The US-China Tension, Global Supply Disruptions and the Agricultural Commodity Markets: Evidence from new datasets and new methods

Afees A. Salisu[1,2], AbdulHameed AbdulHakeem[3]

Data Availability Statement
We have included all relevant sources for the data used in the analyses presented in our paper. We are also willing to share the data and the estimation codes once we receive a 'Revise and Resubmit' decision on our manuscript. However, all the data are publicly available, and we encourage our readers to refer to the data sources and links provided in the main text.

Declaration of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[1] Centre for Econometrics & Applied Research, Ibadan, Nigeria. Email: aa.salisu@cear.org.ng.
[2] Department of Economics, University of Pretoria, South Africa.
[3] Corresponding Author. Centre for Econometrics & Applied Research, Ibadan, Nigeria. Email: mobolhak631@gmail.com.

The US-China Tension, Global Supply Disruptions and the Agricultural Commodity Markets: A Dynamic Multivariate Panel Data Analysis

Abstract:

Purpose:

The US–China trade friction represents a major geopolitical shock that disrupts global trade flows, supply chains, and commodity markets. This study aims to provide new evidence on how US–China trade tensions (UCT) influence the realized volatility of agricultural commodity prices, with a focus on both futures and spot markets, and to examine the differential responses of these markets to geopolitical and supply chain shocks.

Design/methodology/approach

Using a dynamic multivariate analysis with data spanning April 1998 to February 2024, which encompasses multiple trade cycles, including the 2018–2019 US–China trade war and the post-pandemic recovery, we uncover how geopolitical tensions transmit to commodity markets via the global disruption channel.

Findings

Our findings show that the futures market tends to exhibit stronger and more persistent volatility in response to trade tensions than spot markets, reflecting the forward-looking nature of futures trading and the role of speculation in amplifying uncertainty. Moreover, our robustness analysis confirms that volatility responses areresponses are more pronounced for certain commodities directly exposed to the US-China trade nexus. In contrast, globally traded commodities in the spot market exhibit more muted reactions.

Originality/value

This study makes three key contributions. We (1) introduced the US-China trade tensions (UCT) as a novel source of geopolitical uncertainty in global agricultural commodity markets (2) employed the new indices of the US-China Tension Index and the Global Supply Chain Pressure Index (GSCPI) to capture multidimensional global risks (3) applied the dynamic multivariate panel framework to assess how UCT shocks propagate through commodity spot and futures markets, influencing volatility and price dynamics.

Keywords: US-China tension, realized volatility, commodity prices, futures prices, spot prices, Global supply chain.

1. Introduction

The global economy has recently faced significant challenges due to geopolitical tensions and supply chain disruptions, both of which have substantially impacted commodity markets. Notably, tensions between the United States (US) and China are a major source of uncertainty, influencing trade patterns, production costs, and investor behaviour. The US and China comprise over 40% of global GDP and more than a third of international trade (World Bank, 2019). Their close economic ties mean that any bilateral issues, such as tariffs, technology restrictions, or strategic trade policies, can have immediate and widespread effects on global supply chains (see Bahmani-Oskooee & Brooks, 1999; Bahmani-Oskooee & Hegerty, 2007). For example, tariffs increased during the 2018-2019 trade war, disrupting agricultural exports, such as soybeans, with US shipments to China dropping by over 50% (see, for example, Xu, 2025). These cases demonstrate how US-China tensions (UCT) pose systemic risks, directly distorting commodity flows and, through supply chain disruptions, indirectly increasing market volatility. Trade conflicts, tariffs, currency fluctuations, and rare crises like financial downturns, wars, pandemics, or policy uncertainties often trigger such disruptions. An example is the trade war initiated by the Trump administration, which led to a 58% decrease in US agricultural exports to China (Grant et al., 2019).

China is among the United States' top export destinations, while the US ranks third among suppliers of agricultural imports to China (Jiang, 2020; Xu et al., 2025). This mutual dependence underscores how US farmers and agribusinesses heavily rely on export markets to sustain their revenue, as US agricultural productivity typically outpaces domestic food demand (Bakst and Beaumont-Smith, 2018; Cheng et al., 2023; Tanveer et al., 2025). Conversely, Chinese imports of certain agricultural products are crucial because consumer demand in China often surpasses local supply. A notable example is soybeans: China dominates the global soybean market, importing approximately 61% of the world's traded soybeans, surpassing the combined imports of all other countries. Historically, the US was China's main supplier, accounting for up to 31% of US soybean exports in 2020/21. Before the 2018 US-China trade war, approximately 60% of US soybean exports, valued at around $12.8 billion annually, were shipped to China. The trade war tariffs sharply reduced US soybean exports, costing American farmers an estimated $9.4 billion yearly, or 71% of total US farm export losses. Post-pandemic, US exports to China have partially recovered but remain below pre-trade war levels, with only 22% of US production reaching China in 2023/24. Meanwhile, Brazil has emerged as China's preferred supplier, benefiting from lower production costs, favourable exchange rates, and Chinese infrastructure investments. By 2019/20, Brazil surpassed the US in soybean production and now dominates Chinese imports, supplying 112 million metric tons (MMT) in 2024/25, about the same as China's total soybean imports[4]. Besides China, many countries imposed retaliatory tariffs on US agricultural exports in response to US tariffs on their goods. For instance, China levied tariffs on nearly all US agricultural products, including soybeans, corn, cotton, and wheat. Canada imposed tariffs on coffee, the European Union imposed tariffs on grains, and Turkey imposed tariffs on rice (Chinn & Plumley, 2020; Durante, 2022; Aftab et al., 2023). Third, disruptions at sea have increased pressure: in 2021, global container freight costs surged by over 300%, mainly due to bottlenecks at Chinese ports and shipping restrictions, leading to higher input costs worldwide for commodity producers (UNCTAD, 2022)[5].

Additionally, the Russian invasion of Ukraine in 2022 disrupted global commodity markets, particularly cereals and vegetable oils, as Ukraine and Russia accounted for over a quarter of global wheat exports (Ferguson & Ubilava, 2022). Wheat and maize prices surged further, echoing past crises such as Russia's 2010 export ban. Rising energy and fertilizer costs compounded these shocks, underscoring the vulnerability of global food systems (Vos et al., 2022). Like the Ukraine war, US-China tensions (UCT) can act as geopolitical shocks that amplify supply disruptions and commodity price volatility through trade and market linkages. Nonetheless, compared with other geopolitical shocks, the literature on UCT-driven commodity market effects remains relatively sparse, constituting a key research gap this study seeks to address.

Theoretical and empirical literature provides a basis for understanding these dynamics. On the theoretical front, trade theories, such as the Stolper-Samuelson theorem, suggest that tariffs and other trade restrictions alter relative prices, redistributing welfare between producers and consumers. Commodity price transmission models describe how shocks in one market, such as the energy market, can influence agricultural and metal markets through cost linkages and substitution

[4] See https://soygrowers.com/news-releases/soybeans-without-a-buyer-the-export-gap-hurting-u-s-farms/
[5] See https://unctad.org/rmt2022

effects. Asset pricing models, particularly the Arbitrage Pricing Theory (APT), emphasize that geopolitical risks, such as UCT, can be factored into commodity futures as a distinct risk element. Empirical studies support these insights. For example, Algieri & Leccadito (2017) find that trade restrictions increase food price volatility. Baumeister & Kilian (2014) demonstrate the global spread of oil shocks into other commodity markets. Bahmani-Oskooee & Wang (2007) found that changes in the Yuan–dollar exchange rate significantly affect US–China trade at the commodity level. Recent research by Adjemian et al. (2021) suggests that US-China tariffs resulted in asymmetric price effects, reducing US soybean export prices by $0.74 per bushel while increasing Brazilian soybean prices by nearly $1 per bushel. Likewise, Boulanger et al. (2016) and Gullstrand (2020) demonstrate that sanctions and counter-sanctions distort agricultural commodity prices and trade flows, highlighting the connection between policy disruptions and market fundamentals. However, the literature examining UCT alongside global supply chain disruptions remains incomplete, with most studies focusing on single markets or isolated shocks. Importantly, several recent contributions emphasize the macro-financial relevance of supply chain pressures (e.g., Wang, 2024; Bouri et al., 2025; Ullah et al., 2025). These studies motivate our use of the Global Supply Chain Pressure Index (GSCPI) as a complementary channel linking geopolitical tensions to agricultural commodity price dynamics.

