			2017/18	7.300
			2018/19	5218.701
			2019/20	2981.345
			2020/21	9350.301
			2021/22	6.269
			2022/23	9.502
			2023/24	7.773
IT	Maize (Incl. processed products)	Ukraine	2014/15	743875.856
			2015/16	1323966.814
			2016/17	1639091.646
			2017/18	1652040.567
			2018/19	1660731.156
			2019/20	993939.756
			2020/21	688508.233
			2021/22	881643.337
			2022/23	1814196.765
			2023/24	946184.479
	Soft wheat (incl. flour and groats)		2014/15	431762.392
			2015/16	621391.441
			2016/17	414144.777
			2017/18	361522.965
			2018/19	243290.458
			2019/20	121462.446
			2020/21	160596.027
			2021/22	107201.235
			2022/23	548038.563
			2023/24	319612.093
	Maize (Incl. processed products)	Russia	2014/15	11746.274
			2015/16	204167.368
			2016/17	137336.946
			2017/18	15038.854
			2018/19	0.000
			2019/20	0.000
			2020/21	85334.211
			2021/22	20017.210
			2022/23	9000.000
			2023/24	18229.128
	Soft wheat (incl. flour and groats)		2014/15	93844.451
			2015/16	128450.260
			2016/17	29834.617
			2017/18	36013.044
			2018/19	43837.689
			2019/20	47785.550
			2020/21	40575.644

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Country Code	Commodity	Importer	Year	Tonnes imported
			2021/22	119167.281
			2022/23	3018.716
			2023/24	1500
DK	Maize (Incl. processed products)	Ukraine	2014/15	16963.962
			2015/16	7384.522
			2016/17	0.000
			2017/18	7680.225
			2018/19	434639.285
			2019/20	27500.000
			2020/21	3499.820
			2021/22	0.000
			2022/23	12560.524
			2023/24	31834.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	5.480
			2017/18	5060.880
			2018/19	11520.766
			2019/20	35.894
			2020/21	0.198
			2021/22	0.011
			2022/23	0.000
			2023/24	30.693
	Maize (Incl. processed products)	Russia	2014/15	42119.303
			2015/16	76697.421
			2016/17	46411.936
			2017/18	25480.568
			2018/19	17929.386
			2019/20	12557.160
			2020/21	5269.920
			2021/22	0.000
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.137
			2015/16	0.000
			2016/17	1.233
			2017/18	3311.077
			2018/19	36569.718
			2019/20	1979.828
			2020/21	6600.000
			2021/22	6800.000
			2022/23	8185.866
			2023/24	0.000
CZ	Maize (Incl. processed products)	Ukraine	2014/15	5.035
			2015/16	20.095
			2016/17	11.033
			2017/18	0.262
			2018/19	0.725
			2019/20	0.000
			2020/21	0.487
			2021/22	3964.269
			2022/23	25104.367
			2023/24	37000.698

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Country Code	Commodity	Importer	Year	Tonnes imported
	Soft wheat (incl. flour and groats)		2014/15	44.398
			2015/16	2.184
			2016/17	0.493
			2017/18	1.090
			2018/19	0.987
			2019/20	0.000
			2020/21	293.911
			2021/22	43.090
			2022/23	20411.310
			2023/24	22273.110
	Maize (Incl. processed products)	Russia	2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.293
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.461
			2022/23	0.000
			2023/24	0.000
CY	Maize (Incl. processed products)	Ukraine	2014/15	16394.780
			2015/16	38311.349
			2016/17	77165.833
			2017/18	41519.530
			2018/19	49284.129
			2019/20	31087.922
			2020/21	33162.060
			2021/22	11751.520
			2022/23	195530.750
			2023/24	134654.114
	Soft wheat (incl. flour and groats)		2014/15	4358.567
			2015/16	6531.355
			2016/17	11615.300
			2017/18	1261.998
			2018/19	3.817
			2019/20	6.946
			2020/21	8.839
			2021/22	3.789
			2022/23	13687.836
			2023/24	5786.828
	Maize (Incl. processed products)	Russia	2014/15	2815.147
			2015/16	36822.513
			2016/17	33014.516

