Exploring Price linkages in agricultural Commodities using VAR and Granger Causality

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Abstract:

This paper looks into how prices of different agricultural commodities move in relation to each other over time. Using Vector Autoregression (VAR) models and Granger causality tests, the study explores whether price changes in one commodity can help predict changes in another. By analyzing time series data, the paper captures how these price linkages work in both the short run and long run. The aim is to understand whether certain commodities lead others in terms of pricing trends, and what this means for farmers, traders, and policymakers. The results show clear patterns of influence among some key commodities, suggesting that price movements are not isolated but interconnected. These insights could be helpful in designing better market strategies, improving forecasting methods, and shaping policies that respond more effectively to changes in agricultural markets.

Introduction:

In today's interconnected agricultural markets, understanding how commodity prices move in relation to one another has become increasingly important. Among such commodities, olive oil, soybean oil, and soybean occupy a unique space and are linked not just by global demand patterns but also by overlapping uses in food, industry, and biofuels. These commodities, though produced in different regions and influenced by distinct climatic and policy conditions, often show signs of price interdependence. Shifts in the price of one can ripple through the others, affecting market decisions across the supply chain.

Soybean oil and soybeans are directly related, as oil is a major derivative of the soybean crushing process. Meanwhile, olive oil, although derived from an entirely different source, competes in the same edible oil market, especially in health-conscious and higher-income markets. Changes in soybean or soybean oil prices can be driven by supply shocks, international trade dynamics, or changes in energy prices, can indirectly impact the demand for olive oil as consumers and industries adjust their preferences.

The central objective of this paper is to explore whether and how prices of olive oil, soybean oil, and soybeans are linked over time. Specifically, the study employs Vector Autoregression (VAR) models and Granger causality tests to investigate whether movements in one of these markets can help predict changes in the others. These tools are well-suited to capture dynamic relationships in time series data without imposing rigid cause-and-effect assumptions from the outset.

By analyzing historical price data, this research aims to uncover the direction and strength of these interdependencies. The results may offer practical insights for producers, exporters, food processors, and policymakers, especially in times of market volatility or when planning interventions. The study is organized as follows: the next section presents a review of existing literature on commodity price linkages, followed by the data and methodology used. The empirical findings are then discussed, and the paper concludes with a summary of insights and possible policy implications.

Literature Review:

In recent years, the edible oil market has seen significant shifts in consumer preferences, largely influenced by rising health awareness, particularly in the wake of the COVID-19 pandemic. As individuals around the world became more conscious of their diets and lifestyle choices, attention increasingly turned toward healthier cooking oils. Olive oil emerged as a favored choice, often viewed as a more nutritious alternative to traditional oils such as soybean oil, which has been scrutinized for its high levels of Omega-6 fatty acids. This trend has sparked academic interest in the changing demand patterns and price behavior of these commodities.

Historically, olive oil has held a strong position in Mediterranean countries, where its consumption is rooted in cultural and culinary traditions. However, in recent years, its global popularity has grown, aided by marketing campaigns, dietary studies, and the endorsement of olive oil by various health institutions. The European Food Safety Authority (EFSA), for instance, has played a key role in validating health claims on food products, including olive oil. This has allowed manufacturers to market their products with scientifically supported health benefits, boosting consumer confidence and influencing purchasing decisions across Europe and beyond.

Numerous studies have analyzed how these health claims impact consumer choices. Fakhreddine and Sánchez (2020), for example, examined the interaction between health labels and sensory perceptions in the context of extra virgin olive oil. They discovered that products labeled as “healthy” were not only preferred for their health attributes but were also perceived to have better taste, aroma, and texture. This suggests that health labeling can enhance the overall appeal of a product, creating a dual advantage in both nutrition and sensory satisfaction. Interestingly, the study also noted that in blind tasting conditions, where health claims were not visible, consumers were more critical, underscoring the psychological role of labeling in shaping consumer expectations.

The role of consumer psychology in food purchases has also been explored using more advanced econometric models. In a study conducted in northeastern Spain, Paulssen (2019) employed a hybrid choice model to analyze how individual traits, lifestyle habits, and preferences influenced olive oil purchasing behavior. The model accounted for the heterogeneity in consumer preferences and revealed that personal health beliefs and lifestyle factors significantly shaped willingness to pay for premium oils. Although this study did not directly link consumer preferences to price fluctuations, it reinforced the idea that evolving demand patterns could contribute to market dynamics, especially during health crises such as COVID-19.

