

Energy, Fertilizers and Biofuels

Understanding the Transmission of Geopolitical Risk Across Commodity Futures Markets

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1. Introduction

Geopolitical shocks are usually priced first in the markets most directly exposed to the threatened supply chain. In the case of Iran-related tensions around the Strait of Hormuz, the most immediate pricing channel is crude oil. The Strait of Hormuz is one of the world's most important oil chokepoints, with EIA estimating that oil flows through the strait averaged around 20 million barrels per day in 2024, equivalent to roughly 20% of global petroleum liquids consumption [7]. Yet the market response does not necessarily stop at oil. Energy prices affect transportation costs, storage, processing margins and agricultural inputs. Gasoline prices affect the relative attractiveness of ethanol and other biofuels. Natural gas is linked to ammonia and nitrogen fertilizer production. Soybean oil is a more direct input into biodiesel and renewable diesel than soybeans themselves. For this reason, an energy shock can become a cross-commodity shock.

This paper uses the 2026 Iran-Hormuz shock as a case study to analyse how geopolitical risk may transmit from energy futures to agricultural and biofuel-linked futures. The purpose is not to forecast commodity prices, nor to claim that a single geopolitical event explains all movements in corn and soybean markets. Instead, the objective is to study whether the observed pattern of prices, volatility and abnormal returns is consistent with an indirect transmission mechanism from energy markets to agricultural futures.

2. Theoretical Background

Commodity futures are central to price discovery because they aggregate information about expected supply, demand, storage, inventory pressure, hedging demand and risk premia. In an efficient futures market, new information should be reflected quickly in prices, especially when the shock affects a highly traded benchmark such as Brent crude oil or RBOB gasoline.

The relevant object is not only the price level, but also the distribution of risk around that price. A futures curve may reprice because traders expect a short-term physical shortage, because inventories are expected to tighten, or because risk premia increase even without an immediate supply loss. This distinction matters for geopolitical events: a sharp move in near-term energy contracts may signal short-run disruption risk, while a broader cross-

commodity move may suggest a more persistent repricing of input costs and substitution channels.

Volatility also provides information. Financial returns often display volatility clustering: large shocks tend to be followed by large shocks, and tranquil periods tend to be followed by tranquil periods. ARCH and GARCH models formalize this property [1, 2]. The GJR-GARCH extension allows volatility to respond asymmetrically to positive and negative innovations [3].

3. Transmission Channels

3.1. Oil supply-risk channel

The first channel is the oil supply-risk channel. A threat to tanker traffic or the Strait of Hormuz is immediately relevant for crude oil futures, tanker insurance, shipping risk and the geopolitical risk premium embedded in energy prices. Recent 2026 reporting described Hormuz-related shipping disruptions and closure warnings as a central market concern during the Iran-Hormuz shock [4, 11].

3.2. Fuel and biofuel channel

The second channel is the fuel and biofuel channel. When oil and gasoline become more expensive, biofuels can become relatively more attractive. In the United States, corn is the main feedstock for fuel ethanol [8], while soybean oil is an important feedstock in biodiesel and renewable diesel markets [5, 10]. This does not mean that corn and soybeans must mechanically rise when oil rises. It means that a sufficiently large energy shock can alter expected feedstock demand through the relative economics of fuel blending, ethanol and biodiesel.

The empirical implication is that soybean oil should be more informative than soybeans for the biodiesel channel. Soybeans are a broad agricultural contract. Soybean oil is closer to the biofuel feedstock. If the biofuel channel is economically relevant, it should appear more clearly in RBOB gasoline and soybean oil than in soybeans alone.

3.3. Fertilizer and ammonia channel

The third channel is the fertilizer and ammonia channel. Natural gas matters because ammonia production is energy-intensive and relies heavily on fossil-fuel feedstocks. EIA notes that natural gas is used both as a feedstock and fuel for nitrogen-based fertilizers, with hydrogen from methane combined with nitrogen to make ammonia [6]. USDA-ERS also emphasizes the role of natural gas in nitrogen fertilizer production [9]. Since ammonia is the foundation for nitrogen fertilizers, natural gas volatility can influence agricultural input-cost expectations.

