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The Impact of Energy Prices on Food Prices

A Case Study Using Norwegian Monthly Data from 2015 to 2023

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Abstract

This study examines the relationship between energy prices and food prices in Norway. It specifically focuses on the period following a significant spike in food prices, commonly referred to as a breakpoint, which occurred in January 2022. We also explore the effect of energy prices on wheat, meat, and rice. We find a breakpoint in energy prices in April 2020 and a breakpoint in food prices in January 2022.

The empirical analysis reveals mixed results in the period before the breakpoint in January 2022. The Ordinary Least Squares (OLS) and the Autoregressive (AR) model identify a significant 18-month lag effect of energy prices on food prices, while the Cochrane-Orcutt model does not show this effect. However, all three models are consistent in showing that the impact of energy prices on food prices becomes more amplified after the breakpoint in January 2022.

We observe varying impacts of energy price changes across different food commodities. While wheat and rice prices increased 18 months after energy price changes, meat prices remain largely unaffected, except after the breakpoint in the food prices. Our analysis uncovers a unique trend in food price adjustments: Price increases predominantly take place in February and July, contributing to 68% of the total increase. Following the breakpoint in food prices, these two months account for an even larger share of the overall food price surge, rising to 76%.

Keywords – Energy prices, Food prices, Structural breaks

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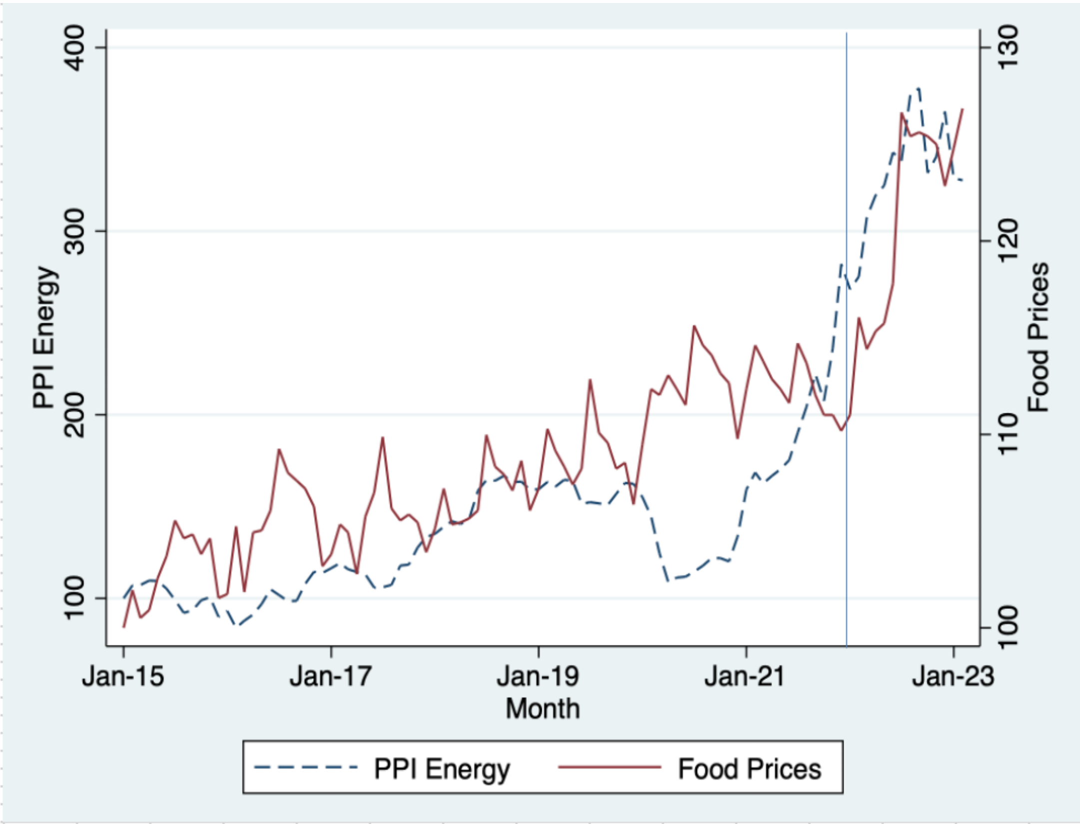
1 Introduction

Figure 1.1: Food prices and producer prices for energy



Source: (SSB, 2023)

In this paper, we explore the impact of energy prices on food prices in Norway from 2015 to 2023. Our primary focus is to find the impact of large energy spikes on food prices, especially after a break in food prices occured in January 2022.

By using models known as Ordinary Least Squares (OLS), Autoregressive (AR(1)) and the Cochrane-Orcutt model, we have found an interesting pattern: changes in energy prices seem to take about 18 months to affect food prices in Norway. To put it simply, based on the findings from the AR(1) model, if energy prices rise by 10%, food prices rise approximately by 0.59% over a year and a half later. The Cochrane-Orcutt model says the opposite, indicating no effect of the 18th lag of energy prices on food prices.

However, we notice something different happening after January 2022. Following this date, every 10% increase in energy prices led to a greater increase in food prices, somewhere between 1.17% to 1.38%. This suggests that the relationship between energy prices and food prices changed after this point, with energy prices having a greater impact on food prices.

By using the same method we used before – looking at the effect of energy prices 18 months later – we were also able to see how commodities individually respond to changes in energy prices.

For wheat, it appears that if energy prices increase by 10%, we can expect wheat prices to rise by about 1.21% a year and a half later. Interestingly, after the breakpoint (January 2022), this impact of energy prices on wheat prices seemed to strengthen, with the same 10% increase leading to a substantial 4.8% rise in wheat prices in the long run.

Meat tells a slightly different story. Changes in energy prices did not seem to significantly affect meat prices 18 months later. But, after the breakpoint in food prices, we did see that high energy prices did have a more pronounced effect on meat prices. Specifically, following the breakpoint, an escalation of 10% in energy prices translates into a 1.71% increase in meat prices 18 months later.

Lastly, we studied rice. Similar to wheat, a 10% increase in energy prices results in a roughly 1.16% increase in rice prices after 18 months. However, unlike wheat, the impact of energy prices on rice prices did not intensify notably in the period after the breakpoint in food prices.

Moreover, through our analysis, we discover a significant disparity in monthly changes of food prices, with February and July accounting for approximately 68% of the price increases - a calculation that excludes any decrease in prices. Interestingly, these two months alone account for 76% of the annual price increases after the breakpoint in food prices.

1.1 Motivation for topic

Following the global financial crisis, there was a significant increase in food prices worldwide, sparking interest in the study of food prices (Mittal, 2009). In light of the COVID-19 pandemic, as well as the war between Russia and Ukraine (Ukraine war), this topic has become even more popular, as these crises have disrupted global supply chains and led to escalations in food prices. As a result, researchers have delved into various factors that cause changes in food prices, and one critical area of investigation has been the impact of energy resources.

As the global economy undergoes rapid transformations, understanding the relationship between energy prices and food prices is crucial for effective policymaking and market stability. In the Norwegian context, this relationship has not been extensively explored, especially when considering the effect of sudden shifts in energy prices. While Statistics Norway has conducted research in this area, the involvement of other actors has been relatively scarce. This study aims to fill this gap by providing empirical evidence on the impact of energy price rises on food prices before and after the significant rise in food prices in January 2022.

1.2 Research question

Given the observed significant rise in energy and food prices in Norway, this study aims to address the following research question:

"What is the relationship between changes in energy prices and changes in food prices in Norway? Is this relationship affected by the breakpoint in food prices? What impact do energy prices have on wheat, rice, and meat before and after the breakpoint?"

To answer this question, the study will use monthly data from Statistics Norway (SSB). Further, we will conduct an empirical analysis focusing on key aspects such as establishing a connection between energy and food prices in Norway using econometric techniques like regression analysis. Moreover, we will investigate the seasonality of these price changes, as well as how the increases in energy prices in recent times influence the specific months during which food prices tend to fluctuate.

1.3 Outline

The thesis is organized in the following way:

II. Literature Review

This section explores the existing body of research on the connection between energy and food prices, focusing on topics such as the long-term drivers of food prices, the effects of energy prices on food prices, and the relationship between energy and food prices during high volatility periods. Furthermore, we also review literature on price adjustments.

III. Background

In this part, we introduce the Consumer Price Index (CPI) and provide a detailed explanation of the food and energy markets.

IV. Data

Here, we include the sources and characteristics of the data on food and energy prices.

V. Methodology

In this section, we present our analytical approach, justifying structural breaks and the selected model. We also discuss potential issues, such as autocorrelation, stationarity and heteroscedasticity, and the techniques we use to handle them. Lastly, we introduce models for selected food commodities.

VI. Analysis

This section presents the empirical findings of our research, exploring the relationship between energy and food prices in Norway. We also investigate the factors contributing to price fluctuations and seasonality.

VII. Discussion

In the final section, we summarize the main findings of our study, emphasizing their significance and limitations. We also suggest areas for future research to deepen the understanding of the connection between energy and food prices.

2 Literature Review

2.1 Effects of energy prices on food prices

To the best of our knowledge, the most comprehensive study on the drivers of food prices is conducted by Abbott et al. (2008). They examined 25 studies that investigated the factors that influence food prices. They argued that energy costs, particularly those associated with oil, have a direct impact on the cost of agricultural production, and consequently, food prices. They pointed out that energy costs affect the price of fertilizers and the operation of agricultural machinery, in addition to influencing the cost of processing and transporting food.

Supporting this perspective, Baffes and Dennis (2013) studied what impacted the prices of maize, wheat, rice, soybeans, and palm oil in the period from 1960 to 2012. The findings from the study suggest that crude oil prices were a significant contributor to the observed price hikes, accounting for over 50% of the increases, crude oil prices mattered most during the boom in the prices in 2007. This further emphasizes the link between energy resources and food prices, identifying energy prices as long-term drivers of food prices.

A study by Esmaeili and Shokoohi (2011) linked crude oil prices to food prices. Using a principal component analysis of eggs, meat, milk, oilseeds, rice, sugar and wheat against macroeconomic variables, they discovered that crude oil prices indirectly impact food prices through their influence on the food production index. This finding sets a premise that energy resources, particularly oil, can indirectly shape food prices.

However, according to a more recent study conducted by Roman et al. (2020), the authors argue that the linkage between crude oil prices and food commodities is more direct. Their empirical findings uncovered long-term relationships between crude oil prices and meat prices, alongside short-term linkages with other food commodities. Interestingly, this interpretation contrasts with Baumeister and Kilian (2014) who, despite acknowledging a linkage, found that oil price shocks had negligible impact on US retail food prices. They propose that the impact of oil prices is filtered through other macroeconomic determinants rather than a direct pass-through mechanism.

2.2 The role of biofuels in food and energy markets

As the world tries to fight climate change and reduce its reliance on fossil fuels, the switch to more sustainable energy sources like biofuels has become more popular. Biofuels are derived from organic materials such as plants or animal waste, and have gained significant popularity due to their renewable nature and the potential to lower greenhouse gas emissions (Demirbas, 2009). However, this shift has also brought about consequences, most notably the impact on food prices due to the increasing demand for biofuels.

The relationship between biofuels, food, and energy markets has been comprehensively explored in various studies. Serra and Zilberman (2013) conducted an extensive review of the rapidly growing biofuel-related time-series literature, examining the data used, the modeling techniques, and the main findings of this literature. 20 of the studies reviewed found that energy prices, which are affected by biofuel production, have an impact on the long-term trend of agricultural prices, while 13 of the studies discovered the opposite.

Moreover, Abbott et al. (2008) found that oil price changes have an impact on food through biofuels. As oil prices increase, biofuels become more attractive as an alternative energy source, which increases the demand for biofuel feedstocks such as corn and sugarcane. This increased demand results in higher prices for these agricultural commodities. Chakravorty et al. (2015) did similar findings, proposing that an increase in the use of agricultural commodities for biofuel production can exert upward pressure on food prices. Similarly, Mitchell (2008) found that EU and US biofuel policies, particularly those that promote the use of crops for biofuel production, contribute to increased food prices by heightening the demand for these crops.

Lastly, the work of Baier et al. (2009) contributes an innovative tool for understanding the impact of biofuels on crop and food prices. They have created an interactive spreadsheet that allows users to change various assumptions to see how changes in factors such as country, time period, supply and demand elasticity, and the size of indirect effects impact the estimated effect of biofuels production on prices. Their analysis suggests that the increase in biofuels production has had a significant impact on specific crops like corn, sugar, barley, and soybeans, but a much smaller impact on global food prices.

2.3 Energy and food prices during high volatility periods

The interplay between energy and agricultural markets has evolved over time. Tyner (2010) addressed the evolving links between these markets. According to the author, prior to 2005, there was little correlation between energy and agricultural commodity prices. However, during 2006-2008, in the wake of the ethanol boom in the United States, a significant link emerged between crude oil, gasoline, and corn prices.

In a study by Nazlioglu et al. (2013), the authors analyzed how oil prices affect the prices of certain agricultural products (like corn, soybeans, wheat, and sugar) from 1986 to 2011. They divided this period into two main parts: before the crisis (from January 1, 1986 to December 31, 2005) and after the crisis (01 January 2006–21 March 2011).

Before the crisis, changes in oil prices had a small impact on agricultural product prices. In other words, if oil prices fluctuated, the prices for corn, soybeans, wheat, and sugar stayed relatively steady. This finding is important because it shows that, during this time, food prices did not respond much to increased energy prices. However, after the crisis, the dynamics shifted. Nazlioglu et al. (2013) found that there was a clear transmission of volatility from oil prices to agricultural commodity prices. In other words, when oil prices became more volatile, it led to increased volatility in the prices of these agricultural products.