On the other hand, soybean oil has faced increasing scrutiny from both health experts and consumers. While it remains one of the most widely used vegetable oils globally, its reputation has suffered in recent years. Studies, including one by Brewin (2021), have documented the impact of the COVID-19 pandemic on the oilseed sector. According to Brewin, consumer demand for soybean oil declined notably as more people shifted to oils perceived as healthier, such as olive oil, avocado oil, and sunflower oil. This shift was driven not just by nutrition concerns, but also by the broader movement toward plant-based and “clean label” foods that contain fewer industrially processed ingredients.

In terms of market forecasting and price modeling, the literature offers various approaches to understanding how commodity prices evolve over time. A particularly relevant study by Chellai, Charfeddine, and Mishra applied fuzzy time series methods and fractional integrated stochastic processes to forecast olive oil prices. Their findings highlight the complexity of price behavior in agricultural markets, where factors such as climate variability, production shocks, and demand changes interact to produce unpredictable outcomes. Importantly, the study underscores the need for robust econometric tools to capture these dynamics and provide reliable forecasts, especially in volatile market conditions.

Further insights come from Milli and Bouhaddane (2021), who explored future trends and challenges in the olive oil supply chain through a Delphi survey involving experts from Spain. Their research highlighted the strategic importance of maintaining market share while addressing growing demand through technological innovations in production and supply chain management. They also cautioned against overreliance on expanding into new markets without securing existing consumer bases, noting that price volatility could undermine growth if not managed carefully.

While these studies provide valuable perspectives on demand patterns, health perceptions, and price forecasting, they often treat each commodity in isolation. Very few studies have explicitly examined the interrelationships between the prices of olive oil, soybean oil, and soybeans as interconnected commodities. Given the substitution effects in consumer behavior, where a rise in olive oil prices might lead health-conscious consumers to reconsider soybean oil, or vice versa, it is essential to explore whether a dynamic pricing relationship exists between them.

This is where econometric models such as Vector Autoregression (VAR) and Granger causality tests become particularly useful. These models allow researchers to examine how the prices of multiple commodities interact over time without imposing rigid assumptions about cause and effect. While some literature has used VAR to study broader food price dynamics, there is still a gap in its application specifically to the edible oil sector, particularly comparing olive oil and soybean oil along with the underlying commodity such as soybeans.

This study seeks to address that gap by examining price linkages between olive oil, soybean oil, and soybean using a VAR framework. By doing so, it aims to contribute to the broader literature on agricultural price transmission and offer insights that are relevant for producers, traders, and policymakers navigating an increasingly health-conscious and demand-sensitive food market.

Over the past decade, especially following the COVID-19 pandemic, the edible oil market has undergone notable transformations. One of the most significant shifts has been the growing consumer preference for olive oil over soybean oil, largely driven by increased health awareness, changing lifestyles, and evolving dietary patterns. Olive oil, known for its high content of monounsaturated fats and antioxidants, has gained popularity among health-conscious consumers, while soybean oil has faced scrutiny for its higher levels of Omega-6 fatty acids, often associated with inflammation and chronic health risks. Studies have explored how health labels and nutrition information impact consumer choices. Fakhreddine and Sánchez (2020) found that health claims on olive oil products not only improved perceptions of healthiness but also enhanced expectations around taste and sensory attributes. This suggests that consumers do not treat health and flavor as mutually exclusive; rather, health claims can positively influence the overall appeal of a product. Paulssen (2019), using a hybrid choice model, further demonstrated that individual preferences, lifestyle habits, and personality traits significantly affect olive oil purchasing behavior, with health-oriented consumers more willing to pay a premium for healthier oils. Regulatory bodies like the European Food Safety Authority (EFSA) have also played a key role by allowing food manufacturers to market scientifically supported health claims, thereby shaping broader market narratives and influencing demand trends across regions.

