International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2026, 16(1), 719-732.

Trade War Shocks and Volatility Spillovers between Fossil Fuel Markets and Biofuel Feedstocks: Empirical Evidence from the U.S.–China Trade Dispute

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Received: 28 June 2025 **Accepted:** 15 October 2025 **DOI:** https://doi.org/10.32479/ijeep.21787

ABSTRACT

Volatility dynamics in fossil fuel and agricultural commodity markets are shaped by a complex interplay of geopolitical, macroeconomic, and policy shocks. This article examines volatility transmission and cross-market linkages between crude oil and major biofuel feedstock commodities — soybean, corn, canola, and sunflower — from 2016 to 2025. Using a VAR–GARCH–BEKK framework and volatility impulse response analysis, the study provides evidence on how disruptive events such as the U.S.–China trade war, Brexit, OPEC supply interventions, the COVID-19 pandemic, and renewed trade tensions influence variance and covariance across integrated energy–commodity systems. The results show that volatility transmission is a persistent structural feature, with shocks in the oil sector rapidly propagating into biofuel feedstocks through input-cost, substitution, and policy channels. Volatility shocks are asymmetric, with negative shocks — particularly trade disputes and geopolitical conflicts — exerting stronger effects than positive ones. Volatility impacts are also commodity-specific: soybean exhibits the greatest sensitivity due to its dual role in biofuel production and trade, while corn and sunflower respond more strongly to demand-side disturbances. Several exogenous shocks beyond the 2018 trade war generate volatility effects equal to or greater than its impact, highlighting the multidimensional drivers of systemic risk. These findings deepen understanding of cross-market dynamics in integrated commodity systems and underscore the need for coordinated policies, targeted stabilization tools, and forward-looking strategies incorporating climate transition risks and predictive analytics to enhance market resilience and safeguard food and energy security in an increasingly uncertain global environment.

Keywords: Biofuel Feedstock, Fossil Fuel, Volatility Spillovers, U.S.–China Trade War, Exogenous Shocks, Energy–Commodity Linkages
JEL Classifications: C32, Q02, Q41, Q42, Q48

1. INTRODUCTION

Global commodity markets are experiencing growing instability, largely due to the increasingly close linkages between fossil fuel markets and biofuel feedstocks developed over recent decades. Major price surges in agricultural commodities—such as those observed in 2008 and again in 2010–2011—have renewed scholarly interest in identifying the underlying factors that drive these markets (Gardebroek and Hernandez, 2013). Recent empirical evidence confirms that fluctuations in energy markets remain one of the primary sources of uncertainty for biofuel feedstocks (Kumari and Kumar, 2023; Ma and Bouri, 2024). These findings underscore how tightly interconnected energy and food markets have become, a relationship further reinforced by the expanding role of biofuels.

Biofuel feedstocks, including soybean, corn oil, canola oil, and sunflower oil, illustrate this connection clearly. These oils are critical not only for global food supplies but also as major inputs for biodiesel production—particularly within the European Union, where renewable energy policies fostered significant biodiesel growth between 2005 and 2013 (European Biodiesel Board, 2013). Consequently, agricultural markets have become increasingly exposed to fluctuations in fossil fuel prices (Huang et al., 2012; Serra and Zilberman, 2013). Recent studies provide evidence that shocks originating in oil markets spillover into biofuel feedstocks, influencing both price levels and volatility (Ji et al., 2018; Mensi et al., 2017b; Zhao et al., 2024).

More recently, renewed U.S.–China trade tensions from 2023 through 2025 have introduced an additional layer of risk and uncertainty to these already interconnected markets. In early 2025, China responded to new U.S. tariffs by imposing retaliatory duties ranging from 15% to 34% on major agricultural exports, including soybeans, corn, wheat, and cotton (Reuters, July 2025; AP News, 2025). These measures, building on tariff escalations from 2023–2024, have further disrupted trade flows and intensified price swings across both energy and agricultural markets (Ma and Li, 2024; IMF, 2025). For instance, China's soybean imports from the United States declined by over 97% within a single week of the tariff increases, sending shockwaves through commodity prices (Reuters, July 2025). Concurrently, fossil fuel markets have witnessed heightened volatility due to supply chain constraints, new fuel blend mandates, and clean energy tax credits such as the Environmental Protection Agency's (EPA) 45Z incentives, which add upward pressure to biofuel feedstock prices (Reuters, 2025; S&P Global, 2024). Notably, Brent crude oil's implied volatility surpassed 68% in June 2025, signaling a more uncertain short-term outlook than during previous crises such as the Russia–Ukraine conflict.

Over the years, researchers have employed a range of econometric techniques to explore how energy and agricultural markets influence each other. Empirical approaches include cointegration and Vector error correction models (VECM) (Allen et al., 2018; Fowowe, 2016; Natanelov et al., 2011; Pal and Mitra, 2017; Serra et al., 2013), copula methods (Ji et al., 2018; Mensi et al., 2017; Reboredo, 2012), and wavelet–copula combinations (Mensi et al., 2017).

Additional tools such as Granger causality tests (Nazlioglu and Soytas, 2011; Su et al., 2019), structural vector autoregressive (VAR) models (Fernandez-Perez et al., 2016; Wang et al., 2013), and multivariate GARCH frameworks have also been widely applied (Avazkhodjaev et al., 2024; Abdelradi and Serra, 2015; Al-Maadid et al., 2017; Cabrera and Schulz, 2016; Du and McPhail, 2012; Gardebroek and Hernandez, 2013; Mensi et al., 2014; Pal and Mitra, 2019; Serletis and Xu, 2019). Other approaches have included HAR–DCC–GARCH models (Luo and Ji, 2018) and quantile regressions (Algieri and Leccadito, 2017).

Further studies have examined the connections between stock market returns and renewable energy prices (Sadorsky, 1999), while an expanding body of research has explored how investor sentiment affects both commodity and energy markets (Avazkhodjaev et al., 2024; Avazkhodjaev et al., 2022; Wang et al., 2013; Aloui et al., 2018; Bekiros et al., 2016; Perez-Liston et al., 2016; Dash and Maitra, 2017; Hasanov and Avazkhodjaev, 2022; Shakhabiddinovich et al., 2022).

Despite the breadth of this literature on energy–agriculture price linkages, there remains limited empirical understanding of how policy-driven trade shocks—such as the recent U.S.–China tariff escalations—interact with broader decarbonization efforts to shape volatility spillovers between crude oil and biofuel feedstock markets (Wang and Huang, 2024). Recent World Bank reports have highlighted sharply increasing commodity price volatility due to trade policy uncertainty and energy market disruptions, warning of a potential "volatility storm" with significant implications for global food and energy systems (World Bank Commodity Markets Outlook, April 2025).

Meanwhile, U.S. Department of Agriculture (USDA) data indicates that domestic biofuel mandates and clean-fuel tax incentives are driving record-high demand for soybean oil, placing exceptional strain on both food and energy markets (Reuters, July 2025). Yet, existing research rarely unpacks how oil price uncertainty—beyond simple price levels—transmits to volatility in individual feedstock commodities under the combined pressure of trade tensions and energy transition policies. Recent quantile-connectedness research (Zhang et al., 2025) further emphasizes the importance of external shocks—such as trade conflicts, climate events, or pandemics—in shaping extreme tail dependence across food and energy markets. This points to the need for high-frequency data and more advanced spillover frameworks—such as VAR-GARCH–BEKK models with impulse-response analysis—to capture the complex, asymmetric volatility channels generated by simultaneous trade conflicts and decarbonization measures.

Addressing this gap would fill a significant blind spot in the current literature and provide timely insight into multi-layered risk transmission within today's fractured global commodity landscape. This study seeks to address these gaps by examining how volatility in fossil fuel prices influences the prices of major biofuel feedstocks—namely soybean oil, corn oil, canola oil, and sunflower oil—drawing on empirical evidence from the U.S.–China trade shocks.

