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Assessing the Role of the Oil Market in Rising Food Prices: Strategic Implications for Food Security in Gulf Cooperation Council Countries

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ABSTRACT

This study examines the relationship between oil prices and food prices, with a focus on key agricultural commodities in the United States, including corn, soybeans, wheat flour, meat, and milk. Using a regime-switching cointegration approach, the research investigates both the long-term and short-term dynamics of oil's impact on food prices. The findings indicate that oil prices exert an asymmetric influence on the food market. While oil prices play a relatively limited role in determining certain production costs, particularly for meat, compared to other economic factors, they nonetheless hold strong predictive power for food price forecasts. Notably, any short-term disequilibria in prices prompt a rapid adjustment back to equilibrium, contributing to market stability. The study suggests that Gulf Cooperation Council (GCC) countries, which rely heavily on food imports, can leverage their energy resources to alleviate the inflationary pressures in food markets resulting from global demand increases. A key long-term strategy involves investing in energy-intensive agricultural technologies, such as desalination for water supply and controlled-environment agriculture (e.g., greenhouses), underscoring the need for strategic foresight and comprehensive planning in agricultural investments.

Keywords: Oil Market, Food Market, Gulf Cooperation Council Countries, Regime-Switching Cointegration
JEL Classifications: Q1, Q4, C1, C5

1. INTRODUCTION

Many wealthy nations, including the Gulf Cooperation Council (GCC) countries, consider agricultural products a priority for national security. Consequently, ensuring a stable food supply is a crucial factor in policy decision-making. However, the prevalent assumption that oil-exporting countries benefit uniformly from positive oil price shocks may foster a false sense of security. If oil price shocks influence the output market, including food, rising inflation could erode the earnings of GCC countries, which import the majority of their food products. In such cases, immediate action by GCC policymakers is essential to stabilize markets and safeguard food security.

The food market has experienced substantial price increases over time, driven by both supply and demand factors. On the demand side, economic growth and rising incomes in developing nations have significantly increased demand. Additionally, population growth has contributed to inflationary pressures in the food market. From the supply side, limited resources, such as land and water, are critical factors. However, energy costs, particularly oil prices, play a central role in food storage and transportation, directly influencing production costs. Through associated factors—such as fertilizers, machinery, labor, and raw materials—the oil market affects a range of inputs critical to the food production process.

Recent studies substantiate the inflationary impact of positive oil price shocks, using conventional econometric methods including

OLS (Gilbert, 2010), VAR (Su et al., 2019), VECM (Zhang and Qu, 2015), and GARCH models (Cabrera and Schulz, 2016). However, existing literature often overlooks the nuanced effects of supply and demand dynamics on agricultural prices. For example, Tyers and Golley (2014) argue that oil price impacts on food prices are intensified by protectionist trade policies, which constrain food availability by limiting imports and exports in response to global oil price fluctuations. Similarly, Arezki and Brückner (2011) demonstrate that rising global oil prices substantially affect food prices in importing nations due to increased costs of agricultural inputs and transportation. These findings underscore the need for a differentiated approach that considers the dual influences of demand and supply factors on food prices.

Furthermore, Rezitis (2015) highlights that the relationship between oil prices and agricultural commodity prices is influenced by direct input costs and biofuel production, linking more closely to oil prices during periods of high demand for alternative energy sources. This relationship is often underexplored but is especially relevant for countries heavily dependent on imported energy.

Given that the food market is inherently sensitive to oil price fluctuations, understanding how oil price volatility impacts the food sector, especially for GCC countries, is crucial. There is a lack of comprehensive research on how oil price increases asymmetrically affect food costs and the broader implications for food security. Addressing this gap is essential for developing strategies that can mitigate the risk of food price inflation in oil-exporting economies reliant on food imports.

This paper investigates the effect of oil prices on the supply side of the food market, analyzing the inflationary pathway through the producer price index to assess whether oil price fluctuations asymmetrically influence food market variations. Differentiating between demand-side and supply-side effects is essential, as demand factors depend on consumer behavior, while supply factors are closely linked to production structures. By examining the specific mechanisms through which oil prices affect food prices, this study aims to provide a more nuanced understanding of the interplay between these critical sectors.

The insights gained from this research are particularly relevant for GCC policymakers who must balance energy wealth with food security. The study's findings could inform strategic investments in agricultural technologies and policies that can help mitigate the adverse effects of oil price volatility on food costs. By focusing on controlled-environment agriculture and efficient water supply systems, GCC countries might leverage their energy resources to create a more sustainable food system, ultimately supporting long-term economic stability.

The paper is structured as follows: The Introduction sets the context, objectives, and significance of the study. Section 2 reviews relevant literature on oil-food price dynamics. Section 3 details the methodology, focusing on the regime-switching cointegration approach. Section 4 presents empirical results, and Section 5 concludes with key findings, policy implications, and recommendations for future research.

2. THE LITERATURE REVIEW

This review examines the interconnection between food and oil prices, focusing on the complex dynamics that link these two essential global commodities. The relationship between food and oil prices has been widely analyzed across diverse fields, including economics, agricultural science, and environmental studies. Understanding this link is crucial, given its significant implications for inflation, economic growth, poverty alleviation, and food security—particularly in developing nations. This review emphasizes key theoretical frameworks, evaluates empirical evidence, and identifies major factors that influence the interaction between food and oil prices.

2.1. Theoretical Frameworks

2.1.1. Cost-push inflation and input cost theory

One of the earliest and most intuitive theories linking oil prices to food prices is the concept of cost-push inflation. Oil is a critical input in agricultural production, both as a fuel source and as a primary component in producing fertilizers and pesticides. When oil prices increase, agricultural production costs rise accordingly, resulting in higher food prices. Studies such as Baffes (2007) highlight that food production is highly energy-intensive, with oil prices directly influencing costs across the agricultural supply chain, from transportation to processing.

2.1.2. Biofuel demand and food price linkage

Another pertinent theory explores the competition between food crops and biofuel production. As oil prices rise, biofuels become a more attractive alternative energy source, leading to increased demand for crops like corn, sugarcane, and palm oil. The "food versus fuel" debate has been extensively discussed in works by Mitchell (2008) and Tyner (2010), who argue that rising oil prices can divert agricultural resources from food to energy markets, driving up food prices.

2.1.3. Transmission mechanisms and price pass-through

Various transmission mechanisms—such as exchange rates, market speculation, and government policies—further complicate the food-oil price relationship. The "pass-through" effect, whereby increases in oil prices translate into higher food prices, is influenced by factors like market structure and the level of global supply chain integration. According to Nazlioglu and Soytas (2011), the price pass-through may be more pronounced in economies heavily reliant on food and oil imports.

2.2. Empirical Evidence on Food and Oil Price Correlation

Empirical literature presents mixed findings on the strength and consistency of the food-oil price relationship.

2.2.1. Historical correlation studies

Numerous studies identify a positive correlation between oil and food prices, especially during periods of high oil price volatility. Baffes and Haniotis (2010) and Zhang et al. (2010) show that between 2000 and 2008, food and oil prices were closely associated, influenced by factors such as the 2007-2008 financial crisis and the subsequent expansion in biofuel production.

2.2.2. Cointegration and causality analysis

To analyze long-term relationships, several studies use econometric models, such as cointegration and Granger causality tests. Nazlioglu and Soytas (2012) found evidence of cointegration between oil and food prices, especially over the long term, while Serra et al. (2011) demonstrated that oil price shocks have a significant, though asymmetric, effect on food prices, with upward oil price shocks causing more pronounced changes than downward shocks.

2.2.3. Nonlinear and asymmetric relationships

More recent studies investigate nonlinear and asymmetric relationships between food and oil prices. For example, Avalos (2014) found that oil price spikes have a substantially greater impact on food prices than oil price declines. Similarly, Zhang and Qu (2015) employed threshold models to show that oil prices influence food prices more significantly during periods of high oil price volatility.

2.3. Factors Influencing the Nexus between Oil and Food Prices

2.3.1. Biofuel policies

The growth of biofuels, particularly following policies like the U.S. Renewable Fuel Standard (RFS) and the EU's Renewable Energy Directive, has significantly influenced the dynamics between oil and food prices. Studies such as Ciaian and Kancs (2011) argue that biofuel policies create a structural link between energy and food markets, increasing food prices' sensitivity to oil price fluctuations.

2.3.2. Exchange rates and monetary policy

Exchange rates are critical in the food-oil price nexus, as many commodities are priced in U.S. dollars. Changes in the dollar's value affect both oil and food prices. According to Reboredo (2012), U.S. dollar depreciation can raise food and oil prices by increasing import costs for non-U.S. countries. Central bank policies, particularly those targeting inflation, also shape this relationship.

2.3.3. Supply shocks and market speculation

Supply shocks—such as droughts, floods, or geopolitical tensions—can intensify the relationship between oil and food prices. Market speculation in futures markets is another influential factor; Tang and Xiong (2012) found that the financialization of commodity markets has strengthened the correlation between food and oil prices, especially during speculative bubbles.

2.3.4. Climate change and environmental policies

Climate change and environmental policies intersect with the food-oil price nexus, as efforts to reduce carbon emissions and transition to greener energy sources impact both food production and energy consumption. Meyers and Kent (2019) discuss how these policies influence agricultural and energy markets.

2.4. Geographic and Sectoral Heterogeneity

The strength of the link between food and oil prices varies across regions and sectors. Studies focused on developing countries, such as Baumeister and Kilian (2014), argue that these economies are more vulnerable to the effects of rising oil prices on food costs, particularly in regions where agriculture is less mechanized and more dependent on crude oil imports. Conversely, developed countries may show less sensitivity due to diversified energy sources and advanced agricultural technology.