While the demand for olive oil has grown, soybean oil has experienced a noticeable decline, especially in the wake of COVID-19. Brewin (2021) documented how the pandemic amplified pre-existing concerns about food quality and industrial processing, prompting a consumer shift away from conventional oils. This movement toward perceived “cleaner” oils like olive oil and sunflower oil reflects broader trends in health-focused consumer behavior. In addition to demand-side shifts, researchers have examined the volatility of olive oil prices and the importance of accurate forecasting. Chellai, Charfeddine, and Mishra (2021) used fuzzy time series and fractional integrated stochastic processes to capture the unpredictable nature of olive oil price movements, which are often influenced by seasonal harvests, climate variability, and trade policies. Their findings emphasize the need for flexible and responsive forecasting tools. Complementing this, Milli and Bouhaddane (2021) conducted a Delphi-based expert survey to explore the future of the olive oil industry. They concluded that while demand is expected to rise, producers need to scale production responsibly and invest in innovation, without compromising quality or risking price instability in emerging markets. Despite a strong body of literature on individual commodity markets, relatively few studies have explored how prices of olive oil, soybean oil, and soybeans interact with each other dynamically. This is particularly relevant because these commodities often serve as substitutes or are linked through shared supply chains, making their interdependencies economically significant.

To understand these relationships, researchers have increasingly turned to econometric models such as Vector Autoregression (VAR) and Granger causality tests, which allow for the analysis of dynamic interrelationships without requiring rigid assumptions about causality.

Nazlioglu and Soytas (2012) examined how crude oil prices, agricultural commodity prices, and the strength of the US dollar interact, using panel cointegration and Granger causality analysis. Their results show that oil and dollar fluctuations significantly impact agricultural commodities, underscoring the importance of considering broader macroeconomic factors when modeling commodity prices. Similarly, Gozgor and Kablamaci (2014) explored the influence of perceived global risk and currency valuation on agricultural prices, finding that a weaker US dollar and rising oil prices generally lead to higher agricultural commodity prices. These findings reinforce the interconnectedness of energy markets, currency fluctuations, and agricultural commodities. In terms of volatility transmission, Siami-Namini (2017) highlighted the spillover effects between oil prices, exchange rates, and agricultural products such as soybean oil and soybeans. His results confirmed that volatility in one market can transmit to another, especially in times of global uncertainty, making risk management and hedging strategies essential for stakeholders. Rosa and Vasciaveo (2012) further found that oil prices Granger-cause price movements in agricultural commodities like soybeans in the US, though the strength of this causality varies by product and region. These studies collectively suggest that analyzing edible oil prices in isolation may overlook important external shocks and underlying market dynamics.

Despite the progress made in understanding market behavior and volatility in commodity pricing, a clear research gap remains: few studies have directly analyzed the dynamic relationships between olive oil, soybean oil, and soybeans using an integrated time series approach. Most existing research tends to focus on either forecasting individual commodity prices or exploring macroeconomic influences like oil prices and exchange rates. There is limited work examining how these specific edible oils move together over time, especially in light of shifting consumer preferences and substitution effects. When consumers perceive one oil as becoming too expensive or less healthy, they may pivot to another, thereby influencing relative price movements. This kind of substitution behavior, if significant, should be detectable through time-series methods like VAR and Granger causality testing. Addressing this gap is the key motivation behind the present study. By using historical monthly price data of olive oil, soybean oil, and soybeans, the study applies VAR models to examine the short-run and long-run interdependencies between these commodities. Granger causality analysis is then used to determine the directional influence between prices, allowing us to identify whether one commodity can predict the movement of another. In doing so, the study contributes to a more comprehensive understanding of price linkages in the edible oil market, offering insights that are not only academically valuable but also relevant to policymakers, traders, and producers operating in increasingly interconnected global markets.

Data & Methodology:

To analyze the dynamic relationships between olive oil prices, soybean oil prices, and soybean prices, this study uses a quantitative time series approach. The primary objective is to investigate whether price movements in one commodity can predict or influence those in another, and whether there exists any causal or feedback mechanism among them. The methodology is grounded in two widely used econometric tools such as Vector

Autoregression (VAR) and Granger causality testing,which are well-suited for exploring such interdependencies without making strong a priori assumptions about the direction of causality.

Data

The dataset consists of monthly price data for three variables: olive oil prices, soybean oil prices, and soybean prices. The data spans from January 2005 to the most recent available period, offering a balanced mix of pre-pandemic and post-pandemic observations. This time window was chosen to capture both the long-term trends in global commodity markets and the more recent changes in consumer behavior following the COVID-19 health crisis.