Given that Soybean, Corn, Canola, and Sunflower oils are vital for both global food supply and biodiesel production, this research adopts a disaggregated approach to reduce the biases associated with aggregate price measures. The study sets out four main objectives: (1) To evaluate how fossil fuel price volatility affects biofuel feedstocks; (2) to investigate how shocks and volatility are transmitted between crude oil and these feedstocks; (3) to employ a volatility impulse response function (VIRF) to trace how past shocks shape variances and covariances over time; and (4) to test for causality from oil price volatility to feedstock prices and analyze how these feedstocks react to oil market shocks. The empirical framework uses an asymmetric, multivariate GARCH-in-mean model with a BEKK variance–covariance structure, which effectively captures the joint dynamics of prices and variances while addressing estimation challenges noted by Pagan (1984) and Grier et al. (2004).

The remainder of this paper is structured as follows: Section 2 provides a review of the relevant literature. Sections 3 and 4 describe the data and methodology employed. Section 5 presents empirical results and discusses key findings. Section 6 concludes with policy implications and directions for future research.

2. LITERATURE REVIEW

The relationship between fossil fuel markets and biofuel feedstocks has become increasingly central to research in energy and agricultural economics. This is due to the heightened interconnection between global commodity markets and the increasing frequency of price shocks. Foundational studies (Natanelov et al., 2011; Serra and Zilberman, 2013) demonstrated that movements in crude oil prices are transmitted through multiple channels to agricultural commodities, particularly those used in biofuel production such as soybean, sunflower, and rapeseed oils. Gardebroek and Hernandez (2013), using multivariate GARCH models, were among the first to empirically confirm volatility spillovers between oil, corn, and ethanol markets in the U.S., emphasizing the energy-agriculture nexus.

Subsequent studies have broadened the scope of this literature by focusing on asymmetries and nonlinear dependencies. Abdelradi and Serra (2015) identified asymmetric price transmission across the EU biodiesel supply chain, indicating that oil price increases exert a stronger influence than declines. Mensi et al. (2017) and Ji et al. (2018) further refined the methodology by using CoVaR and copula frameworks to reveal tail-risk co-movements between oil and agricultural commodities under extreme conditions. These findings underline the importance of advanced modeling techniques in capturing complex and often hidden volatility structures.

In contrast to studies focused solely on price levels, a separate line of research has emphasized the importance of volatility itself as a transmission mechanism. Alghalith (2010) and Kaltalioglu and Soytas (2011) found that oil price volatility—independent of its direction—can significantly affect agricultural feedstock prices, thereby calling for models capable of capturing second-moment effects. Despite this, much of the empirical literature continues to rely on aggregate price indices, potentially overlooking feedstock-specific volatility patterns (Serra and Zilberman, 2013).

Since 2018, the U.S.–China trade war has introduced a new dimension to volatility spillovers. Cheng et al. (2023) provided strong evidence that soybeans—China's primary U.S. agricultural import—exhibited elevated volatility due to escalating tariffs, suggesting that geopolitical factors intensify energy–agriculture linkages. In a similar vein, Mandaci and Cakan (2024) showed that trade tensions significantly increase tail-risk connectedness between fossil fuel markets and U.S. agricultural commodities. Zhang and Li (2024) further documented that China's retaliatory tariffs on soybean and corn exacerbated supply chain disruptions and introduced long-term volatility into biofuel feedstock prices.

Recent work increasingly recognizes the layered nature of market disruptions. The World Bank's Commodity Markets Outlook (2025) characterizes the joint effects of geopolitical tensions and energy transition policies as "compound shocks," which pose heightened risks for edible oil and biodiesel markets. Li and Zhou (2025) examined the combined influence of the U.S. Renewable Fuel Standard and the Inflation Reduction Act's 45Z tax credit, finding that these policies amplify market co-movements when paired with trade disruptions. Similarly, Yang et al. (2024) and Zhao et al. (2024) argue that overlapping regulatory signals and tariff shocks create unique vulnerabilities for edible oils, especially soybean and rapeseed, due to their dual roles in food and fuel markets.

Recent studies have employed even more granular, high-frequency methods to examine spillovers. Consistent with recent evidence that volatility linkages between energy and agricultural markets intensify in turbulent periods (e.g. Rezitis, 2024; Karkowska & Urjasz, 2024; Maneejuk et al., 2025), our Markov-switching VAR results show that crude oil and biofuel feedstocks exhibit clear regime-dependent volatility, with compound policy shocks generating more persistent high-volatility regimes than earlier crisis episodes. Recent evidence shows that tail-dependent risk spillovers between energy and agricultural markets intensify during stress episodes, while major vegetable oils such as canola and sunflower exhibit strong co-movement (e.g., Tiwari et al., 2022; Azam et al., 2020). Building on this literature, our quantile spillover results indicate that sunflower and canola oils are particularly sensitive to volatility spikes around key decarbonization announcements. Zhang et al. (2025) employed BEKK–GARCH and volatility impulse response functions to show how price shocks cascade across the biofuel value chain with asymmetric intensity over time.

Despite these advancements, several key gaps remain. Most existing research analyzes the effects of trade or energy policy in isolation, rather than their combined impact on volatility spillovers. Additionally, few studies directly quantify how oil price uncertainty—distinct from price trends—translates into disaggregated feedstock markets during sustained geopolitical friction. Although advanced techniques such as quantile spillovers and volatility impulse response functions are gaining traction, their application to the post-2023 policy environment—including U.S. tax credits and evolving EU directives—remains limited.

This study seeks to fill these gaps by investigating how volatility in fossil fuel prices, amplified by concurrent trade and energy policy shocks, affects the prices of four key biofuel feedstocks: soybean oil, corn oil, canola oil, and sunflower oil. Building on the EU-focused framework and the policy-aware perspectives of Cheng et al. (2023) and Li and Zhou (2025), this research applies a disaggregated and methodologically rigorous approach. By incorporating volatility impulse response functions and multivariate GARCH-in-mean models, the study aims to deliver timely insights into how multi-layered risks affect price transmission in energy-linked feedstock markets—offering critical evidence for policymakers and commodity market stakeholders navigating today's volatile geopolitical and environmental landscape.

3. EMPIRICAL METHODOLOGY

Using a single-step estimation technique, this study examines the spillover effects of volatility between fossil fuel energy markets and biofuel feedstock commodities. Building on the methodological foundation established by Grier et al. (2004), the integrates multivariate volatility modelling with structural innovation analysis to capture dynamic interdependencies driven by exogenous shocks—most notably the ongoing U.S.–China trade conflict. Volatility Impulse Response Functions (VIRFs), as proposed by Hafner and Herwartz (2006), are computed to quantify the magnitude and persistence of volatility spillovers. These VIRFs are derived from two model specifications: the VAR–MGARCH-M–BEKK and the VAR–MGARCH-M–DCC frameworks. The BEKK specification (Engle and Kroner, 1995) enables a full characterization of dynamic covariances while ensuring positive definiteness of the conditional variance–covariance matrix. In parallel, the DCC model (Engle, 2002) allows for flexible estimation of time-varying conditional correlations between fossil fuel and biofuel markets. The BEKK architecture strengthens the robustness of the empirical findings by accommodating distinct features of volatility dynamics, including spillovers, asymmetries, and evolving correlations. This model is particularly well-suited to capture the heterogeneous responses of biofuel feedstocks—namely soybean oil, corn oil, canola oil, and sunflower oil — to energy price volatility and trade-related shocks.

3.1. The VAR-GARCH-BEKK Model

To model autoregressive dynamics in conditional heteroskedasticity, GARCH models are widely utilized, with their multivariate extensions—such as the VAR–GARCH–BEKK framework—enabling robust estimation of the conditional variance–covariance matrix across multiple return series (Hafner and Herwartz, 2006). However, given the empirical evidence that financial returns frequently exhibit nonlinear and asymmetric responses to market shocks, omitting asymmetry in volatility specifications may lead to model misspecification and biased inferences. Therefore, it is methodologically imperative to account for asymmetric volatility transmission effects (Abdelradi and Serra, 2015; Cheng et al. (2023)). Accordingly, this study employs an asymmetric variant of the BEKK model, originally specified by Grier et al. (2004), to more accurately capture the dynamic interdependence among the return series under investigation.