4. Data and Methodology

The empirical dataset contains daily close or settlement-proxy prices for the period 1 July 2025 to 30 June 2026. The core series are Brent crude oil, WTI crude oil, natural gas, corn, soybeans, soybean oil and RBOB gasoline futures. All series are cleaned, sorted in chronological order and transformed into daily log returns, normalized price indices and rolling volatility measures.

The paper applies five empirical tools. First, all price series are indexed to 100 on 27 February 2026, the last trading day before the March–June event window used in the charts. Second, daily log returns are computed. Third, 20-day annualized rolling volatility is calculated from daily log returns to evaluate whether the event window is associated with changes in market uncertainty. Fourth, an event study measures abnormal returns around selected Hormuz-related news events using a constant-mean benchmark estimated over a pre-event window. Fifth, a GJR-GARCH(1,1) model is estimated on daily log returns to formalize volatility clustering, aggregate persistence and asymmetric volatility responses.

$$r_t = 100 \times (\ln(P_t) - \ln(P_{t-1})), \quad (1)$$

$$I_t = 100 \times \frac{P_t}{P_{t_0}}, \quad (2)$$

$$AR_{i,t} = r_{i,t} - E(r_i), \quad CAR_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_{i,t}. \quad (3)$$

The GJR-GARCH(1,1) specification is defined as:

$$r_t = \mu + \varepsilon_t$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1}, \quad I_{t-1} = 1\{\varepsilon_{t-1} < 0\}.$$

In this model, ω captures the constant component of conditional variance, α measures the immediate impact of recent shocks, β captures the sensitivity of current conditional variance to lagged conditional variance, and γ captures asymmetric volatility responses to negative innovations. Aggregate volatility persistence is computed as:

$$\text{Persistence} = \alpha + \beta + \frac{\gamma}{2}.$$

A persistence value close to one indicates that volatility shocks decay slowly, while lower values imply faster mean reversion. The model estimates are reported together with p-values to distinguish statistically significant coefficients from parameters that are not significantly different from zero at conventional confidence levels.

Daily returns are expressed in percentage points. Annualized volatility is computed as the daily return standard deviation multiplied by $\sqrt{252}$, where 252 approximates the number of trading days in one year. Event-window cumulative abnormal returns are also expressed in percentage points.

Asset	Obs.	Mean (%)	Ann. volatility (%)	Min (%)	Max (%)
Brent	257	0.03	49.3	-15.7	8.8
RBOB Gasoline	259	0.14	47.9	-12.0	11.9
Natural Gas	260	-0.02	109.6	-64.4	35.6
Corn	255	0.01	21.4	-5.6	5.9
Soybeans	257	0.04	16.7	-4.7	3.9
Soybean Oil	257	0.08	23.5	-7.1	4.6
Gold	232	0.08	29.4	-12.1	5.9
DXY	258	0.02	5.8	-1.2	1.0
VIX	259	-0.01	118.0	-20.4	33.4

Table 1: Descriptive statistics of daily log returns.

5. Empirical Analysis

5.1. Energy Futures Repricing

The first empirical step isolates the energy market. Brent is used as the main oil benchmark because a Hormuz-related shock is a global supply-risk event rather than a purely U.S. crude-oil event. Natural gas is included not as an oil substitute, but as the key input-cost proxy for the fertilizer and ammonia channel. Figure 1 shows that the energy-market reaction is visually concentrated in Brent, which rises sharply during the early part of the event window.