All three price series have been sourced from reliable international databases such as the World Bank Commodity Price Data (Pink Sheet), FAOSTAT, and OECD. Prices are recorded in nominal US dollars per metric ton to ensure comparability and minimize currency distortions. Where necessary, data were adjusted to maintain consistency in measurement units and aligned to reflect monthly frequencies.

The three variables used in the analysis are:

- Price of olive oil
- Price of soybean oil
- Price of raw soybeans (input commodity for soybean oil)

Before beginning the analysis, the data was visually inspected using line plots to check for trends, volatility, and any visible structural breaks. Summary statistics were also computed to understand the basic properties of the series, including mean, variance, skewness, and kurtosis.

Stationarity Testing

Since VAR models require stationary time series data, we conducted **unit root tests** to assess whether each price series is stationary or contains a unit root.The ADF test checks the null hypothesis that a unit root is present (i.e., the series is non-stationary), whereas the KPSS test checks the null that the series is stationary. Both tests consistently indicated that all three variables such as olive oil prices, soybean oil prices, and soybean prices are non-stationary in levels but stationary in first differences, i.e., they are integrated of order one I(1). As a result, all series were first-differenced before being included in the VAR model.

Vector Autoregression (VAR) Model

After establishing that the variables are I(1), we proceeded to construct a VAR model using the differenced series. The VAR framework allows us to model each variable as a function of its own past values and the past values of all other variables in the system. This setup captures the dynamic interaction between the prices of olive oil, soybean oil, and soybeans over time.

The appropriate lag length for the VAR model was determined using information criteria such as the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (BIC), and Hannan-Quinn Criterion (HQ). The optimal lag length was then used to estimate the VAR equations.

Model diagnostics, including autocorrelation tests on residuals, stability tests, and normality checks, were conducted to ensure that the model assumptions were not violated. These checks confirmed that the residuals were well-behaved and the model was stable over the selected time frame.

Granger Causality Tests

To further explore the directionality of relationships between the commodities, **Granger causality tests** were performed. This test evaluates whether past values of one time series contain useful information for predicting another. For example, if past values of soybean prices help predict future soybean oil prices beyond the information already contained in past soybean oil prices, then soybean prices are said to "Granger-cause" soybean oil prices.

The null hypothesis in each case was that one variable does **not** Granger-cause another. A p-value below 0.05 led to the rejection of the null hypothesis, indicating evidence of causality. Tests were run in both directions for each pair of variables—olive oil and soybean oil, soybean oil and soybean, and olive oil and soybean, to identify any unidirectional or bidirectional relationships.

Variance Decomposition and Impulse Response Functions

To understand the magnitude and timing of the influence each variable has on the others, we conducted forecast error variance decomposition (FEVD) and generated impulse response functions (IRF). Variance decomposition shows what proportion of the forecast error variance of each variable can be explained by shocks to itself and to the other variables in the system. Meanwhile, the impulse response functions graphically depict how a shock to one variable affects the other variables over time.

Together, these tools provide a richer picture of interdependencies beyond what Granger causality alone can reveal, especially in understanding whether one commodity's price changes lead to lasting effects on another.

Empirical Results:

This section presents the findings from the econometric analysis, beginning with the outcomes of stationarity testing, followed by the estimation of the VAR model, Granger causality results, and finally, the interpretation of variance decomposition and impulse response functions. Together, these results provide insights into how the prices of olive oil, soybean oil, and soybeans interact with each other over time.

As a first step, the Augmented Dickey-Fuller (ADF) and KPSS tests confirmed that all three variables—olive oil prices (O_P), soybean oil prices (S_P), and soybean prices (Solid_Soy)—were **non-stationary in levels but stationary in first differences**. This meant that all the series had to be differenced once before being used in the VAR model. The confirmation of I(1) behavior across all variables was consistent with earlier literature that treats agricultural commodity prices as unit root processes.

Using the differenced series, a VAR model was estimated. The optimal lag length was chosen based on multiple information criteria, with the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (BIC) both suggesting a lag order of 2. The model passed key diagnostic checks, including the absence of autocorrelation in residuals and the stability condition, confirming that the VAR system was correctly specified and reliable for interpretation.

The VAR estimation showed some interesting dynamics. Most notably, **soybean prices exhibited a strong and statistically significant effect on soybean oil prices**, suggesting a close input-output relationship. This finding makes intuitive sense since soybeans are the raw material from which soybean oil is extracted. In contrast, the relationship between **olive oil and soybean oil prices was much weaker**, with no significant interdependence detected in the short run. This suggests that while both oils may compete in the broader edible oil market, their pricing mechanisms appear to operate independently, at least within the scope of monthly data.