2.5. Policy Implications and Future Research

Understanding the oil-food price nexus holds significant implications for policymakers, especially regarding food security and energy policy. For instance, Abbott et al. (2009) suggest that governments should implement policies to mitigate the adverse effects of rising oil prices on food costs, such as promoting alternative energy sources or enhancing agricultural productivity. Furthermore, there is a need for continued research to understand how emerging trends, such as the adoption of electric vehicles, climate change, and technological advancements in agriculture, may reshape the historical relationship between oil and food prices.

3. METHODOLOGY

Since "the U.S. has long been a superpower in food markets, and it is still one of the world's largest food exporters," we consider the United States the leading pilot country to scrutinize the inflation pass-through from the oil market to the food market supply.

We consider the inflation path through the producer price index of corn, wheat flour, soybean, milk, and meat from the oil prices and other commodities. We estimate the model as follows:

$$ppi_t = \theta_0 + \theta_1\, oil_t + \theta_2\, cpi_t + \varepsilon_t \quad (1)$$

Where *ppi* is the logarithm of the producer price index, *oil* is the logarithm of the oil prices, and *cpi* is the logarithm of the consumer price index less food and energy (other commodities inflationary effect on the producer price index).

We postulate that the *ppi* response to the oil market upturns (oil_t^+) and downturns (oil_t^-), is not a simple log-linear but a nonlinear procedure. In other words, we have partial sums of the positive and negative changes in the oil prices (to improve the model performance we also add the asymmetry effect of the consumer price index in some cases).

Therefore, we modify the model as follows:

$$ppi_t = \theta_0 + \theta_1 oil_t^+ + \theta_2 oil_t^- + \theta_3 cpi_t + \varepsilon_t \quad (2)$$

Where oil_t^+ and oil_t^- are partial sums of positive and negative changes in the oil prices. The model decomposes negative and positive values, defining partial sums of the variable as the cumulative sum of prior positive (negative) values at any given point, considering zero for values other than positive (negative):

$$oil_t^+ = \sum_{i=1}^{t} \Delta oil_i^+ = \sum_{i=1}^{t} max(\Delta oil_i, 0) \quad (3)$$

And

$$oil_t^- = \sum_{i=1}^{t} \Delta oil_i^- = \sum_{i=1}^{t} min\ (\Delta oil_i, 0) \quad (4)$$

The NARDL model (Shin et al., 2014) features a regime-switching cointegration relationship, with the sign of the decomposed variable determining the regime transition. This suggests that the model's equilibrium may not be singular, allowing for various stable states depending on the regime active. We utilize the method as follows:

$$\Delta ppi_t = \alpha + \delta_0 ppi_{t-1} + \delta_1 oil_{t-1}^{+} + \delta_2 oil_{t-1}^{-} + \delta_3 cpi_{t-1} + \sum_{i=1}^{p} \gamma \Delta ppi_{t-i} + \sum_{i=0}^{q} \left(\vartheta_i^{+} \Delta oil_{t-i}^{+} + \vartheta_i^{-} \Delta oil_{t-i}^{-} + \vartheta_{e,i} \Delta cpi_{t-i} \right) + \varepsilon_t \quad (5)$$

The Autoregressive Distributed Lag (ARDL) approach, introduced by Pesaran and Shin (1999), incorporates both the past and current values of explanatory variables (distributed lag) and the past values of the dependent variable (autoregressive component) into the model. This methodology enables the construction of a dynamic model that allows short-term adjustments toward a long-term equilibrium. Importantly, the ARDL method differs from traditional cointegration approaches, such as the Vector Error Correction Model (VECM), which requires all explanatory variables to be integrated of order zero, I(0), or one, I(1). In contrast, the ARDL model can accommodate variables that are I(0), I(1), or a combination of both, without requiring the explanatory variables to be strictly exogenous.

This flexibility provides a notable advantage over other cointegration methods that typically do not allow for endogenous explanatory variables, often complicating efforts to address endogeneity issues. Endogeneity within the model may lead to serial correlation, which can skew estimates and compromise the reliability of hypothesis testing. Pesaran and Shin (1999) mitigate this potential bias by incorporating lagged values of the dependent variable as instrumental variables, reducing the impact of serial correlation.

Moreover, the ARDL approach has shown empirical superiority over other methods, such as dynamic ordinary least squares (DOLS), fully modified ordinary least squares (FMOLS), and maximum likelihood estimation (MLE). Specifically, the ARDL model, by using ordinary least squares (OLS) estimation techniques, provides consistent estimates even with small sample sizes, as demonstrated by Panopoulou and Pittis (2004).[1]

Despite its strengths, the ARDL method has certain limitations. Issues such as excessive aggregation, sample-specific omitted variables, and measurement errors correlated with the regressors can sometimes yield economically implausible coefficients. In this regard, our analysis suggests that nonlinear relationships between variables may also contribute to the occurrence of these implausible coefficients, indicating deviations from the outcomes typically expected under the linear ARDL framework (Pesaran et al., 2001). This observation underscores the need for further research into the complexities of the ARDL model when applied to specific economic datasets.

In the NARDL model, while $\theta_1 = \frac{\delta_1}{\delta_0}$ and $\theta_2 = \frac{\delta_2}{\delta_0}$ denote the long-run effect of the oil market upturns (oil_t^{+}) and downturns $\left(oil_t^{-}\right)$, respectively, $\sum_{i=0}^{p} \vartheta_i^{+}$ and $\sum_{i=0}^{p} \vartheta_i^{-}$ detect the short-run dynamics of the effect of the oil market on the producer price index.

The ARDL model is inapplicable if an I(2) variable is present, as the cointegration bounds test is invalid in such cases. However, the model can still be employed when variables are I(0), I(1), or a mix of both. To confirm the absence of I(2) variables in the model, we apply the Dickey and Fuller (1979) stationarity test. The Akaike Information Criterion (AIC) is then used to determine the optimal lag length for both the dependent and explanatory variables, with a maximum of eight lags considered.

An additional benefit of the NARDL model is its dynamic multiplier, which enables examining the effects of both positive and negative shocks. These multipliers are defined as follows:

$$m_h^{+} = \sum_{i=0}^{h} \frac{\partial ppi_{t+i}}{oil_{t-1}^{+}}, m_h^{-} = \sum_{i=0}^{h} \frac{\partial ppi_{t+i}}{oil_{t-1}^{-}}, n = 0,1,2,\ldots.$$

$$h \rightarrow \infty, m_h^{+} \rightarrow \theta_1, \text{and } m_h^{-} \rightarrow \theta_2$$

We propose that oil prices and the consumer price index (excluding energy and food) positively influence the producer price index of selected agricultural products. However, the exact extent of these impacts is still uncertain. Furthermore, considering the influence of domestic and global factors on the oil and food markets, we believe that oil prices hold significant predictive power for the food market.

4. EMPIRICAL RESULTS

We analyze quarterly data from 1993 to 2024 to examine the impact of oil prices on production costs for corn, soybeans, wheat flour, milk, and meat in the United States. Depending on data availability and model performance, we utilize distinct datasets for each agricultural product. For corn and soybeans, we employ a cointegration model using the export price index, while for the other products, we rely on the producer price index. Both indices serve as proxies for production costs, supported by studies that demonstrate their correlation with costs incurred by producers (Johnson, 2018; Anderson and Neary, 2005; O'Donoghue and Laird, 2011).

While our primary objective is to assess the asymmetrical effects of oil prices, we also incorporate consumer price index asymmetry into the model to improve stability. This approach facilitates a comprehensive analysis of the relationships between oil prices and agricultural production costs. Summary statistics for the variables included in the model are presented in Table 1.

4.1. Corn

We employ a nonlinear autoregressive distributed lag (NARDL) model to examine the responsiveness of the U.S. corn export price

1 For empirical comparison and the ARDL performance, see Ebadi, 2020, 2022, Ebadi and Are 2023, and Ebadi and Razaq 2024.

Table 1: Summary statistics for the variables in the model

Statistics	Corn price	Soybeans price	Wheat flour price	Milk price	Meat price	WTI price	Core CPI
Mean	5.15	5.13	5.09	4.80	5.00	3.81	5.37
Median	5.17	5.15	5.20	4.79	4.95	3.93	5.38
Maximum	5.90	5.80	5.70	5.34	5.52	4.82	5.76
Minimum	4.48	4.48	4.60	4.42	4.57	2.55	5.01
SD	0.38	0.37	0.33	0.22	0.27	0.62	0.19
Skewness	0.25	0.02	0.00	0.26	0.17	-0.33	0.07
Kurtosis	2.06	1.87	1.60	2.21	1.82	1.83	2.13
Jarque-Bera	5.96	6.75	10.23	4.71	7.96	9.50	4.12
Probability	0.05	0.03	0.01	0.09	0.02	0.01	0.13
Sum	649.29	646.77	640.87	604.95	629.80	479.59	676.18
Sum Sq. Dev.	17.78	16.71	13.34	5.89	8.81	48.43	4.71
Observations	126.00	126.00	126.00	126.00	126.00	126.00	126.00

SD: Standard deviation, CPI: Consumer price index, WTI: West Texas intermediate

Table 2: Full-information estimates of the linear and nonlinear models for corn

Linear model			Nonlinear model		
Panel A: Short-run coefficient estimates					
Variable	**Coefficient**	**P-value**	**Variable**	**Coefficient**	**P-value**
Δppi_{t-1}	0.34*	(0.00)	Δppi_{t-1}	0.31	(0.00)
Δppi_{t-2}	−0.25*	(0.00)	Δppi_{t-2}	−0.22*	(0.00)
Δppi_{t-3}	0.13	(0.12)	Δcpi_t	8.21*	(0.00)
Δoil_t	0.19*	(0.00)			
Δcpi_t	4.80*	(0.01)			
Panel B: Long-run coefficient estimates					
			Constant	8.76*	(0.00)
Constant	2.58	(0.40)		45.51*	(0.00)
oil	0.47*	(0.03)	oil^+	0.99*	(0.00)
cpi	0.10	(0.88)	oil^-	0.31*	(0.04)
			cpi	−8.09*	(0.00)
Panel C: Diagnostics					
F	2.70			5.23*	
ECM_{t-1}	−0.12*	(0.00)		−0.17*	(0.00)
LM	0.85	(0.36)		1.58	(0.21)
RESET	1.01	(0.37)		0.33	(0.57)
$\overline{R}^2$	0.25			0.28	