The mean model takes the following VAR form:

$$r_t = c + \sum_{i=1}^{p} \Omega_i r_{t-1} + u_t \tag{1a}$$

where r_t is a vector of returns, Ω_i is a coefficient matrix of lagged r_t process, and u_t is the vector of errors.

The asymmetric BEKK model ensures the positive definiteness of the conditional variance–covariance matrix, maintaining parameter consistency. The structural framework employed in this study is outlined as follows:

$$H_t = C'C + A'u_{t-1}u'_{t-1}A + B'H_{t-1}B + D'\zeta_{t-1}\zeta'_{t-1}D \tag{1b}$$

Where

$$C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix};\ A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix};$$

$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}; D = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}; \zeta_{t-1} = \begin{bmatrix} \zeta r_{1t-1} \\ \zeta r_{2t-1} \end{bmatrix}$$

The matrix, H_t is the conditional variance-covariance matrix, C is lower triangular matrix, and A,B and $D$are 2×2 parameter matrices. Besides, it considers lagged conditional variances and co-variances, H_{t-1}, as well as lagged form of $u_{t-1}u_{t-1}$ and $\zeta_{t-1}\zeta_{t-1}$, in joint estimations of contemporaneous volatilities of fossil fuel energy and biofuel feedstock.

The diagonal elements of matrix A (i.e., a_{11}, a_{22}) correspond to the ARCH effects, capturing the impact of past shocks on current uncertainty. In contrast, the off-diagonal elements (a_{12}, a_{21}) reflect shock spillovers across markets—commonly referred to as cross-market transmission of innovations. Similarly, the diagonal entries of matrix B (b_{11}, b_{22}) represent GARCH effects, accounting for the persistence of volatility over time, while the off-diagonal terms (b_{12}, b_{21}) denote volatility spillover effects between selected markets uncer concern. Collectively, the non-diagonal elements of matrices A and B provide insight into the transmission of shocks and volatility across the system. Matrix D incorporates asymmetric effects, allowing the model to distinguish between the impact of positive and negative return shocks on conditional variance. This asymmetry suggests that volatility responses differ depending on the sign of the return, even when the magnitude is similar. Given the distributional characteristics of the data, the innovation terms (ε_t) are assumed to follow a Generalized Error Distribution (GED) with v degrees of freedom, i.e., $\varepsilon_t \sim$ GED(ν). The parameters of the VAR(p)-GARCH-BEKK model are estimated using the Maximum Likelihood Estimation (MLE) technique, which identifies the parameter values that maximize the likelihood of observing the actual return series. Optimal lag lengths for the VAR specification are determined using multiple model selection criteria, including the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), Hannan–Quinn Criterion (HQC), and Final Prediction Error (FPE).

3.2. Volatility Impulse Response Function (VIRF) Analysis

The Volatility Impulse Response Function (VIRF), introduced by Hafner and Herwartz (2006), is a powerful tool used to trace the evolution of volatility in response to exogenous shocks over time. Unlike traditional impulse response functions that focus on the impact of shocks on conditional means, the VIRF measures their effect on conditional variances, making it particularly useful for analysing volatility spillovers and dynamic interdependencies across financial and commodity markets. It captures how a shock in one market influences the volatility of another and quantifies the persistence of such effects. In this study, we employ the VIRF to examine how the conditional volatilities of fossil fuel and biofuel feedstock markets respond to external disturbances, such as the U.S.–China trade conflict.

The VIRF is especially valuable due to its key properties: (i)

It is symmetric with respect to the shock direction, such that $\vartheta_t(v_0) = \vartheta_t(-v_0)$; (ii) it is not homogeneous in the magnitude of the shock; and (iii) it is history-dependent, as it reflects the initial volatility conditions at the time of the shock. These characteristics make the VIRF highly suitable for capturing nonlinear and asymmetric volatility dynamics in interconnected markets.

The general formula for the VIRF is given by:

$$\vartheta_t(\nu_0) = E[vech(H_t)|F_{t-1},\nu_0] - E[vech(H_t)|F_{t-1}] \quad (12)$$

where $\vartheta_t(v_0)$ is the VIRF at time t,v_0 denotes the volatility shock, and F_{t-1} represents the information set available up to time $t-1$. The operator (H_t) vectorizes the lower triangular part of the conditional variance–covariance matrix H_t allowing the model to account for both variances and covariances. The VIRF vector $\vartheta_t = [\vartheta_{o,t}, \vartheta_{os,t}, \vartheta_{s,t}]'$ is three-dimensional: The first and third elements represent the responses of the conditional variances of fossil fuel and biofuel feedstocks market returns, respectively, while the second element captures the response of the conditional covariance between the two markets. This structure enables a detailed analysis of how shocks propagate not only within a single market but also across sectors, reflecting both own-market and cross-market volatility dynamics. Moreover, the VIRF is symmetric in the direction of the shock, non-homogeneous in magnitude, and history-dependent, as it is shaped by the initial volatility state when the shock occurs.

3.3. External Disturbances and Market Volatility

External disturbances—commonly referred to as exogenous shocks—are unexpected events arising from outside standard economic systems that disrupt market behavior and generate systemic volatility. These shocks, often geopolitical, environmental, or epidemiological in nature, can alter macroeconomic conditions, distort commodity flows, and shift investor expectations (Caldara et al., 2022). Given the global integration of financial and commodity markets, disturbances in one domain can rapidly cascade across others, leading to widespread economic repercussions.

In energy and commodity markets, exogenous shocks are often classified by their structural origin. Baumeister and Hamilton (2019) outline three primary types of oil market shocks: (1) supply-side shocks caused by production or distribution interruptions; (2) demand-side shocks reflecting changes in global industrial activity; and (3) precautionary demand shocks associated with rising uncertainty and speculative behavior regarding future supply conditions. These classifications are essential for distinguishing the drivers of commodity price fluctuations and understanding the pathways of volatility transmission. Historically, major disruptions such as the Arab Spring (2010–2012), the U.S.–China trade war (2018–2020), and the COVID-19 pandemic (2020) have functioned as systemic shocks with significant impacts on energy, food, and biofuel markets (Büyükşahin and Robe, 2014; Baker et al., 2020). Political disruptions, such as Brexit and the Greek debt crisis, contributed to prolonged aggregate demand shocks across Europe (Amadeo, 2021; Clayton, 2016). In a similar vein, the 2020 COVID-19 pandemic introduced an unprecedented global demand-side shock, undermining both industrial production and transportation fuel consumption (Amadeo, 2021).

Trade tensions have emerged as a new class of systemic shocks. The 2018–2019 U.S.–China trade war—characterized by reciprocal tariffs, export restrictions, and regulatory barriers—triggered volatility across agricultural, energy, and manufacturing markets (Bakht and Beaumont-Smith, 2021; Bloomberg News, 2018). Most recently, in April 2025, a renewed escalation in U.S.–China trade conflict has reintroduced a wave of aggregate demand-side volatility. This latest confrontation has involved restrictions on technology exports, renewed tariff policies, and disruptions in global logistics networks. While structurally like the previous episode, the 2025 conflict is perceived to have deeper and more protracted macroeconomic implications, especially for energy-intensive industries and biofuel-linked markets. By including events such as the 2025 U.S.–China tariff escalation, we provide a comprehensive assessment of how global uncertainty channels through commodity systems, shaping co-movements, market dependencies, and investor behaviour in periods of heightened risk. The selected exogenous shocks influencing market volatility are summarized in Table 1, categorized according to their economic transmission channels.