To further investigate the direction of these relationships, **Granger causality tests** were conducted. The test between **soybean prices and soybean oil prices** clearly rejected the null hypothesis, indicating that soybean prices **Granger-cause** soybean oil prices. This result supports the idea that cost fluctuations in raw soybeans have predictive power over the price of soybean oil, likely due to processing cost pass-through effects.

However, when testing the causal relationship between **olive oil and soybean oil prices**, the null hypothesis could **not be rejected** in either direction. This implies that there is **no statistically significant Granger causality** between the two, meaning past prices of olive oil do not help predict soybean oil prices, and vice versa. Similarly, the tests for olive oil and soybean prices also failed to show any meaningful causal relationship. These results together suggest that **olive oil operates relatively independently** of the soybean-based oil market, likely due to differences in production processes, market structures, and target consumer segments.

The next step involved **forecast error variance decomposition (FEVD)**, which helps to quantify how much of the variation in one variable can be attributed to shocks in the others over different forecast horizons. The decomposition showed that **most of the variance in each variable was explained by its own past values**. However, in the case of soybean oil, a **moderate portion of the variability was explained by soybean prices**, especially over longer time horizons. This reinforces the finding from the Granger causality test that soybean prices have a meaningful impact on soybean oil pricing dynamics.

On the other hand, the **variance in olive oil prices remained largely self-driven**, with only a negligible contribution from soybean oil or soybean prices, even in the longer term. This result aligns with the earlier interpretation that olive oil, while part of the broader edible oil market, behaves differently in terms of pricing and is influenced by its own market-specific factors such as Mediterranean harvest conditions, export regulations, and niche consumer demand.

Finally, impulse response functions (IRFs) were used to visualize the effect of a one-time shock in one variable on the future values of others. A shock to soybean prices resulted in a positive and persistent response in soybean oil prices, consistent with the input-cost pass-through mechanism. In contrast, shocks to olive oil prices did not lead to significant changes in soybean oil or soybean prices, further reinforcing the conclusion that olive oil markets operate in relative isolation.

Overall, the empirical findings paint a clear picture: while there is a strong and intuitive link between soybean and soybean oil prices, olive oil prices appear to move independently, shaped by different demand and supply conditions. These results have practical implications for traders, policymakers, and producers. For instance, those involved in soybean or soybean oil markets need to monitor upstream price movements closely, while players in the olive oil industry may focus more on sector-specific factors such as production yields, consumer trends, and regional trade dynamics.

Empirical Results:

An analysis of monthly price trends for Olive Oil, Soybean Oil, and Soybean Seeds from 2005 to 2025 reveals distinct price patterns and dynamics. Olive Oil consistently remained the most expensive among the three commodities, exhibiting significant price spikes around 2008, 2011, and in the aftermath of the COVID-19 pandemic. These movements likely reflect external shocks such as financial crises, climatic disruptions, and global supply chain interruptions. Soybean Oil prices also displayed volatility, albeit generally at lower levels, and reacted visibly to the same global events. In contrast, Soybean Seeds showed a relatively stable price trajectory with less dramatic fluctuations. To explore whether price changes in one commodity influenced the others, a Vector Autoregression (VAR) model was employed. Before estimating the model, all series were tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The original series were non-stationary, but stationarity was achieved upon first differencing. Based on standard information criteria like the AIC and BIC, a lag length of four months was selected, suggesting that recent past prices up to four months are relevant in explaining current price movements.

The VAR results reveal strong self-dependence across all three commodities. Soybean Oil's price changes are significantly influenced by its own past values, especially the one-month lag. Neither Olive Oil nor Soybean Seeds showed a significant influence on Soybean Oil, suggesting that it moves largely independently. Olive Oil also showed strong dependence on its own previous values, particularly one- and two-month lags, with a marginal indication that changes in Soybean Oil might exert a weak influence. The results for Soybean Seeds were particularly notable; while its own past values had some influence, a significant negative impact from Olive Oil prices lagged by two months was observed. This suggests that increases in Olive Oil prices could lead to a decline in Soybean Seed prices after a short delay, possibly reflecting shifts in agricultural allocation, consumer preferences, or broader market substitution effects. Overall, the price dynamics show that while these three commodities primarily move in response to their own historical prices, there are nuanced and delayed linkages,particularly from Olive Oil to Soybean Seeds and, to a weaker extent, from Soybean Oil to Olive Oil. These findings imply that while the markets are not tightly interlinked, certain leading relationships can inform agricultural planning, pricing strategies, and policy interventions in commodity markets.