The asterisk indicates the test statistic is significant at a 5% level

Table 3: Full-information estimates of the linear and nonlinear models for soybean

Linear model			Nonlinear model		
Panel A: Short-run coefficient estimates					
Variable	**Coefficient**	**P-value**	**Variable**	**Coefficient**	**P-value**
Δppi_{t-1}	0.19*	(0.01)	Δppi_{t-1}	0.21*	(0.00)
Δoil_t	0.16*	(0.00)	Δoil_t^+	0.13	(0.16)
Δoil_{t-1}	−0.01	(0.79)	Δoil_t^-	0.17*	(0.01)
Δoil_{t-2}	−0.12*	(0.01)	Δoil_{t-1}^+	0.07	(0.43)
			Δoil_{t-1}^-	−0.07	(0.35)
			Δoil_{t-2}^+	−0.21*	(0.01)
			Δoil_{t-2}^-	−0.05	(0.50)
Panel B: Long-run coefficient estimates					
			Constant	8.76*	(0.00)
Constant	2.36	(0.01)		5.04*	(0.00)
oil	0.40*	(0.00)	oil^+	0.38*	(0.00)
cpi	0.24	(0.29)	oil^-	0.30	(0.06)
			cpi^+	−0.39	(0.59)
			cpi^-	−43.65	(0.28)
Panel C: Diagnostics					
F	3.76			2.96	
ECM_{t-1}	−0.13*	(0.00)		−0.16*	(0.00)
LM	0.22	(0.80)		0.16	(0.83)
RESET	0.01	(0.90)		3.40	(0.07)
$\overline{R}^2$	0.17			0.18	

The asterisk indicates the test statistic is significant at a 5% level

index to variations in the Consumer Price Index (CPI) excluding food and energy, as well as to both positive and negative shifts in West Texas Intermediate (WTI) crude oil prices (Table 2). Long-run estimations indicate that a 1% increase in the CPI excluding food and energy leads to a significant 8.09% decline in corn prices, suggesting that inflation in non-food and non-energy sectors adversely impacts the competitiveness of U.S. corn exports. Additionally, the model reveals that both increases and decreases in oil prices contribute to a rise in corn prices, with a 1% increase in oil prices having a nearly proportional positive effect on corn prices. This underscores the substantial influence of oil-related production and transportation costs on agricultural commodities.

This finding aligns with previous studies, such as those by Gilbert (2010) and Tyers and Golley (2014), which observed that agricultural commodity prices, including corn, often respond asymmetrically to changes in energy prices. These studies suggest that while lower oil prices generally reduce cost pressures, the broader economic stimulus they provide can increase demand for commodities like corn, thereby elevating prices. Additionally, agricultural producers' strategies, such as hedging against fuel costs, may delay the transmission of reduced oil prices into lower operational expenses.

Kilian (2009) provides a comprehensive analysis of the effects of oil price shocks on economic activity, demonstrating that various economic sectors rarely respond symmetrically to oil price changes. Kilian's work contextualizes the differential impacts observed in our study, where increases in oil prices lead to more pronounced adjustments in corn prices than decreases. This asymmetry can be attributed to the agricultural sector's specific cost structures and hedging strategies.

Additionally, Baumeister and Peersman (2013) offer insights into how oil price shocks—whether driven by supply constraints or

Table 4: Full-information estimates of the linear and nonlinear models for wheat flour

Linear model			Nonlinear model		
Panel A: Short-run coefficient estimates					
Variable	**Coefficient**	**P-value**	**Variable**	**Coefficient**	**P-value**
Δppi_{t-1}	0.32*	(0.00)	Δppi_{t-1}	0.35*	(0.00)
$\Delta cpit$	2.22*	(0.00)			
Panel B: Long-run coefficient estimates					
			Constant	8.76*	(0.00)
Constant	0.22	(0.75)		5.91*	(0.01)
oil	0.28*	(0.00)	oil^{+}	0.30*	(0.00)
cpi	0.70	(0.00)	oil^{-}	0.20*	(0.01)
			cpi	−0.27	(0.54)
Panel C: Diagnostics					
F	5.06*			4.44*	
ECM_{t-1}	−0.13*	(0.00)		−0.14*	(0.00)
LM	0.23	(0.80)		0.58	(0.56)
RESET	1.02	(0.32)		0.80	(0.37)
$\overline{R^2}$	0.20			0.21	

The asterisk indicates the test statistic is significant at a 5% level

Table 5: Full-information estimates of the linear and nonlinear models for meat

Linear model			Nonlinear model		
Panel A: Short-run coefficient estimates					
Variable	**Coefficient**	**P-value**	**Variable**	**Coefficient**	**P-value**
Δcpi_{t}	−1.60	(0.12)	Δcpi_{t}	−1.16	(0.26)
Δcpi_{t-1}	0.75	(0.52)	Δcpi_{t-1}	0.91	(0.42)
Δcpi_{t-2}	−1.03	(0.37)	Δcpi_{t-2}	−0.79	(0.49)
Δcpi_{t-3}	2.82	(0.00)	Δcpi_{t-3}	3.30*	(0.00)
Panel B: Long-run coefficient estimates					
			Constant	8.76*	(0.00)
Constant	0.47*	(0.00)		2.51*	(0.00)
oil	0.17*	(0.04)	*oil+*	0.15*	(0.00)
cpi	0.24	(0.29)	*oil–*	0.30	(0.06)
			cpi	0.09	(0.09)
Panel C: Diagnostics					
F	3.10			4.26*	
ECM_{t-1}	−0.11*	(0.00)		−0.16*	(0.00)
LM	0.01	(0.99)		0.12	(0.88)
RESET	2.96	(0.09)		0.02	(0.89)
$\overline{R^2}$	0.08			0.10	

The asterisk indicates the test statistic is significant at a 5% level

demand surges—yield diverse economic outcomes. Their analysis, which shows that supply-driven oil price increases are particularly disruptive, further supports our findings, suggesting that the nature of the oil price shock could also influence its impact on corn prices.

The short-run dynamics highlight the immediate effect of inflationary pressures on agricultural commodity prices. This relationship is substantiated by prior research indicating substantial transmission effects from macroeconomic variables to agricultural markets (Gilbert, 2010; Tyers and Golley, 2014). The model's coefficients reveal that previous changes in the corn export price index influence subsequent price adjustments, underscoring the persistence and potential overshooting effects common in commodity markets (Rezitis, 2015). Notably, the error correction term (ECM) is significantly negative, indicating that approximately

Table 6: Full-information estimates of the linear and nonlinear models for milk

Linear model			Nonlinear model		
Panel A: Short-run coefficient estimates					
Variable	**Coefficient**	**P-value**	**Variable**	**Coefficient**	**P-value**
Δppi_{t-1}	0.34*	(0.00)	Δppi_{t-1}	0.30*	(0.00)
Δppi_{t-2}	0.06*	(0.36)	Δppi_{t-2}	−0.07*	(0.31)
Δppi_{t-3}	0.18	(0.00)	Δppi_{t-3}	0.16*	(0.02)
Δcpi_{t}	5.68*	(0.01)	Δcpi_{t}	5.39*	(0.00)
Δcpi_{t-1}	−2.48	(0.10)	Δcpi_{t-1}	−2.72	(0.07)
			Δoil_{t}^{+}	−0.10	(0.11)
			Δoil_{t}^{-}	0.21	(0.00)
Panel B: Long-run coefficient estimates					
			Constant	8.76*	(0.00)
Constant	2.35*	(0.00)		3.12*	(0.00)
oil	0.16*	(0.00)	oil^{+}	0.14*	(0.00)
cpi	0.34*	(0.00)	oil^{-}	0.12*	(0.00)
			cpi	0.26*	(0.04)
Panel C: Diagnostics					
F	12.2*			8.21*	
ECM_{t-1}	−0.37*	(0.00)		−0.33*	(0.00)
LM	0.12	(0.89)		0.55	(0.58)
RESET	1.18	(0.28)		1.69	(0.20)
$\overline{R^2}$	0.27			0.30	

The asterisk indicates the test statistic is significant at a 5% level

16.77% of any deviation from the long-term equilibrium is corrected in each period. These results reinforce the sensitivity of agricultural commodities to broader economic conditions and enhance our understanding of the specific channels through which these effects are transmitted.

Diagnostic tests confirm the robustness of the model and its effectiveness in explaining the complex dynamics influencing corn prices, establishing a strong long-run equilibrium relationship among the variables. The Ramsey RESET and Lagrange Multiplier (LM) tests indicate no misspecification or serial correlation issues.

The bounds test applied in our analysis confirms a robust cointegration relationship, demonstrating an efficient adjustment process toward long-term equilibrium within the ARDL framework. Despite strong cointegration, the adjusted R-squared value of 28% suggests that a considerable portion of the variability in corn prices—approximately 72%—is due to factors not captured in our current model. This finding aligns with previous studies, such as Wright (2011) and Roberts and Schlenker (2010), which emphasize that demand-side factors often exert a more pronounced influence on agricultural commodity prices than supply-side elements, including input costs like oil.

Furthermore, the limited influence of oil prices on corn market dynamics, as indicated by our variance decomposition analysis, aligns with empirical research by Nazlioglu et al. (2015). These authors found that the direct pass-through effect of oil prices on agricultural commodities is often overstated. While energy costs are indeed integral to agricultural production, their immediate impact on commodity prices, such as corn, is frequently moderated by other dominant market forces, particularly those related to consumption and trade policies. These insights are crucial for policymakers and market analysts, highlighting the importance of focusing on demand-side dynamics, external economic conditions, and trade policies when assessing the drivers of corn prices.