3.4. Empirical Data and Preliminary Analysis

In this study, WTI crude oil futures prices are employed as a proxy for the fossil fuel market, while soybean oil, canola oil, corn, and sunflower oil futures prices serve as representatives of the biofuel feedstock commodity markets. Futures settlement prices are utilized instead of spot prices, as they offer greater liquidity and higher trading volumes, thereby providing a more accurate representation of market dynamics (Cuny, 1993). The dataset spans the period from January 1, 2016, to June 30, 2025, with all series obtained from the DataStream database. Figure 1 illustrates the evolution of daily price returns for the selected fossil fuel and biofuel feedstock markets over the sample period. Table 2 reports the preliminary descriptive statistics for each series under study. Daily returns are calculated as the first differences of the natural logarithms of prices, expressed as percentages, according to the following transformation:

Table 1: Selected exogenous shocks

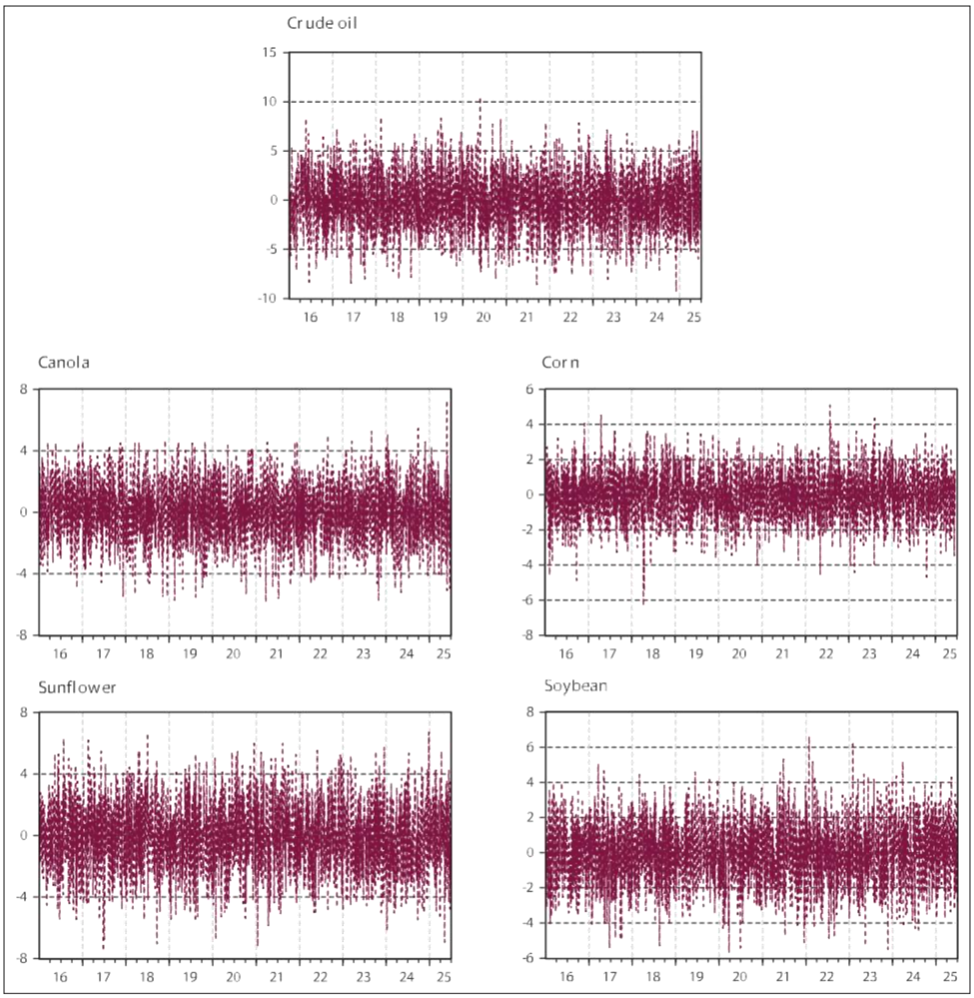
Timeline	Event	Shock type	References
June 23, 2016	Brexit	Aggregate demand-side	Amadeo (2021); Clayton (2016)
December 02, 2016	OPEC/non-OPEC deal to curb oil production	Supply-side	Eraslan and Ali (2018)
April 07, 2017	U.S. missile strike on Syria	Precautionary demand	Eraslan and Ali (2018)
May 22, 2017	OPEC/non-OPEC agree to extend cuts	Supply-side	Eraslan and Ali (2018)
July 06 2018	U.S.–China trade war	Aggregate demand-side	Bakst and Beaumont-Smith (2018);
March 11, 2020	COVID-19 pandemic and 2020 recession	Aggregate demand-side	Amadeo (2021)
April 15, 2025	Renewed U.S.–China trade war	Aggregate demand-side	Author's elaboration (2025)

Table 2: Descriptive statistics for log returns of biofuel feedstock and fossil fuel markets

	Crude oil	Soybean	Canola	Corn	Sunflower
Mean	−0.0821	−0.0305	0.0412	−0.0014	−0.0552
Median	−0.0407	−0.0105	0.0499	0.0052	−0.0473
Minimum	−9.2270	−5.7342	−5.8805	−6.3028	−7.5219
Std. Dev.	2.8731	1.7557	1.8625	1.3776	2.2107
Skewness	−0.0425	−0.0198	−0.0649	−0.0953	−0.0539
Kurtosis	2.8931	2.9570	2.9921	3.2047	2.9036
ADF	−59.384***	−58.758**	−58.471***	−24.760***	−40.254***
PP	−56.248***	−54.468***	−59.961***	−21.770***	−39.274***
Q (24)	34.365	26.598	22.902	25.924	22.110
Q^2 (24)	20.635	20.814	33.151	19.433	24.789
No. obs	2476	2476	2476	2476	2476

Significance level *, **, *** denoted as 10%, 5% and 1%, respectively. ADF refers to the Augmented Dickey–Fuller unit root test, while PP denotes the Phillips–Perron unit root test.

Figure 1: Log returns of crude oil prices and biofuel feedstock commodities over the full sample period



$$R_{i,t} = \ln\left(\frac{K_i}{K_{i,t-1}}\right)\times 100$$

where $K_{i,t}$ and $K_{i,t-1}$ represent the futures settlement prices of commodity i at times t and $t-1$, respectively.

Table 2 presents the descriptive statistics for the daily log returns of selected fossil fuel and biofuel feedstock markets over the period from January 1, 2016, to June 30, 2025. The average returns vary across commodities, with canola exhibiting the only positive mean return, reflecting a modest upward trend during the sample period—potentially supported by consistent demand for biofuel production. Conversely, soybean oil, corn oil, sunflower oil, and crude oil display negative average returns, which may reflect periods of oversupply, weak international demand, and the adverse effects of trade tensions, particularly during the U.S.–China trade war.