Further to the above, our research advances the current literature in several key ways. While prior work has focused on other forms of shocks, including oil shocks, financial crises, or climate risks as primary sources of uncertainty in commodity markets (see Kilian & Park, 2009; Bakas & Triantafyllou, 2020; Salisu & Isah, 2017; Gogas & Serletis, 2009), we expand the analysis to include US-China trade tensions (UCT) and their impact on global commodity markets. UCT is a persistent, multi-faceted geopolitical shock that disrupts trade flows, reshapes supply chains, and influences commodity demand and prices. Including UCT in our empirical framework bridges the gap between geopolitical economics and commodity market behaviours, an area that remains underexplored despite its increasing significance since the 2018 trade war. Moreover, we use new datasets to more accurately measure these risks. The US–China Tension Index assesses bilateral tensions through media-based text analysis, identifying articles that mention both countries and employ language related to tension, thereby reflecting perceptions in business and policy circles. Additionally, we incorporate the Global Supply Chain Pressure Index (GSCPI), which combines shipping costs, delivery times, and backlogs across major economies to gauge worldwide supply chain stress. These indices enable us to present a multidimensional view of global uncertainty. Our contribution, therefore, lies in integrating trade frictions (UCT) and global supply chain pressures within a unified empirical framework, offering a more complete representation of the forces shaping commodity markets.

Furthermore, we employ a dynamic multivariate panel data model to effectively capture both temporal variations and cross-sectional dependencies inherent in commodity spot and futures markets. This framework, applied over the period of 1998M04 – 2024M02, enables us to analyze how shocks from US-China tensions impact the global supply chain, spread across various commodities, and how these effects evolve. It also considers feedback loops, persistence, and volatility clustering, key features of commodity markets under uncertainty. By integrating this dynamic approach with high-frequency datasets, our study provides a detailed, system-wide understanding of geopolitical and supply chain disruptions beyond what conventional econometric methods offer.

We provide evidence highlighting the importance of jointly accounting for US-China trade tensions and global supply disruptions when analyzing commodity market volatility. Specifically, within the dynamic multivariate framework, we find contrasting responses between the futures and spot commodity markets to the US-China trade tensions. While the response is negative for the futures market, it appears positive for the spot market, albeit with transient responses. In other words, the commodity futures markets tend to price geopolitical and supply-related uncertainties more persistently than spot markets, reflecting their forward-looking nature. In contrast, spot market volatility responds more sharply but briefly to immediate supply shocks. Overall, the analysis reveals that US-China trade tensions impact commodity markets through the global supply chain.

2. Data and some preliminary analysis

In this paper, we utilize futures and spot data for 11 agricultural products listed by the Food and Agriculture Organisation of the United Nations (FAO), sourced from Investing.com and the World Bank Commodity Price Data (The Pink Sheet), covering the period of 1998M04–2024M02. We obtained our futures price data for 11 agricultural products (Coffee, Cocoa, Soybean Oil, Orange, US Corn, US Soybean, US Soybean meal, US wheat, Rice, Sugar, and Cattle) from investing.com and spot price data from the World Bank Commodity Price Data (The Pink Sheet). The agricultural products used for the spot price are: Cocoa, Soybean, Soybean Oil, Soybean meal, wheat (Wheat (US), no. 2, hard red winter), Corn (Maize (US), no. 2, yellow), Rice, Sugar, Cattle, Coffee, and Orange.[6] Meanwhile, the realized volatility is computed by estimating the annualized variance of commodity price returns using a three-month rolling window. The three-month (approximately 60 trading-day) rolling window is chosen because it provides the best balance between capturing short-term volatility dynamics, particularly those associated with geopolitical tensions and supply-chain disruptions, while smoothing out very high-frequency noise that would arise from using much shorter windows. In commodity markets, volatility tends to adjust within relatively short horizons in response to shocks such as weather events, trade frictions, shipping constraints, and even policy announcements.

For the US-China Trade tension (UCT) measure, the Index by Rogers et al. (2024) is utilized.[7] Rogers et al. (2024) developed the US-China Tension Index, which measures bilateral tensions by analyzing the share of articles in major US newspapers that mention both the United States and China, cite contentious issues, and use tension-related language. Search terms are identified using

[6] Please note that the apparent discrepancies between the spot and futures series arise solely from differences in naming conventions and product labelling across our two data sources (FAO from Investing.com for futures and the World Bank "Pink Sheet" for spot prices), rather than from any difference in the underlying commodities themselves. Both sources refer to the same set of 11 agricultural products employed in this study. For instance, the World Bank reports Maize (US, no. 2, yellow) and Wheat (US, no. 2, hard red winter) as spot prices, while Investing.com lists the corresponding futures as US Corn and US Wheat. Similar naming differences occur for soybean products (Soybean versus US Soybean; Soybean Meal versus US Soybean Meal), as well as for other commodities, where market terminology varies slightly between sources. Consequently, the underlying commodities are equivalent, and the naming variations do not introduce inconsistencies that would bias the empirical results or the motivation of the paper. More importantly, each commodity has a matched spot–futures pair representing the same product category and internationally recognized benchmark. All series follow the standard global classifications used by the FAO, the World Bank, and futures exchanges, meaning that the fundamental market information is aligned across sources. Indeed, Table 1 already reflects consistent labelling across all commodities, and the details provided in the opening paragraph of Section 2 simply serve to enhance the transparency and credibility of our data description.

[7] https://www.policyuncertainty.com/US_China_Tension.html

topic-modelling tools, such as K-means, guided LDA, and Newsmap, which are applied to a large set of manually selected articles related to tension. Following the methodology by Baker et al. (2016), the index reflects business and policy perceptions, correlates with mentions of tension in corporate earnings calls and presidential speeches, and aligns with indicators such as anti-China legislation and voting divergence at the UN.

For robustness, we expand our analysis to include the Global Supply Chain Pressure Index (GSCPI) available at https://www.newyorkfed.org/research/policy/gscpi#/interactive. The Global Supply Chain Pressure Index (GSCPI) is a composite measure of worldwide supply chain stress by combining global transportation cost indicators and supply chain-related survey data. Specifically, it integrates shipping cost measures such as the Baltic Dry Index, the Harpex index, and airfreight rates from the US Bureau of Labor Statistics with Purchasing Managers' Index (PMI) components particularly supplier delivery times and order backlogs across seven key economies (China, the euro area, Japan, South Korea, Taiwan, the United Kingdom, and the United States). Each series is first standardized to ensure comparability, after which a principal component analysis (PCA) is then applied to extract the common factor representing global supply chain pressures. The resulting index is then normalized to have a mean of zero and a standard deviation of one, such that positive values indicate above-average pressure while negative values denote below-average pressure relative to historical norms.