Building on this research, a study by Taghizadeh-Hesary et al. (2019) examined eight Asian economies, and found that 64% of food price variance is explained by oil price movement. Further, Tadesse et al. (2014) collected data on the nominal prices of maize, wheat, soybeans, and crude oil from the World Bank database. The authors identified a significant impact of oil price volatility on medium-term food price volatility.

In the context of the COVID-19 pandemic and the Ukraine War, this literature implies that the energy price rises could have consequential impacts on food prices. The post-COVID-19 period may have witnessed similar dynamics, with large increases in energy prices due to increased demand and the Ukraine war potentially leading to a corresponding rise in food prices. This underlines the importance of monitoring and managing energy price rises in the aftermath of significant crises, such as the COVID-19 pandemic and the Ukraine war, to mitigate its potential impact on food price stability.

2.4 Price adjustments

In the study by Rudolf and Seiler (2021), an increase in the frequency of price changes over the last decade was observed, particularly with the rise of e-commerce, with price changes more synchronized within individual stores than across different ones. Similarly, Nilsen et al. (2021) found significant synchronization of price changes within Norwegian firms, but less at an industry level, suggesting potential monopoly power or high costs associated with price changes. This is in line with the findings of Bhattarai and Schoenle (2014). They found that multi-product firms engage in frequent, synchronized, and smaller price adjustments, suggesting potential cost savings through economies of scope in menu costs. These findings emphasize the importance of considering menu costs and coordination within firms.

A fourth perspective is provided by Wulfsberg (2016), who examined Norwegian consumer prices from 1975 to 2004, covering both high-inflation periods in the 1970s and 1980s and low-inflation periods since the early 1990s. Wulfsberg's findings highlighted that during high and volatile inflation, prices changed more frequently but in smaller magnitudes, whereas in periods of low and stable inflation, prices changed less frequently but in larger magnitudes. This article is highly relevant in the aftermath of the COVID-19 pandemic because it explores how businesses adjust their prices during periods of high inflation.

Understanding the importance of price adjustments is crucial, especially considering that energy price fluctuations take time to impact food prices. Currently, we find ourselves in a period of high inflation. Based on past research, this implies that price adjustments should occur more frequently, with prices changed with lower amounts.

2.5 Gap in the literature

To the best of our knowledge, there has not been a comprehensive analysis investigating the impact of energy price fluctuations on food prices following an energy shock specifically in Norway. While numerous studies have explored this relationship in other countries, it has not been done within the Norwegian context. It is important to note that there has been limited literature examining this relationship in the aftermath of significant events such as the COVID-19 pandemic and the Ukraine war. Therefore, our research fills a critical gap in understanding the potential effects of energy shocks on food prices, providing valuable insights for policymakers, economists, and stakeholders in Norway.

3 Background

To demonstrate the recent escalation in food prices in Norway, we can analyze the increasing expense of preparing a homemade pizza. This example is particularly relevant since pizza was the most consumed meal in the country every day of the week in 2018 (NRK, 2018). By examining the provided table, which highlights the annual percentage change of crucial pizza ingredients (flour, spices and sauce, meat, vegetables, and cheese), we can gain valuable insights into this trend.

Table 3.1: Nominal prices of pizza ingridients

% Δ In NOK	**Flour**	**Sauce and Spices**	**Meat**	**Cheese**	**Vegetables**	**Pizza**
Before Covid[a]	3.48	5.60	3.28	4.89	10.92	4.20
During Covid[b]	3.96	5.78	4.86	5.34	8.30	4.72
After Covid[c]	26.55	7.10	20.34	9.40	12.66	20.21

[a] Jan 2015 - Dec 2019 [b] Dec 2019 - May 2021 [c] May 2021 - Feb 2023

Assumptions: Flour: 50% Sauce and Spices: 5% Meat: 20% Cheese: 20% Vegetables: 5%

Source: (SSB, 2023a)

The table shows that the annual change in ingredient prices before and during the COVID-19 pandemic is relatively consistent. However, after the pandemic (assumed to be post-May 2021), the prices of these ingredients increased significantly, causing the homemade pizza price to rise by 20.21%. The table specifically highlights that meat and flour have experienced the most substantial growth of the ingredients needed to make a standard pizza.

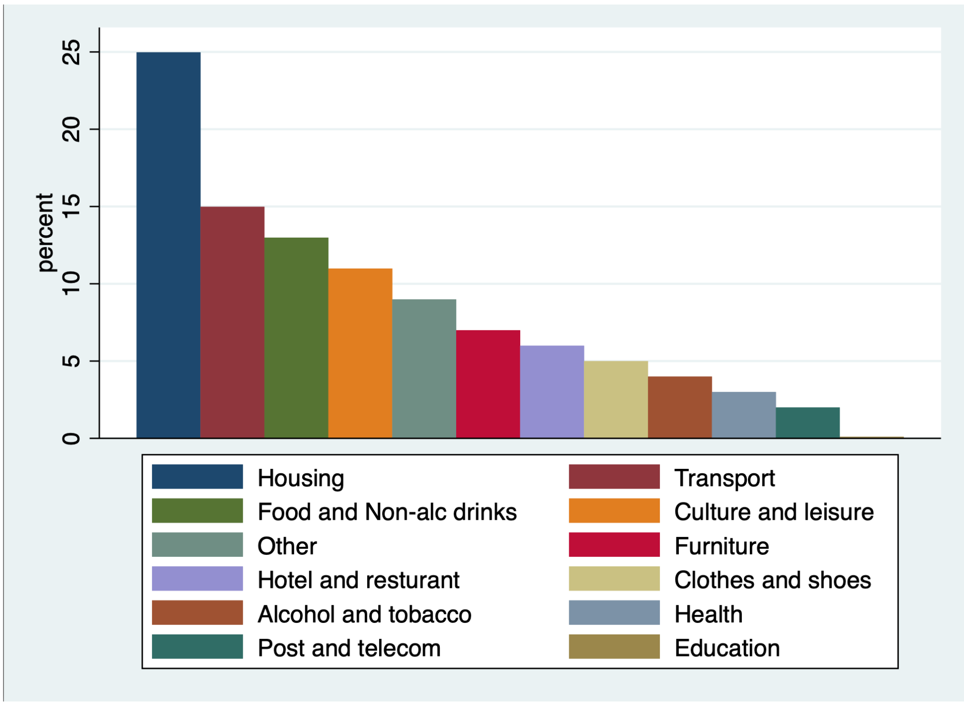
The broader implications of rising food prices on the Norwegian economy and households are large. For households, increased food prices can lead to reduced purchasing power, forcing families to allocate a larger portion of their income towards food expenses. This, in turn, can lead to reduced expenditure in other areas, such as leisure activities or healthcare. Moreover, lower-income households are disproportionately affected by rising food prices, as they spend a higher percentage of their income on food.

At the macroeconomic level, rising food prices can contribute to increased inflation rates, affecting the overall stability of the economy. High food prices may also put pressure on the government to intervene with subsidies or price controls, which can further strain public budgets (Sand and Støholen, 2008).

3.1 CPI

The Norwegian Consumer Price Index (CPI) represent a critical measure of inflation and cost of living for households in Norway. The CPI is based on a comprehensive basket of goods and services consumed by households, with weights assigned to each item based on its relative importance in the average household's expenditure (SSB, 2023). The product category of food and non-alcoholic beverages makes up nearly 13 percent of the total Consumer Price Index, as observed by Figure 3.1. This significant percentage highlights the importance of food and non-alcoholic beverages within the consumer market, as well as their influence on the general cost of living.

Figure 3.1: Weights of CPI in percent



Source: SSB, 2023

3.2 Food market

The food market in Norway is characterized by a well-developed and competitive landscape, catering to the needs of a population that values quality and sustainability. This market is dominated by a few major players such as NorgesGruppen, Coop Norge, and REMA 1000 (Dagligvarehandelen, 2023). Norwegian consumers exhibit a strong preference for local and organic products, which has led to a surge in demand for eco-friendly and health-conscious products (Forbrukerrådet, 2021). Furthermore, Litleskare and Hagen (2022) discovered that during and after the COVID-19 pandemic, the market has adapted to shifting consumer preferences and technological advancements by adopting digital solutions and online shopping. Additionally, the study reveals that Norwegians now shop less frequently, often opting for weekly shopping trips.

Suppliers can adjust their prices to food retailers twice a year in Norway (February 1st and July 1st), based on changes in their costs, which often affect in-store prices for food in these months. The prices of fresh products, such as berries, fruits, vegetables, wild fish, and meat, change more frequently due to seasonal variations, weather, catch, or other external factors (Dagligvarehandelen, 2023).

3.3 Energy market

Through the EEA Agreement, Norway is a part of the EU's internal energy market (Regjeringen, 2021). The EEA agreement is an international agreement that guarantees equal rights and obligations within the Internal Market for individuals and economic operators in the EEA (European Free Trade Association, 2021). Norway, a country rich in natural resources, plays a significant role in the global energy market. As one of the largest producers and exporters of oil in World (Aizarani, 2023), it contributes significantly to meeting the world's energy demands. Hydropower also plays a vital role in Norway's energy landscape, as it accounts for over 90% of the country's electricity production (Statkraft, 2023), making it one of the world's largest hydropower producers.

Kuik et al. (2022) provide an in-depth examination of the relationship between energy price developments and consumer prices after the COVID-19 pandemic and the Ukraine war. The authors highlight that the pandemic led to disruptions in energy markets, with oil prices experiencing a sharp decline in early 2020 before rebounding to pre-pandemic levels later in the year. The recovery in oil and gas prices during 2020 was driven primarily by the rebound in economic activity and energy demand following the first wave of the pandemic. Moreover, the war in Ukraine has caused energy prices to increase and become unstable. Since Europe depended a lot on Russia for energy before the conflict, it faced serious challenges. Following the invasion, sanctions reduced the supply of oil and gas, thereby causing a rise in these commodities (Adolfsen et al., 2023). This has also affected the cost of electricity in Europe. The situation remains uncertain and continues to influence energy prices.

3.4 Theory behind the impact of energy prices on food prices

The relationship between energy and food prices can be better understood by examining the underlying economic theories. According to supply-side theory, higher energy prices directly impact food prices by increasing the cost of production (Kirikkaleli and Darbaz, 2021). As crude oil prices rise, the expenses associated with agricultural processes such as land preparation, planting, fertilizing, and transporting increase. This causes the supply curve to shift to the left, leading to higher food prices. Since agricultural production is a long-term operation, the influence of energy prices on food prices is gradual and takes time to have an effect on food prices.

On the demand side, higher energy prices can also affect food prices by increasing the demand for energy crops, which are used to produce biofuels (Serra et al., 2010). As demand for biofuels rises, farmers may allocate more land to grow energy crops, which in turn reduces the availability of land for traditional food crops. This shift can lead to an increase in the prices of grains and other food commodities (Bastianin et al., 2013; Mitchell, 2008). However, the transition from traditional crops (e.g., wheat and rice) to energy crops (e.g., corn and sugarcane) is not immediate, as farmers may face various barriers such as waiting for the new season, lack of knowledge, and insufficient machinery. As a result, the demand-side impact of higher energy prices on food prices is also observed over the long term, rather than immediately (Kirikkaleli and Darbaz, 2021).

3.5 Food prices in Norway compared to Europe

Although food prices have increased considerably in Norway in recent times, they have risen even more in other European countries. Between January 2020 and February 2023, consumer food prices in Norway experienced a growth of approximately 12%. In contrast, the average increase for all European countries during the same period was 28% (Eurostat, 2023a).[1] This comparison highlights that although food prices in Norway have risen significantly, the country has experienced a relatively lower rate of increase compared to the European average.

3.6 Exploring food price rises

Table 3.2: Summary statistics food

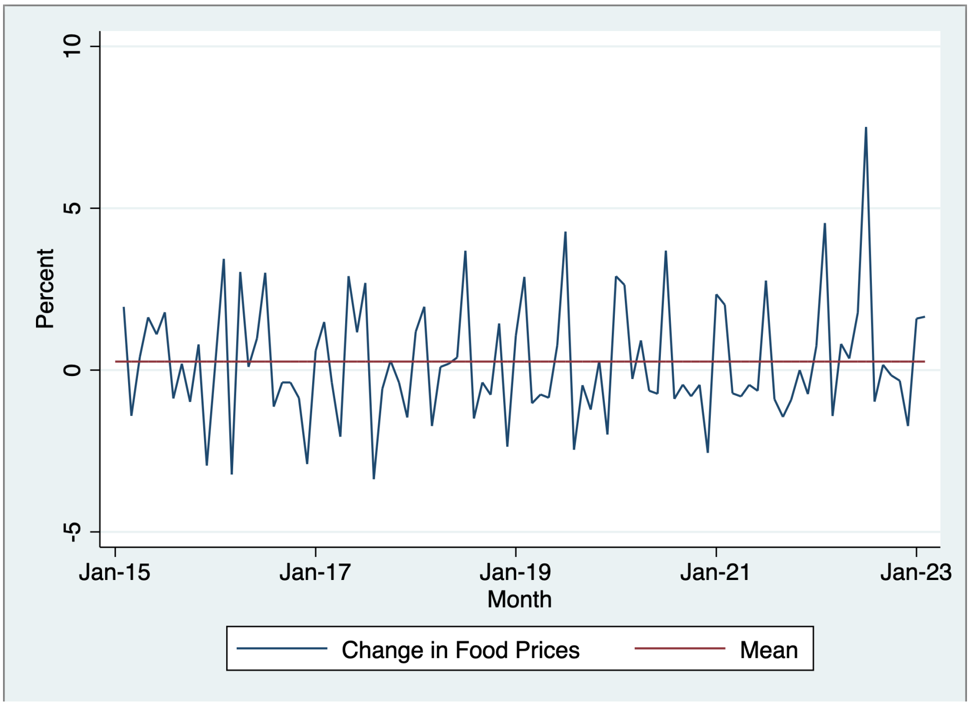
Food prices	Obs	Mean	Std. dev.	Min	Max
Before Break (Jan15-Jan22)	85	107.87	**3.84**	100	115.64
After Break (Jan22-Feb23)	13	120.92	**5.53**	111.19	126.85

The growth in food prices has experienced a significant shift in recent years, as evidenced by the change in standard deviation values before and after a specific breakpoint in the food prices (January 2022).[2] From January 2015 to January 2022, the average food price was 108.9 with a relatively low standard deviation of 3.8, reflecting a period of stable prices ranging from 100 to 115.6. However, from January 2022 until February 2023, the average price increased to about 120.9, accompanied by a higher standard deviation of 5.5. This increase in standard deviation denotes a rise in price growth. This shift highlights the growing uncertainty and unpredictability in the food market.