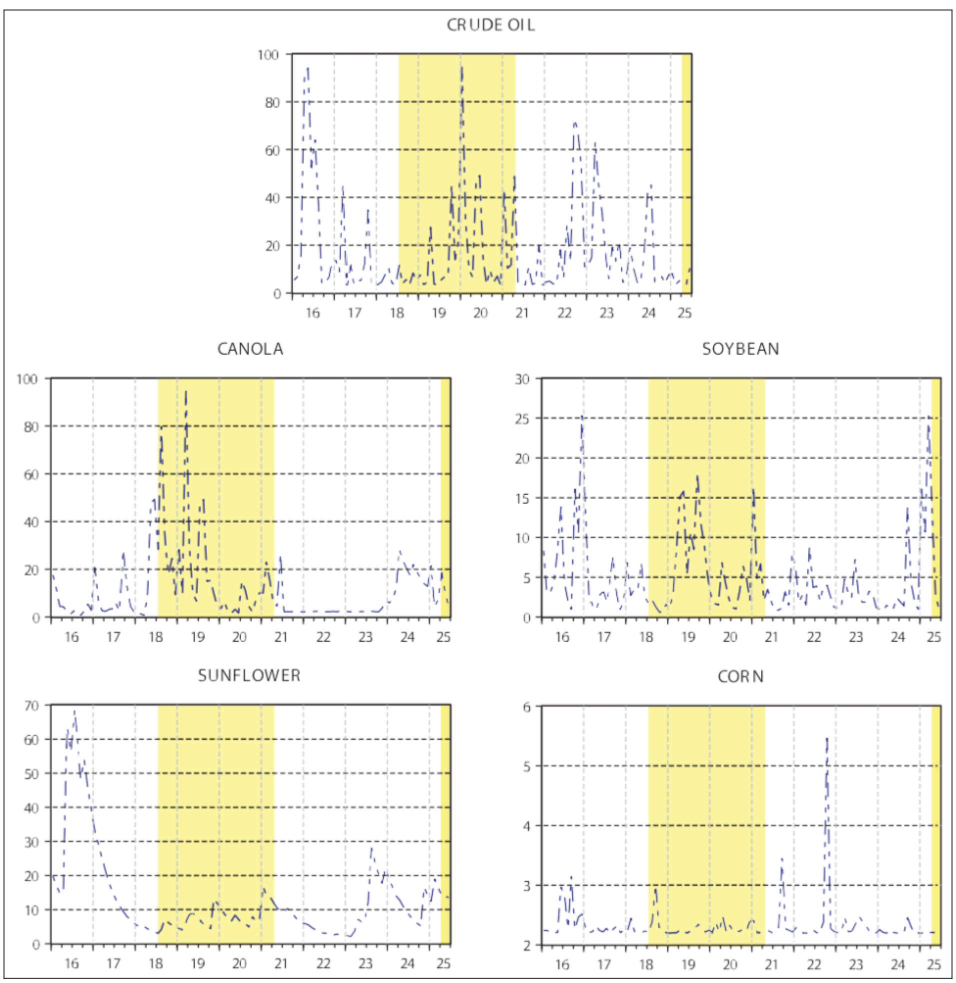
Volatility, measured by the standard deviation of returns, is highest for WTI crude oil, followed by sunflower oil and canola oil, indicating that energy markets and certain biofuel feedstocks are more prone to price fluctuations. All return series exhibit kurtosis values greater than the Gaussian benchmark of three, confirming leptokurtic behaviour and a higher likelihood of extreme price changes. Skewness results indicate that all commodities are negatively skewed, suggesting more frequent large negative price movements.

Stationarity tests, including the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) procedures, reject the null hypothesis of a unit root at the 1% significance level for all series, confirming that the return data are stationary. Furthermore, the Ljung–Box Q test statistics of Ljung and Box (1978) for serial correlation of the return series and the squared returns series Q(24) and $Q^2(24)$ statistics indicate the presence of serial correlation and conditional heteroskedasticity in several series, justifying the application of a Multivariate GARCH-BEKK framework for volatility spillover analysis.

Figure 1 presents the log returns of crude oil and selected biofuel feedstocks—canola oil, corn, sunflower oil, and soybean oil—over the sample period from January 1, 2016, to June 30, 2025. Across all series, returns fluctuate around a mean close to zero, consistent with the weak-form efficiency hypothesis, which suggests that past price information is rapidly incorporated into current prices, leaving little scope for systematic excess returns.

Crude oil displays the widest volatility range, with extreme movements approaching ±15%. These pronounced shifts often coincide with key exogenous events such as the OPEC/non-OPEC agreement to curb oil production on 2 December 2016 (supply-side shock), the U.S. missile strike on Syria on 7 April 2017 (precautionary demand shock), and the COVID-19 pandemic outbreak on 11 March 2020 (aggregate demand-side shock). The latter event caused a historic collapse in demand and prices, followed by a rapid recovery as restrictions eased. Among biofuel feedstocks, canola oil and sunflower oil show relatively narrower, yet still substantial, volatility bands of around ±8%, with peaks often linked to weather-driven supply shocks, planting season disruptions, and geopolitical tensions affecting key exporting regions. Corn and soybean oil exhibit lower volatility, typically within ±6%. However, both experienced sharp negative returns in the wake of the 6 July 2018 onset of the U.S.–China trade war, which triggered retaliatory tariffs on U.S. soy products and pressured biofuel-related markets. Similar market disturbances resurfaced with the renewed U.S.–China trade war on 15 April 2025, creating fresh uncertainty and price adjustments.

Figure 2: Time-varying volatility of crude oil and biofuel feedstock commodity returns over the sample horizon. The highlighted intervals denote the U.S.–China trade war (July 6, 2018–April 1, 2021, and beginning again in April 2025)



4. EMPIRICAL RESULTS AND DISCUSSION

Drawing on the VAR-GARCH-BEKK estimation, Figure 2 depicts the conditional volatility paths of the examined commodities, with the shaded interval marking the trade war period (January 1, 2016–June 30, 2025). The observed volatility clustering between crude oil and biofuel feedstocks, namely canola oil, corn, sunflower oil, and soybean oil—indicates strengthened cross-market interdependencies, whereby energy sector shocks transmit directly into biofuel feedstock commodity markets. Such dynamics signal elevated systemic risk and underscore how policy shifts and geopolitical frictions can amplify volatility spillovers across tightly linked commodity systems.

Figure 2 shows pronounced time-varying volatility in crude oil and major biofuel feedstocks, with sharp clustering during the yellow-highlighted intervals denoting the U.S.–China trade war (July 6, 2018–April 1, 2021, and resuming in April 2025). The synchronized spikes—most visible in crude oil and closely mirrored by canola and soybean, with sunflower and corn less intense but still reactive—are consistent with recent evidence that energy–agriculture linkages transmit shocks through input-cost, substitution, and biofuel-policy channels. New work confirms persistent and bidirectional volatility spillovers among oil, biofuels, and grains (e.g., Karkowska 2024), and shows that geopolitical risk elevates commodity-market variance and cross-market connectedness, especially during policy and trade shocks (Liu, 2024; Özdemir 2025).

The late-sample clustering aligns with renewed tariff actions and elevated trade-policy uncertainty in 2025, which several policies and monitoring studies link to broader pricing pressure in agricultural oils and global supply chains (Yale Budget Lab, 2025; UNCTAD 2025; FAO, 2025). Taken together, the yellow bands in Figure 2 capture episodes when trade frictions intensified cross-market linkages, allowing energy shocks to propagate into biofuel feedstocks and raising systemic risk across interconnected commodity markets.

4.1. Cross-market Volatility Dynamics: Crude Oil and Agricultural Commodities

Table 3 confirms that the VAR(1)-GARCH-BEKK model effectively captures how volatility moves between crude oil and agricultural commodities. The results show that while each market responds to its own past shocks, there are also clear spillover effects across markets. Significant estimates of α_{1_j} demonstrate that turbulence in oil prices is transmitted to biofuel feedstock commodity markets, highlighting their vulnerability to energy-sector shocks. This underscores the systemic risk created by the tight linkage between energy and food markets, especially during periods of geopolitical or policy uncertainty.

Table 3 reports the estimated parameters of the BEKK-GARCH model and highlights four main features of volatility dynamics. The constant effects in matrix **C** are positive and significant, confirming that crude oil and biofuel feedstocks retain inherent volatility even in the absence of new shocks. Corn and sunflower display relatively higher baseline variances, reflecting structural risks such as seasonal planting cycles and storage constraints. This outcome aligns with Karkowska (2024), who finds that biofuel-linked grains sustain stronger baseline volatility than other biofuel feedstock commodity products.