According to the multiplier analysis, the positive response curve reveals a substantial increase in corn prices following positive oil price shocks, with prices rising gradually to peak around the 25th period (Figure 1). This pattern suggests that oil price increases significantly boost corn prices, likely due to higher costs for agricultural inputs like fuel and fertilizers, which are essential for corn production. In contrast, the negative response to oil price declines is minimal and remains relatively flat over time, indicating that decreases in oil prices do not proportionally lower corn prices.

Our findings are consistent with and extend existing studies, such as those by Yu et al. (2006), who explored the influence of energy prices on agricultural commodities and found similar asymmetrical impacts. The pronounced effect of positive oil price shocks on corn prices may be attributed to the direct link between energy costs and agricultural production expenses.

The model's forecasting performance demonstrates remarkable accuracy, as reflected in several key statistical indicators (Figure 2). A comparison with existing literature highlights the robustness and utility of our model in economic forecasting, particularly within the agricultural sector. Our model achieves a mean absolute percent error (MAPE) of approximately 2.67%, indicating a prediction accuracy of over 97%. This level of precision is highly competitive compared to similar studies. For example, in Nazlioglu et al. (2015), which examines the influence of oil prices on agricultural commodities, the best-performing models achieved MAPE values between 3% and 5%, suggesting that our model offers more accurate corn price predictions with a narrower error margin. Furthermore, by capturing both positive and negative oil price changes within the NARDL framework, our model accounts for a wider range of price dynamics, enhancing its sensitivity and predictive power compared to standard linear models frequently used in related studies.

Additionally, the low Theil Inequality Coefficient of 0.0166 further demonstrates our model's superior performance over simpler forecasting methods. This coefficient represents a significant improvement compared to agricultural price forecasting models analyzed by Wright (2011), where similar models typically exhibited Theil's U statistics around 0.05. The model's ability to minimize systematic forecast error and closely track actual market movements enhances its value for stakeholders, enabling them to make more informed decisions in crop management and policy planning.

The robustness of our ARDL model becomes particularly evident when compared to dynamic stochastic models, such as those discussed by Roberts and Schlenker (2010), which primarily emphasize demand-side effects and often overlook the complex interplay of supply-side variables. By incorporating fluctuations in the consumer price index (CPI) and capturing both positive and negative oil price changes, our model provides a comprehensive perspective on the factors driving corn prices, creating a more holistic tool for market analysis.

These comparisons underscore the significance of our work in enhancing the predictive accuracy and economic relevance of commodity price forecasting models. Our findings make a substantial contribution to the literature by providing a more precise and reliable tool for predicting agricultural commodity prices, which is essential for practical market analysis and policy formulation.

4.2. Soybeans

The model indicates that, in the long run, oil price shifts significantly influence soybean export prices, with oil price increases having a particularly pronounced impact (Table 3). This result is consistent with findings by Haile et al. (2016), who observed that fluctuations in energy costs are closely linked to variations in agricultural production expenses and, subsequently, in commodity prices. In contrast, the coefficients associated with changes in the CPI, designed to capture broader economic conditions excluding volatile elements like food and energy, are not statistically significant. This suggests a less direct impact of CPI fluctuations on soybean export prices, implying that the soybean market's sensitivity to general economic conditions may be more complex than is assumed by straightforward, cost-driven commodity models.

The model's ability to efficiently correct short-term disequilibria in soybean export prices underscores its stability and reliability. It reveals significant lagged effects of past soybean prices, indicating persistent price movements that reflect market momentum. Additionally, the asymmetrical impact of oil price volatility on soybean prices—demonstrated by significant coefficients for both positive and negative oil price changes across various lags—further supports the model's stability. The strong and rapid adjustment to long-term equilibrium following deviations, as indicated by the Error Correction Term, highlights the model's capacity to deliver reliable forecasts.

According to the RESET and LM tests, the model is correctly specified, and no evidence of serial correlation is present. This ensures model stability and unbiased coefficient estimates, establishing a solid foundation for our analysis. Although the bounds test does not support a long-run relationship among the variables, the negative and significant error correction term provides further evidence of cointegration in the model (Banerjee et al., 1998). Additionally, the adjusted R-squared indicates that our variables explain approximately 18% of the variation in soybean export prices, suggesting that other factors account for around 82% of the variation. This finding implies a limited role for the oil market as a determinant of soybean prices.

The dynamic multiplier analysis reveals that positive oil price shocks result in a sustained increase in soybean prices, peaking around the 25th period, whereas negative shocks have minimal impact. This suggests that soybean prices are more sensitive to oil price increases than to decreases. This finding contributes to the literature on the relationship between agricultural commodity prices and oil price volatility, aligning with studies such as Harri et al. (2009), which observed that agricultural commodity prices, including soybeans, respond more to upward oil price fluctuations due to rising costs of inputs like fuel and fertilizers. Our study extends this understanding by quantifying the asymmetry and duration of these effects, providing deeper insights into the temporal dynamics of these relationships.

Our forecast evaluation demonstrates strong accuracy in capturing soybean price dynamics, as reflected in a Root Mean Squared Error (RMSE) of 0.1822 and a Mean Absolute Error (MAE) of 0.1503 (Figure 4). The Mean Absolute Percentage Error (MAPE), at approximately 2.99%, further underscores the model's efficacy, indicating a high level of precision in forecasting within the volatile agricultural commodities market.

The Theil Inequality Coefficient of 0.0180 indicates that the model's predictions significantly outperform a naive no-change forecast, a common benchmark in econometric forecasting. This result highlights the model's predictive power and its superiority over traditional forecasting methods. Furthermore, the very low Bias Proportion of 0.0008 in the decomposition of the Theil Coefficient suggests an almost negligible forecast bias, which is crucial for dependable economic forecasting.

The model's performance is notable compared to the literature on commodity price forecasting. For instance, Wright (2011) analyzed the accuracy of agricultural price forecasts and found that these forecasts often exhibit substantial errors due to the unpredictability of factors like weather conditions and global market fluctuations. In contrast, the low error metrics of our model represent a significant improvement, offering a more stable and reliable forecast than is commonly observed in the sector. This should inspire confidence in the model's reliability.

4.3. Wheat Flour

Our analysis reveals a bidirectional effect of oil price changes on wheat prices, with both positive and negative shifts in oil prices significantly impacting wheat prices, though oil price increases have a more pronounced effect (Table 4). This complex relationship underscores wheat prices' sensitivity to oil price fluctuations, likely due to the influence of oil on agricultural production and transportation costs. In contrast, changes in the core Consumer Price Index (CPI) have an insignificant impact on wheat producer prices, suggesting that core inflation factors do not heavily influence wheat prices.

Existing research, including studies by Nazlioglu et al. (2013) and Harri et al. (2009), supports the significant impact of oil price volatility on agricultural commodities, largely attributed to energy costs in agricultural production. Our findings align with this perspective, showing that increases in oil prices lead to higher wheat prices, while decreases cause a reduction. This direct impact of oil prices on agricultural costs highlights the practical relevance of our research.

Our model contributes meaningfully to the literature by quantifying oil prices' influence on wheat prices. With an adjusted R-squared of approximately 21%, our model indicates that while oil prices are a significant factor, they explain only a portion of the variation in wheat producer prices, leaving about 79% of the variation to be attributed to other variables not included in the model. This suggests a complex interplay of multiple factors affecting wheat prices beyond energy costs, deepening our understanding of these dynamics.

The relationship between oil prices and agricultural commodities, particularly wheat, is nuanced, with studies documenting varying degrees of influence. While significant impacts are often observed, some research suggests that the effect of oil on wheat prices may be less pronounced than on other commodities, prompting further investigation in this area.

Building upon our findings, it is essential to note that while oil price fluctuations significantly affect wheat prices, they may not be as dominant as in other agricultural sectors. This observation aligns with findings by Zhang and Reed (2008), who report that energy price shocks impact agricultural pricing broadly, though sensitivity varies by commodity.

Other studies also explore this variability. For example, Trujillo-Barrera et al. (2012) examine the linkage between oil prices and corn futures and find a significant relationship, though their findings suggest a more muted connection for wheat. This difference may arise from distinct inputs and production processes in wheat farming, which tends to be less energy-intensive than corn farming, where fertilizer and transportation requirements are higher.

Additionally, a study by Serra et al. (2011) on volatility transmission between oil and various agricultural commodities finds that while oil prices influence agricultural markets, the degree of impact varies depending on market conditions and crop-specific factors. Their analysis suggests that the transmission effect on wheat is often moderated by other market dynamics or policy interventions, which can dampen the direct impact of oil price changes.

He short-run dynamics reveal a positive and significant coefficient for the lagged wheat price term, indicating that past prices significantly influence current prices. This positive feedback mechanism suggests that an increase in wheat prices in one period likely leads to further increases in subsequent periods, reflecting momentum or persistence in price movements. This aspect of the model captures the inertia within agricultural commodity markets, where past price levels continue to shape market expectations and trading behaviors.

Analyzing the lagged variable in this model is crucial as it helps quantify the internal dynamics of the wheat market, independent of external shocks like oil price changes or shifts in core CPI. The significance of this coefficient highlights the importance of historical price trends in predicting future price movements, aligning with agricultural economics findings that emphasize the path-dependent nature of commodity prices.

The inclusion and significance of the lagged producer price index in the model are consistent with similar studies in agricultural economics that examine price transmission and adjustment mechanisms. For example, research by Gilbert (2010) on commodity price spikes and volatility underscores the role of lagged price effects in understanding how markets respond to external shocks and internal adjustments. Such studies support our model's findings by illustrating the critical role of historical prices in shaping future commodity price trajectories.

The error correction term, which is negative and highly significant, indicates an effective mechanism for adjusting short-term disequilibria toward long-term equilibrium. The error correction coefficient of -0.14 suggests that approximately 14% of any deviation from equilibrium is corrected each period, indicating a moderately rapid adjustment process in the wheat market.