[1]These figures refer to consumer prices rather than the CPI-AT (Consumer Price Index Adjusted for Tax Exclusion) which further will be used in this paper, ensuring consistency with European indices. The increase in the CPI-AT for food for the same period was approximately 15%, highlighting the difference between the two measures.

[2]We will discuss the breakpoint in the food prices more in the methodology section.

Figure 3.2: Analysis of growth in monthly food prices



Source: SSB, 2023

3.7 Exploring energy price rises

Table 3.3: Summary statistics energy

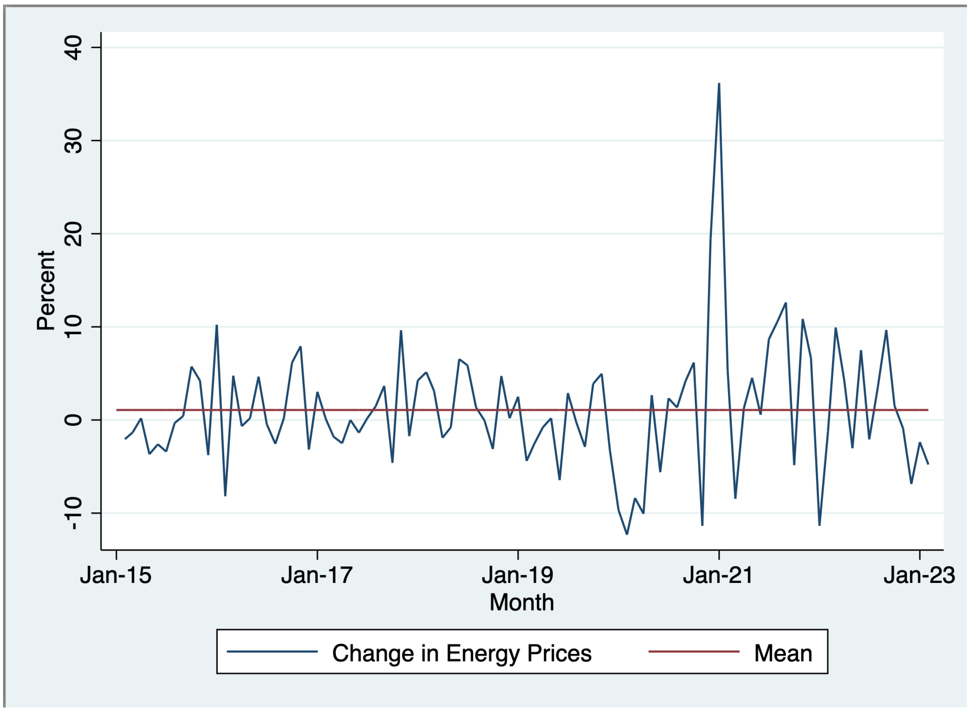
Energy price index	Obs	Mean	Std. dev.	Min	Max
(Jan15-Apr20)	64	126.20	**26.53**	83.92	166.84
(Apr20-Feb23)	34	232.97	**92.38**	111.32	377.85

The table provides summary statistics for the Energy Price Index, emphasizing the standard deviation before and after a specific breakpoint in the energy prices (March 2020).[3] From January 2015 to March 2020, the standard deviation of the Energy Price Index is 26.5, indicating a certain level of variability around the average. However, there is a significant increase in the standard deviation in the next period, from March 2020 to February 2023, where it rises to 92.4.

In conclusion, the summary analysis reveals a significant upward trend in both energy prices and food prices following the breakpoints. Due to this escalation in energy prices,

[3]We will discuss the breakpoint in the energy prices more in the methodology section.

Figure 3.3: Analysis of Growth in monthly energy prices



Source: SSB, 2023

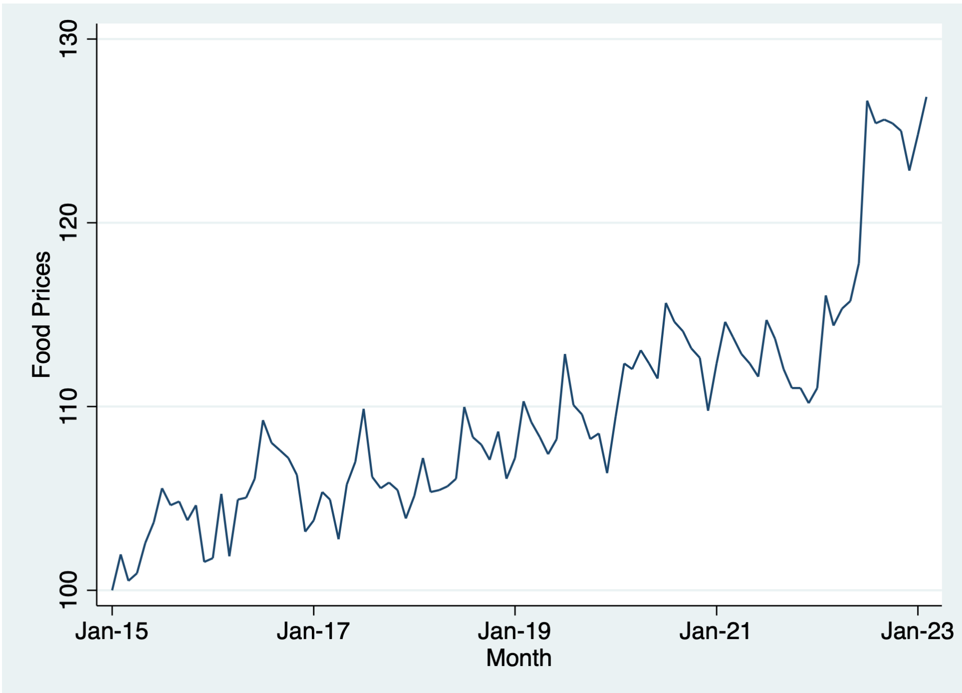
it is reasonable to infer that it has been a crucial factor contributing to the surge in food prices.

4 Data

We examine food and energy data obtained from Statistics Norway (SSB). The data ranges from January 2015 through February 2023 and is presented with a monthly frequency. All the indices used in this dataset have been set to be equal to 100 in January 2015. This standardization process ensures that all indices share a common starting point, allowing for meaningful analysis of their relative changes and growth patterns throughout the study period.

4.1 Food prices

Figure 4.1: Food prices



Source: (SSB, 2023b)

We are using food prices specifically from the Consumer Price Index adjusted for tax changes (CPI-AT). Since the CPI-AT has been adjusted for tax changes, it allows for a more accurate analysis of the relationship between energy and food prices, providing a more isolated effect without any confounding influences from fluctuations in tax adjustments.

4.2 Production prices of energy

Figure 4.2: Energy prices

Source: (SSB, 2023c)

When estimating the effect of energy prices on food prices, it is generally more appropriate to use energy prices from the Producer Price Index (PPI) rather than the Consumer Price Index (CPI). The reasoning behind this choice lies in the different perspectives these indices represent in the economy.

The Producer Price Index (PPI) measures the average change in prices that producers receive for their output (SSB, 2023c). It includes the prices of energy goods at different stages of production, such as crude oil, refined petroleum products, and electricity. Using PPI data for energy prices allows us to capture the cost of energy as a production input. Since energy is an essential input in the production and transportation of food, changes in energy prices can directly influence food prices through increased production and transportation costs (Abbott et al., 2008).

On the other hand, the Consumer Price Index (CPI) measures the average change in prices paid by consumers for a fixed basket of goods and services, including energy goods for household consumption. While CPI data reflects the prices consumers pay for energy, it does not directly account for the cost of energy used in the production and transportation of goods (SSB, 2023b).

4.3 Justification for independent variables

Understanding food prices can be complicated because many factors can play a role. Several studies have included different independent variables. For example, when Baffes and Dennis (2013) investigated what drove food prices, they used exchange rates, interest rates and GDP together with the oil price as independent variables. Contrarily, Nazlioglu and Soytas (2012) followed a different approach in their research. They made a conscious choice to keep their model relatively simple and did therefore only had the oil price as the only independent variable, much like our own approach. Rather than using oil prices, we have decided to employ energy prices. As energy prices in general include a larger variety of energy sources, it could be more reflective of current market conditions than a model that only accounts for oil prices.

We considered including the I44-index, but decided to exclude it from the regression after determining that the variable, in addition to its lags, was not statistically significant and had little effect on the other variables. Also, by avoiding too many right-hand variables, we can lower the probability of overfitting and biased estimates. The danger of overfitting in regression analysis is that it can lead to misleading interpretations of the data. Including too many variables can result in unstable estimates of the regression coefficients and difficulty in interpreting the effects of variables (Wooldridge, 2019).

5 Methodology

5.1 Justification for break points

We have a hypothesis that there are structural breaks in the energy and food prices, as both have experienced sharp increases in recent times. Our objective is to identify these structural breaks. The motivation for doing so lies in the potential to isolate a specific breakpoint for in-depth analysis. We can then explore if changes in energy prices have had a more pronounced impact on food prices subsequent to this point. This approach could provide a more nuanced understanding of how rises in energy prices translate into changes in food prices under unique global circumstances, such as COVID-19 and the Ukraine war. In addition, we want to find the 'response gap' - the delay between changes in energy prices and subsequent changes in food prices.

In order to detect structural breaks in the energy and food prices, we employ a technique outlined by Hansen (1999).

5.1.1 Least squares estimation

We want to find the specific parameter value, represented as γ, that minimizes the sum of squared residuals in our model. This is a form of least squares optimization, where $\hat{\gamma}$ are denoting the point of a structural break in the price series. This process is mathematically represented as follows:

$$\hat{\gamma} = \arg\min_{\gamma} S_1(\gamma) \tag{5.1}$$

The symbol $\hat{\gamma}$ is the time where the sum squared residuals are the least. $S_1(\gamma)$ is used to denote the sum of squared residuals for a given γ.

5.1.2 Testing the significance of the breaks

After finding the γ that gives the least squares, we can now test the significance of the break using an F-test. The value from the F-test serves as a comparative measure of the goodness-of-fit between two distinct models - one which includes the estimated threshold (equations (5.6) and (5.7)) and one which does not (equations (5.4) and (5.5)). The intent behind this comparison is to identify a statistical value that we can compare with a critical value to determine the statistical significance of the estimated threshold. If the F-value exceeds the critical value, we have evidence suggesting that the model with the structural break significantly improves the explanatory power of our model. The F-value is defined by:

$$F_1 = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2} \tag{5.2}$$

The denominator, $\hat{\sigma}^2$ is the estimated variance. $n-k$ is the degrees of freedom. $\hat{\sigma}^2$ can be written as:

$$\hat{\sigma}^2 = \frac{S_1(\hat{\gamma})}{n-k} \tag{5.3}$$

To find S_0 we need to run regressions without allowing for a structural break. This forms the baseline models (equations (4) and (5)) and provides the sum of squared residuals (SSR) when no break is assumed.

$$\text{FoodPrices}_t = \alpha + \beta_1(t - \mathrm{t}_0) + \sum_{i=2}^{12}(\beta_i \times D_{M_i}) + \epsilon_t \tag{5.4}$$

$$\text{EnergyPrices}_t = \alpha + \beta_1(t - \mathrm{t}_0) + \sum_{i=2}^{12}(\beta_i \times D_{M_i}) + \epsilon_t \tag{5.5}$$

Next, we estimate models that allow for a structural break at a specific time point (equations (6) and (7)). These models incorporate an interaction variable denoting a structural break, thus allowing the slope of the time trend to change. For the energy prices, we are also allowing for a change in the constant as we observe a significant drop in April 2020. The sum of squared residuals (SSR) derived from these regressions represents the minimum SSR in our analysis, denoted as $S_1(\hat{\gamma})$.

$$\text{FoodPrices}_t = \alpha + \beta_1(t - \mathrm{t}_0) + \beta_2(t - \hat{\gamma}) \cdot D(t \geq \hat{\gamma}) + \sum_{i=3}^{13}(\beta_i \times D_{M_{i-1}}) + \epsilon_t \tag{5.6}$$

$$\text{EnergyPrices}_t = \alpha + \beta_1(t - \mathrm{t}_0) + \beta_2(D(t \geq \hat{\gamma})) + \beta_3(t - \hat{\gamma}) \cdot D(t \geq \hat{\gamma}) + \sum_{i=4}^{14}(\beta_i \times D_{M_{i-2}}) + \epsilon_t \tag{5.7}$$

5.1.3 Determination of asymptotic significance level

Further, we want to see whether the threshold effect is statistically significant. This can be shown as testing the following hypotheses:

- Null Hypothesis (H_0): For food prices, the null hypothesis posits that there is no threshold effect, meaning the coefficients for the periods before and after the threshold are identical, i.e., $b_1 = b_2$. For energy prices, the null hypothesis states that the slope and the constant term are the same before and after the threshold. In both cases, under H_0, the threshold γ is unidentifiable, leading to non-standard distributions in classical tests. This is often referred to as the "Davies Problem" (Davies, 1977, 1987)
- In contrast, the alternative hypothesis suggests that a threshold effect is present. For food prices, this implies that the slope changes at the threshold, with $b_1 \neq b_2$. For energy prices, a threshold effect indicates a change in the slope and/or the constant term. The threshold parameter γ becomes identifiable under H_1.