Table 1 presents summary statistics that highlight key insights into the realized volatility of agricultural commodities and bilateral uncertainty (UCT). Generally, futures prices exhibit a higher mean realized volatility than their corresponding spot prices, suggesting that futures markets incorporate information about anticipated risks more quickly and more strongly. In contrast, spot prices display greater relative fluctuations, as indicated by their higher coefficients of variation, implying that spot markets experienced more pronounced proportional variability over the sample period – likely reflecting changing trade policies and shocks associated with U.S.–China trade frictions in major producing countries. This difference underscores how various segments of the commodity market respond to uncertainty. Meanwhile, the UCT index, with its high average and notable variation, suggests a common source of uncertainty influencing both futures and spot prices through trade policy changes and global supply chain disruptions. Although the UCT exhibits a high mean, its relatively low coefficient of variation indicates that these tensions are persistent but less volatile than the more volatile movements observed in the commodity market.

Furthermore, the presence of non-zero skewness and the pronounced leptokurtic behaviour (i.e., kurtosis values > 3) observed across nearly all variables in Table 1, together with the statistically significant Jarque–Bera statistics, indicates clear departures from normality. These results confirm the heavy-tailed nature of the series and suggest the likelihood of extreme observations, which are common in commodity market volatility. Consequently, the Student-t distribution is employed, as it more appropriately accommodates fat tails and excess kurtosis relative to the Gaussian specification (See Section 3 and the accompanying footnote 7 for further details).

We also illustrate the relationship between the realized volatility of commodity prices (both futures and spot) and the UCT in Figures 1 and 2. These figures show how the UCT interacts with the realized volatility (RV) of various agricultural commodities, providing a graphical complement to the numerical results reported in Table 1. Overall, both futures and spot markets exhibit similar responses to changes in the UCT, confirming the patterns already observed in Table 1. However, the spot market appears to respond more strongly to UCT variability. This heightened sensitivity may reflect the spot market's closer connection to immediate supply-demand conditions, physical inventory adjustments, and short-term price shocks, whereas futures markets tend to incorporate expectations over longer horizons and are somewhat buffered by hedging and speculative activity.

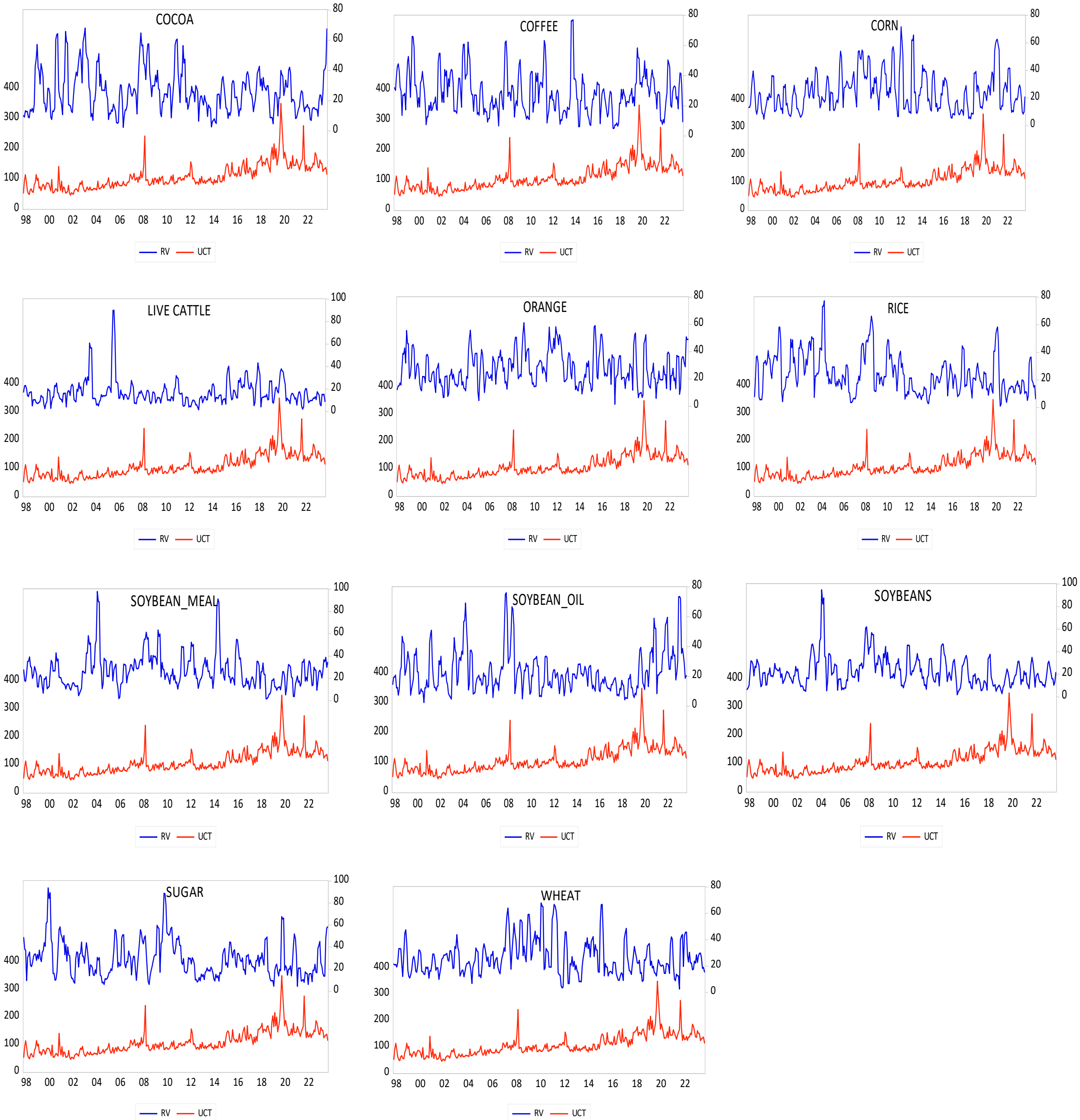
Table 1: Summary statistics for realized volatility across the agricultural commodities

	Futures prices					
	Cocoa	Coffee	Corn	Live cattle	Orange	Rice
Mean	26.134	28.495	24.809	16.891	27.617	24.356
Std. dev.	14.238	13.886	13.876	11.179	12.471	14.340
CoV	54.482	48.731	55.932	66.182	45.158	58.878
Skew	0.858	0.828	0.890	2.934	0.496	0.928
Kurt	3.311	3.765	3.346	16.510	2.572	3.660
JB	39.402***	43.083***	42.574***	2811.537***	15.153***	50.258***
	Soybean meal	Soybean oil	Soybeans	Sugar	Wheat	UCT
Mean	26.7945	23.391	22.585	29.351	26.565	108.313
Std. dev.	15.069	14.076	13.143	16.251	13.325	41.661
CoV	56.240	60.178	58.194	55.367	50.158	38.464
Skew	1.616	1.439	1.662	1.129	1.017	1.617
Kurt	7.373	5.348	8.196	4.647	3.824	7.826
JB	383.079***	178.777***	492.944***	101.223***	62.376***	437.356***
	Spot prices					
	Cocoa	Coffee	Corn	Live cattle	Orange	Rice
Mean	17.823	18.848	18.370	11.586	31.533	14.371
Std. dev.	9.719	9.151	10.755	7.849	18.748	11.848
CoV	54.529	48.552	58.547	67.745	59.455	82.445
Skew	1.029	1.581	0.772	1.444	1.239	3.931
Kurt	4.233	8.592	3.281	5.754	4.461	27.528
JB	74.541***	534.826***	31.954***	206.456***	107.264***	8596.672***
	Soybean meal	Soybean oil	Soybeans	Sugar	Wheat	
Mean	17.063	16.106	15.761	23.062	19.483	
Std. dev.	9.485	11.215	9.329	11.824	11.108	
CoV	55.590	69.633	59.192	51.271	57.016	
Skew	1.009	2.482	1.492	0.939	1.376	
Kurt	3.678	12.501	6.890	4.085	5.400	
JB	58.708***	1488.973***	311.408***	60.940***	172.708***	