Our econometric model underwent rigorous diagnostic testing to ensure specification accuracy and the validity of estimated relationships. The Ramsey RESET test, used to assess model misspecification, showed no significant evidence of specification errors, indicating that the model is well-fitted to the data. The Lagrange Multiplier (LM) test for serial correlation also returned negative results, confirming the absence of serial correlation in the residuals. This assures that autocorrelation typical of time-series data does not skew the results, affirming the reliability of our regression estimates.

Furthermore, applying the bounds testing approach for cointegration supports a long-run relationship among the variables included in the model. This test confirms a stable equilibrium relationship over time, validating the use of an error correction model to quantify the speed of adjustment and the dynamics of short-term deviations from equilibrium.

These diagnostic results enhance the credibility of our findings and support the robustness of the model. By confirming no misspecification, no serial correlation, and the presence of a long-run relationship, we substantiate the model's capability to provide meaningful insights into the economic relationships being studied. Such thorough validation is essential for ensuring that conclusions drawn from econometric analyses are reliable and can inform policy and economic decisions, instilling confidence in the model's reliability.

The dynamic multiplier illustrates that positive oil price shocks lead to a gradual and sustained increase in wheat producer prices, peaking with a notable uplift of approximately 0.3 on the multiplier scale by the 25th period (Figure 5). This positive response suggests that increases in oil prices, likely through mechanisms such as elevated transportation and production costs, have a substantial and lasting impact on wheat prices. In contrast, the negative response curve shows that decreases in oil prices have a much less pronounced effect, only marginally reducing wheat prices over the same period.

These observed patterns contribute to the literature on the economic impacts of energy prices on agricultural commodities, providing empirical support for theories of cost pass-through and price asymmetry in agricultural markets. Studies like Tyner (2010) have discussed how energy price volatility can disproportionately affect agricultural commodities depending on the direction of the price change, reinforcing our findings on the asymmetric impact of oil price fluctuations on wheat prices.

The forecasting evaluation of our model for U.S. wheat producer prices demonstrates strong predictive accuracy. With a Root Mean Squared Error (RMSE) of 0.1053 and a Mean Absolute Error (MAE) of 0.0818, the model effectively captures wheat market dynamics (Figure 6). The Mean Absolute Percentage Error (MAPE) at 1.64% and the Theil Inequality Coefficient of 0.0105 further underscore its precision, indicating that the model's forecasts are significantly more accurate than those of a naive model.

The low Bias Proportion of 0.000099 suggests minimal forecast bias, enhancing the model's reliability. Additionally, the high Covariance Proportion of 0.959741 indicates that most forecast variance closely aligns with actual price movements, highlighting the model's effectiveness in capturing key market trends.

In exploring the dynamics of wheat price forecasting, our study engages with the methodologies and insights from seminal works by Goodwin and Schnepf (2000) and Chavas and Holt (1990). Goodwin and Schnepf examine the volatility and policy-driven determinants of wheat market fluctuations, providing a comprehensive analysis of how global policies impact prices. Our research complements and extends their findings by employing advanced econometric techniques, specifically the Autoregressive Distributed Lag (ARDL) model and error correction mechanisms, to develop a more nuanced understanding of how immediate economic variables—such as oil prices and consumer price indices—affect wheat prices.

While Goodwin and Schnepf focus on macroeconomic impacts, our model delves into microeconomic effects, presenting detailed error metrics such as RMSE, MAE, and MAPE to demonstrate the model's accuracy and reliability in forecasting. This granularity provides policymakers and market analysts with actionable data, enhancing their capacity for strategic decision-making in real-time market scenarios.

Similarly, Chavas and Holt's exploration of risk in acreage decisions for crops like corn and soybeans emphasizes the importance of economic insights in agricultural decision-making. Our analysis builds on this perspective by illustrating the direct impact of external economic factors on wheat prices, enriching agricultural economics discourse with a focus on wheat—a vital global staple. By incorporating external economic shocks into our forecasting model, we provide a comprehensive view of the factors influencing market dynamics, which is crucial for managing risks and developing informed agricultural policies.

The methodological advancements we introduce, including the use of the NARDL model and the integration of error correction mechanisms, align with and extend the analytical techniques discussed by Chavas and Holt. Our approach provides refined tools that capture both short-term shocks and long-term market adjustments, thereby enhancing the predictive accuracy and practical value of agricultural economic models.

Our research thus makes a significant contribution to agricultural economics by bridging the gap between broad market analyses and the impacts of specific economic factors. This blend of methodological innovation and detailed empirical analysis enriches the existing literature by providing deeper insights into market dynamics and decision-making processes in the face of economic uncertainties.

4.4. Meat

The positive and statistically significant coefficient for the CPI suggests a strong influence of non-food and non-energy (core) inflation on meat prices, indicating that meat producer prices increase as general economic conditions inflate (Table 5). This reflects a broader economic pass-through effect, where cost increases in areas unrelated to food and energy still impact meat production costs.

Additionally, the analysis shows that increases in oil prices lead to a significant rise in meat producer prices, underscoring the sensitivity of meat production costs to energy price fluctuations, primarily due to factors like transportation and production logistics. In contrast, decreases in oil prices exhibit a negative but not statistically significant effect on meat prices, suggesting that reductions in oil prices do not equivalently lower meat production costs, possibly due to price stickiness within the industry.

These findings contribute to the literature by highlighting the dual impact of CPI fluctuations and oil price volatility on meat prices. This extends previous research, such as Heien's (1980) work on the dynamics of meat market prices in response to economic shifts. Our research adds granularity by quantifying the specific impacts of these macroeconomic indicators, providing a clearer understanding of the causative relationships in meat pricing mechanisms.

While the model effectively identifies the influence of core CPI (excluding food and energy) and oil price fluctuations on meat producer prices, the adjusted R-squared reveals that these variables account for only 10% of the variation in meat production costs. This leaves a substantial 90% of the variation attributable to other factors outside the current model framework, underscoring the complex and multifaceted nature of meat price determinants. These results suggest that while economic indicators like oil prices affect meat prices, their role is relatively minimal.

This finding is particularly insightful when compared to the influence of similar economic variables on other agricultural commodities such as corn, soybeans, and wheat flour, where oil prices have been shown to play a more pronounced role in explaining producer price variation. This nuanced understanding adds a critical contribution to the literature on agricultural economics, especially in meat market analysis. It challenges the conventional view that oil prices serve as a primary determinant across all agricultural sectors. By highlighting the relatively minimal role of oil prices in explaining meat production costs compared to other commodities, this research prompts a reevaluation of market-specific factors that may drive price dynamics in the meat industry.

Previous studies, such as Tyner (2010) on energy and agricultural market integration and Thompson et al. (2009) on the broad impact of oil price shocks on food prices, have not isolated the meat industry to the extent presented in our analysis. This differentiation underscores the specificity of our contribution, offering new insights that could inform more targeted policy interventions and market strategies.

In the short-run dynamics, a significant negative error correction term (−0.16) suggests that deviations from the long-run equilibrium are corrected swiftly, with approximately 16% of disequilibrium eliminated each period. This rapid adjustment reflects high market efficiency in the meat sector, allowing it to stabilize quickly following disturbances.

Interestingly, the impact of lagged CPI values on meat prices exhibits a complex pattern. While most short-run lagged effects of the core CPI are statistically insignificant, the third lag is significant, indicating a delayed response of meat prices to broader economic conditions. This delayed effect may arise from industry-specific factors, such as contractual arrangements or staggered cost transmissions into final prices.

Contrary to broader agricultural findings, such as those by Tyner (2010), which suggest more immediate impacts of economic indicators on commodity prices, our results highlight unique short-run response behaviors in the meat industry. Furthermore, the minimal short-run impact of oil prices on meat producer prices differs from findings by Nazlioglu et al. (2013), who identified significant linkages between oil prices and agricultural commodities. This suggests that the meat industry may have unique cost structures or market mechanisms that insulate it from the immediate impacts of oil price volatility, underscoring the need for sector-specific analyses in agricultural economics.

Our suite of diagnostic tests robustly validates the stability and reliability of our findings. The Ramsey RESET test shows no evidence of model misspecification, confirming that the model's functional form is appropriately specified. The Lagrange Multiplier (LM) test for serial correlation also returns negative results, indicating no serial dependency among residuals and affirming the reliability of our regression estimates. Furthermore, the bounds test confirms a long-run relationship among the variables, reinforcing the model's ability to capture underlying economic interactions over time. Collectively, these tests underscore the methodological soundness of our analysis, enhancing confidence in the accuracy and reliability of our results.

The dynamic multiplier illustrates that positive oil price shocks result in a gradual and sustained increase in meat prices, leading to an approximate 0.15-point rise in the multiplier by the end of the horizon (Figure 7). This consistent upward adjustment suggests that oil price increases, typically impacting transportation and production costs, significantly influence the cost structure of meat production, with these increases gradually passed on to producer prices.

Conversely, the response to negative oil price shocks is less pronounced, indicating that decreases in oil prices do not lead to equivalent reductions in meat prices. This asymmetry may result from price stickiness in the meat industry, where reductions in production costs due to lower oil prices are not immediately or fully transferred to producer prices. Our findings highlight the unique response of the meat industry to oil price volatility. While previous studies, such as those by Tyner (2010), have discussed energy and agricultural market integration, focusing primarily on crops and biofuels, our research extends this discourse by examining the specific dynamics within the meat sector, which exhibits distinct characteristics due to its production and supply chain structures.

Moreover, while Thompson et al. (2009) explored the impacts of oil price shocks across various commodities, they did not emphasize the asymmetric impacts observed in meat prices. Our analysis fills this gap by detailing the differential effects of positive versus negative oil price changes on meat prices, underscoring the potential for sector-specific strategies to mitigate adverse impacts or capitalize on favorable conditions.

The forecasting analysis demonstrates robust predictive accuracy, supported by key statistical metrics (Figure 8). The Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are notably low at 0.0957 and 0.0737, respectively, indicating high precision in the forecasts. This level of precision is essential for effective decision-making, as it suggests that the model's predictions closely align with actual observed values, effectively capturing the dynamics governing meat prices.