To overcome the challenge of non-standard distributions, Hansen (1999) proposes the use of critical values for testing purposes. Accordingly, we reject the null hypothesis at a particular significance level if the computed F-value is above the corresponding critical value. This critical value can be derived using the following equation:

$$c(a) = -2\log\left(1 - \sqrt{1-a}\right) \tag{5.8}$$

To assess the statistical significance of the computed F-test, we use a 5% significance level. For a significance level of 5% (i.e., $a = 0.05$), the computed critical value is approximately 7.35. This implies that if the F-value exceeds 7.35, we reject the null hypothesis of no threshold effect at the 5% significance level.

5.1.4 Establishing confidence intervals for the breakpoint

Once the statistical significance of our identified breakpoint has been stated using the F-value, we follow Hansen´s recommendation to create a "no rejection region" surrounding the breakpoint (Hansen, 1997). The establishment of this region is accomplished by employing the likelihood ratio statistic for tests on the γ parameter, also known as the breakpoint. In doing so, we allow for a certain degree of variability around the precise timing of the breakpoint.

The validity of this testing procedure is underpinned by the consistency of the estimated threshold parameter, $\hat{\gamma}$. According to Hansen (1997) and Chan (1993), $\hat{\gamma}$ is a consistent estimator of the true threshold parameter γ_0. This means that as the sample size increases, $\hat{\gamma}$ converges to γ_0.

Note that the null hypothesis for the likelihood-ratio test contrasts with that for the F_1 value. Specifically, the null hypothesis in the context of the likelihood-ratio test suggests that the points falling below the critical value represent breakpoints, while the alternative hypothesis posits that the points exceeding the critical value are not within the 95% confidence interval.

The process for constructing these intervals is dependent on the Likelihood-ratio statistic (LR_1). It uses the same critical value as calculated for the F_1 statistic. Specifically, we compute the LR_1 statistic for each potential breakpoint and plot these values together with the critical value. This gives us a visual overview of the likelihood ratio across all potential breakpoints.

The plot acts as a visual tool to identify those points where the LR_1 statistic falls below the critical value, giving the presence of potential breakpoints. This gives rise to a confidence interval, the range within which the true breakpoint is likely to be located.

The LR_1, is defined as:

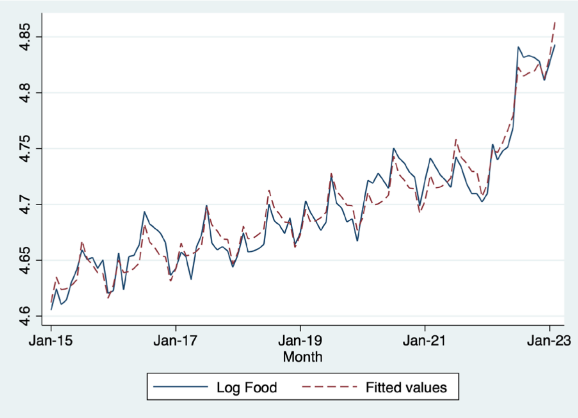
$$LR_1 = \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2} \tag{5.9}$$

Where $S_1(\gamma)$ is the sum of squared residuals under each potential breakpoint, and $S_1(\hat{\gamma})$ is the sum of squared residuals under the breakpoint we found by doing the least squares estimation. $\hat{\sigma}^2$ is the estimated variance.

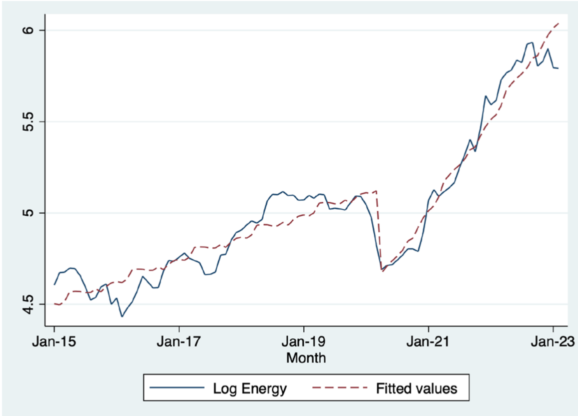
5.2 Justification for model selection

We have chosen to focus on data from 2015, Specifically, we have opted to exclude data from 2014 to avoid the effects of the significant oil price drop that occurred during that year. By excluding the data from 2014, we aim to mitigate the influence of this significant event and minimize any potential distortion it may cause in our results.

Figure 5.1: Food prices, energy prices, and fitted values



(a) Food prices and fitted values



(b) Energy prices and fitted values

In order to accurately account for time-specific factors in the data, we are developing a refined model based on the figure above, which effectively captures relevant time effects. The graph for food demonstrates an upward drift, seasonal patterns, and a distinct break in Janaury 2022. The energy prices are denoting a drop, followed by a steepening of the curve. By addressing these factors, our goal is to improve our confidence in estimating the true impact of energy prices on food prices.

In our analysis, we acknowledge the significant shift in food prices beginning in January 2022. To account for this, we include a time dummy ranging from January 2022 to February 2023. Our logic behind this is to capture some of the effect of the large rise in food prices, an effect we believe is influenced by factors other than energy prices.

If we leave out this variable, we might wrongly assume that energy prices are the only factor affecting food prices, which is not true. By adding this time dummy, we can better see how other omitted variables might also influence food prices. This way, we can be more confident and trust more on the coefficients the energy variables are giving. However, we must also consider a potential complication in this approach. There is a risk that this time dummy might absorb the entire impact of the surge in food prices. The dummy could potentially eat up the whole effect of the energy variable, as it might be overly influential in the model.

Despite this concern, we believe it is crucial to include this variable in our model. While we acknowledge the potential for it to absorb the entire influence of the energy variable, excluding it could lead to a misunderstanding of the broader economic dynamics at play.

5.3 Model

This leads us to this equation (OLS):

$$\begin{aligned}\mathrm{LogFP}_t = \alpha &+ \beta_1 \times LogEN_{t-18} + \beta_2 \times LogEN_{t-18} \times D^{2022Feb \geq t \leq 2023Feb} \\ &+ \beta_3 \times t + \beta_4 \times D^{2022Jan \geq t \leq 2023Feb} \\ &+ \sum_{i=5}^{15} (\beta_i \times D_{M_{i-3}}) + \varepsilon_t\end{aligned} \tag{5.10}$$

$LogFP_t$ is the logarithm of the food prices for time t. Further, $LogEN_{t-18}$ is the 18th lag of the energy variable. $LogEN_{t-18} \times D^{2022jan \geq t \leq 2023Feb}$ is the energy variable after the break in the food prices. t is the time variable. $D^{2022Jan \geq t \leq 2023Feb}$ is the time dummy we recently described, $\sum_{i=5}^{15} (\beta_i \times \mathrm{M}_{i-3})$ is the month dummies.

5.4 Autocorrelation

In our analysis we detect autocorrelation. To correct for this, we also employ an autoregressive model of order 1 as well as a Cochrane-Orcutt model. The autoregressive model, while bearing similarities to the ordinary least squares (OLS) method, additionally incorporates the first lag of the residuals of the food variable. On the other hand, the Cochrane-Orcutt model takes into account the autocorrelation among the residuals and goes a step further to apply a transformation that addresses autocorrelation across the complete series of error terms, as discussed in Wooldridge (2012).

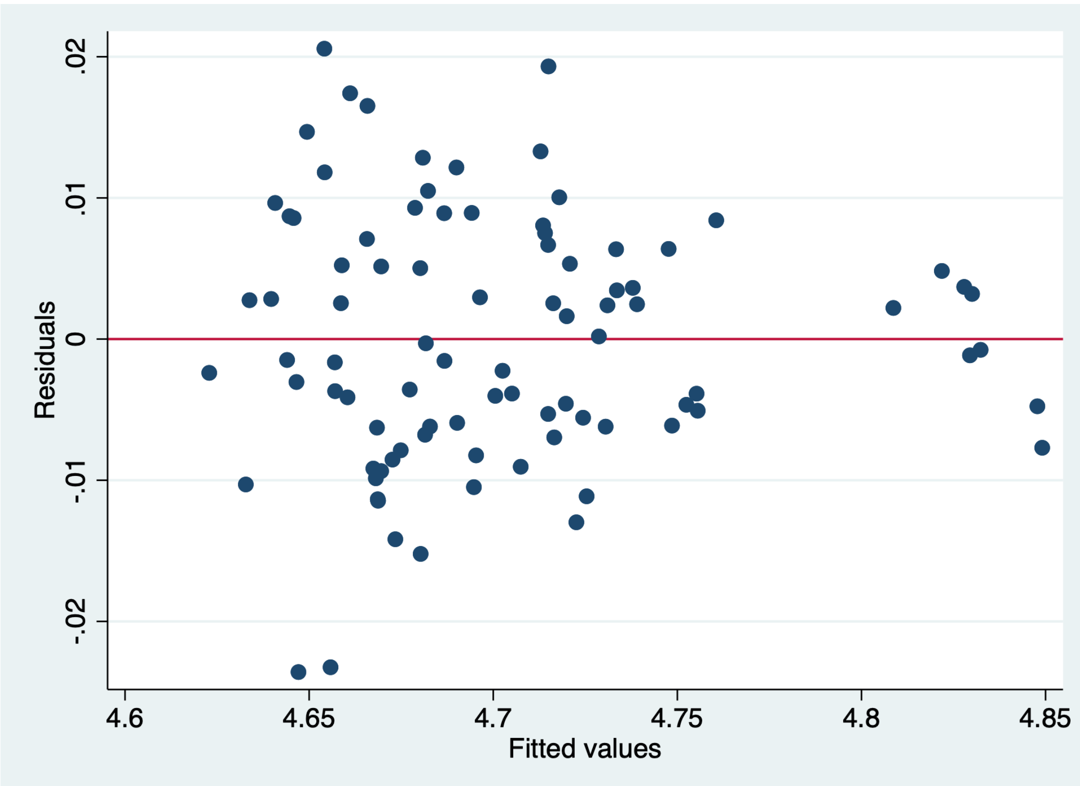
5.5 Stationarity

We acknowledge that taking the first difference can make the variables in our dataset stationary, eliminating trends and seasonality from the data. However, in our analysis, we rather include different time variables and seasonal dummies to investigate the effect of energy prices on food prices before and after the break. By doing so, we can gain insights into how these patterns change over time and across seasons.

Furthermore, when we exclude the dummy denoting the large rise in food prices from January 2022 - February 2023, the residuals of the regression do not appear to be stationary. However, the situation changes when we incorporate the dummy variable. When we then perform the Engle-Granger test, the results indicate cointegration. To determine the appropriate lag structure for the ADF test on the residuals, we use the Akaike Information Criterion (AIC) (Bozdogan, 1987).

5.6 Heteroskedasticity

Figure 5.2: Residuals versus fitted



Source: Statistics Norway, 2023

In Figure 5.2, we observe a potential indication of heteroskedasticity, as the residuals appear to be moving closer to the red line as the fitted values increase.

We failed to reject the null hypothesis of the Breusch-Pagan test, which indicates the presence of heteroskedasticity, it is essential to address this issue in our analysis (Breusch and Pagan, 1979). To account for heteroscedasticity, we are using robust standard errors in the models.

5.7 Commodities

This research also aims to investigate the impact of energy prices on the prices of rice, meat, and wheat, which are essential components of global food security. By understanding the relationship between energy prices and the prices of these commodities, a more comprehensive insight into the consequences of energy price fluctuations on food markets can be attained.

We detect autocorrelation in the OLS model for rice and meat, but not for wheat. We are therefore employing the AR(1) model for rice and wheat, while using an OLS model for wheat.