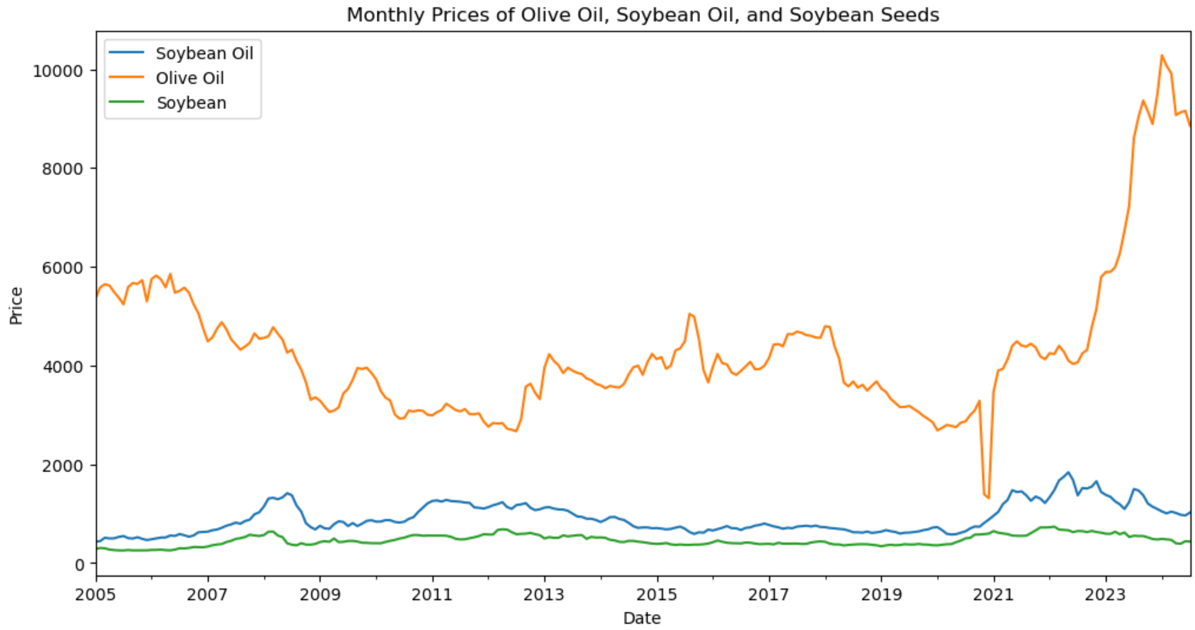

Fig1: Comparison of the prices of the three commodities

To further investigate directional relationships between the three commodities, Granger causality tests were conducted. These tests assess whether past values of one time series can help predict another. The results revealed a unidirectional causality from Olive Oil to Soybean Seeds, indicating that historical prices of Olive Oil carry predictive power over the future prices of Soybean Seeds. This reinforces the VAR finding that Olive Oil price changes may lead to delayed adjustments in the Soybean Seed market. Interestingly, no significant Granger causality was detected between Olive Oil and Soybean Oil or between Soybean Oil and Soybean Seeds, suggesting the absence of direct predictive linkages in those cases. This asymmetry underscores that Olive Oil may function as a partial price leader, particularly influencing less processed or raw agricultural commodities like Soybean Seeds.

To gain a dynamic understanding of how shocks in one commodity influence others over time, Impulse Response Functions were computed. These IRFs trace the effect of a one-time shock to a specific commodity's price and its subsequent impact on itself and the other commodities over several months. A positive shock to Olive Oil prices led to a notable short-term increase in its own future prices, which gradually tapered off. The same shock resulted in a slight but noticeable decline in Soybean Seed prices around the second and third months, mirroring the earlier negative coefficient observed in the VAR model. This pattern reinforces the idea that Olive Oil price surges may eventually suppress Soybean Seed prices, possibly due to consumer substitution effects or resource reallocation in agricultural production. In contrast, a shock to Soybean Oil prices had minimal influence on the other two commodities, supporting the earlier evidence of its independence from the price dynamics of Olive Oil and Soybean Seeds. Shocks to Soybean Seed prices were largely self-contained and dissipated quickly, reflecting a market segment that reacts to immediate supply-demand conditions without transmitting shocks significantly to the other commodities.