Source: Authors' own work

Note: UCT refers to US-China Trade Tension; std. dev. denotes the standard deviation, and CoV represents the Coefficient of variation, calculated as the ratio of the standard deviation to the mean and expressed as a percentage. Similarly, Skew, Kurt, and JB denote skewness, kurtosis, and the Jarque-Bera statistic, respectively.

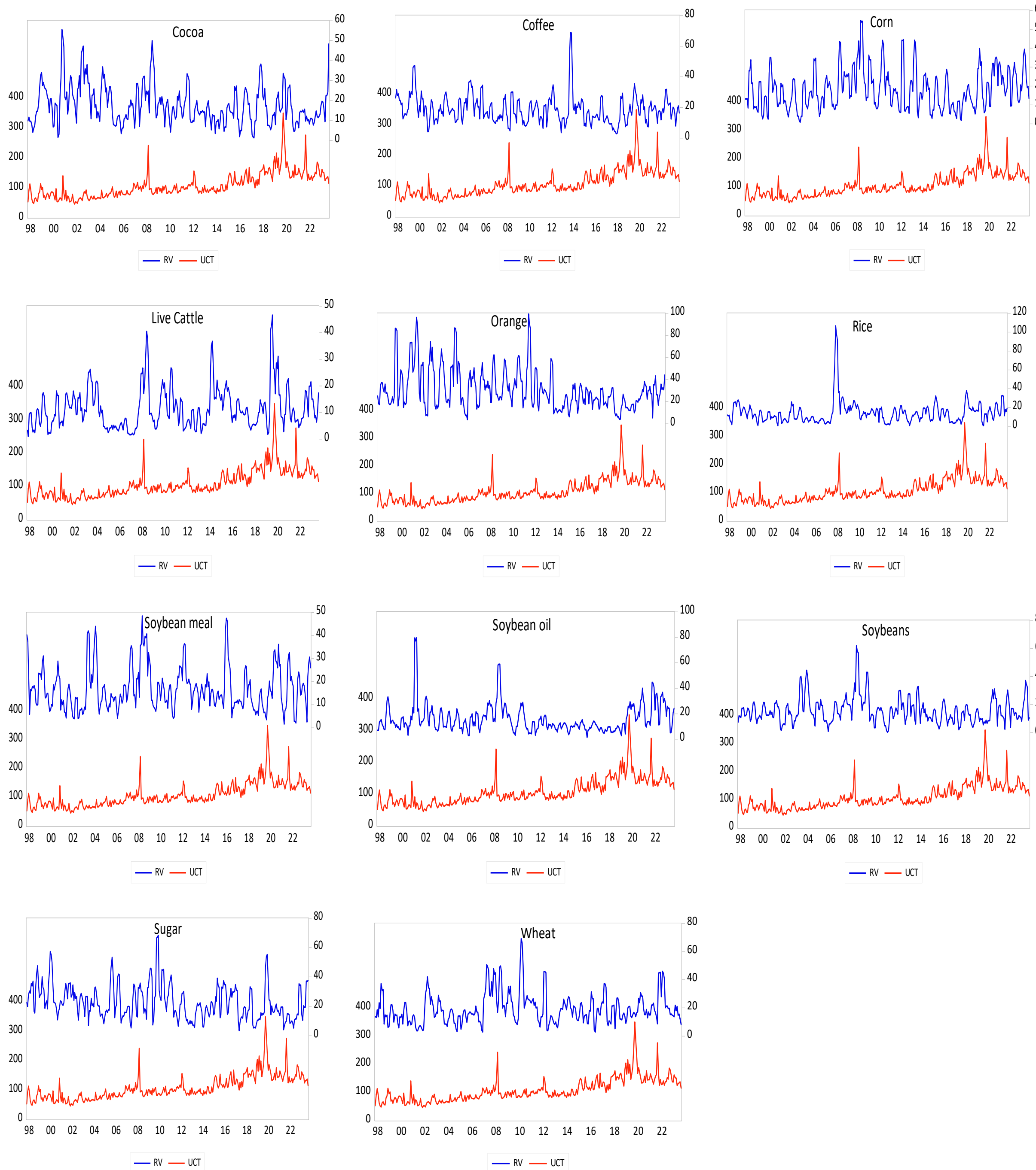
Figure 1: Realized Volatility for Futures prices and the US-China Tension index (UCT)



Source: Authors' own work

Note: UCT denotes US-China Tension, RV means Realized volatility, while Coffee, Cocoa, Soybean Oil, Orange, US Corn, US Soybean, US Soybean meal, US wheat, Rice, Sugar, and Cattle are the futures agricultural commodity prices used in this paper.

Figure 2: Realised Volatility for Spot prices and the US-China Tension index (UCT)



Source: Authors' own work

Note: UCT denotes US-China Tension, RV means Realized volatility, while Coffee, Cocoa, Soybean Oil, Orange, US Corn, US Soybean, US Soybean meal, US wheat, Rice, Sugar, and Cattle are the spot agricultural commodities prices used in this paper.

Additionally, we provide a graphical illustration that connects UCT and global supply chain disruptions, proxied by the Global Supply Chain Pressure (GSCP) Index (see Figure 3). The dynamics of UCT and the GSCP reveal that heightened UCT, such as during the 2018-2019 trade war and the COVID-19 outbreak in 2020, is associated with noticeable increases in the GSCP (see also Xu, 2025). This reflects how escalating geopolitical rivalry could exacerbate global supply bottlenecks. Conversely, when UCT levels ease, the GSCP also tends to normalize, as observed in the post-2022 period, when declining supply pressures persisted despite structurally elevated geopolitical tensions. This pattern suggests that UCT shocks are a significant driver of global supply disruptions, particularly when combined with other systemic shocks, amplifying volatility in commodity markets.