The regression for rice is:

$$\begin{aligned}\text{LogRice}_t = \alpha &+ \beta_1 \times LogEN_{t-18} + \beta_2 \times LogEN_{t-18} \times D^{2022Feb \geq t \leq 2023Feb} \\ &+ \beta_3 \times t + \beta_4 \times D^{2022Jan \geq t \leq 2023Feb} \\ &+ \beta_5 \times LogRice_{t-1} + \sum_{i=6}^{16} (\beta_i \times D_{M_{i-4}}) + \varepsilon_t\end{aligned} \tag{5.11}$$

The regression for meat is:

$$\begin{aligned}\text{LogMeat}_t = \alpha &+ \beta_1 \times LogEN_{t-18} + \beta_2 \times LogEN_{t-18} \times D^{2022Feb \geq t \leq 2023Feb} \\ &+ \beta_3 \times t + \beta_4 \times D^{2022Jan \geq t \leq 2023Feb} \\ &+ \beta_5 \times LogMeat_{t-1} + \sum_{i=6}^{16} (\beta_i \times D_{M_{i-4}}) + \varepsilon_t\end{aligned} \tag{5.12}$$

The regression for wheat is:

$$\begin{aligned}\text{LogWheat}_t = \alpha &+ \beta_1 \times LogEN_{t-18} + \beta_2 \times LogEN_{t-18} \times D^{2022Feb \geq t \leq 2023Feb} \\ &+ \beta_3 \times t + \beta_4 \times D^{2022Jan \geq t \leq 2023Feb} \\ &+ \sum_{i=5}^{15} (\beta_i \times D_{M_{i-3}}) + \varepsilon_t\end{aligned} \tag{5.13}$$

6 Analysis

6.1 Detection of structural breaks

We are now assessing the statistical significance of structural breaks in the food and energy prices, as well as determining the 95% confidence intervals around the breaks. According to the least squares estimation, the lowest SSR for energy prices is in April 2020, while the lowest SSR for food prices is in January 2022. We are proceeding with these breakpoints.[4]

6.1.1 F-Test for energy prices

For the energy prices, we get a F-value of

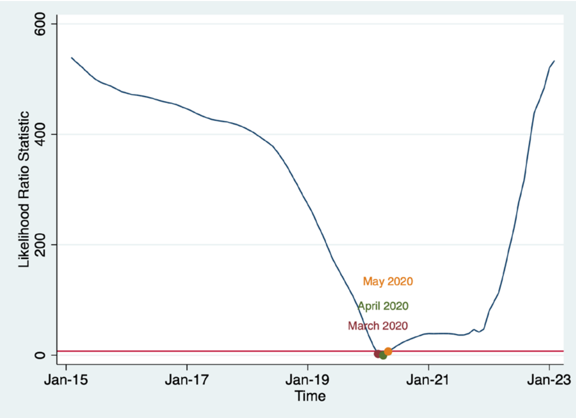
$$F_1 = \frac{202,262 - 42,072}{42,071/(98-14)} = 320 \tag{6.1}$$

As the F-value of 320 exceeds the critical value of 7.35 at the 5% significance level, we find strong evidence to reject the null hypothesis. This result indicates that it exists a difference in the slope, as well as the constant before and after the threshold, affirming the presence of a structural break in the energy prices, specifically in April 2020.

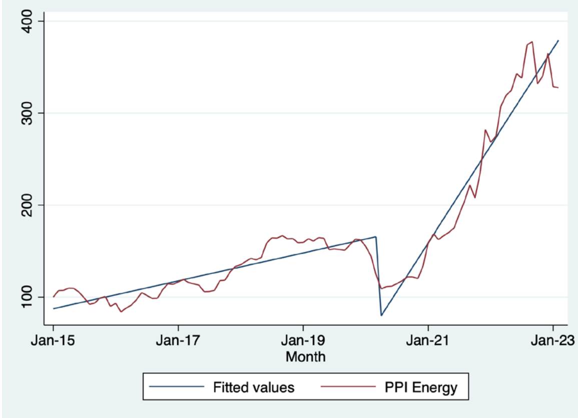
[4]We program a loop in the statistical software Stata, performing 98 separate regressions. Throughout this process, we collect and store each SSR. The value with the smallest SSR is then identified, indicating the point of a structural break in the price series.

6.1.2 Confidence interval around break point

Figure 6.1: Likelihood-ratio plot and fitted values (energy)



(a) Likelihood-ratio plot



(b) Fitted values

What we want to find now, is the confidence interval around the breakpoint.[5] The null and the alternative is slightly different now.

The null hypothesis asserts the presence of breakpoints if the likelihood ratio (LR_1) falls below the critical value of 7.35. Conversely, the alternative hypothesis posits the absence of breakpoints if the LR_1 exceeds 7.35.

From the likelihood-ratio plot for energy prices seen in Figure 6.1, we observe that the minimum value corresponds to April 2020. Consequently, we will refer to April 2020 as the point of the structural break in energy prices. The confidence interval around the break in energy prices ranges from March 2020 until May 2020, meaning that with 95% probability, the break appears to be in one of those months. Furthermore, examining the fitted values, it is evident that there is a change in the constant, as well as the slope after the breakpoint. The trend before April 2020 is followed by a drop in the curve, which then is followed by a steepening of the curve, indicating a more rapid upward drift in energy prices.

6.1.3 F-test for food prices

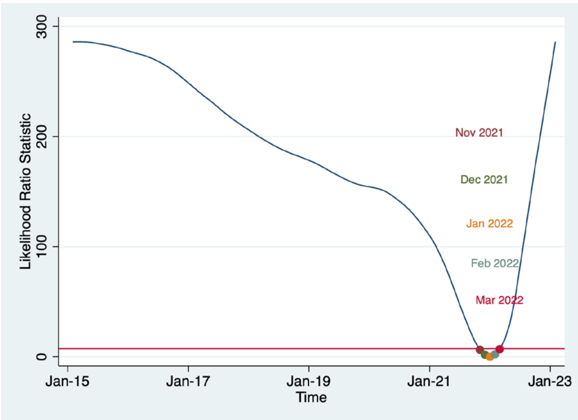
$$F_1 = \frac{689 - 172}{172/(98 - 13)} = 255 \tag{6.2}$$

[5]We also programmed a loop to find the confidence interval. We collected and stored each likelihood ratio (LR_1) such that we could make the plot in Figure 6.1 and Figure 6.2.

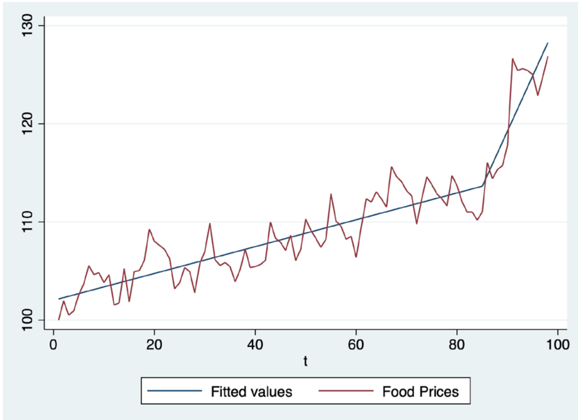
Similar to the energy prices, we observe a substantial F-value of 255 for the food prices. This value is significantly greater than the critical value of 7.35 at the 5% significance level. This large F-value provides us with evidence to reject the null hypothesis of no threshold effect for food prices. Therefore, we can confidently state that there is a statistically significant structural break in the food price data, specifically in January 2022.

6.1.4 Confidence interval around break point

Figure 6.2: Likelihood-ratio plot and fitted values (food)



(a) Likelihood-ratio plot



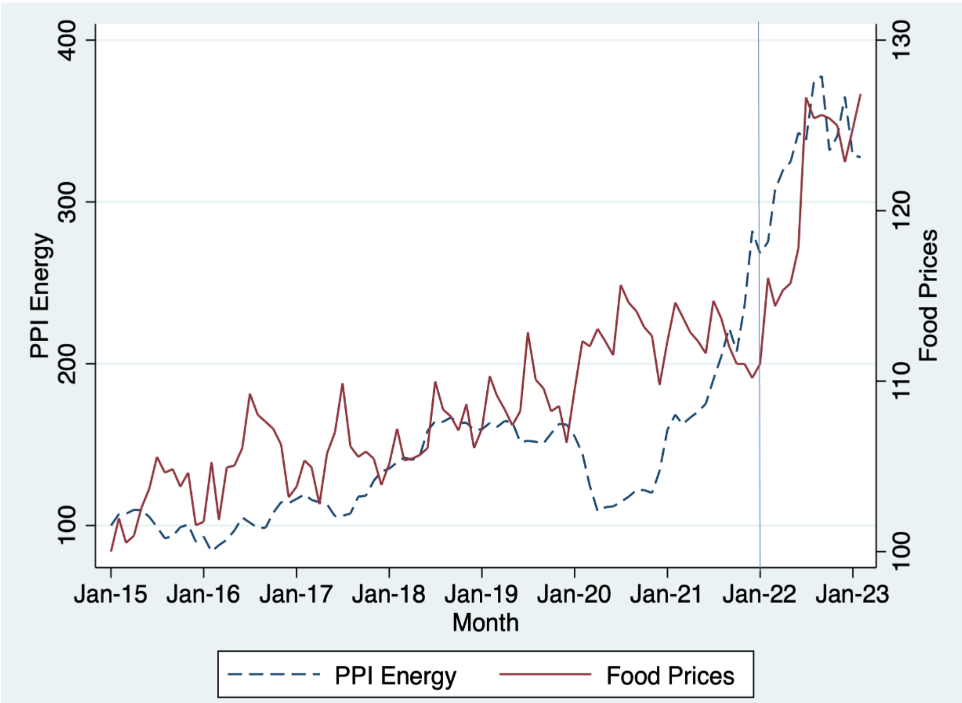
(b) Fitted values

Analyzing the likelihood-ratio plot for the food price regressions, we identify a distinct structural break occurring in January 2022, which we further in this thesis assume to be the break in food prices. the 95% confidence interval around the break is from November 2021 until March 2022. Specifically, we see a steeper slope after January 2022, indicating a more rapid upward drift in food prices following the break.

6.2 Empirical analysis

The central objective of this paper is to explore and uncover the effect of energy prices on food prices in Norway in recent times.

Figure 6.3: Food and energy prices



Source: (SSB, 2023)

A careful examination of Figure 6.3 reveals a stable correlation between food and energy prices in Norway from January 2015 through January 2020. However, a significant shift in this trend was observed post-January 2020, when a substantial drop in energy prices was recorded, presumably due to the COVID-19 pandemic's global economic disruptions, which affected oil prices and energy demand (Gharib et al., 2021; Kuik et al., 2022).

Notably, energy prices rebounded strongly from January 2021 to December 2022, tripling in value. Subsequently, food prices in Norway rose by 14% from January 2022 to February 2023. We are now going to determine to which extent the energy prices have been a contributor to the rise in food prices.

6.3 Lag structure

Table 6.1: Estimation results for food with different lags (in logarithm)

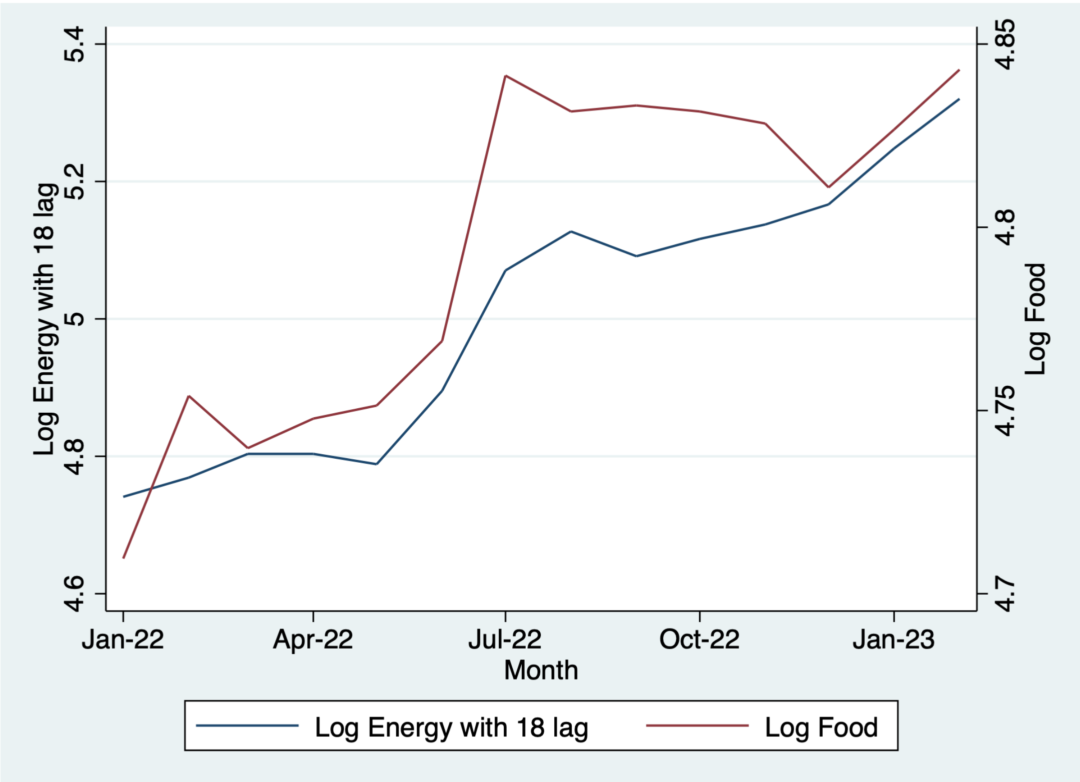
Econometric technique	(1) OLS
$LogEN_{t-3}$	-0.02 (0.018)
$LogEN_{t-6}$	-0.024 (0.018)
$LogEN_{t-9}$	-0.012 (0.017)
$LogEN_{t-12}$	0.026 (0.017)
$LogEN_{t-18}$	0.033*** (0.014)
$LogEN_{t-22}$	0.006 (0.018)
$lEN_{t-18} \cdot D_{2022m1\_2023m2}$	0.170*** (0.021)
D_{2022m1_2023m2}	-0.78*** (0.106)
t	0.001*** (0.00)
Monthly Dummies	Yes
Constant	4.521***, (0.075),
Observations	80

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Observations from January 2015 - February 2023.

First, we want to justify the lag structure used. In our initial approach, we aimed to be comprehensive and pragmatic by incorporating several temporal lags into our model. This included the 3rd, 6th, 9th, 12th, 18th, and 22nd lag of the energy variable, with the objective of understanding the latency of influence of these lags on food prices. However, upon analyzing the results, it became evident that only the 18th lag displayed statistical significance. Therefore, we removed the 3rd, 6th, 9th, 12th, and 22nd lags from our analysis, moving forward exclusively with the 18th lag in subsequent studies.