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Country Code	Commodity	Importer	Year	Tonnes imported
			2017/18	5915.644
			2018/19	5811.590
			2019/20	0.025
			2020/21	17370.367
			2021/22	15513.798
			2022/23	0.000
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	6200.312
			2015/16	12005.755
			2016/17	11514.887
			2017/18	12226.040
			2018/19	15729.520
			2019/20	5815.372
			2020/21	3105.153
			2021/22	14326.444
			2022/23	9275.546
			2023/24	7088.440
EE	Maize (Incl. processed products)	Ukraine	2014/15	1610.730
			2015/16	129.810
			2016/17	1269.410
			2017/18	1928.375
			2018/19	9019.800
			2019/20	1974.705
			2020/21	396.225
			2021/22	1851.100
			2022/23	5671.825
			2023/24	4699.579
	Soft wheat (incl. flour and groats)		2014/15	0.000
			2015/16	0.000
			2016/17	3.683
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	380.600
			2023/24	30.140
	Maize (Incl. processed products)	Russia	2014/15	2687.600
			2015/16	8572.610
			2016/17	2968.200
			2017/18	10367.400
			2018/19	1023.500
			2019/20	0.000
			2020/21	0.001
			2021/22	0.485
			2022/23	30013.580
			2023/24	350.000
	Soft wheat (incl. flour and groats)		2014/15	0.268
			2015/16	0.000
			2016/17	0.000
			2017/18	2.812
			2018/19	2881.466
			2019/20	0.051

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Country Code	Commodity	Importer	Year	Tonnes imported
			2020/21	0.010
			2021/22	1.022
			2022/23	0.230
			2023/24	0.115
LV	Maize (Incl. processed products)	Ukraine	2014/15	6446.138
			2015/16	1099.348
			2016/17	3877.550
			2017/18	4274.650
			2018/19	38830.135
			2019/20	9776.630
			2020/21	0.000
			2021/22	10553.206
			2022/23	9446.549
			2023/24	1694.350
	Soft wheat (incl. flour and groats)		2014/15	31.674
			2015/16	172.682
			2016/17	110.000
			2017/18	0.069
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	25457.991
			2023/24	39413.620
	Maize (Incl. processed products)	Russia	2014/15	12091.010
			2015/16	82668.516
			2016/17	36077.895
			2017/18	173907.874
			2018/19	101376.207
			2019/20	61640.033
			2020/21	65888.837
			2021/22	151376.935
			2022/23	226293.193
			2023/24	139584.930
	Soft wheat (incl. flour and groats)		2014/15	3.685
			2015/16	12652.553
			2016/17	30378.774
			2017/18	58530.288
			2018/19	207265.853
			2019/20	0.352
			2020/21	45.034
			2021/22	131.554
			2022/23	80008.615
			2023/24	74650.711
MT	Maize (Incl. processed products)	Ukraine	2014/15	0.000
			2015/16	7904.044
			2016/17	3135.000
			2017/18	2773.986
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.001

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Country Code	Commodity	Importer	Year	Tonnes imported
			2023/24	0.000
	Soft wheat (incl. flour and groats)		2014/15	35391.255
			2015/16	0.000
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	63.020
			2020/21	32.510
			2021/22	31.510
			2022/23	0.000
			2023/24	65.760
		Russia	2014/15	0.000
			2015/16	8169.017
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	12274.500
			2020/21	3002.175
			2021/22	3288.895
			2022/23	0.000
			2023/24	0.000
LU	Maize (Incl. processed products)	Ukraine	2014/15	0.000
			2015/16	0.045
			2016/17	0.000
			2017/18	0.000
			2018/19	0.000
			2019/20	0.000
			2020/21	0.000
			2021/22	0.000
			2022/23	0.000
			2023/24	137.000