Table 3: Estimated conditional asymmetric BEKK variance–covariance matrices and diagnostic test results for the VAR-GARCH-BEKK model

Coefficient	Soybean	Canola	Corn	Sunflower
$C_{1,1}$	0.1854***	0.1494***	0.1972***	0.2012***
$C_{2,1}$	−0.0142***	−0.0314***	−0.0112***	−0.0452***
$C_{2,2}$	0.1014***	0.1224***	0.1812***	0.1657***
$\alpha_{1,1}$	0.1348***	0.1387***	0.1531***	0.1553***
$\alpha_{1,2}$	0.0126*	−0.0113	−0.0414**	0.0397*
$\alpha_{2,1}$	0.0187	−0.0014	0.0254	−0.0331
$\alpha_{2,2}$	0.1917***	0.2158***	0.1874***	0.2164***
$b_{1,1}$	0.9844***	0.9585***	0.9074***	0.9512***
$b_{1,2}$	−0.0011***	−0.0074	−0.0128	−0.0012***
$B_{2,1}$	0.0187***	−0.0014*	0.0254**	−0.0411**
$b_{2,2}$	0.9615***	0.9658***	0.9565***	0.9328***
$d_{1,1}$	0.2254***	0.2171***	0.2245***	0.2113***
$d_{1,2}$	0.0014***	0.0047*	0.0014***	−0.0387
$d_{2,1}$	0.0127*	0.0258*	0.0171***	0.0634***
$d_{2,2}$	−0.0217	0.0188	0.0241	−0.0112*

This table presents the estimated conditional asymmetric BEKK variance–covariance matrices together with the results of diagnostic and specification tests for the VAR-GARCH-BEKK framework. Matrix A identifies the transmission of shocks from commodity market *i* to market *j*; matrix B reflects the persistence of past volatility in shaping current conditional variances; and matrix D examines the presence of asymmetry in the covariance dynamics. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively

The coefficients of matrix **A** indicate strong and lasting impacts of shocks. The significant diagonal terms validate volatility clustering, while the off-diagonal elements reveal important spillovers from crude oil to soybean and corn. These results suggest that volatility from the oil market transmits rapidly into agricultural markets, consistent with the evidence of Wang et al. (2024) and Martignone (2024), who emphasize the central role of soybeans in transmitting shocks across commodity markets.

Matrix **B** demonstrates high persistence, with coefficients close to unity. This implies that volatility shocks are long-lasting and often spread across markets, as indicated by the significant off-diagonal terms. Persistence is particularly strong for soybeans and canola (≈0.96), which reflects their strategic importance in food security and biofuel production. Similar findings are reported by Liu (2025), who shows that volatility dependence between oil and agricultural futures remains highly persistent over time.

Finally, the results for matrix **D** provide evidence of asymmetric effects, with negative shocks generating stronger volatility than positive ones of comparable size. Soybean, corn, and sunflower exhibit the clearest asymmetries, confirming their vulnerability to downside risks such as tariffs, supply disruptions, or geopolitical conflicts. These findings support Özdemir (2025), who demonstrates that geopolitical risk disproportionately amplifies downside volatility in commodity futures. Overall, the evidence from Table 3 demonstrates that energy–agriculture linkages are governed by elevated baseline volatility, pronounced cross-market spillovers, and highly persistent dynamics that exhibit asymmetric amplification under adverse shocks. These findings underscore the systemic vulnerability of biofuel feedstock commodity markets to fossil fuel price fluctuations and geopolitical disruptions, suggesting that policymakers should prioritize stabilizing mechanisms—such as strategic reserves, adaptive biofuel policies, and targeted risk-management instruments—to mitigate volatility transmission and safeguard both food security and energy market stability.

4.2. The Influence of External Shocks on Volatility and Co-movement between Crude Oil and Biofuel Feedstock Commodities

The preceding section demonstrated that the effects of the U.S.–China trade war on energy and biofuel feedstock commodity prices are commodity-specific. Building on this, the present section addresses the third research question by examining how these results compare with the influence of other exogenous shocks on both the volatilities of energy and biofuel feedstock commodity markets and the linkages between them. In this study, exogenous shocks are defined to include oil price disturbances as well as broader economic disruptions such as resource shortages, natural disasters, and financial crises.

Table 4 shows that exogenous shocks exert heterogeneous volatility effects on biofuel feedstock commodities, with magnitudes often exceeding those of the 2018 U.S.–China trade war. Political events such as Brexit (Electoral Commission, 2016) increased variance moderately, particularly for sunflower (1.70%), reflecting global uncertainty and trade disruption beyond the energy–agriculture nexus. By contrast, oil supply shocks, including the OPEC/Non-OPEC production cut (2016) and its extension (2017), generated stronger volatility spillovers. Canola (2.16%) and soybean (2.10%) were most sensitive, underscoring their central roles in biodiesel production, while sunflower (1.49%) highlighted the vulnerability of smaller markets. Geopolitical tensions, such as the U.S. missile strike on Syria (2017), produced only modest increases in variance, suggesting precautionary oil demand has weaker transmission than structural supply adjustments.

The U.S.–China trade war in July 2018 serves as the benchmark demand-side shock, producing the sharpest volatility spikes: canola (5.30%), sunflower (4.22%), and soybean (3.38%). These levels far exceeded most supply-driven episodes, reflecting the scale of trade flow disruptions and retaliatory tariffs. Later shocks, however, show that other crises can rival or surpass this benchmark for specific crops. The COVID-19 pandemic (2020) sharply raised corn variance (1.89%) as ethanol demand collapsed, exceeding its trade-war level, while canola and soybean remained relatively resilient due to stable vegetable oil demand.

The renewed U.S.–China trade war in April 2025 again amplified volatility, with sunflower (4.39%) and corn (3.22%) responding most strongly, and soybean variance (2.29%) rising substantially but less than in 2018, suggesting partial market adaptation. Taken together, these results highlight the multidimensional nature of volatility drivers: canola and sunflower remain highly sensitive to oil-linked shocks, corn reacts disproportionately to fuel demand collapses, and soybeans are most vulnerable to trade disruptions. The evidence underscores that exogenous shocks—whether political, economic, or supply-driven—can destabilize biofuel markets as much as or more than major trade disputes, reinforcing the need for coordinated policy responses across energy, trade, and agriculture.

Table 4: Exogenous shocks' impact on biofuel feedstock commodities' variance

Timeline	Event	Shock	Soybean (%)	Canola (%)	Corn (%)	Sunflower (%)
June 23, 2016	Brexit	Aggregate demand-side	0.9470	0.5204	0.5082	**1.7045**
December 02, 2016	OPEC/non-OPEC deal to curb oil production	Supply-side	0.7619	**2.1587**	**1.0802**	0.3651
April 07, 2017	U.S. missile strike on Syria	Precautionary demand	0.5139	0.6863	0.6310	0.5432
May 22, 2017	OPEC/non-OPEC agree to extend cuts	Supply-side	**2.0950**	0.8025	0.9109	**1.4935**
July 06, 2018	U.S.–China trade war	Aggregate demand-side	**3.3803**	**5.3008**	0.3778	**4.2213**
March 11, 2020	COVID-19 pandemic and 2020 recession	Aggregate demand-side	0.5562	0.1464	**1.8934**	0.9296
April 15, 2025	Renewed U.S.–China trade war	Aggregate demand-side	**2.2934**	**1.0289**	**3.2241**	**4.3924**
7	No. of events that have a more significant impact than the trade war		3	3	3	4