From the structural break results, we find a structural break for energy prices to be in April 2020, and for food prices in January 2022, this gap is 22 months. We are not using this lag period because of the stable period in energy prices that are occurring in the months after the break. Looking at Figure 6.3, we can see that after the break (April 2020), the energy prices follow a stable period for a couple of months before starting to spike.

Figure 6.4: Log energy prices with a lag of 18, and log food prices (after break)



Source: (SSB, 2023)

The decision to use an 18-month lag becomes even more evident when examining Figure 6.4. This figure shows a high correlation between the 18th lag of the energy prices and the food prices. As we specifically want to see how energy prices affect food prices after the breakpoint in food prices (January 2022), the figure is only showing the period from January 2022 - February 2023.

Numerous studies, implementing comparable research methodologies, have reported significantly shorter lag structures. Baffes et al. (2015) found that an 8-month lag structure was appropriate when examining the effect of oil prices on the consumer price index (CPI). Similarly, Kilian (2008) found that exogenous oil supply shocks influenced CPI inflation after approximately 9 months. In the research paper by Blanchard and Gali (2007), the authors explored the varied impact of oil shocks on the economy across different decades using quarterly data, incorporating a lag structure of four quarters in their model to account for delayed effects.

Our study employs a longer lag structure to examine the impact of energy prices on food prices, which deviates from the shorter lag structures found in prior research such as Baffes et al. (2015), Kilian (2008), and Blanchard and Gali (2007). However, these studies primarily focused on the aggregate effect on the Consumer Price Index (CPI). The food sector, on the other hand, could present a different response pattern due to industry-specific factors, such as the complexities of food supply chains (Abbott et al., 2008).

Furthermore, in the context of Norway, food stores mainly increase prices in February and July (NRK, 2023). This practice may introduce additional delays in reflecting changes in energy prices, necessitating a longer lag structure for our analysis. Empirical findings from our research also support this, revealing an 18-month lag in the transmission of energy price changes to food prices, thus backing the appropriateness of a longer lag structure.

6.4 Empirical evidence of the relationship between energy and food prices

Table 6.2: Estimation results for food (in logarithm)

Econometric technique	(1) OLS	(2) AR(1)	(3) CO
$LogEN_{t-18}$	0.053*** (0.009)	0.059*** (0.021)	0.027 (0.018)
$LogEN_{t-18} \cdot D_{2022m1\_2023m2}$	0.138*** (0.023)	0.117*** (0.038)	0.137*** (0.029)
D_{2022m1_2023m2}	-0.63*** (0.119)	-0.195** (0.094)	-0.649*** (0.140)
t	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)
$LogFood_{t-1}$		0.622*** (0.088)	
Constant	4.381*** (0.044)	1.654*** (0.388)	4.482*** (0.084)
Month Dummies	Yes	Yes	Yes
DW Estimates	0.78	1.91	1.94
ADF (5% Critical value in Parantheses)	-3.045 (-2.912)	-3.712 (-2.912)	-3.062 (-2.912)
Observations	80	80	80

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Observations from January 2015 - February 2023.
Nonlinear transformations have been applied to the
coefficients and standard errors in the AR model to compute long-run estimates.
F test shows that $LogEN_{t-18}$ and $LogEN_{t-18} \cdot D_{2022m1\_2023m2}$ together gives significant results

We are now confident with our regression models, and can now proceed to examine the results. An analysis of the regression table reveals that both the Ordinary Least Squares (OLS) and Autoregressive (AR) model of order 1 indicates a lag of 18 months in the impact of energy prices on food prices over the whole sample. In other words, these models suggest that changes in energy prices may take around a year and a half to reflect in food prices. As both the food prices and the energy prices is in log, we can interpret the results as the elasticity. Specifically, a 10% increase in the energy prices would on average lead to an 0.53% increase in the food prices if we trust the OLS, and 0,59% increase in the food prices if we trust the AR(1). However, the results from the CO model do not support this finding; it does not signal any statistically significant effect of the 18-month lag in energy prices on food prices.

Intriguingly, following the breakpoint identified in January 2022, all models uniformly exhibit statistically significant coefficients. The impact of a 10% increase in energy prices on food prices ranges from an additional 1.17% to 1.38% after the break. This means that the long-run effect of a 10% increase in the energy prices by adding the effect before and after the break, is 1,91% for the OLS, 1,76% for the AR(1), and 1,64% for the CO.

Based on the given long-run results (1.91% for OLS, 1.76% for AR(1), and 1.38% for Cochrane-Orcutt), it suggests that all three models offer somewhat different results, implying a different degree of relationship between the independent and dependent variables. However, the difference between these results seems to be small, which could suggest that the general direction of the relationship between variables remains consistent across the three models. Furthermore, as we consider the presence of autocorrelation detected in the OLS model, it becomes evident that the results from the AR(1) and CO models should hold more credibility. These models are specifically designed to correct for autocorrelation and provide a more robust analysis under such circumstances.

This suggests that when energy prices are increasing, food prices are increasing 18 months after. With the effect being even stronger after the breakpoint in food prices. This observation aligns with the study conducted by Tadesse et al. (2014) which concluded that periods of high energy price volatility tend to result in increased volatility in food prices.

These findings are insightful. They show that when energy prices rise significantly, they have a bigger impact on food prices. One plausible explanation for this is that businesses might overlook energy costs until a drastic escalation forces them to face the consequential impact on their bottom line. Moreover, the statistical significance of the 18th lag is intriguing. It underscores that it requires considerable time for shifts in energy prices to pass through the supply chain and to have effects on food prices.

Table 6.3: Estimation results for Wheat, Meat, and Rice (in logarithm)

Econometric technique	Wheat	Meat	Rice
$LogEN_{t-18}$	0.117***	0.024	0.116***
	(0.027)	(0.044)	0.032
$LogEN_{t-18} \cdot D_{2022m1\_2023m2}$	0.363***	0.171***	0.023
	(0.056)	(0.787)	(0.057)
D_{2022m1_2023m2}	-1.67***	-0.172	-0.030
	(0.245)	(0.116)	(0.175)
t	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)
$LogMeat_{t-1}$		0.766***	
		(0.088)	
$LogRice_{t-1}$			0.401***
			(0.123)
Constant	4.130***	1.045***	2.468***
	(0.120)	(0.335)	(0.494)
Month Dummies	Yes	Yes	Yes
DW Estimates	1.870	2.133	1.923
ADF (5% Critical value in Parantheses)	-3.078	-3.316	-3.872
	(-2.912)	(-2.912)	(-2.912)
Observations	80	80	80

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Observations from January 2015 - February 2023.
Nonlinear transformations have been applied to the coefficients and standard errors in the AR model to compute long-run estimates.

Building on the analysis of energy's influence on food prices, our focus expands to study the effects of energy prices on the prices of wheat, meat, and rice. By using the same 18-month lag model, we can maintain consistency in our analytical approach, while also observing how these commodities respond under similar conditions.

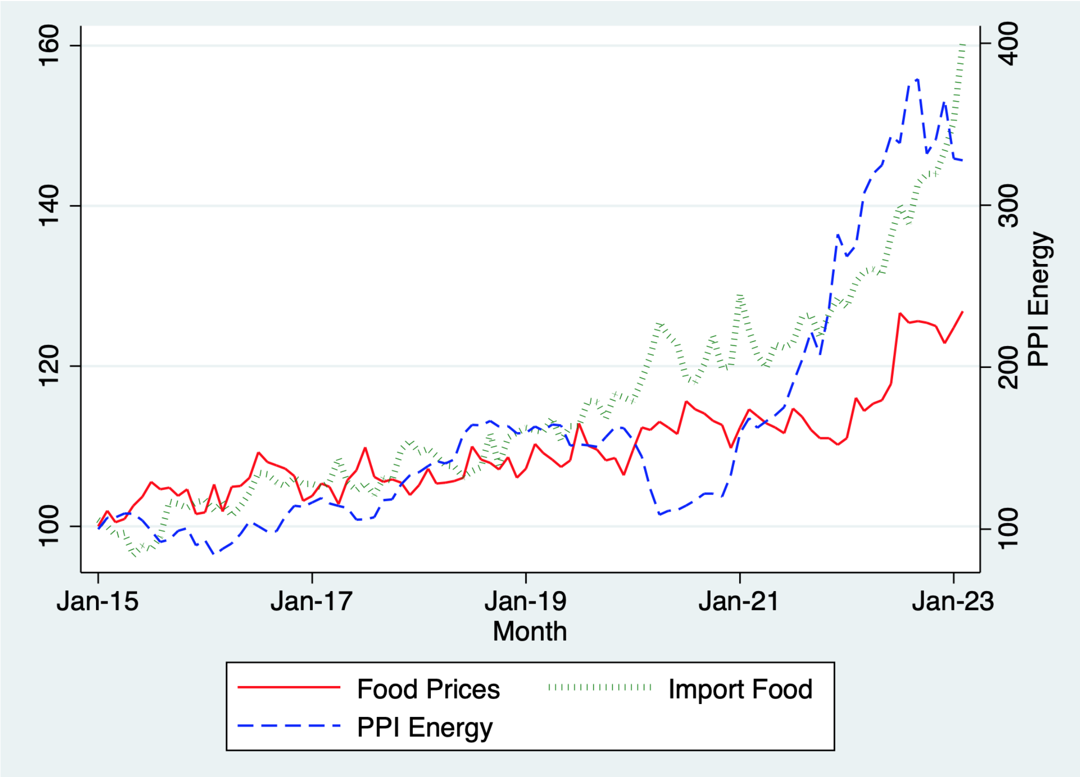
Analyzing the effect of energy prices on wheat prices, we find that a 10% increase in energy prices leads to a roughly 1.17% increase in wheat prices 18 months later. After the breakpoint, a 10% change in the 18th lag of energy prices would on average lead the wheat prices to increase by 4.8% maintaining all other conditions constant. This aligns with the insights from Nazlioglu et al. (2013) highlighting that wheat prices demonstrate increased sensitivity under conditions of heightened energy price volatility.

For meat, the 18-month lag of energy prices is not statistically significant, indicating that changes in energy prices have no effect on meat prices after 18 months. However, after the break, the interaction term is statistically significant, indicating that from January 2022 - February 2023, energy prices have an impact on meat prices. A 10% increase in energy prices after the breakpoint leads to a 1.71% increase in meat prices 18 months later.

For rice, the 18-month lag of energy prices is statistically significant with a coefficient of 0.116, suggesting that a 10% increase in energy prices is resulting in approximately a 1.16% increase in rice prices 18 months later. After the breakpoint, energy prices do not have an additional effect on food prices 18 months after. The article written by Rob Vos and Joseph Glauber (2022) suggests that the price of rice experienced a decline following the onset of the COVID-19 pandemic. This context helps explain the lack of a notable intensification in the influence of energy prices on rice prices after the breakpoint.

6.5 Comparison of prices

Figure 6.5: Food prices, import prices for food, and producer prices for food

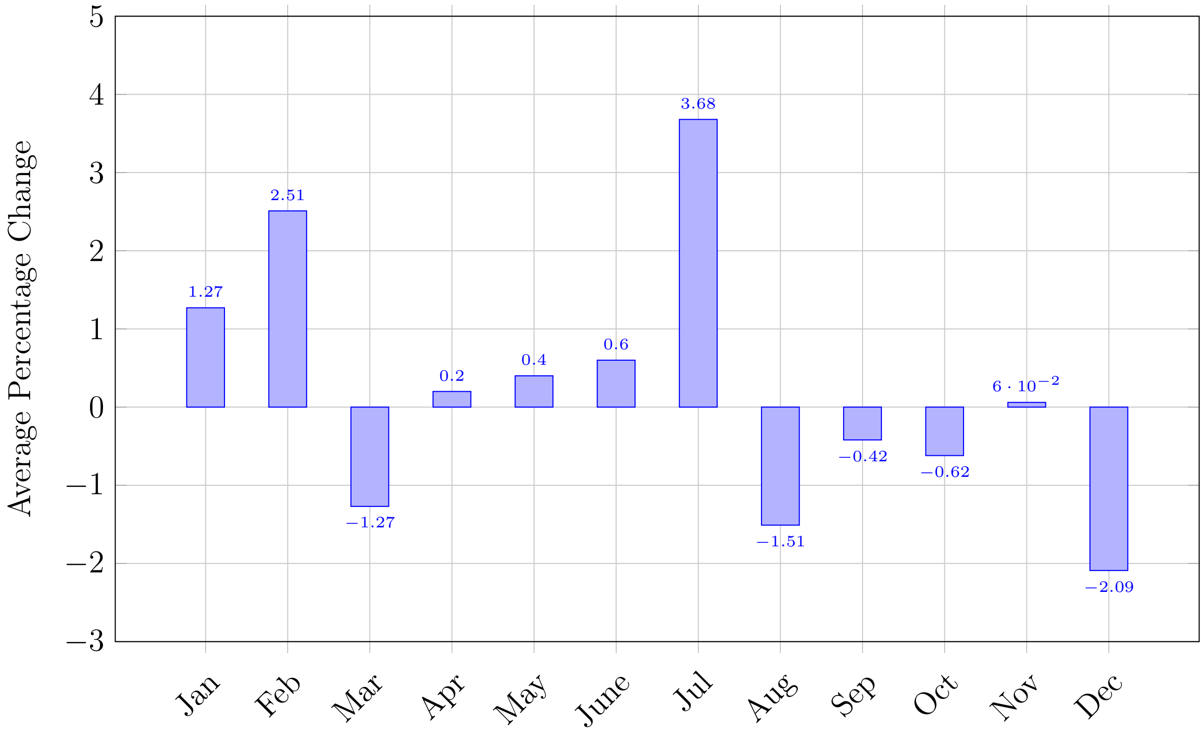


Source: (SSB, 2023)

Since February 2022, food prices in Norway have experienced a substantial increase; however, it is important to note that the imported food prices and producer prices for food have risen significantly more during this period. Our analysis indicates that energy prices have a measurable impact on food prices after a lag of 18 months, though the full extent of this effect may be somewhat mitigated by the role of grocery stores in exerting downward pressure on prices. It is possible that these retailers, in an effort to remain competitive, have absorbed some of the cost increases associated with higher energy prices and other factors, thereby preventing consumer food prices from escalating as dramatically as their imported and producer counterparts.