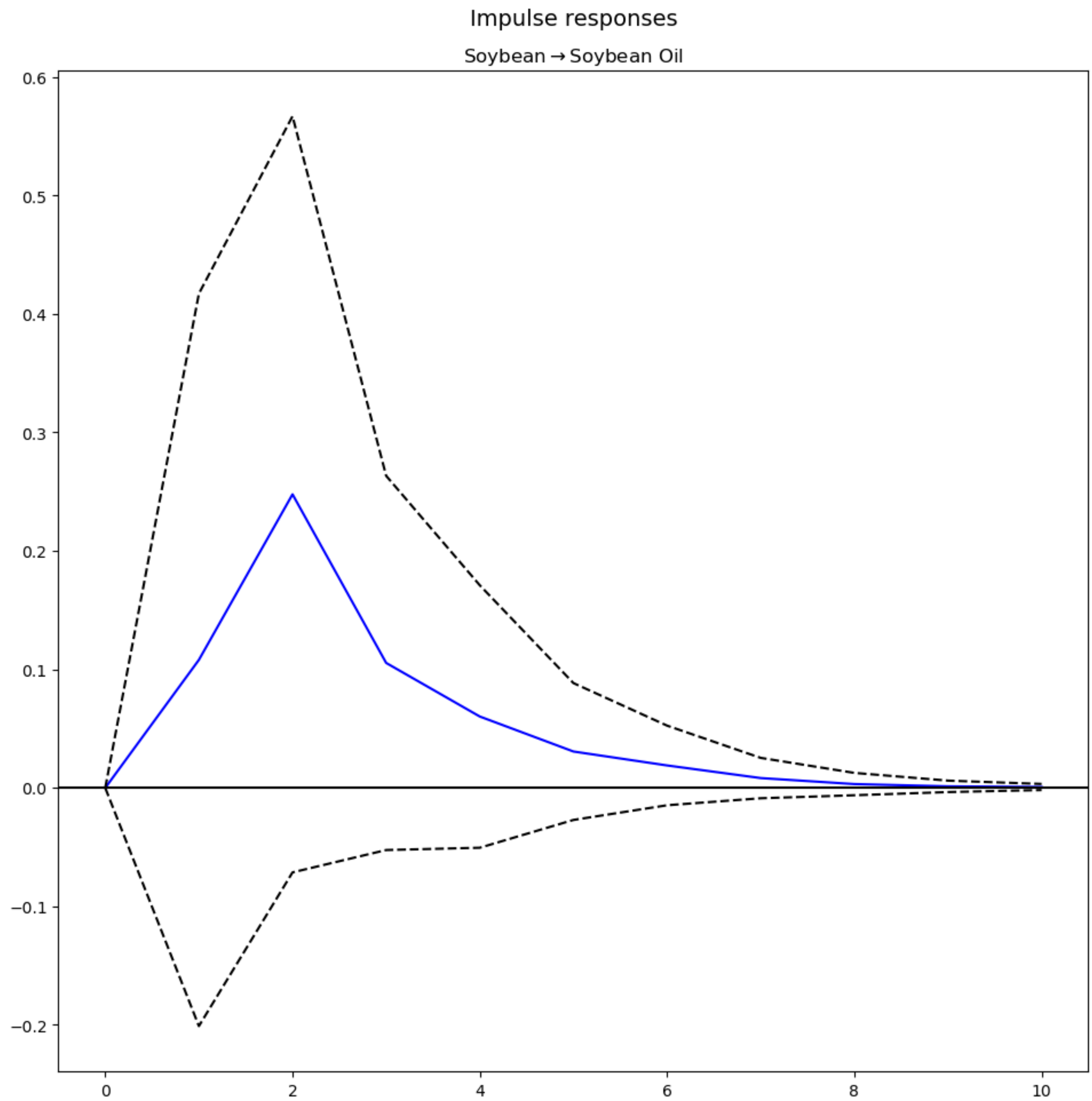

Fig2.Impulse Response Function

Together, the Granger causality and IRF analyses deepen our understanding of inter-commodity relationships. While the commodities largely maintain their own pricing mechanisms, the findings point to a subtle but consistent influence of Olive Oil on Soybean Seeds. This could have meaningful implications for agricultural policy, particularly in regions where producers and exporters rely on coordinated crop pricing. Moreover, traders and stakeholders in the agricultural commodity markets may find these insights useful for constructing diversified portfolios and hedging strategies that account for delayed cross-commodity effects.