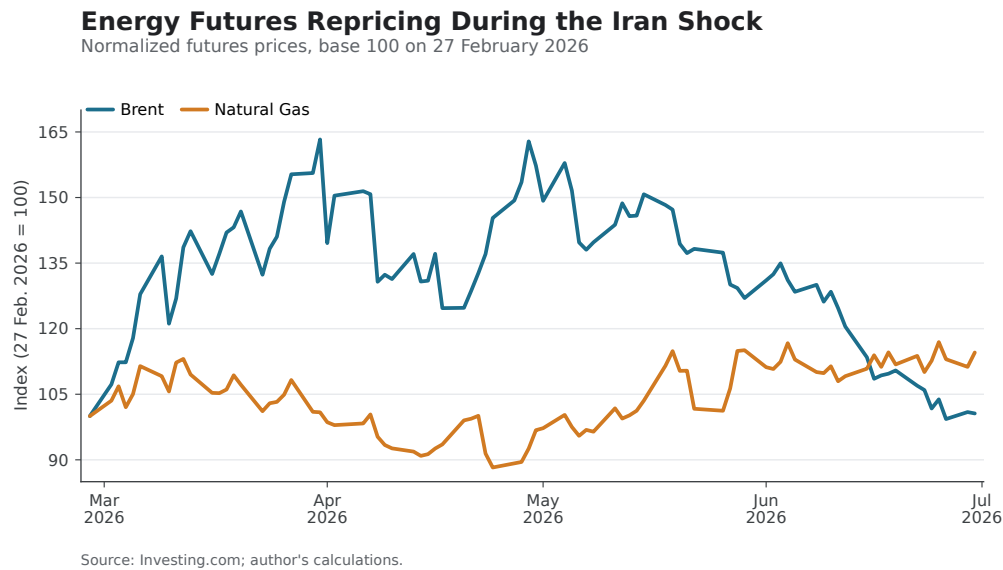


Figure 1: Energy futures as the origin of the transmission mechanism. Brent and Natural Gas represent two distinct energy channels: Brent captures the geopolitical oil-supply risk embedded in global crude markets, while Natural Gas proxies the input-cost channel linked to ammonia and nitrogen fertilizers. Reading the two series together helps distinguish between a direct oil-risk repricing and a broader energy-cost mechanism potentially relevant for agricultural commodities.

5.2. Agricultural Futures During the Event Window

Figure 2 shows the direct agricultural futures. Corn and soybeans display a much smaller range than Brent and RBOB gasoline. This is economically intuitive. Agricultural futures should not mechanically replicate oil futures, because their pricing also reflects weather, inventories, crop conditions, export demand and USDA information. A weaker response is therefore not evidence against transmission; rather, it is consistent with the fact that the transmission mechanism is indirect.