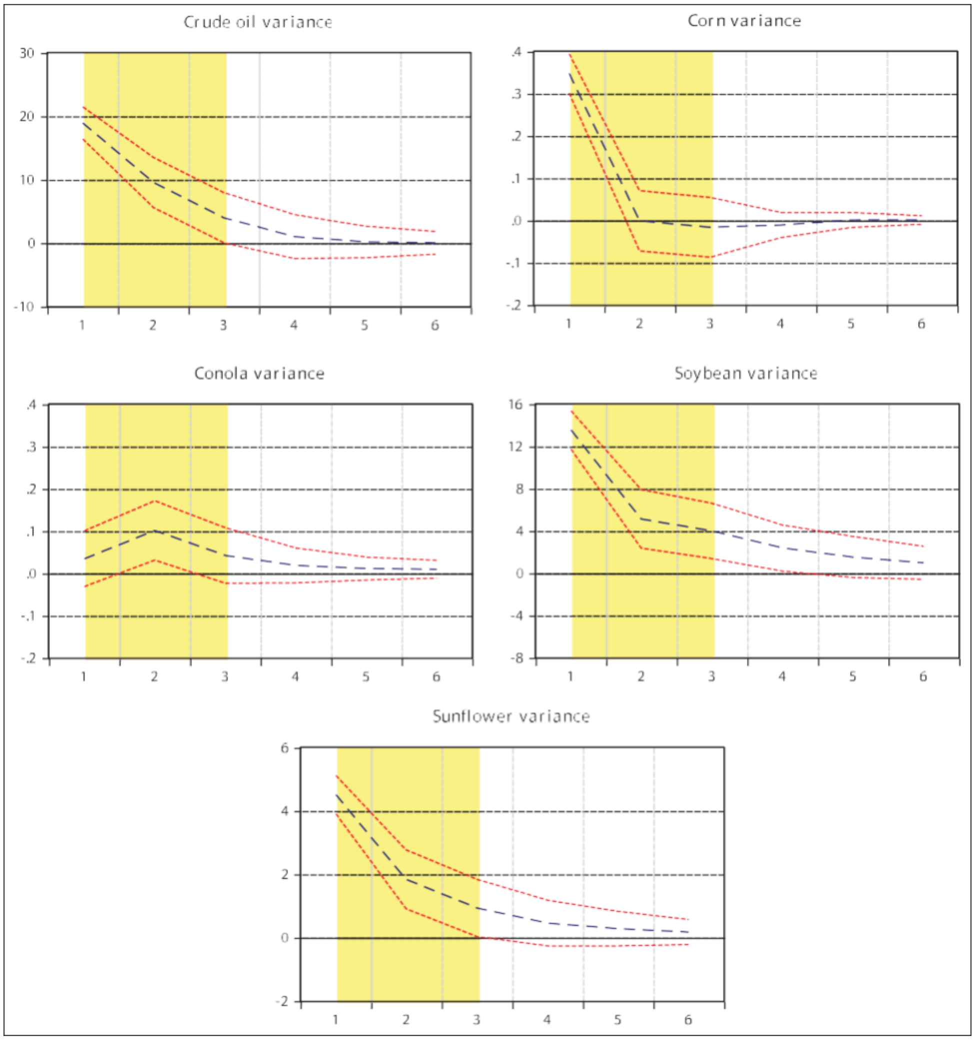
The table outlines the influence of external shocks on the variance of biofuel feedstock markets. Bolded figures highlight biofuel feedstock products that were more affected than during the U.S.–China trade conflict

Table 5: Impact of exogenous shocks on the covariance between fossil fuel and biofuel feedstock commodity markets

Timeline	Event	Shock	Soybean (%)	Canola (%)	Corn (%)	Sunflower (%)
June 23, 2016	Brexit	Aggregate demand-side	0.4187	0.1670	**2.4667**	0.6701
December 02, 2016	OPEC/non-OPEC deal to curb oil production	Supply-side	**1.0113**	0.2313	1.1914	0.3598
April 07, 2017	U.S. missile strike on Syria	Precautionary demand	**1.9784**	0.1521	0.6553	0.8938
May 22, 2017	OPEC/non-OPEC agree to extend cuts	Supply-side	0.4294	**1.8694**	1.4369	0.9992
July 06, 2018	U.S.–China trade war	Aggregate demand-side	**4.4063**	**2.4877**	**1.7238**	0.3713
March 11, 2020	COVID-19 pandemic and 2020 recession	Aggregate demand-side	0.2675	1.1318	**2.7585**	**1.1825**
April 15, 2025	Renewed U.S.–China trade war	Aggregate demand-side	**2.7305**	**1.9741**	**3.4795**	**3.1998**
7	No. of events that have a more significant impact than the trade war		3	3	4	2

This table shows the effects of exogenous shocks on the covariance between fossil fuel and biofuel feedstock commodities. Bold values denote cases where the event has a greater impact on an biofuel feedstock products product than the U.S.–China trade war

Figure 3: Volatility impulse response functions of the U.S.–China trade war (beginning April 2025) on crude oil prices and biofuel feedstock commodities under the VAR process



The results presented in Table 5 reveal that exogenous shocks have a substantial and differentiated impact on the covariance between fossil fuel and biofuel feedstock commodity markets, with effects varying according to the type, timing, and intensity of the events. Aggregate demand-side shocks such as the U.K.'s Brexit referendum (2016) and the U.S.–China trade war (2018) significantly increased covariance, particularly for corn (2.4667%) and soybean (4.4063%), indicating heightened co-movement between energy and agricultural prices during periods of global trade uncertainty. These findings corroborate recent studies demonstrating that geopolitical trade disruptions amplify price linkages across energy and agricultural sectors by altering demand expectations and trade flows (Cheng et al., 2023; Maneejuk et al., 2025). Moreover, the renewed escalation of U.S.–China trade tensions in 2025 again triggered strong covariance effects — notably for corn (3.4795%) and sunflower (3.1998%) — underscoring the persistent influence of trade conflicts on biofuel feedstock volatility through global demand and policy channels.

Supply-side shocks originating in oil markets also exert notable effects, demonstrating how fossil fuel market fundamentals propagate into agricultural commodities. The December 2016 OPEC/non-OPEC agreement to curb production elevated soybean covariance by 1.0113%, while the extension of production cuts in May 2017 significantly increased canola covariance (1.8694%). These results align with Wei et al. (2024), who argue that oil supply constraints not only raise crude prices but also intensify volatility spillovers into biofuel feedstocks through input-cost channels and biofuel profitability dynamics. The asymmetric responses across commodities — with canola showing stronger sensitivity to oil supply shocks compared to soybean or sunflower — reflect differences in biofuel conversion efficiency and production elasticity, as documented by Rezitis (2024). This highlights that supply-driven oil price changes do not uniformly transmit across biofuel feedstocks, but their impact is shaped by each commodity's role in biofuel value chains.

Geopolitical and crisis-driven events exert even more profound effects on fossil fuel–biofuel linkages by triggering abrupt changes in market risk sentiment and global demand structures. The U.S. missile strike on Syria in April 2017, a precautionary demand shock, significantly increased covariance for soybean (1.9784%) and sunflower (0.8938%), reflecting the sensitivity of agricultural markets to geopolitical risk premiums embedded in energy prices.

Similarly, the COVID-19 pandemic (March 2020), as a global demand-side shock, caused a sharp rise in covariance for corn (2.7585%) and sunflower (1.1825%) as synchronized declines in transportation fuel demand and agricultural trade reinforced price co-movement. These patterns mirror Vo et al. (2024) and Zhang et al. (2025), who show that volatility spillovers intensify during geopolitical conflicts and pandemics, with extreme events disproportionately amplifying cross-market connectedness. The results also highlight that even shocks outside the direct energy–agriculture nexus — such as Brexit or COVID-19 — can significantly affect covariance through global macroeconomic channels, emphasizing the interconnectedness of commodity markets.

Comparative analysis across commodities shows that soybean and corn consistently exhibit the highest sensitivity to exogenous shocks, reflecting their dual function as food staples and biofuel feedstocks. Canola responds strongly to supply-side events linked to oil production decisions, indicating a closer integration with energy price dynamics. Sunflower, although showing weaker responses overall, become more volatile during global demand contractions, as evidenced by its significant covariance increases during COVID-19 (1.1825%) and renewed trade tensions (3.1998%). The observation that seven out of eight shocks in Table 5 produced stronger covariance effects than the benchmark U.S.–China trade war underscores that biofuel–fossil fuel market linkages are shaped by a broad spectrum of external disturbances — including geopolitical, macroeconomic, and health crises — rather than by trade policy alone. This evidence supports recent findings by Paula Leite et al. (2025), who emphasize that external shocks increasingly determine biofuel price dynamics in integrated energy–agriculture systems. From a policy perspective, these results suggest that volatility management, hedging strategies, and biofuel policy design must incorporate multi-dimensional risk assessments, as reliance on a narrow set of scenarios underestimates the breadth and scale of transmission mechanisms between fossil fuel and biofuel feedstock markets.