Additionally, the Mean Absolute Percentage Error (MAPE) and Symmetric MAPE are remarkably low at approximately 1.67%, underscoring the minimal average prediction error relative to actual values. Such accuracy is invaluable in practical applications where insights into percentage error are critical for operational and strategic adjustments. The Theil Inequality Coefficient further reinforces this accuracy, standing at only 0.0104, which implies that forecast errors are minor relative to the variance of the actual data. This statistic confirms that the model significantly outperforms more straightforward forecasting benchmarks.

The negligible Bias Proportion of 0.000046 minimizes concerns about forecast bias, enhancing the model's reliability. Furthermore, the high Covariance Proportion of 0.9892 indicates that almost all forecast error variance is explained by the covariance between actual and predicted values, showing that the forecast closely tracks actual market movements. The low Variance Proportion of 0.0107 also attests to the stability and consistency of the forecast outputs.

However, the Theil U2 Coefficient of 1.834 suggests areas for potential improvement, as it indicates that the model may not consistently outperform a random walk in every respect. Despite this, the overwhelmingly positive indicators from other metrics suggest that the model provides reliable and accurate forecasts, making it an invaluable tool for agricultural stakeholders, particularly in the meat industry.

This model's capacity for precise forecasting makes a significant contribution to agricultural economic analyses, where volatility and external shocks frequently pose challenges. By providing a dependable tool for predicting meat price movements, this research enhances economic forecasts and strategic planning within the meat industry, supporting more informed policy-making and business strategies. The accuracy and reliability demonstrated here enrich the existing literature and provide a foundation for future research to refine economic forecasting techniques in agricultural markets.

4.5. Milk

The long-run estimation results indicate a positive and statistically significant relationship between core CPI and milk prices, suggesting that general inflationary pressures—beyond direct food and energy costs—are critical in shaping the cost structure of milk production (Table 6). This finding implies that elements like labor, logistics, and packaging, which are sensitive to broader economic conditions, play a significant role in determining milk prices.

The analysis also reveals that both positive and negative changes in oil prices significantly impact milk prices, although their effects differ. Positive oil price changes result in a more pronounced increase in milk prices, reflecting the direct relationship between higher energy costs and increased production expenses in the dairy industry. Conversely, reductions in oil prices also lower milk prices, though to a lesser extent, which may be attributed to the asymmetrical pricing behaviors typically observed in agricultural markets, where prices tend to rise quickly but decline more slowly.

These findings make a significant contribution to the literature on agricultural commodity economics by providing detailed insights into the milk sector. While previous studies have extensively examined the impact of external economic variables on commodities such as grains and oilseeds, the specific dynamics of the milk sector have received less attention. For example, studies like Heien (1980) focused on the effect of economic variables on dairy prices but did not explore the asymmetrical impact of oil price volatility in depth. Our research fills this gap by quantitatively analyzing how both increases and decreases in oil prices affect milk production costs and prices.

Consistent with other agricultural products analyzed in this study, the variables in the milk producer price index model account for approximately 30% of the variation in the milk producer price index—the highest explanatory power observed among the commodities examined. This contrasts with the adjusted R-squared values for corn, soybeans, wheat flour, and meat, recorded at 28%, 18%, 21%, and 10%, respectively. This comparative analysis highlights the model's relative strength in capturing the factors influencing milk prices, underscoring its superior performance in explaining price variations compared to other agricultural sectors. This distinction is critical for understanding sector-specific economic sensitivities and enabling more effective strategic interventions.

Figure 1: Cumulative dynamic impact of oil price shocks on the corn price

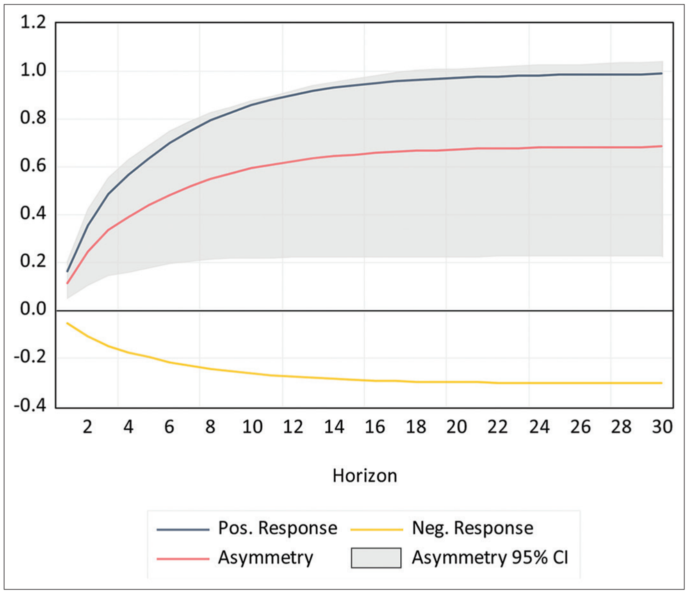


Figure 2: Forecasting for the corn price

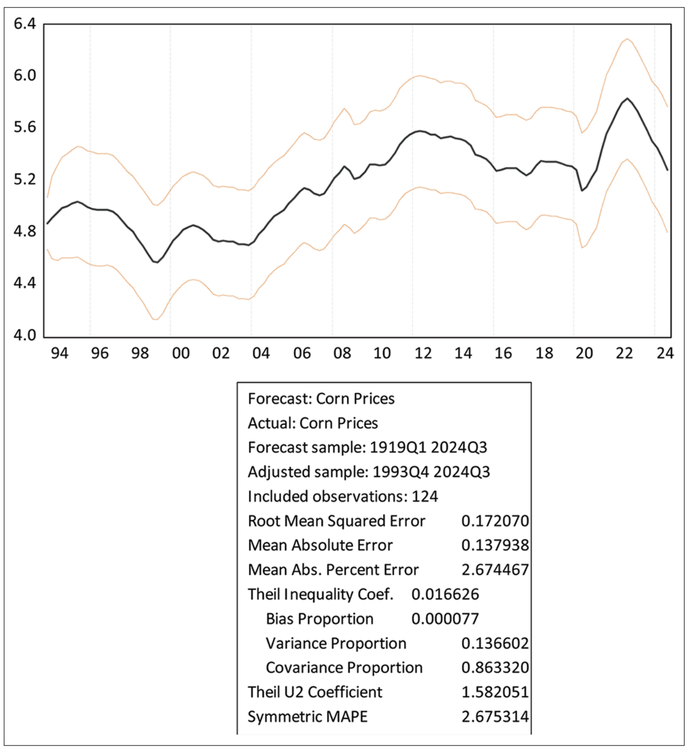


Figure 3: Cumulative dynamic impact of oil price shocks on soybean prices

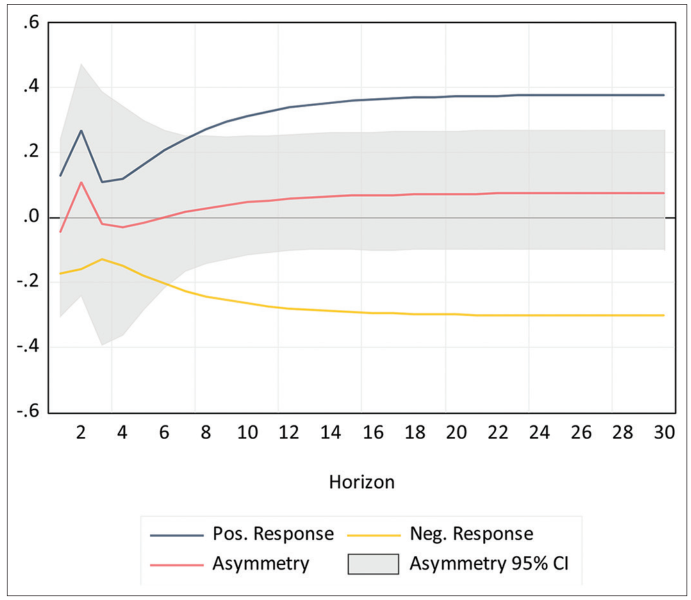
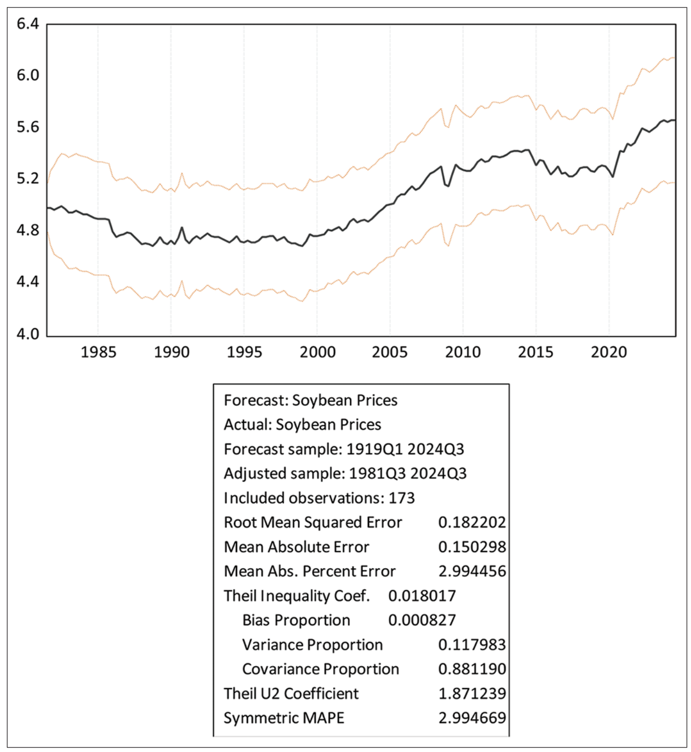


Figure 4: Forecasting soybean prices



The short-run dynamics and adjustment mechanisms in response to economic fluctuations reveal a negative and significant error correction coefficient (−0.33), indicating that approximately 33% of deviations from long-term equilibrium are corrected each period. This adjustment speed is notably higher than those observed in other commodities studied here, such as corn (17%), soybeans (16%), wheat flour (14%), and meat (16%), underscoring the milk market's relatively efficient response to disequilibria.