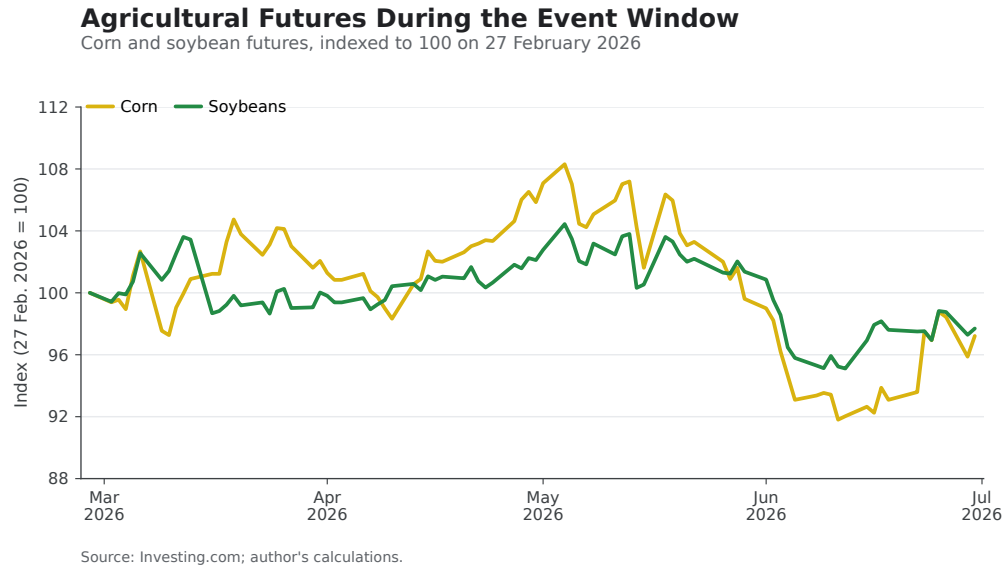


Figure 2: Agricultural futures as the downstream segment of the shock. Corn and Soybeans are not directly exposed to Middle Eastern supply risk, but they may react indirectly through biofuel demand expectations and agricultural input costs. Their joint behavior provides a first indication of whether the energy shock remains confined to oil and gas markets or begins to propagate toward crop futures.

5.3. Volatility Response

Price levels show where the market moved; volatility shows how uncertainty changed. Figure 3 separates energy and fuel-linked volatility from agricultural volatility. Brent volatility rises strongly early in the event window and then declines as the risk premium begins to compress. RBOB gasoline remains volatile because it sits closer to the fuel-consumption channel. Natural gas has its own volatility profile, which should be interpreted cautiously due to seasonality and contract-specific behavior.

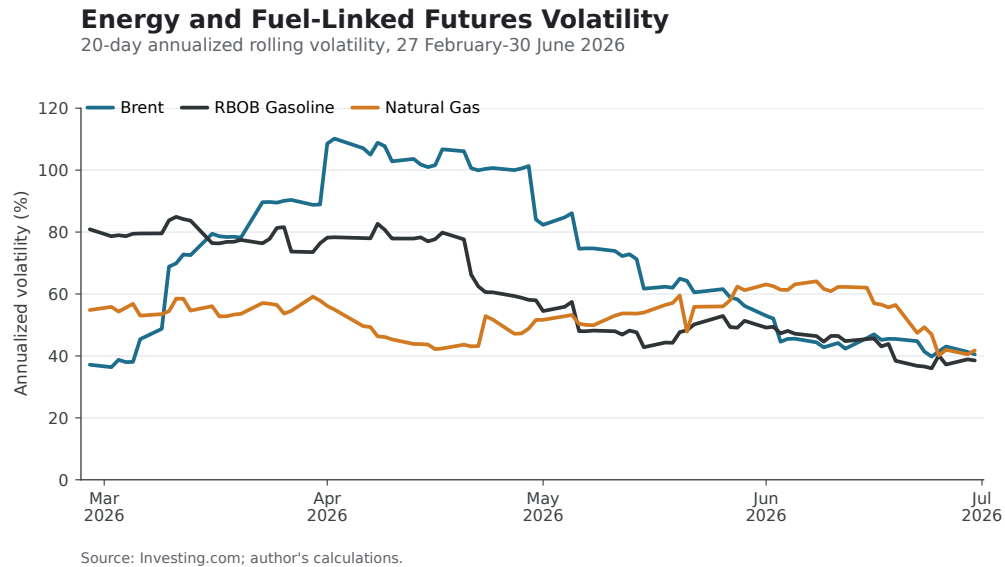
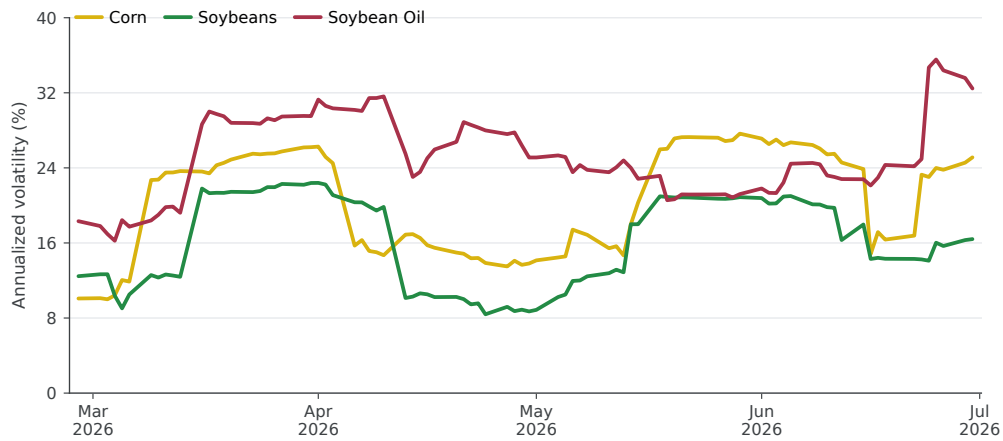