Country Code	Year	Commodity	Imported from Ukr in %	Imported from Rus in %
AT	2022/23	Maize (Incl. processed products)	74	0
	2022/23	Soft wheat (incl. flour and groats)	35	0
	2023/24	Maize (Incl. processed products)	40	0
	2023/24	Soft wheat (incl. flour and groats)	65	0
BE	2022/23	Maize (Incl. processed products)	99	0
	2022/23	Soft wheat (incl. flour and groats)	1	0
	2023/24	Maize (Incl. processed products)	95	3
	2023/24	Soft wheat (incl. flour and groats)	1	0
BG	2022/23	Maize (Incl. processed products)	75	0
	2022/23	Soft wheat (incl. flour and groats)	95	0
	2023/24	Maize (Incl. processed products)	4	0
	2023/24	Soft wheat (incl. flour and groats)	94	0
CY	2022/23	Maize (Incl. processed products)	79	0
	2022/23	Soft wheat (incl. flour and groats)	57	38
	2023/24	Maize (Incl. processed products)	94	0
	2023/24	Soft wheat (incl. flour and groats)	31	38
CZ	2022/23	Maize (Incl. processed products)	95	0
	2022/23	Soft wheat (incl. flour and groats)	99	0

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Country Code	Year	Commodity	Imported from Ukr in %	Imported from Rus in %
	2023/24	Maize (Incl. processed products)	96	0
	2023/24	Soft wheat (incl. flour and groats)	99	0
DE	2022/23	Maize (Incl. processed products)	97	0
	2022/23	Soft wheat (incl. flour and groats)	96	0
	2023/24	Maize (Incl. processed products)	97	0
	2023/24	Soft wheat (incl. flour and groats)	95	0
DK	2022/23	Maize (Incl. processed products)	59	0
	2022/23	Soft wheat (incl. flour and groats)	0	98
	2023/24	Maize (Incl. processed products)	82	0
	2023/24	Soft wheat (incl. flour and groats)	0	0
EE	2022/23	Maize (Incl. processed products)	15	83
	2022/23	Soft wheat (incl. flour and groats)	97	0
	2023/24	Maize (Incl. processed products)	90	6
	2023/24	Soft wheat (incl. flour and groats)	74	0
EL	2022/23	Maize (Incl. processed products)	61	26
	2022/23	Soft wheat (incl. flour and groats)	62	24
	2023/24	Maize (Incl. processed products)	53	18
	2023/24	Soft wheat (incl. flour and groats)	51	28
ES	2022/23	Maize (Incl. processed products)	39	0
	2022/23	Soft wheat (incl. flour and groats)	73	1
	2023/24	Maize (Incl. processed products)	57	0
	2023/24	Soft wheat (incl. flour and groats)	86	2
FI	2022/23	Maize (Incl. processed products)	0	0
	2022/23	Soft wheat (incl. flour and groats)	0	0
	2023/24	Maize (Incl. processed products)	0	0
	2023/24	Soft wheat (incl. flour and groats)	16	0
FR	2022/23	Maize (Incl. processed products)	34	0
	2022/23	Soft wheat (incl. flour and groats)	3	0
	2023/24	Maize (Incl. processed products)	38	0
	2023/24	Soft wheat (incl. flour and groats)	20	0
HR	2022/23	Maize (Incl. processed products)	74	0
	2022/23	Soft wheat (incl. flour and groats)	44	0
	2023/24	Maize (Incl. processed products)	69	0
	2023/24	Soft wheat (incl. flour and groats)	20	0
HU	2022/23	Maize (Incl. processed products)	94	0
	2022/23	Soft wheat (incl. flour and groats)	97	0
	2023/24	Maize (Incl. processed products)	46	0
	2023/24	Soft wheat (incl. flour and groats)	32	0
IE	2022/23	Maize (Incl. processed products)	3	0
	2022/23	Soft wheat (incl. flour and groats)	0	0
	2023/24	Maize (Incl. processed products)	3	0
	2023/24	Soft wheat (incl. flour and groats)	9	0
IT	2022/23	Maize (Incl. processed products)	58	0
	2022/23	Soft wheat (incl. flour and groats)	50	0
	2023/24	Maize (Incl. processed products)	74	1
	2023/24	Soft wheat (incl. flour and groats)	40	0
LT	2022/23	Maize (Incl. processed products)	77	21
	2022/23	Soft wheat (incl. flour and groats)	83	11
	2023/24	Maize (Incl. processed products)	99	0
	2023/24	Soft wheat (incl. flour and groats)	99	0
LU	2022/23	Maize (Incl. processed products)	0	0
	2022/23	Soft wheat (incl. flour and groats)	0	0
	2023/24	Maize (Incl. processed products)	100	0