6.6 Seasonalities

Figure 6.6: Histogram of average percentage change in food prices by month (Jan 2015-Dec 2022)



Excludes Jan 2023 and Feb 2023 for consistency. **Source:** (SSB, 2023)

This leads us to an interesting topic. In our examination of monthly variations in food prices, we observe a significant disparity. Notably, February and July account for approximately 68% of the total price increases, with price decreases excluded from this calculation. The primary driver of this trend appears to be that food suppliers mainly adjust their prices in February and July (Bråtun, 2023). It looks like food retailers are exploiting "price windows" in February and July for coordinated price adjustments. By doing so, they can raise prices simultaneously without suffering competitive disadvantages. In such a scenario, retailers may feel more comfortable raising prices in February and July, knowing that their competitors are doing the same. This approach maintains relatively stable prices for a while, but leads to significant price increases in both February and July. NRK has published an article addressing this phenomenon, stating that Norway's competition authorities plan to investigate the issue, suspecting potential coordination and price adaptation among retailers (NRK, 2023).

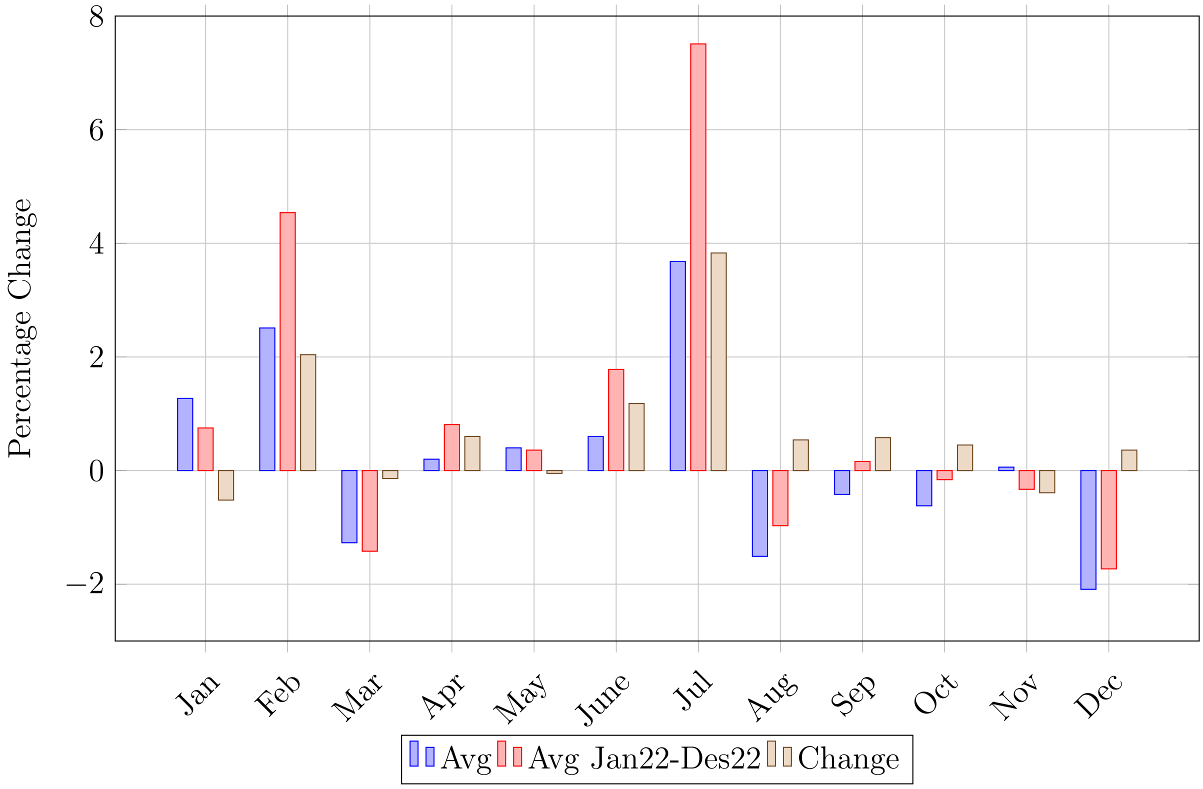
A possible explanation for this pattern may be attributed to price adjustments and menu costs. The paper written by Nilsen et al. (2021) supports the idea of economies of scope in menu costs, where firms within are adjusting prices for multiple products simultaneously to save on menu costs. Grocery stores can be exhibiting this behavior by making significant price adjustments in February and July. They may synchronize these changes to minimize costs and streamline the price adjustment process. Nonetheless, the same study revealed minimal evidence of industry synchronization. Analyzing the monthly price fluctuations in our research, it is apparent that most food stores tend to adjust their prices in February and July, which indicates a level of industry synchronization.

Furthermore, this trend implies that food prices are expected to rise sharply in July 2023. Given the significant increase in producer prices and the soaring costs of food imports, In addition, Kiwi, a grocery store in Norway, decided to hold prices low in February 2023 when everybody else increased prices. This lead the other competitors of Kiwi to reduce the prices as much as they did. Norway is also among the countries that have increased food prices the least among European countries. Only Iceland, Luxembourg and Switzerland had lower growth in food prices during 2022 (Eurostat, 2023b).

This restraint in price increases might be a strategic decision by food retailers, who may be willing to absorb additional costs themselves to supply affordable products for their consumers. This would have suggested a new pricing pattern in Norway. However, this approach is not without risks. By absorbing extra costs, retailers may face challenges to their profit margins. Norgesgruppen did for instance reduce the net results from 3.6B NOK to 2,6B NOK from 2021-2022. Reitan-group, the owner of REMA 1000, reduced the net results from 2.6B NOK to 1.8B NOK (Norgesgruppen, 2023; Retain retail, 2023). If those retailers continue to not increase the prices as much as their suppliers, their results can potentially reduce even more in future years. This indicates that prices would increase in the near future.

Further, "Høstjakta," or the autumn hunt, is an annual event in the Norwegian grocery industry where Norgesgruppen, Rema 1000, and Coop negotiate with suppliers to secure the best purchase prices on goods. This enables the food retailers to offer special deals, discounts, and promotions in the autumn months to attract customers and increase sales. This could be a contributing factor to why food stores reduce prices in September, October, and November (Aurdal, 2015).

Figure 6.7: Histogram of percentage change in food prices by month (Jan 2015- Dec 2022)



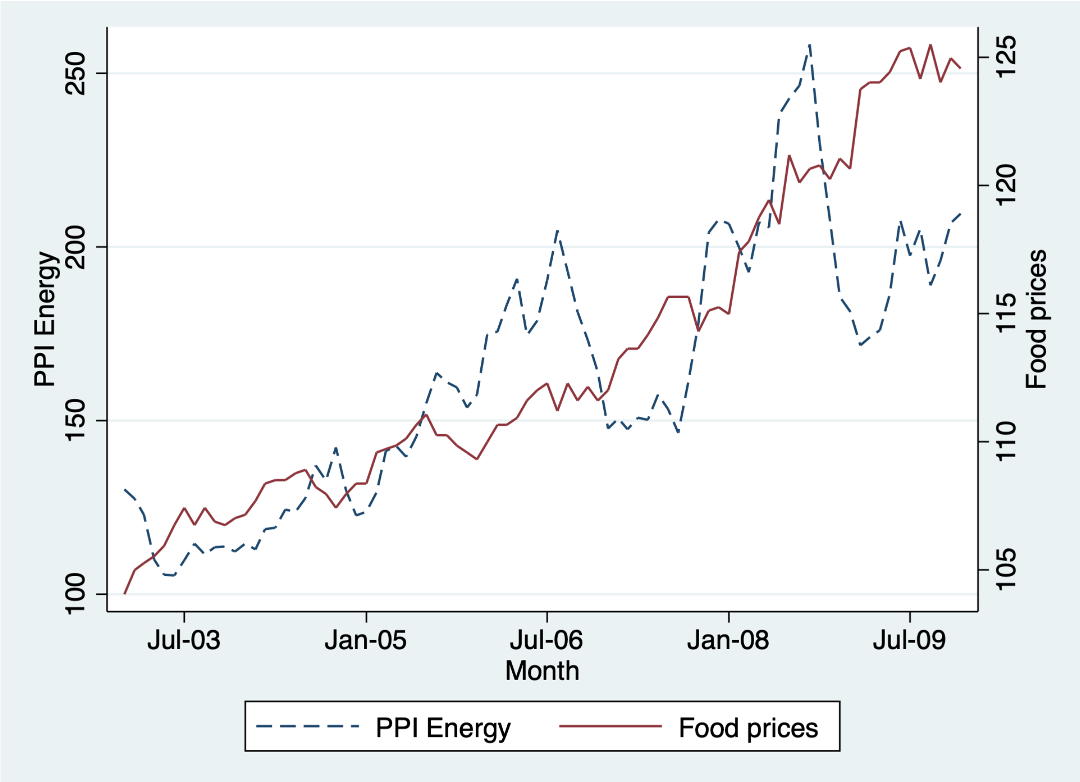
Excludes Jan 2023 and Feb 2023 for consistency. **Source:** (SSB, 2023)

Observing the figure above, we can see that food prices have increased even more in February and July from January 2022 - December 2022 compared to the overall sample. In fact, they went up by an extra 95%. This observed pattern goes against the findings that high inflation leads to more frequent, yet lower price changes (Wulfsberg, 2016).

Our calculations show that February and July account for 76% of the annual price increases during such times. Since February and July are responsible for 76% of the food price increases, and energy prices significantly impact food prices after a lag of 18 months. This is an indication that when energy prices are increasing much, the magnitude of the food prices tends to be even more pronounced in February and July compared to the rest of the year.

6.7 Comparison with the financial crisis

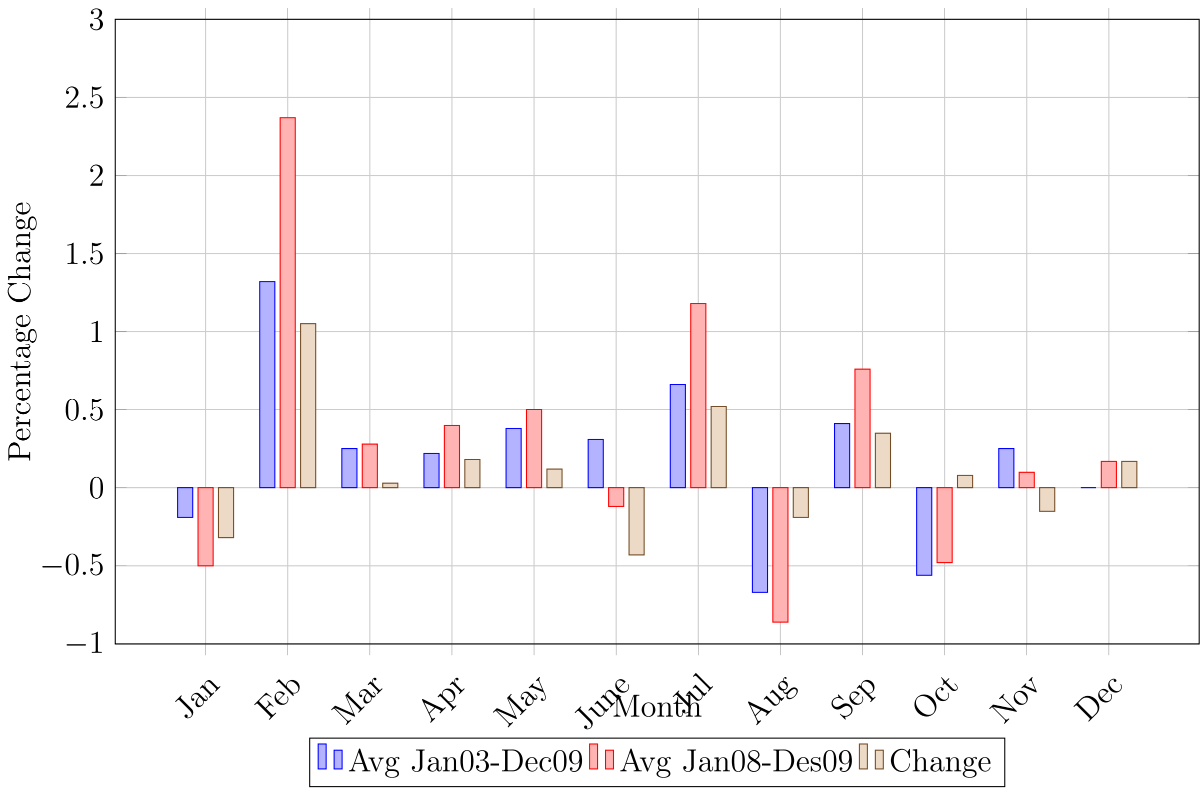
Figure 6.8: Energy and food prices from January 2003 - December 2009



Source: (SSB, 2023)

Figure 6.8 show the development of energy prices and food prices from January 2003 - December 2009. You can see that after the spike in energy prices at the end of 2007, the food price growth is intensifying. Additionally, the pattern of energy price fluctuations during and after the financial crisis is similar to those observed during and after the COVID-19 pandemic. In both instances, energy prices dropped during the crises, only to experience a sharp rebound when the crises were beginning to stabilize.