Figure 3: Volatility transmission within the energy complex. Brent, RBOB Gasoline and Natural Gas capture different layers of the energy market: crude oil supply risk, refined-fuel pricing and gas-related input costs. Comparing their volatility helps assess whether uncertainty is concentrated in crude oil alone or extends to fuel-linked markets that are more directly connected to biofuel substitution incentives.

Figure 4 focuses on agricultural and oilseed volatility. Soybean oil is systematically more volatile than soybeans, which is consistent with its closer exposure to biofuel-related pricing. Corn and soybeans remain less volatile than energy futures, supporting the idea of indirect rather than immediate transmission.

Agricultural and Oilseed Futures Volatility

20-day annualized rolling volatility, 27 February-30 June 2026



Source: Investing.com; author's calculations.

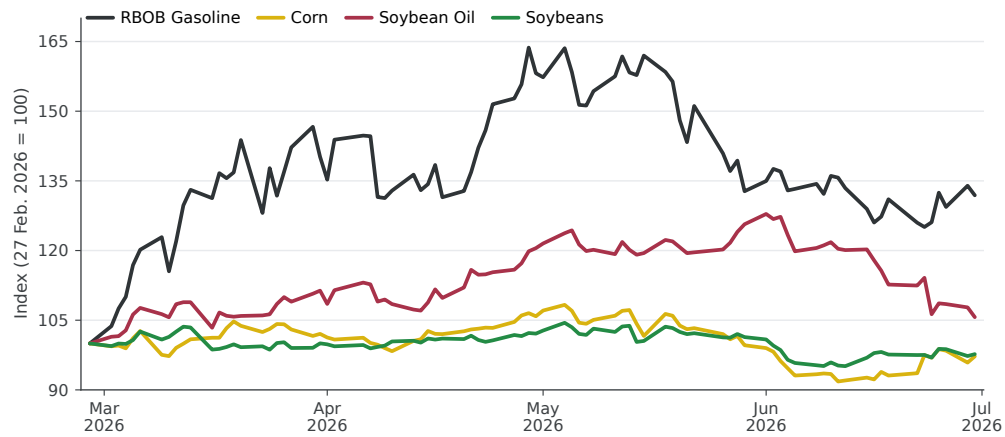
Figure 4: Volatility transmission within agricultural and oilseed markets. Corn, Soybeans and Soybean Oil represent progressively more specific exposures to the biofuel channel. While Corn and Soybeans capture broad crop-market dynamics, Soybean Oil is more directly connected to biodiesel and renewable diesel markets. Comparing their volatility helps identify whether uncertainty is stronger in the agricultural contracts most closely linked to energy substitution.

5.4. Biofuel-Linked Futures

The strongest evidence for the biofuel mechanism comes from adding RBOB gasoline and soybean oil. Corn and soybeans are broad agricultural contracts. RBOB gasoline is closer to the fuel-pricing shock, while soybean oil is closer to biodiesel and renewable diesel feedstock demand. Figure 5 therefore provides a more precise channel test than a simple comparison between crude oil and soybeans.

Biofuel-Linked Futures During the Event Window

RBOB gasoline, corn, soybean oil and soybean futures, indexed to 100 on 27 February 2026



Source: Investing.com; author's calculations.

Figure 5: Biofuel-linked futures and the energy-to-agriculture bridge. RBOB Gasoline represents the refined-fuel benchmark against which biofuels become relatively more or less attractive, while Corn and Soybean Oil are tied to ethanol and biodiesel feedstock markets. The comparison with Soybeans helps separate movements in the broader oilseed complex from those in the derivative most directly connected to biofuel demand.