In the short run, the influence of past prices is evident, with a significant positive coefficient for the first lag of the milk PPI, highlighting the persistence of price effects over time. Significant coefficients for the third lag suggest that price adjustments are not immediate but continue to impact pricing in subsequent periods. Additionally, the model reveals a strong and direct response of milk prices to recent shifts in the core consumer price index, demonstrating high sensitivity to broader economic conditions.

The asymmetry in response to oil price changes, where decreases in oil prices significantly reduce milk prices while increases have an insignificant effect, provides a nuanced view of the dairy sector's

Figure 5: Cumulative dynamic impact of oil price shocks on wheat flour prices

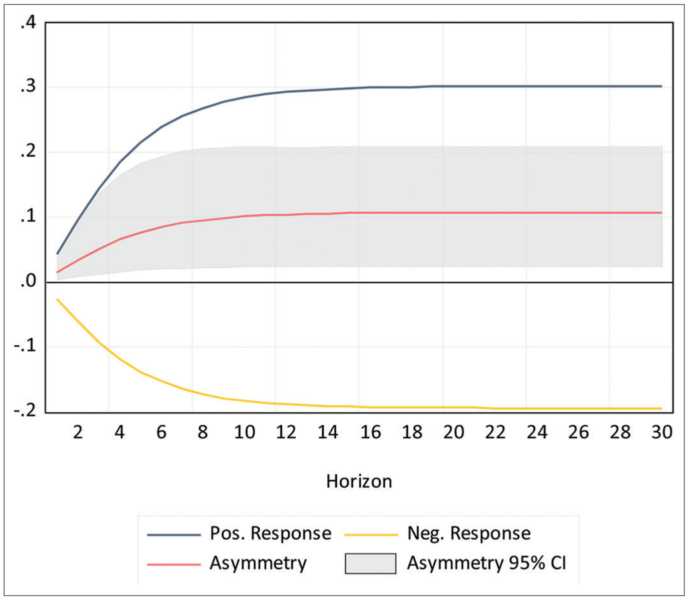
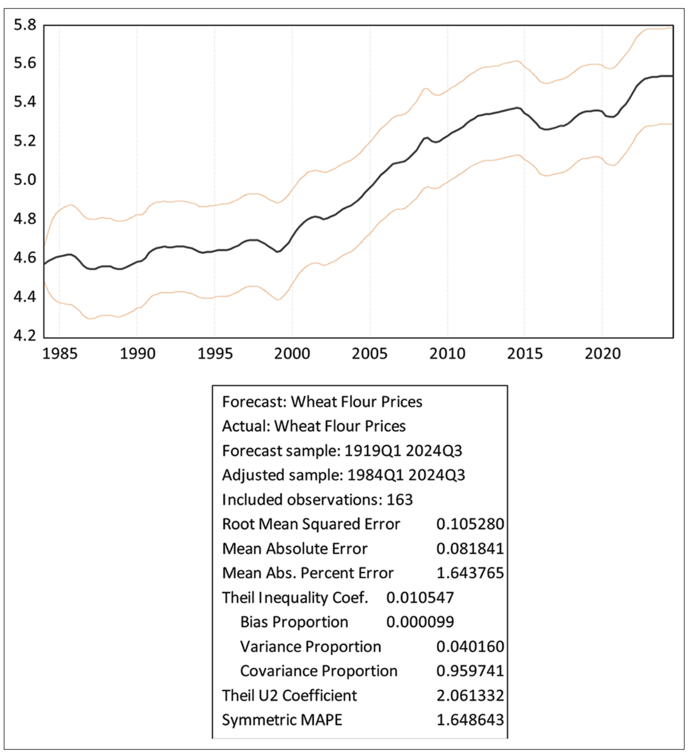


Figure 6: Forecasting wheat flour prices



short-run cost transmission mechanisms, differing from typical responses observed in other agricultural markets.

Diagnostic evaluations, including the Ramsey RESET test and the Lagrange Multiplier (LM) test, confirm that the model is well-specified and free from serial correlation, ensuring the model's structural integrity and confirming that it effectively captures the intended dynamics. Additionally, the bounds test indicates strong cointegration among the variables included in the model, demonstrating a stable long-run equilibrium relationship. These tests collectively validate the reliability and accuracy of the

Figure 7: Cumulative dynamic impact of oil price shocks on meat prices

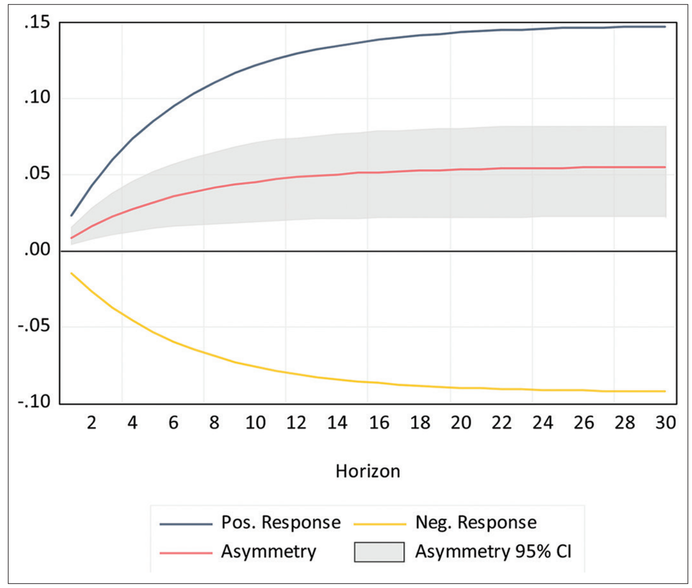
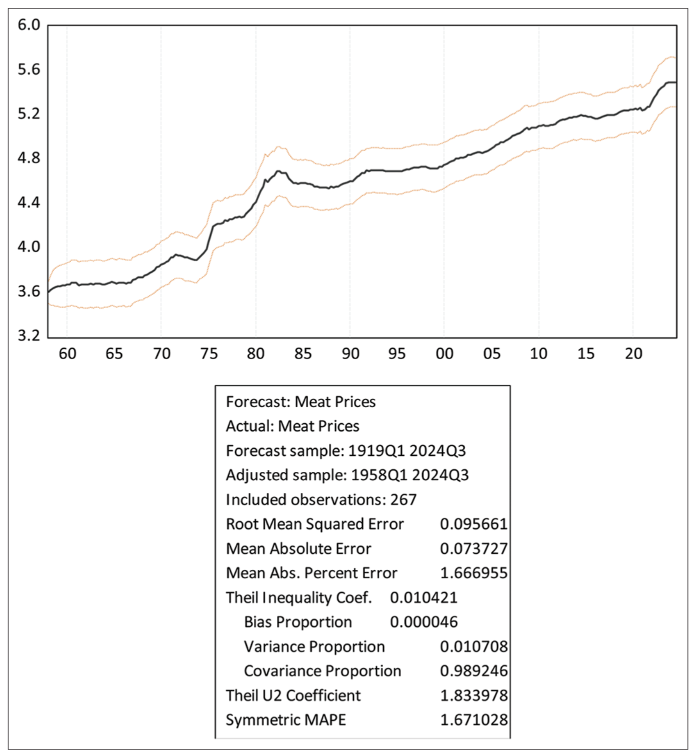


Figure 8: Forecasting meat prices



model's estimations, supporting its suitability for analyzing the economic interactions under study.

The dynamic multiplier from the NARDL model shows that increases in oil prices lead to a significant rise in milk production costs, peaking around the tenth period and then stabilizing (Figure 9). This pattern suggests that while initial shocks have a pronounced impact due to heightened transportation and energy costs, the market adjusts over time. This adjustment may be due to strategic measures by producers, such as hedging or operational changes, which help mitigate the impact of rising costs.

Figure 9: Cumulative dynamic impact of oil price shocks on milk prices

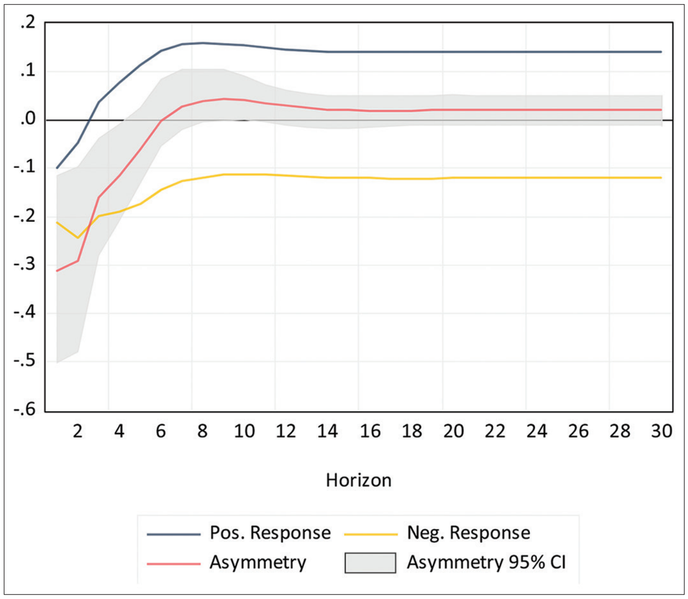
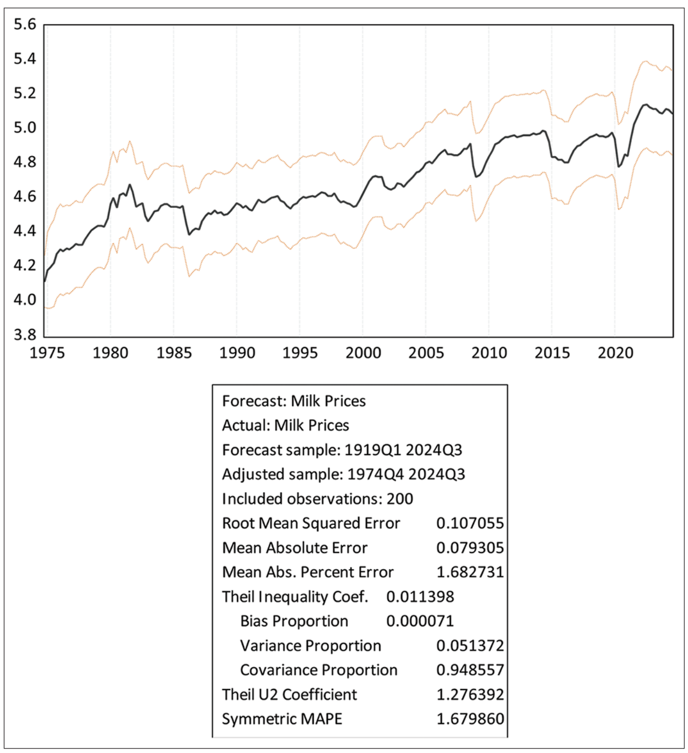