Figure 6.9: Histogram of percentage change in food prices by month (Jan 2003 - Dec 2009)



Jan 2003 was the earliest observation we could find. **Source:** (SSB, 2023)

Although we have not investigated whether a direct cause-and-effect relationship existed between energy and food prices from 2003-2009, the observed patterns bear striking similarities. As illustrated in the histogram, following the energy price spike at the end of 2007, we observe that food prices increases even more in February and July from January 2008 to December 2009 compared to the overall sample, specifically, 43% more. These observations lend support to the hypothesis that high energy price rises lead food prices to increase even more in February and July than usual.

By examining these two periods and identifying parallels, we uncover crucial information that can guide Norwegian policymakers and stakeholders in tackling challenges related to energy and food price stability. After the financial crisis, the food price increases in February and July increased by 43% compared to the sample used. After the breakpoint we found, food price increases were 95% higher than usual in February and July. Furthermore, these findings underline the importance of monitoring and managing energy price rises in Norway, as it may have far-reaching consequences on food prices. This investigation also lays the groundwork for additional research, spurring a more profound exploration into the underlying causes and potential mitigation strategies to minimize the impact of such price rises.

7 Discussion

7.1 Summary of key findings

1. **Structural Breaks:** We find significant structural breaks in both food and energy prices at specific points in time, namely, January 2022 for food prices and April 2020 for energy prices.

2. **Energy Price Influence:** Our research reveals mixed results in the period before the breakpoint in January 2022. The Ordinary Least Squares (OLS) and the Autoregressive AR(1) model identify a significant 18-month lag effect of energy prices on food prices, while the Cochrane-Orcutt model does not show this effect. However, all three models are consistent in showing that the impact of energy prices on food prices becomes more amplified after the breakpoint in January 2022.

3. **Differential Impact:** The effect of the 18th lag of energy price changes varies across different food items. Before the breakpoint, we observe notable price increases for wheat and rice, but not for meat, following changes in energy prices. After the breakpoint, meat prices also start to react, with both meat and wheat prices showing an amplified effect in response to energy price changes.

4. **Price Adjustment Periods:** Our observations indicate a pattern of food price adjustments in February and July, with this trend becoming more pronounced after the structural break in January 2022. This suggests an increased likelihood of food price increases in these months during periods of high energy price rises.

7.2 Limitations

This study, while offering valuable insights, has certain limitations that need to be taken into account when interpreting the findings. The first limitation concerns the time period analyzed, from 2015 to 2023, which might not fully encompass all possible factors influencing food prices. Expanding the analysis to cover additional years or even decades could shed light on longer-term trends and structural changes affecting the economy.

Another limitation lies in the regression model's ability to account for every relevant factor impacting food prices. Despite incorporating lagged variables and control variables to minimize confounding factors, unobserved variables could still influence the results. To enhance the robustness of the findings, future research might consider employing alternative econometric methods, such as a VAR model.

Lastly, the study's focus on the Norwegian food market offers a valuable understanding of the relationship between energy prices and food prices in this specific context. However, it is crucial to acknowledge that these findings might not be universally applicable to other countries or regions. To gain a more comprehensive understanding of the interplay between energy prices and food prices worldwide, future research could broaden the scope of the analysis by exploring different countries and contexts.

7.3 Further research

The findings in this paper offer valuable insights into the relationship between energy prices and food prices in Norway, yet there is room for further research. Future studies could investigate the reasons for the substantial food price increases in February and July, focusing on industry synchronization, menu costs, and economies of scope to help policymakers develop targeted strategies to address these fluctuations. Additionally, analyzing the role of food stores in exerting downward pressure on food prices and their competitive strategies could provide insights for fostering healthy competition and ensuring affordable prices for consumers. Finally, examining the impact of government policies, such as subsidies, import/export restrictions, and price controls, on the relationship between energy and food prices would help determine the most effective policy interventions to mitigate the impacts of energy price volatility on food prices. This would contribute to the development of strategies for maintaining food price stability and ensuring affordability for consumers in Norway.

8 Conclusion

This study was specifically designed to investigate the impact of energy prices on food prices within the framework of Norway's economy, also focusing on the prices of wheat, meat, and rice. The empirical analysis revealed a notable lag effect of 18 months of energy prices impacting food prices, as evidenced by the Ordinary Least Squares (OLS) and an Autoregressive AR(1) model. Notably, the CO model did not present this lag effect. Interestingly, after January 2022, a distinct breakpoint in food prices, the three models consistently indicated that the 18th lag of energy prices exerted an even stronger impact on food prices compared to before the breakpoint.

A key discovery from this study concerns the differential impacts of energy price rises on wheat, meat, and rice prices. Before the identified breakpoint, the 18-month energy price lag had a statistically significant impact on wheat and rice prices. In contrast, meat prices exhibited resilience to this lag in energy prices, showing significant responses only after the breakpoint. Notably, wheat prices, but not rice, showed an intensified effect after this breakpoint.

We also discover a profound impact of market competition and industry synchronization on food pricing. We noted that food retailers commonly adjust their prices in February and July. Interestingly, following the structural break in January 2022, the relevance of these two months for food price adjustments increased, contributing to 76% of all food price increases, as opposed to 68% across the complete data set.

By examining the relationship between energy and food prices in Norway, we have uncovered valuable information that can guide policymakers and stakeholders in tackling challenges related to energy and food price stability. Furthermore, these findings underline the importance of continued research, spurring a more profound exploration into the underlying causes and potential mitigation strategies to minimize the impact of such price fluctuations on Norway's economy and society.

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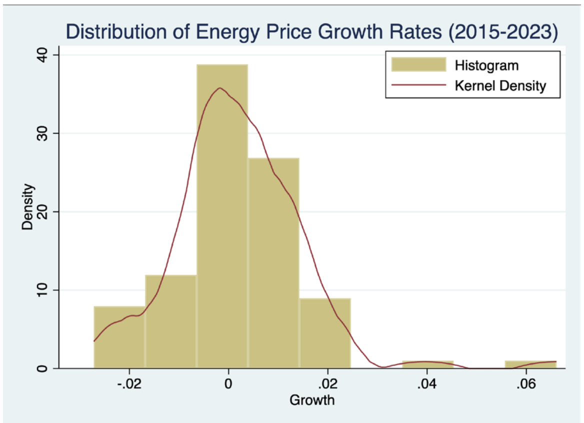
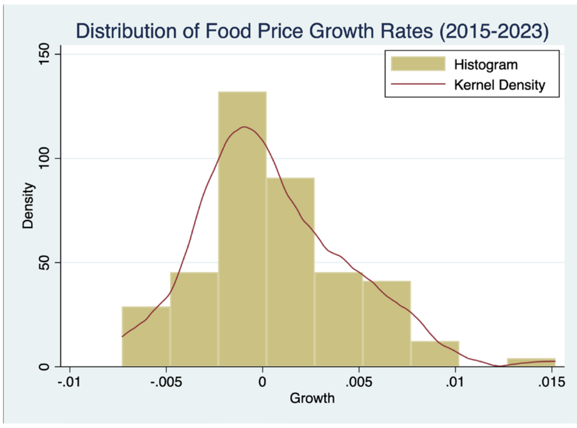
Appendix

A1 Figures and tables

Figure A1.1: Kernel Density Distribution of Energy and Food Prices (First Difference, Logarithmic)

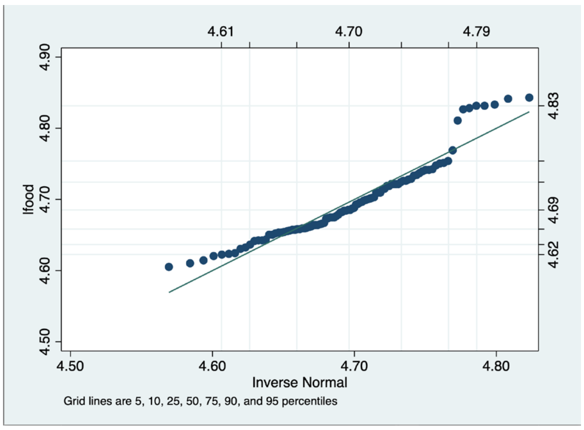


(a) Kernel Density Distribution of First Difference Logarithmic Energy Prices

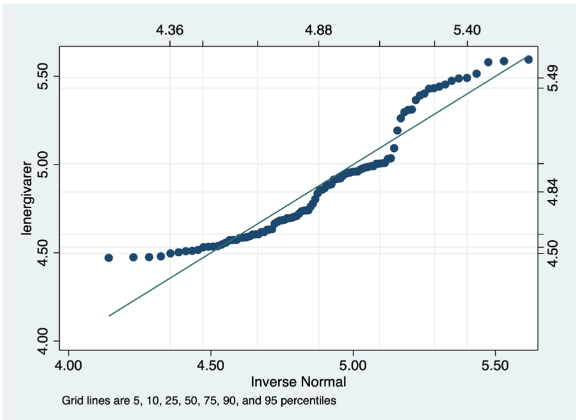


(b) Kernel Density Distribution of First Difference Logarithmic Food Prices

Figure A1.2: Quantile Plots: Energy Prices and Food Prices (First Difference, Logarithmic)



(a) Quantile Plot of Food Prices



(b) Quantile Plot of Energy Prices

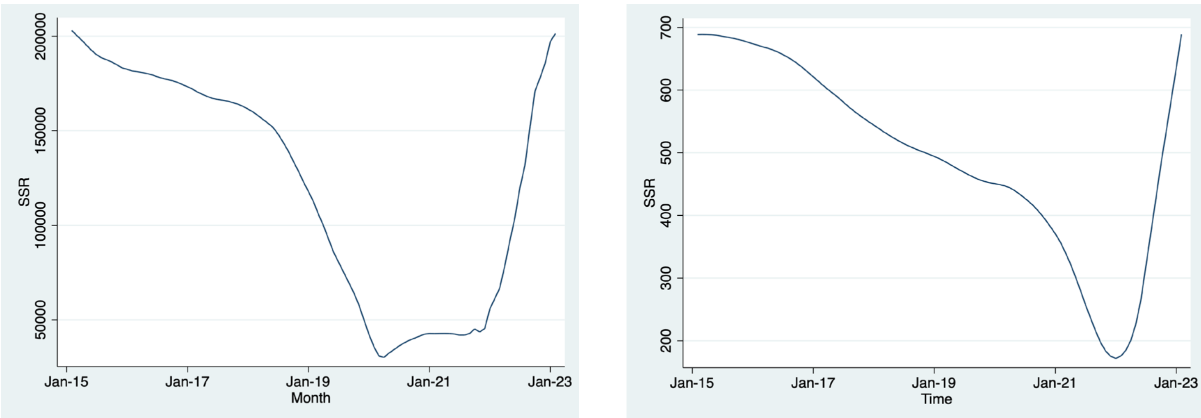
Figure A1.3: Wheat, meat and rice change from 2015-2023

(a) Wheat prices

(b) Meat prices

(c) Rice prices

Figure A1.4: Figure showing minimal SSR (breakpoint) for energy and food



(a) SSR energy

(b) SSR food

Figure A1.5: Growth in food prices in months from 2015-2023

	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sept	Oct	Nov	Dec
2015	0,20 %	1,95 %	-1,41 %	0,41 %	1,63 %	1,10 %	1,79 %	-0,88 %	0,20 %	-0,98 %	0,79 %	-2,95 %
2016	0,60 %	3,44 %	-3,23 %	3,03 %	0,10 %	0,98 %	3,01 %	-1,13 %	-0,38 %	-0,38 %	-0,86 %	-2,90 %
2017	1,19 %	1,49 %	-0,39 %	-2,06 %	2,90 %	1,17 %	2,69 %	-3,37 %	-0,58 %	0,29 %	-0,39 %	-1,46 %
2018	1,07 %	1,96 %	-1,73 %	0,10 %	0,20 %	0,39 %	3,69 %	-1,50 %	-0,38 %	-0,76 %	1,44 %	-2,37 %
2019	2,90 %	2,88 %	-1,03 %	-0,75 %	-0,85 %	0,77 %	4,28 %	-2,46 %	-0,47 %	-1,22 %	0,29 %	-1,99 %
2020	2,34 %	2,63 %	-0,27 %	0,92 %	-0,64 %	-0,73 %	3,69 %	-0,89 %	-0,45 %	-0,81 %	-0,45 %	-2,56 %
2021	0,75 %	2,01 %	-0,72 %	-0,81 %	-0,46 %	-0,64 %	2,76 %	-0,90 %	-1,45 %	-0,92 %	0,00 %	-0,74 %
2022	2,34 %	2,63 %	-0,27 %	0,92 %	-0,64 %	-0,73 %	3,69 %	-0,89 %	-0,45 %	-0,81 %	-0,45 %	-2,56 %
2023	1,59 %	1,65 %										
Avg	**1,44 %**	**2,29 %**	**-1,13 %**	**0,22 %**	**0,28 %**	**0,29 %**	**3,20 %**	**-1,50 %**	**-0,49 %**	**-0,70 %**	**0,04 %**	**-2,19 %**

Source: (SSB, 2023)