5.5. Event-Study Evidence

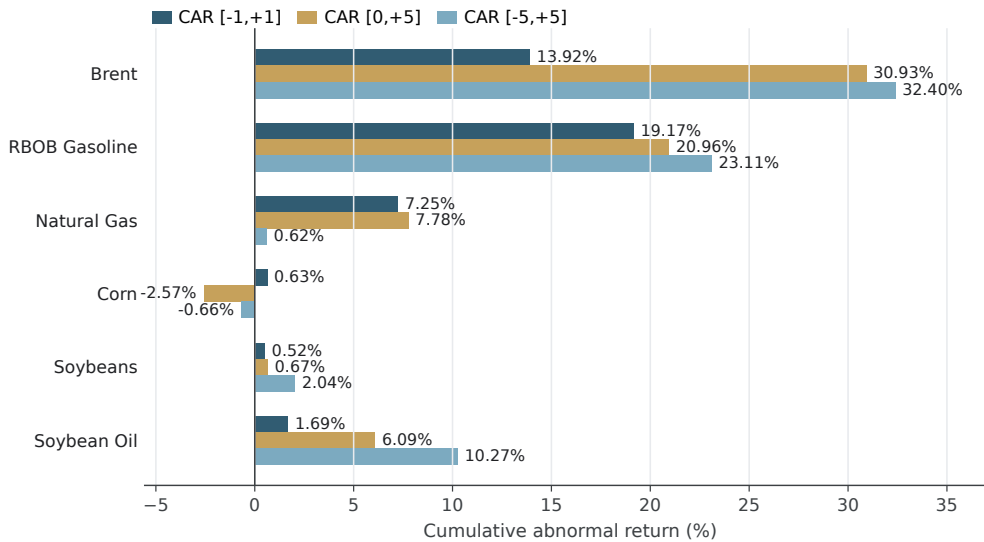
The event study focuses on the first trading day after Hormuz closure warnings. Abnormal returns are computed relative to a constant-mean benchmark estimated before the event window. The result is not a causal proof, but it helps quantify whether the immediate repricing was concentrated in the assets theoretically closest to the shock.

Asset	CAR [-1,+1] (%)	CAR [-5,+5] (%)	CAR [0,+5] (%)
Brent	13.92	32.40	30.93
RBOB Gasoline	19.17	23.11	20.96
Natural Gas	7.25	0.62	7.78
Corn	0.63	-0.66	-2.57
Soybeans	0.52	2.04	0.67
Soybean Oil	1.69	10.27	6.09

Table 2: Cross-market abnormal returns around the geopolitical shock. The event-study comparison links the immediate energy response to the more indirect agricultural reaction. Brent and RBOB Gasoline capture the direct oil and fuel-market repricing, while Soybean Oil, Soybeans and Corn indicate whether the shock also appears in biofuel-related and crop futures. The contrast across assets is useful for assessing whether the transmission mechanism is strongest near the energy source and weaker in downstream agricultural markets.

Event-Window Abnormal Returns After Hormuz Warnings

CARs in %, constant-mean benchmark



Source: Investing.com; author's calculations.

Figure 6: Event-window abnormal returns after Hormuz warnings. The figure reports cumulative abnormal returns in percentage points for Brent, Natural Gas, Corn, Soybeans, Soybean Oil and RBOB Gasoline futures around the first trading day after Hormuz closure warnings. Abnormal returns are computed relative to a constant-mean benchmark estimated before the event window. The stronger response in Brent and RBOB Gasoline is consistent with immediate repricing in energy and fuel-linked futures, while the larger reaction in Soybean Oil relative to Soybeans suggests that the biofuel channel is more visible in oilseed-derivative markets than in broader agricultural futures.

The results are economically coherent. Brent records a 32.40% CAR over the $[-5, +5]$ window and RBOB gasoline records 23.11%. Soybean oil records 10.27%, while soybeans record 2.04% and corn records -0.66%. This ordering supports the interpretation that the initial event-window repricing was strongest in energy and fuel-linked markets, with a weaker but relevant signal in the oilseed-derivative market.