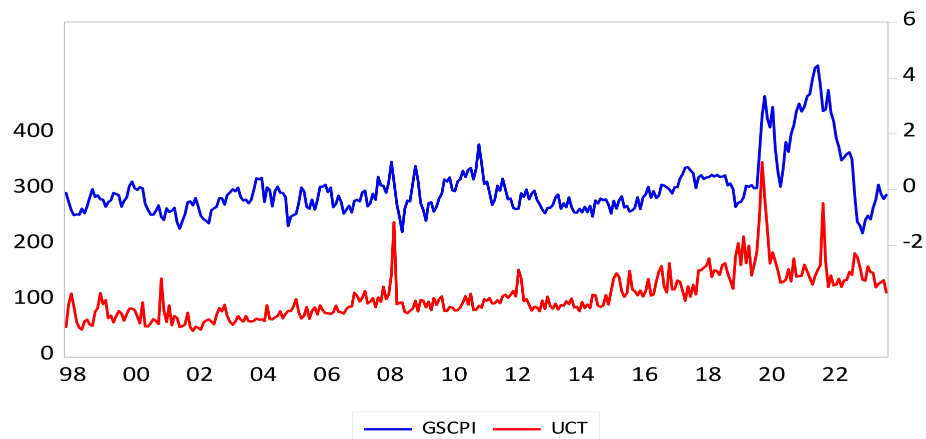


Figure 3: GSCPI vs UCT

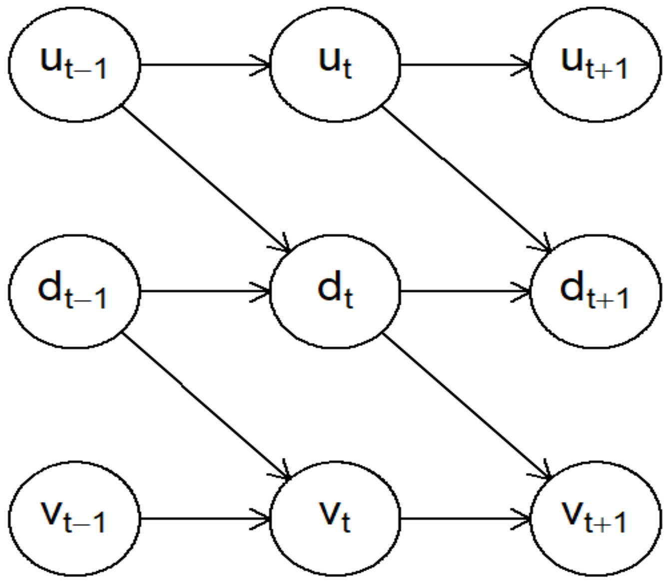
Source: Authors' own work

Note: UCT denotes the US-China Tension, and GSCPI means Global Supply Chain Pressure Index.

3. Testing the dynamic role of the US-China tension in the commodity market

This section captures the dynamic effect of US-China Tensions on the realized volatility of commodity prices. This is achieved by providing additional insights into the evidence regarding global supply disruption. We employ the dynamic multivariate panel data model of Helske & Tikka (2024), which allows for multiple equations constructed in a structural form. The goal is to assess how trade-related geopolitical frictions are transmitted through global supply chains to influence the realized volatility of commodity prices. We establish three equations and a recursive form in which rising global supply disruptions raise concerns about US-China tensions, which, in turn, affect the realized volatility of commodity prices. One interesting way to represent the connections across the relevant variables is using a Directed Acyclic Graph (see Figure 4). The motivation behind the acyclicity in the dynamic multivariate model is to ensure internal consistency in the connections[8].

Figure 4: A Directed Acyclic Graph (DAG) for a structural dynamic multivariate panel data model



Source: Authors' own work

Note: The DAG represents the dynamic response of stock market volatility to sustainability uncertainty. Where u stands for US-China trade tension, d indicates global supply disruptions, and v is the realized volatility of commodity prices.

The dynamic multivariate panel data model is then expressed in Equation (1):

$$x_{t,i} \sim p(x_{t,i} \mid x_{t-1,i}, \beta) = \prod_{m=1}^{M} p_{m,t}(x_{m,t,i} \mid x_{k(m),t,i}, x_{1:t-1,i}, \beta) \qquad (1)$$

where $x_{t,i} = (x_{1,t,i}, \dots, x_{M,t,i})$ denotes the vector of observed variables with $t = 1, \dots, T$, $i = 1, \dots, N$; and at each period, we have M observations from N units, where M is the number of different response variables that have been measured. We have three observed variables in our case: US-China trade tension (u), global supply disruptions (d), and the realized volatility of commodity prices (v). Each response variable includes at least its first lag $(x_{t-1,i})$, and the model

[8]We are also mindful of the potential for multicollinearity between UCT and GSCPI. However, their correlation is moderate (0.509) and falls well below the conventional thresholds of 0.7–0.8 typically associated with multicollinearity concerns. Accordingly, multicollinearity is unlikely to pose an issue in our specification.

is structural, implying that it follows a particular ordering $(u \rightarrow d \rightarrow v)$ as stated earlier, acyclic$(v \nrightarrow u)$. Consequently, the response variables are ordered so that the distribution of $x_{t,i}$ factorizes according to an ordering k of the responses. We denote the observations at the same time point before observation $x_{m,t,i}$ in this ordering by $x_{k(m),t,i}$. The conditional distributions $p_{m,t}$ can be distinct distributions for the various response variables. The estimation procedure follows a Bayesian approach, utilizing MCMC algorithms with 4000 iterations. In our analysis, however, we assume a Student-t distribution for all the equations, given the underlying statistical properties of the response variables, which exhibit heavier tails than the normal distribution[9].

We present the estimation results for the model parameters in Table 2, which provide evidence of the dynamic interactions among US-China trade tensions, global supply disruptions, and the realized volatility of commodity spot and futures prices. The results reveal notable differences. Disruptions in global supply have a quantifiable, albeit unequal, impact on commodity price volatility. As physical market participants react to shortages and delivery restrictions, disruptions typically cause instantaneous, but transient, volatility in spot prices. On the other hand, futures markets exhibit a more subdued but consistent volatility response, reflecting the forward-looking nature of derivative pricing, where traders account for sustained uncertainty. This asymmetry aligns with insights from behavioural finance and speculative-positioning dynamics: futures traders – often institutional and better informed – adjust their positions based on expectations, risk premia, and sentiment around prolonged supply chain uncertainty. Such anticipatory behaviour dampens the initial volatility spike but prolongs the adjustment process, reinforcing the persistent volatility patterns we observe. Furthermore, our findings demonstrate that heightened trade tensions between the US and China contribute to global supply chain disruptions, albeit to a limited extent. The low spillover from trade tensions to supply disruptions (beta_d_u_lag1≈ 0.005), although statistically significant, is economically small because such tensions often affect supply chains through indirect and policy-mediated channels rather than through immediate physical constraints. Unlike geopolitical shocks that directly obstruct logistics or production, US–China

[9]To ascertain the appropriateness of the Student-t distribution, Table 1 has been updated to include key summary statistics for each commodity's RV series, including skewness, kurtosis, and the Jarque-Bera (JB) test. The results reveal significant departures from Gaussian properties: most series exhibit non-zero skewness and excess kurtosis, and the JB test rejects normality in all cases. These findings empirically justify the use of the Student-t distribution, which accommodates heavy tails and extreme observations commonly observed in commodity markets.

frictions largely manifest in tariff changes, regulatory uncertainty, and strategic posturing – all of which alter expectations and trading behaviour more than they induce instant shortages in commodity availability. Put together, when geopolitical frictions rise, through tariffs, trade restrictions, or diplomatic confrontations, they undermine the efficiency of international logistics and the smooth flow of intermediate goods. This connection underscores the interconnectedness of global supply networks, as disruptions originating from two large economies immediately impact supply chains worldwide.

However, trade tensions exhibit strong persistence, suggesting that geopolitical strains between the US and China tend to persist. This persistence reflects the clustering of uncertainty, in which similar episodes often follow periods of elevated tension. This finding is consistent with several studies in the literature. For instance, Adjemian et al. (2021) report that the US–China trade disruption created a significant wedge in the global soybean market. Similarly, Cheng et al. (2023) show that the US–China trade war heightened volatility across energy and agricultural commodities, with soybeans exhibiting the greatest responsiveness. They further highlight that the trade war affected most agricultural commodities more extensively than other exogenous shocks, including the global financial crisis and the COVID-19 pandemic and its associated recession. In contrast, global supply disruptions exhibit a weaker, less persistent pattern, suggesting that while they affect market stability, their effects dissipate more quickly than those of trade tensions. Put technically, the small but positive spillover from trade tensions to supply disruptions suggests limited cross-market transmission, implying that while geopolitical shocks can influence both markets, their impact is more direct and short-lived in the spot market but more persistent in futures trading.