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Country Code	Year	Commodity	Imported from Ukr in %	Imported from Rus in %
	2023/24	Soft wheat (incl. flour and groats)	0	0
LV	2022/23	Maize (Incl. processed products)	4	95
	2022/23	Soft wheat (incl. flour and groats)	24	75
	2023/24	Maize (Incl. processed products)	1	98
	2023/24	Soft wheat (incl. flour and groats)	34	65
MT	2022/23	Maize (Incl. processed products)	0	0
	2022/23	Soft wheat (incl. flour and groats)	0	0
	2023/24	Maize (Incl. processed products)	0	0
	2023/24	Soft wheat (incl. flour and groats)	1	0
NL	2022/23	Maize (Incl. processed products)	60	0
	2022/23	Soft wheat (incl. flour and groats)	8	0
	2023/24	Maize (Incl. processed products)	74	0
	2023/24	Soft wheat (incl. flour and groats)	85	0
PL	2022/23	Maize (Incl. processed products)	97	0
	2022/23	Soft wheat (incl. flour and groats)	99	0
	2023/24	Maize (Incl. processed products)	6	0
	2023/24	Soft wheat (incl. flour and groats)	92	0
PT	2022/23	Maize (Incl. processed products)	36	0
	2022/23	Soft wheat (incl. flour and groats)	21	0
	2023/24	Maize (Incl. processed products)	33	0
	2023/24	Soft wheat (incl. flour and groats)	70	0
RO	2022/23	Maize (Incl. processed products)	87	0
	2022/23	Soft wheat (incl. flour and groats)	73	0
	2023/24	Maize (Incl. processed products)	8	0
	2023/24	Soft wheat (incl. flour and groats)	0	0
SE	2022/23	Maize (Incl. processed products)	6	0
	2022/23	Soft wheat (incl. flour and groats)	5	0
	2023/24	Maize (Incl. processed products)	8	0
	2023/24	Soft wheat (incl. flour and groats)	59	0
SI	2022/23	Maize (Incl. processed products)	67	0
	2022/23	Soft wheat (incl. flour and groats)	18	0
	2023/24	Maize (Incl. processed products)	77	0
	2023/24	Soft wheat (incl. flour and groats)	22	0
SK	2022/23	Maize (Incl. processed products)	99	0
	2022/23	Soft wheat (incl. flour and groats)	99	0
	2023/24	Maize (Incl. processed products)	49	0
	2023/24	Soft wheat (incl. flour and groats)	99	0

B

Supplement tables

The table gives an extended view using the F statistics. The graph represents p-values depending on the lag size. Lag size can be explained as the ordinal number of the data point used for the prediction. The lag of size 1 shows that the immediate predecessor of the predicted value is used for the prediction. For every lag, the p-value determines the strength of the predictive power of the lag. The smaller the p-value is, the bigger the predictive strength of the lag is.

Lags	Wheat -> FPI		Maize -> FPI	
	F-Statistic	P-Value	F-Statistic	P-Value
1	4.3223	0.0398	1.7985	0.1825
2	2.5924	0.0792	1.3934	0.2524
3	2.1741	0.0951	0.9061	0.4406
4	2.0668	0.0902	0.7863	0.5365
5	1.7182	0.1368	0.7672	0.5755
6	1.7715	0.1123	0.6233	0.7112
7	1.8303	0.0897	0.8300	0.5649
8	1.6330	0.1255	0.7596	0.6390
9	1.4419	0.1817	0.6588	0.7439
10	1.3800	0.2023	0.7286	0.6957
11	1.1658	0.3226	0.8062	0.6336
12	1.5427	0.1252	0.9492	0.5032
13	1.8673	0.0464	1.0867	0.3822
14	1.9980	0.0285	1.0890	0.3806
15	1.8153	0.0479	1.0930	0.3775

Table B.1: Granger Causality Test results for Wheat/Maize affecting FPI