5.6. GJR-GARCH Extension

The GJR-GARCH extension provides a formal volatility layer to complement the graphical and event-study evidence. The rolling-volatility figures describe how realized volatility evolved during the event window, while the GJR-GARCH model decomposes conditional volatility into short-run shock sensitivity, lagged-volatility sensitivity, aggregate persistence and asymmetric responses.

The estimated model is:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1}, \quad I_{t-1} = 1\{\varepsilon_{t-1} < 0\}.$$

The parameter ω captures the constant component of conditional variance. The ARCH coefficient α measures the immediate effect of new return shocks on current volatility. The GARCH coefficient β captures the sensitivity of current conditional variance to lagged conditional variance, namely the extent to which past conditional volatility carries over into current conditional volatility. The asymmetric coefficient γ captures whether negative innovations have a different effect on future volatility than positive innovations of the same magnitude.

Aggregate volatility persistence is computed as:

$$\alpha + \beta + \frac{\gamma}{2}.$$

This measure summarizes the speed at which volatility shocks decay. Values close to one indicate highly persistent volatility dynamics, meaning that shocks to conditional volatility are absorbed slowly. Lower values indicate faster mean reversion.

The results show strong volatility persistence in Brent, RBOB Gasoline and Natural Gas, with persistence estimates of 0.992, 0.968 and 0.964 respectively. This is consistent with the idea that the energy and fuel-linked segments were exposed to persistent uncertainty rather than only one-day price repricing. Soybean Oil also displays high persistence, equal to 0.907, suggesting that the oilseed-derivative segment exhibits more persistent volatility dynamics than broader crop futures.

The asymmetric coefficient γ , however, is not statistically significant at the 5% level for any of the assets. Corn has a positive γ estimate with a p-value of 0.069, which is suggestive but not significant at the conventional 5% threshold. Soybean Oil also has a positive γ , but the p-value is 0.291. This result is notable because commodity futures may theoretically display asymmetric volatility responses around supply shocks. In this sample, however, the model provides stronger evidence of volatility clustering and aggregate persistence than of statistically significant asymmetric volatility. This distinction is important: the GJR-GARCH results support the role of persistent commodity-market uncertainty, but they do not provide conclusive evidence of a leverage-type effect.

In commodity markets, the interpretation of γ should also remain cautious. Unlike equities, where negative returns are usually interpreted as adverse news, commodity price increases can themselves reflect adverse supply shocks. For this reason, the asymmetry term is interpreted as sign-dependent volatility response rather than as a direct equity-style leverage effect.

Asset	Obs.	ω	p_ω	α	p_α	γ	p_γ	β	p_β	Persistence
Brent	257	0.120	0.195	0.132	0.001	0.000	0.999	0.860	<0.001	0.992
RBOB Gasoline	259	0.362	0.046	0.104	0.007	0.000	1.000	0.864	<0.001	0.968
Natural Gas	260	3.279	0.002	0.272	<0.001	0.000	0.999	0.692	<0.001	0.964
Corn	255	1.604	<0.001	0.000	1.000	0.231	0.069	0.000	0.999	0.115
Soybeans	257	0.188	0.888	0.000	0.999	0.000	1.000	0.826	0.504	0.826
Soybean Oil	257	0.209	0.266	0.000	0.999	0.039	0.291	0.888	<0.001	0.907

Table 3: GJR-GARCH(1,1) parameter estimates and aggregate volatility persistence. The table reports coefficient estimates and approximate p-values from Gaussian maximum likelihood estimation on daily log returns. Aggregate persistence is computed as $\alpha + \beta + \gamma/2$. P-values below 0.05 indicate statistical significance at the 5% level.

The p-values clarify which components of the volatility process should receive more weight in the interpretation. For Brent, RBOB Gasoline and Natural Gas, the ARCH and GARCH components are statistically significant, indicating that volatility reacts to new shocks and that current conditional variance is strongly linked to lagged conditional variance. This supports the interpretation that the energy complex was characterized by volatility clustering during the sample period.