We provide graphical evidence of the dynamic relationship in Figures 5 and 6, which illustrate the responses of the realized volatility of commodity futures and spot prices to variations in US-China trade tensions. The figure captures how commodity market volatility evolves under different levels of geopolitical strain, thereby highlighting the time-varying nature of this relationship rather than what is observable on average. Two scenarios are considered to depict this dynamic response: one representing a moderate level of trade tension, roughly corresponding to 75 per cent (see b_1 in the figures), which is 35 per cent below the average level, and another representing a heightened level, around 150 per cent (see b_2 in the figures) which is 40 per cent above the average. The results show distinct adjustment patterns across the two markets. For futures prices, realized volatility declines under moderate and high trade-tension scenarios, with the decline sharper under moderate tension. This suggests that the futures market exhibits a strong adaptive response, as traders anticipate geopolitical risks and adjust their contracts accordingly, leading to short-term adjustments and eventual stabilization when uncertainty persists for an extended period. Meanwhile, the slight decline in futures volatility amid heightened tension may reflect broader market dynamics, such as hedging saturation – where commercial participants intensify hedging activity until marginal volatility effects diminish – or market fatigue, where traders reduce reactive trading as trade uncertainty becomes prolonged and is accounted for. In contrast, spot price volatility exhibits a mild increase followed by a flattening trend. This indicates that spot prices react more directly and immediately to trade tensions, with volatility rising as physical market participants respond to perceived disruptions in trade flows and supply conditions before the market stabilizes.

Table 2: The estimation results

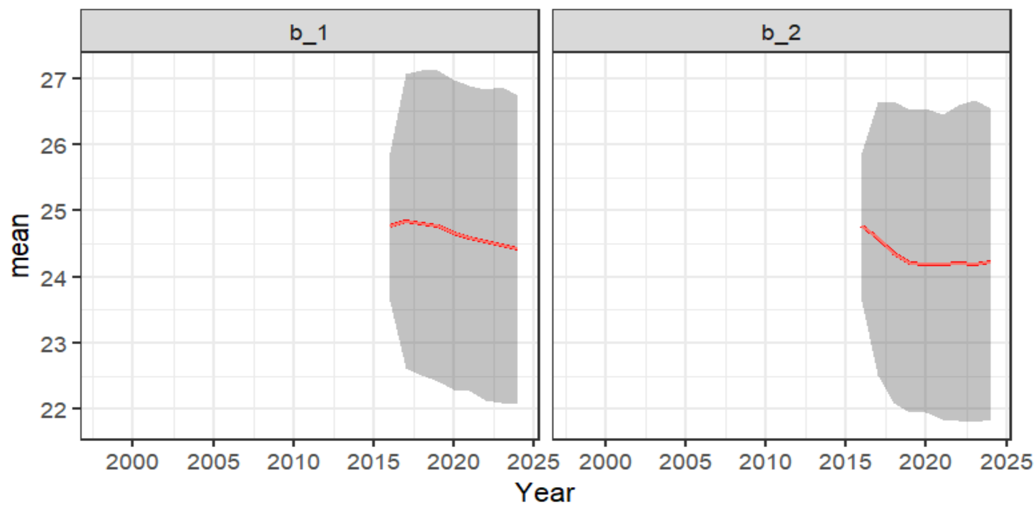
Parameter	Mean	SD	q5	q95
	Futures prices			
alpha_u	33.5703	2.8237	29.0217	38.2338
beta_u_u_lag1	0.6938	0.0278	0.6479	0.7390
alpha_d	-0.5354	0.1730	-0.8300	-0.2693
beta_d_u_lag1	0.0051	0.0017	0.0026	0.0080
beta_d_d_lag1	0.6004	0.0408	0.5302	0.6633
alpha_v	16.2876	1.5028	13.7942	18.7165
beta_v_d_lag1	-0.7638	0.5637	-1.6928	0.1657
beta_v_v_lag1	0.3329	0.0545	0.2428	0.4228
	Spot prices			
alpha_u	33.6104	2.7477	29.1597	38.0759
beta_u_u_lag1	0.6934	0.0275	0.6473	0.7377
alpha_d	-0.5290	0.1728	-0.8224	-0.2611
beta_d_u_lag1	0.0051	0.0017	0.0025	0.0080
beta_d_d_lag1	0.6006	0.0404	0.5298	0.6629
alpha_v	9.1687	1.0230	7.5298	10.8346
beta_v_d_lag1	0.0338	0.4254	-0.6696	0.7496
beta_v_v_lag1	0.4678	0.0530	0.3817	0.5556

Source: Authors' own work

Note: u is for US-China trade tension; d is for global supply disruption; v means realized volatility of commodity prices. beta is used for slope coefficients, while alpha is for the intercepts. The immediate succeeding letter after the parameter is for the equation, while the next letter is for the variable in the equation under examination.

We assess the robustness of the MCMC estimation using standard convergence diagnostics for both the overall model and the posterior parameters. The overall diagnostics show no divergences, saturated tree depths, or low E-BFMI values, indicating stable and efficient sampling. For the parameters, all convergence measures fall well within acceptable thresholds. All the convergence diagnostics are satisfactory based on the relevant thresholds or rule-of-thumb values. We also provide information on the relevant thresholds or rules of thumb in the Appendix for evaluating the convergence performance. These results confirm that the model estimation is robust, well-behaved, and suitable for reliable inference.

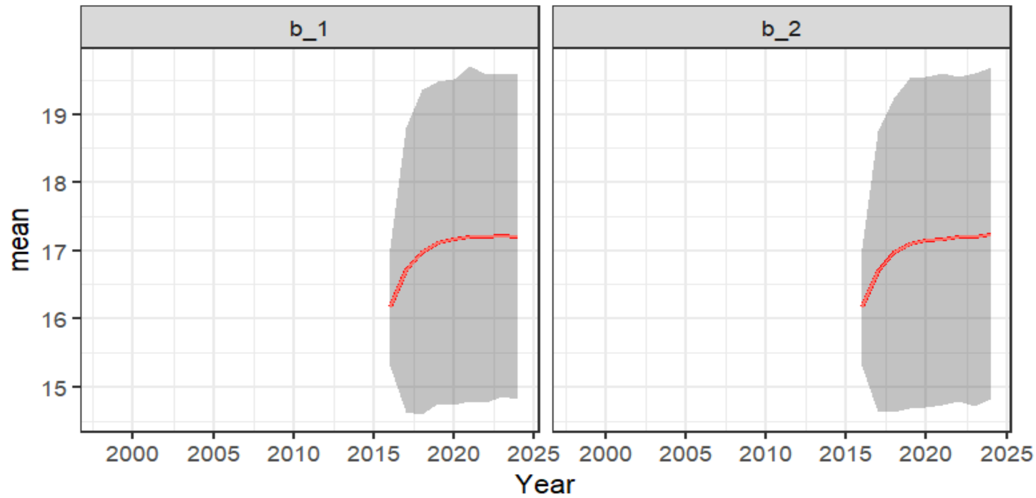
Figure 5: Dynamic effect of the response of the realized volatility of futures commodity prices to the US-China tension.