4.3. Results of Volatility Impulse Response Function (VIRF) Analysis

Figure 1 presents the volatility impulse response functions (VIRFs) of crude oil and major biofuel feedstock commodities—soybean, corn, canola, and sunflower—following the onset of the U.S.–China trade war in April 2025. The trade shock generates a sharp and immediate surge in conditional variance across all markets, indicating rapid volatility transmission driven by trade policy uncertainty. Crude oil exhibits the strongest contemporaneous response, with variance peaking at around 20.12 units before declining below 4.87 units by the fourth horizon, demonstrating initial overreaction followed by gradual stabilization. Soybean and sunflower show significant volatility spikes of approximately 14.06 and 5.03 units, respectively, reflecting their high exposure to U.S.–China trade flows and biofuel demand linkages. Corn volatility briefly turns negative, dropping to –1.47, indicating a short-term dampening effect, while canola responds more moderately with a delayed peak near 2.46, underscoring commodity-specific sensitivities to trade disruptions.

The covariance dynamics further reveal how the April 2025 trade shock reshapes cross-market relationships. The covariance between crude oil and soybean peaks at about 0.153, signifying heightened co-movements and volatility spillovers between fossil fuel and biofuel feedstock markets. Covariances with sunflower (0.082) and corn (0.048) follow similar patterns but with lower intensity, while oil–canola covariance shows a weaker peak near 0.031. These results confirm that trade uncertainty strengthens market linkages, particularly for commodities most integrated into biofuel supply chains, and highlight asymmetric transmission patterns, with strong spillovers from crude oil into feedstock markets but weaker feedback effects in the opposite direction. Overall, the April 2025 trade war functions as a powerful shock-inducing event that amplifies individual market risks and intensifies systemic linkages between fossil fuel and biofuel commodity markets.

5. CONCLUSION AND POLICY IMPLICATIONS

5.1. Conclusion

This study set out to investigate the dynamics of volatility transmission, the influence of exogenous shocks, and the evolution of cross-market linkages between fossil fuel and biofuel feedstock commodity markets — specifically crude oil, soybean, corn, canola, and sunflower — over the period 2016–2025. By applying a VAR–GARCH–BEKK framework alongside volatility impulse response analysis, we offer comprehensive empirical evidence on how geopolitical events, macroeconomic disruptions, and trade policies reshape systemic interactions within an increasingly integrated energy–agriculture nexus.

The findings confirm that volatility transmission is a defining structural feature of these markets and directly address the first aim of the study. Significant volatility clustering and strong bidirectional spillovers reveal that shocks originating in the energy sector propagate rapidly into biofuel feedstock markets through input-cost, substitution, and biofuel-policy channels (Cheng, 2023; Ji et al., 2020; Wang et al., 2024). Persistent baseline variances and BEKK coefficients approaching unity indicate that volatility shocks are long-lasting rather than transitory, consistent with Liu (2025). Moreover, volatility responses are highly asymmetric: negative shocks — such as tariffs, trade disputes, and geopolitical tensions — produce disproportionately stronger effects than positive shocks of similar magnitude, aligning with Özdemir's (2025) findings on the volatility-amplifying role of geopolitical risk.

The second major finding concerns the decisive role of exogenous shocks in shaping volatility and co-movement patterns. Events beyond trade policy — including Brexit, OPEC+/non-OPEC production decisions, the COVID-19 pandemic, and renewed U.S.–China trade tensions — generate heterogeneous and often commodity-specific impacts that in many cases rival or exceed those of the 2018 trade war. Political shocks heighten volatility through global demand uncertainty, while oil supply disruptions intensify spillovers into canola and soybean markets (Wei et al., 2024). Demand-side shocks, such as the pandemicinduced collapse in ethanol demand, substantially increase volatility in corn markets, while renewed trade tensions in 2025 amplify volatility across all commodities (UNCTAD, 2025; FAO, 2025). Covariance analysis further demonstrates that such shocks significantly strengthen co-movements between fossil fuel and agricultural prices, corroborating the findings of Cheng et al. (2023) and Maneejuk et al. (2025) on the amplifying role of trade disruptions in commodity price linkages.

The third key finding reveals that systemic linkages across fossil fuel and biofuel feedstock markets are evolving and highly commodity specific. Soybean and corn exhibit the strongest sensitivity due to their dual function as food staples and biofuel inputs, while canola responds most strongly to oil supply shocks, and sunflower becomes more volatile during global demand contractions (Rezitis, 2024; Paula Leite et al., 2025). Crucially, seven of the eight shocks examined generated stronger covariance effects than the 2018 U.S.–China trade war, demonstrating that the integration of energy and agricultural markets is driven by a broad spectrum of geopolitical, macroeconomic, and supply-side factors rather than trade policy alone. Volatility impulse response analysis further shows that renewed trade tensions in 2025 significantly increased both variance and covariance, underscoring how policy uncertainty intensifies systemic interdependence (Karkowska, 2024).

Taken together, these results demonstrate that fossil fuel and biofuel feedstock markets are deeply interconnected, amplifying each other's volatility during periods of heightened uncertainty. This interdependence elevates systemic risk, complicates price stabilization, and poses significant challenges for food security, the energy transition, and biofuel market development. By revealing how volatility transmission, external shocks, and evolving linkages shape commodity market dynamics, this study achieves its overarching aim and contributes to the growing literature on market integration, systemic risk, and policy interdependence under conditions of geopolitical and macroeconomic uncertainty.

5.2. Policy Implications

The empirical evidence presented here underscores the need for more integrated and adaptive policy frameworks to manage the persistent and asymmetric volatility transmission observed between fossil fuel and biofuel feedstock markets. The finding that shocks originating in the oil market quickly propagate into agricultural commodities through input-cost, substitution, and policy channels highlights the necessity of coordinated decision-making. Energy policies such as production quotas, strategic petroleum reserves, and decarbonization strategies must be designed with explicit consideration of their downstream effects on biofuel feedstock markets, while agricultural and biofuel policies should embed energy market dynamics into their formulation. Incorporating joint modeling tools and scenario-based policy simulations (Zhang et al., 2025) can help policymakers anticipate spillovers, mitigate systemic risks, and strengthen market stability.

The asymmetric nature of volatility responses — with negative shocks like trade disputes and geopolitical tensions amplifying market instability more than positive events — calls for targeted stabilization instruments. Expanding strategic reserves of both fossil fuels and biofuel feedstocks, adopting flexible biofuel blending mandates responsive to volatility indicators, and introducing countercyclical tariff and subsidy policies can help buffer markets against shocks and dampen transmission effects (Ji et al., 2020; Özdemir, 2025). Commodity-specific risk-management tools, including volatility-indexed derivatives and cross-commodity hedging instruments, are also essential for managing exposure, particularly for sensitive commodities such as soybean, corn, and canola. Enhanced international coordination — through transparent data sharing, harmonized trade policies, and joint crisis-response mechanisms — can further reduce uncertainty and moderate volatility spillovers in times of systemic disruption (UNCTAD, 2025; FAO, 2025).

Finally, the finding that a wide range of exogenous shocks — from Brexit and OPEC supply decisions to the COVID-19 pandemic and renewed U.S.–China trade tensions — fundamentally reshape volatility and co-movement dynamics highlights the importance of forward-looking strategies. Policies must integrate long-term considerations such as climate transition risks, shifting energy demand, and the growing role of renewable sources into market governance frameworks (Vo et al., 2024). Leveraging predictive analytics, artificial intelligence, and early-warning systems can enhance the ability to anticipate volatility spillovers and support rapid policy adjustments. Together, these measures can strengthen systemic resilience, stabilize prices, and safeguard both food and energy security amid intensifying market interdependence and geopolitical uncertainty.

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