By contrast, the asymmetric coefficient γ is not statistically significant at the 5% level for any asset. Corn has the largest positive γ estimate, but its p-value of 0.069 falls outside the conventional 5% threshold. Soybean Oil also has a positive asymmetry estimate, but it is not statistically significant. Therefore, the empirical evidence is stronger for aggregate volatility persistence than for statistically significant asymmetric volatility.

The main contribution of the GJR-GARCH extension is therefore not to prove a leverage-type effect, but to quantify aggregate volatility persistence across the transmission chain. Energy and fuel-linked futures display the most persistent conditional volatility, while agricultural contracts show weaker or less statistically robust GJR-GARCH dynamics.

6. Discussion

The empirical pattern points to a hierarchy of transmission. The strongest and fastest reaction occurs in energy and fuel-linked futures. Brent captures the crude oil supply-risk premium, while RBOB gasoline captures the fuel-linked repricing most closely connected to the relative attractiveness of biofuels. Natural gas behaves differently: its price and volatility are relevant for the fertilizer channel, but the series is also shaped by weather, storage, seasonality and contract-specific dynamics. It should therefore not be interpreted as a simple extension of the crude-oil shock.

The agricultural response is weaker and more nuanced. Corn and soybeans do not replicate the magnitude of Brent or RBOB gasoline moves. This is expected if the transmission is indirect. The stronger response of soybean oil relative to soybeans is the most supportive evidence for the biofuel interpretation, because soybean oil is economically closer to biodiesel and renewable diesel feedstock demand than the broader soybean futures contract. The event-study result reinforces this point: Soybean Oil shows a materially larger [-5,+5] CAR than Soybeans around the first trading day after Hormuz warnings.

The GJR-GARCH results add a more formal interpretation of the volatility evidence. The rolling-volatility charts show visually that uncertainty changed during the event window, but the GJR-GARCH estimates quantify whether volatility shocks were persistent in aggregate. The high aggregate persistence estimates for Brent, RBOB Gasoline, Natural Gas and Soybean Oil suggest that volatility dynamics were not purely transitory. However, the asymmetry parameter is not statistically significant at the 5% level, so the model should not be interpreted as evidence of a strong leverage-type effect. In this sense, the GJR-GARCH layer strengthens the paper mainly by supporting the presence of volatility clustering and

aggregate persistence across the energy and biofuel-linked segments.

This distinction is important because β measures the sensitivity of current conditional variance to lagged conditional variance, while the aggregate persistence measure combines shock sensitivity, lagged volatility and asymmetry through $\alpha + \beta + \gamma/2$.

Overall, the results are consistent with partial cross-commodity transmission from energy markets to agricultural and oilseed-related futures. However, the evidence is not sufficient to claim that biofuel substitution or fertilizer costs were the dominant drivers of agricultural futures prices. Weather, crop conditions, inventories, USDA reports, export demand, contract rolls and broader commodity flows remain important confounding factors.

7. Conclusion

The Iran-Hormuz shock provides a useful case study for understanding how geopolitical risk can propagate across commodity futures markets. The evidence shows a sharp repricing in energy and fuel-linked futures, especially Brent and RBOB gasoline. Agricultural futures react more moderately, while soybean oil displays a stronger response than soybeans. The GJR-GARCH estimates further indicate that aggregate volatility persistence is strongest in energy and fuel-linked futures, while the asymmetric volatility term is not statistically significant at the conventional 5% level. This pattern is consistent with the idea that the biofuel channel is more directly visible in fuel-linked and oilseed-derivative markets than in broad agricultural futures alone.

The paper's main contribution is not to prove a single causal chain from oil to corn and soybeans. Rather, it shows how a financial-markets framework can be used to trace the layers of transmission: oil supply risk, fuel-price repricing, biofuel relative attractiveness, natural-gas-linked fertilizer costs and agricultural futures.

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