Source: Authors' own work

Note: b_1 refers to the scenario involving 40 per cent of the average US-China tension, while b_2 refers to the scenario involving 80 per cent of the average US-China tension.

Figure 6: Dynamic effect of the response of the realized volatility of spot commodity prices to the US-China tension



Source: Authors' own work

Note: b_1 refers to the scenario involving 40 per cent of the average US-China tension, while b_2 refers to the scenario involving 80 per cent of the average US-China tension.

4. Conclusion

We contribute to the literature on the uncertainty-commodity market nexus by providing new evidence on how US-China trade tensions (UCT) and global supply chain disruptions (GSCPI) jointly shape the realized volatility of agricultural commodity prices across futures and spot markets. Using the dynamic multivariate panel data model. We demonstrate that while geopolitical and supply-side shocks impact both markets, their responses differ in magnitude, timing, and persistence. The futures market exhibits higher and more persistent volatility, driven by speculative behaviour and forward-looking expectations about trade and policy risks, whereas the spot market reflects immediate responses to physical market conditions, such as supply bottlenecks and short-term demand shocks. Our results further reveal that US-China trade tensions are a dominant and persistent source of global uncertainty, amplifying commodity price fluctuations, particularly for export-oriented crops such as soybeans, corn, and wheat, which lie at the centre of bilateral trade. Moreover, the dynamic panel analysis confirms that geopolitical tension shocks are long-lasting, while global supply disruptions are more transitory, yet both significantly affect market volatility. Notably, the persistence of volatility in the futures market underscores the role of expectations and hedging activity, while the stronger short-term reaction in spot markets captures real-time price adjustments to disruptions in trade and logistics.

These findings carry important implications for agricultural trade policy and market risk management. Policymakers and market participants may consider strategic stockpiling, import diversification, and enhanced hedging strategies to mitigate the impact of geopolitical shocks on commodity markets. Furthermore, the results highlight the need for proactive monitoring of global trade tensions and supply chain vulnerabilities to improve market resilience.

We acknowledge some limitations in this study. The analysis focuses on a selected set of agricultural commodities and primarily captures price volatility, without directly accounting for production, consumption, or broader macroeconomic interactions. Future research could extend this framework to other commodity sectors, explore firm-level exposure to trade tensions, or incorporate alternative measures of supply chain fragility. Such extensions would provide a more comprehensive understanding of how geopolitical tension and other supply-side risks shape global commodity markets over time.

References

Adjemian, M. K., Smith, A., & He, W. (2021). Estimating the market effect of a trade war: The case of soybean tariffs. *Food Policy*, *105*, 102152.

Aftab, M., Bahmani-Oskooee, M., & Karamelikli, H. (2023). Do currency manipulations hurt the US bilateral trade balance?. *Eurasian Economic Review*, *13*(1), 127-144.

Algieri, B., & Leccadito, A. (2017). Assessing contagion risk from energy and non-energy commodity markets. *Energy Economics*, *62*, 312-322.

Bahmani-Oskooee, M., & Brooks, T. J. (1999). Bilateral J-curve between the US and its trading partners. *Weltwirtschaftliches Archiv*, (H. 1), 156-165.

Bahmani-Oskooee, M., & Wang, Y. (2007). United States-China trade at the commodity level and the Yuan-dollar exchange rate. *Contemporary Economic Policy*, *25*(3), 341-361.

Bahmani-Oskooee, M., & Hegerty, S. W. (2007). Exchange rate volatility and trade flows: a review article. *Journal of Economic Studies*, *34*(3), 211-255.

Bakas, D., & Triantafyllou, A. (2020). Commodity price volatility and the economic uncertainty of pandemics. *Economics Letters*, *193*, 109283.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The QuarterlyJjournal of Economics*, *131*(4), 1593-1636.

Bakst, D., & Beaumont-Smith, G. (2018). Agricultural Trade with China: What's at Stake for American Farmers, Ranchers, and Families. *US Department of Agriculture*.

Baumeister, C., & Kilian, L. (2014). Do oil price increases cause higher food prices?. *Economic Policy*, *29*(80), 691-747.

Boulanger, P., Dudu, H., Ferrari, E., & Philippidis, G. (2016). Russian roulette at the trade table: a specific factors CGE analysis of an agri-food import ban. *Journal of Agricultural Economics*, *67*(2), 272-291.

Bouri, E., Cepni, O., Gupta, R., & Liu, R. (2025). Supply chain constraints and the predictability of the conditional distribution of international stock market returns and volatility. *Economics Letters*, *247*, 112176.

Cheng, N. F. L., Hasanov, A. S., Poon, W. C., & Bouri, E. (2023). The US-China trade war and the volatility linkages between energy and agricultural commodities. *Energy Economics, 120,* 106605.

Chinn, M., & Plumley, B. (2020). What is the toll of trade wars on US agriculture? PBS. ORG.

Durante, A. (2022). How Tariffs and the Trade War Hurt US Agriculture.

Ferguson, S., & Ubilava, D. (2022). Global commodity market disruption and the fallout. *Australian Journal of Agricultural and Resource Economics, 66(4),* 737-752.

Gogas, P., & Serletis, A. (2009). Forecasting in inefficient commodity markets. *Journal of Economic Studies, 36(4),* 383-392.

Grant, J., Arita, S., Emlinger, C., Sydow, S., & Marchant, M. A. (2019). The 2018–2019 Trade Conflict. *Choices*, *34*(4), 1-8.

Gullstrand, J. (2020). What goes around comes around: The effects of sanctions on Swedish firms in the wake of the Ukraine crisis. *The World Economy, 43(9),* 2315-2342.

Helske, J., & Tikka, S. (2024). Estimating causal effects from panel data with dynamic multivariate panel models. *Advances in Life Course Research*, *60*, 100617. doi:https://doi.org/10.1016/j.alcr.2024.100617.

Jiang, H. (2020). China: evolving demand in the world's largest agricultural import market. US Department of Agriculture (USDA), Foreign Agricultural Service.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the US stock market. *International Economic Review, 50(4),* 1267-1287.

Rogers, J. H., Sun, B., & Sun, T. (2024). US-China tension. Available at SSRN 4815838. http://dx.doi.org/10.2139/ssrn.4815838

Salisu, A. A., & Isah, K. O. (2017). Revisiting the oil price and stock market nexus: A nonlinear Panel ARDL approach. *Economic Modelling*, *66*, 258-271.

Tanveer, Z., Kalim, R., & Arshad, N. (2025). Role of climate change in altering global agricultural trade dynamics: an empirical analysis. *Journal of Economic Studies*. https://doi.org/10.1108/JES-12-2024-0829

Ullah, A., Bouri, E., Bukhari, A. A. A., & Bukhari, W. A. A. (2025). Global supply chain pressure and Chinese business and consumer confidence. *Research in International Business and Finance*, 102966.

Vos, R., Glauber, J., Hernández, M., & Laborde, D. (2022). COVID-19 and food inflation scares. In: Swinnen, J. & McDermott, J. (Eds.) COVID-19 and global food security: two years later. Washington, DC: International Food Policy Research Institute (IFPRI).