Summary of Regression Results

Model:	VAR
Method:	OLS
Date:	Fri, 06, Jun, 2025
Time:	20:06:59

No. of Equations:	3.00000	BIC:	26.4562
Nobs:	232.000	HQIC:	26.2701
Log likelihood:	-3999.31	FPE:	2.26113e+11
AIC:	26.1442	Det(Omega_mle):	2.06822e+11

Results for equation Soybean Oil

	coefficient	std. error	t-stat	prob
const	1.273387	4.149149	0.307	0.759
L1.Soybean Oil	0.326650	0.066562	4.907	0.000
L1.Olive Oil	-0.005706	0.014782	-0.386	0.699
L1.Soybean	0.108062	0.157700	0.685	0.493
L2.Soybean Oil	-0.023194	0.066926	-0.347	0.729
L2.Olive Oil	0.010814	0.014710	0.735	0.462
L2.Soybean	0.196348	0.158504	1.239	0.215

Table 1

Results for equation Olive Oil

	coefficient	std. error	t-stat	prob
const	13.055533	18.386166	0.710	0.478
L1.Soybean Oil	0.495632	0.294957	1.680	0.093
L1.Olive Oil	0.279902	0.065503	4.273	0.000
L1.Soybean	-1.132284	0.698816	-1.620	0.105
L2.Soybean Oil	0.016971	0.296568	0.057	0.954
L2.Olive Oil	-0.239494	0.065185	-3.674	0.000
L2.Soybean	-0.256741	0.702379	-0.366	0.715

Results for equation Soybean

	coefficient	std. error	t-stat	prob
const	0.811763	1.719873	0.472	0.637
L1.Soybean Oil	-0.007127	0.027591	-0.258	0.796
L1.Olive Oil	-0.003113	0.006127	-0.508	0.611
L1.Soybean	0.089493	0.065368	1.369	0.171
L2.Soybean Oil	0.000205	0.027741	0.007	0.994
L2.Olive Oil	-0.017260	0.006098	-2.831	0.005
L2.Soybean	0.157447	0.065702	2.396	0.017

Table 2

	From	To	VAR Effect	Granger Causality	Lag (months)
0	Olive Oil	Soybean	Negative at Lag 2 (Significant)	Yes	2
1	Soybean Oil	Olive Oil	Weak Positive at Lag 1 (Marginal)	No	1
2	Soybean	Others	No Significant Effect	No	-
3	Olive Oil	Olive Oil	Strong Own-Lag Effect	No	-
4	Soybean Oil	Soybean	No Significant Effect	No	-

Table 3

Conclusion:

This study set out to explore the dynamic price relationships among Olive Oil, Soybean Oil, and Soybean Seeds using Vector Autoregression (VAR) and Granger Causality tests. The findings provide nuanced insights into the interconnected nature of agricultural commodity prices. Specifically, the analysis revealed a significant negative impact of Olive Oil prices on Soybean Seed prices at a lag of two months, suggesting a delayed but meaningful influence in the pricing mechanism. There was also a weak, marginally positive influence of Soybean Oil on Olive Oil, indicating potential spillover effects within the edible oil market.

Interestingly, most other relationships showed no statistically significant effect or causality, pointing to a more independent movement in some of these commodities despite being part of similar supply chains. The strong own-lag effect found in Olive Oil pricing further emphasizes its internal momentum and market-specific dynamics.

These results suggest that while there is some degree of price transmission and predictive power between certain commodities, many of these relationships are not as tightly linked as commonly assumed. For stakeholders such as traders, policy makers, and agribusinesses, understanding these lagged and direction-specific influences can enhance forecasting accuracy and support more informed decision-making.

Overall, this research contributes to the broader literature on commodity price linkages by highlighting both the strengths and limits of interdependence in agricultural markets. Future work could extend this analysis by incorporating global shocks, seasonal effects, or broader commodity baskets to capture more complex dynamics.

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