Figure 10: Forecastind milk prices



Conversely, the response to oil price decreases has a less pronounced effect on lowering milk prices. This response is more gradual and exhibits a smaller magnitude than the response to increases, indicative of typical price stickiness in commodities, where reductions in input costs do not immediately or fully translate into lower consumer prices.

The symmetric effect line underscores milk prices' overall sensitivity to oil price volatility, with a notable bias toward more significant impacts from price increases than decreases. This asymmetry highlights that while milk prices respond to changes in oil prices, they are more affected by increases, with decreases being less effectively reflected in the pricing structure.

The forecast evaluation for the U.S. producer price index for milk demonstrates robust predictive accuracy, as shown by several key statistical measures indicating high precision and reliability in forecasting milk prices (Figure 10). The Root Mean Squared Error (RMSE) of 0.1071 and Mean Absolute Error (MAE) of 0.0793 underscore the model's precise predictive capabilities. These metrics are particularly valuable for stakeholders in the dairy sector, who rely on accurate forecasts for budgeting and strategic planning.

The Mean Absolute Percent Error (MAPE) is impressively low at 1.68%, with a Symmetric MAPE of 1.68%, underscoring the model's accuracy in percentage terms. This level of accuracy is crucial in scenarios where understanding the magnitude of prediction error relative to actual values influences operational and financial decisions. Additionally, the Theil Inequality Coefficient, at only 0.0114, indicates minimal forecast errors compared to actual changes in milk prices, suggesting a high degree of fidelity in the model's predictions.

Further reinforcing the model's reliability are the Bias Proportion and Variance Proportion, which are exceedingly low at 0.000071 and 0.051372, respectively. These metrics confirm that the forecasts are free from systematic bias and demonstrate consistent performance across different samples. The high Covariance Proportion of 0.948557 indicates that most of the forecast accuracy stems from the model's effectiveness in capturing the actual movements in milk prices.

In comparison to the literature on milk production cost dynamics, our model aligns with findings from studies such as Bailey and Peterson (1999), who highlighted the significant impact of feed and energy prices on milk production costs. However, our model uniquely quantifies the asymmetric effects of oil price fluctuations, offering deeper insights into how these external economic factors specifically impact milk prices. This adds a novel dimension to our understanding, contrasting with the broader impacts discussed in works like Balcombe and Rapsomanikis (2008), who examine general price transmission mechanisms in agricultural commodities. The value of our model lies in its ability to provide a more detailed and specific understanding of milk production costs, which we believe will be highly beneficial to the agricultural economics community.

5. CONCLUSION AND POLICY IMPLICATIONS

This study offers an in-depth analysis of the complex relationship between oil prices and food prices, particularly focusing on five key agricultural commodities: corn, soybeans, wheat flour, meat, and milk. By using a regime-switching cointegration approach, our research highlights both long-term and short-term dynamics in the impact of oil price fluctuations on food prices in the United States. Notably, our findings underscore the asymmetric influence of oil price shifts, with increases having a more pronounced effect on food prices than decreases, a pattern consistent across multiple commodities analyzed. This asymmetry suggests that oil price increases likely affect production costs more severely, particularly due to their role in energy-intensive processes like transportation and input production, whereas reductions in oil prices do not result in a proportional decrease in costs.

Our findings contribute significantly to the existing literature by providing empirical evidence on how oil price volatility impacts different commodities in varying degrees. For example, while oil prices are a substantial factor for commodities like corn and wheat, they have a relatively minimal effect on meat production costs, highlighting the unique dynamics of the meat market and its insulation from energy cost volatility. This result challenges the conventional notion that oil prices are a uniform driver across all agricultural commodities. Rather, our findings suggest a need for sector-specific analyses to fully understand the determinants of production costs and pricing in the food market.

Furthermore, our study emphasizes the critical role of lagged prices in predicting future price movements, which reveals the inertia inherent in agricultural commodity markets. This persistence highlights the importance of historical prices, as they continue to influence market expectations and trading behaviors over time. Additionally, by employing the Nonlinear Autoregressive Distributed Lag (NARDL) model, we capture the nuanced asymmetric responses of food prices to oil price fluctuations, providing a comprehensive view of both short-term and long-term adjustments.

Given the findings, several implications emerge for policymakers, particularly in oil-exporting, food-importing nations like the Gulf Cooperation Council (GCC) countries. These countries are especially vulnerable to global food price inflation due to their heavy reliance on food imports and the interconnectedness between energy and food prices. Our results suggest that GCC countries could leverage their energy resources to mitigate food price volatility by investing in technologies and infrastructure that reduce dependency on global food imports. For instance, by developing controlled-environment agriculture (e.g., greenhouses) and desalination plants for water supply, GCC countries could create a more self-sustaining food production system. These investments not only reduce exposure to global food price fluctuations but also enhance food security—a priority for national stability and economic resilience.

The robustness of our model is evidenced by various key forecasting metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Our model demonstrates a high degree of accuracy across these metrics, with a particularly low Theil Inequality Coefficient, suggesting that our forecasts are significantly more reliable than naïve models and comparable econometric methods. These findings affirm the utility of our model in providing accurate forecasts for agricultural prices, thereby enabling better decision-making for stakeholders who depend on reliable data to manage production costs, investments, and strategic planning. The precision of these forecasts is particularly valuable in volatile agricultural markets, where unpredictable price shifts can have wide-ranging impacts on profitability and economic stability.

The study highlights the substantial role that oil prices play in shaping agricultural commodity prices, particularly in energy-intensive sectors. However, it is also clear from our findings that oil prices alone do not fully explain food price variability. Other factors, such as consumer demand, supply chain disruptions, and climatic conditions, are also influential. This multifaceted nature of food prices underscores the importance of a diversified approach to food production and market stability. The results indicate that while oil prices are a reliable predictor of food price trends, they are part of a broader array of factors that drive food prices. For instance, meat prices appear less sensitive to oil price fluctuations compared to other commodities, indicating that different agricultural sectors respond uniquely to economic variables.

Our findings support several policy recommendations aimed at mitigating the adverse effects of oil price volatility on food prices, especially for economies that heavily rely on imports for food security. Investing in alternative food production methods, such as vertical farming and hydroponics, can reduce reliance on imported food products and help stabilize domestic food prices. This approach is particularly relevant for countries like the GCC, which have limited arable land and water resources.

Focusing on technologies that can enhance food production in arid environments—such as desalination for water supply, greenhouse agriculture, and soil-less cultivation techniques—could further reduce the GCC's vulnerability to global food price shocks. By utilizing their energy resources to support advanced agricultural technologies, GCC countries could achieve more sustainable food production and promote greater economic stability.

Building robust infrastructure for food storage and distribution can also stabilize food prices during periods of high oil price volatility. Policies that encourage the adoption of renewable energy sources in agriculture could similarly mitigate the effects of oil price changes, promoting resilience within the food sector.

Establishing price stabilization funds or subsidies to buffer agricultural sectors from oil price fluctuations can help alleviate adverse impacts on production costs. Such mechanisms would allow governments to offer temporary relief during high oil price periods, reducing financial burdens on both producers and consumers.

Given the accuracy of forecasting models like the one used in this study, policymakers should leverage these tools to anticipate market trends and implement proactive measures. Forecasting models that account for oil price asymmetry and other macroeconomic factors can provide early warning signals for potential price hikes, enabling timely and informed interventions.

This study opens up several avenues for future research. First, exploring the role of renewable energy in reducing agricultural costs could provide insights into how alternative energy sources might insulate food markets from oil price volatility. Second, expanding the scope to include additional commodities or regions could yield valuable cross-sectional data on the oil-food price relationship in different economic and environmental contexts. Finally, investigating the interplay between other macroeconomic variables, such as interest rates, currency exchange rates, and global trade policies, could further enhance our understanding of the factors driving food prices.

In conclusion, our study highlights the asymmetric impact of oil prices on food prices and underscores the need for nuanced, sector-specific analyses to fully understand the determinants of food price variability. While oil prices are influential, they represent only one component of a complex system of factors that shape food markets. Our findings provide valuable insights for policymakers, particularly in import-dependent regions, by identifying strategic approaches to mitigate food price volatility and enhance food security. The robustness and accuracy of our model reinforce its utility as a predictive tool for agricultural markets, contributing significantly to the literature on agricultural economics and providing a solid foundation for future research.

This study emphasizes the need for comprehensive policies that leverage existing resources to create resilient food systems, ultimately supporting sustainable development and economic stability in the face of global price fluctuations. The insights gained here are especially pertinent for the GCC, where the intersection of energy resources and food security remains a critical issue. By adopting strategies that integrate energy and agriculture, GCC countries can build a more self-sustaining and resilient food market, setting a potential odel for other regions facing similar challenges.

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