Xu, X. (2025). The Impact of China's Retaliatory Tariffs on US Agricultural Exports During the 2018/2019 US–China Trade War. *Agricultural Economics*. **https://doi.org/10.1111/agec.70046**

Xu, Y., Elbakidze, L., Gassman, P. W., Yen, H., Ma, Y., Hubbart, J. A., & Arnold, J. G. (2025). US–China agricultural trade and environmental outcomes: The case of nutrient runoff to the Gulf of Mexico. *Applied Economic Perspectives and Policy*. **https://doi.org/10.1002/aepp.13501**

Wang, R. (2024). Global supply chain disruptions, commodity price shocks and inflation in Japan. *International Journal of Empirical Economics*, *3*(02), 2450004.

World Bank Group. (2019). Commodity markets outlook, April 2019. Special focus, food price shocks: channels and implications. Technical report, World Bank, Washington, DC.

Appendix

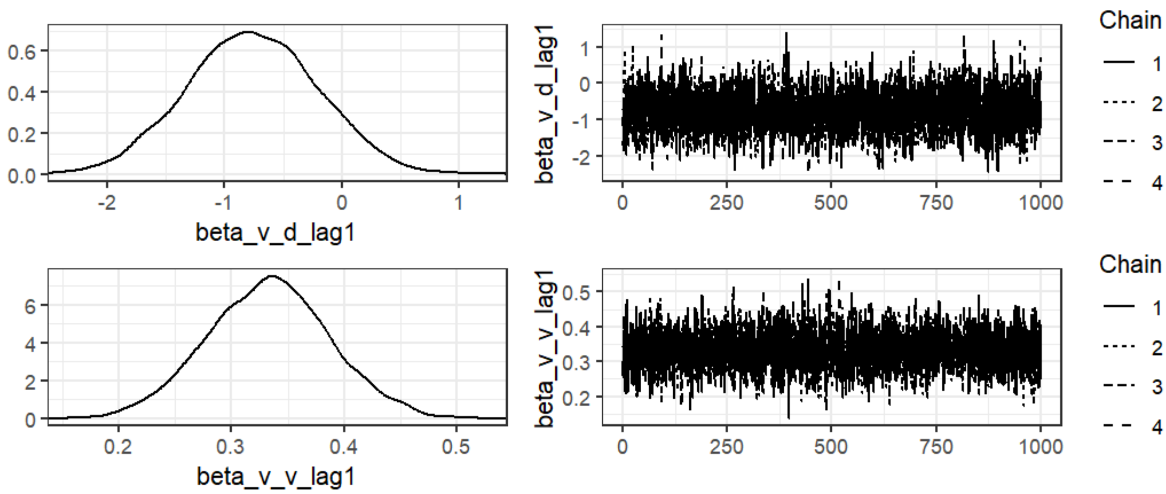
Table A1: Model Diagnostics

Overall Model Convergence Diagnostics	
Futures prices	No divergences, saturated max treedepths or low E-BFMIs
Spot prices	No divergences, saturated max treedepths or low E-BFMIs.
Parameter Convergence Diagnostics	
Smallest bulk-ESS values (rule of thumb: ≥ 400 is good)	
Futures prices	**Spot prices**
sigma_d 2286 alpha_d 2325 beta_d_u_lag1 2339	alpha_d 2337 sigma_d 2381 beta_d_u_lag1 2386
Smallest tail-ESS values (rule of thumb: ≥ 100 is good)	
alpha_d 2459 alpha_u 2478 beta_d_d_lag1 2481	alpha_u 2389 alpha_d 2419 beta_u_u_lag1 2437
Largest Rhat values (values ≤ 1.01 indicate convergence)	
beta_u_u_lag1 1 sigma_v 1 beta_d_u_lag1 1	alpha_u 1 beta_d_u_lag1 1 alpha_d 1

Source: Authors' own work

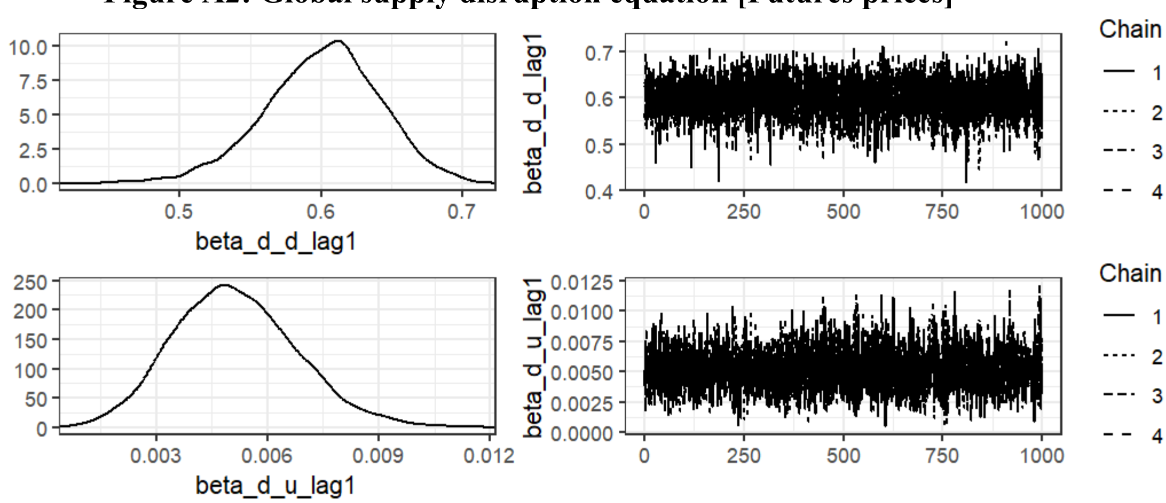
Note: Only three parameters are reported in the convergence diagnostics, and these are the ones with the least performance in terms of convergence. Other parameters that are not reported have better performance.

Figure A1: Realized volatility equation [Futures prices]



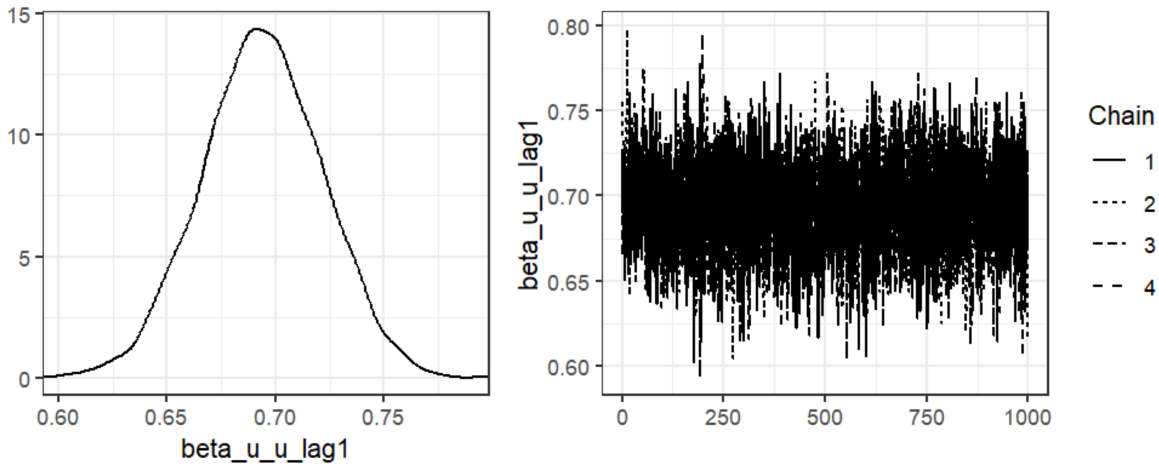
Source: Authors' own work

Figure A2: Global supply disruption equation [Futures prices]



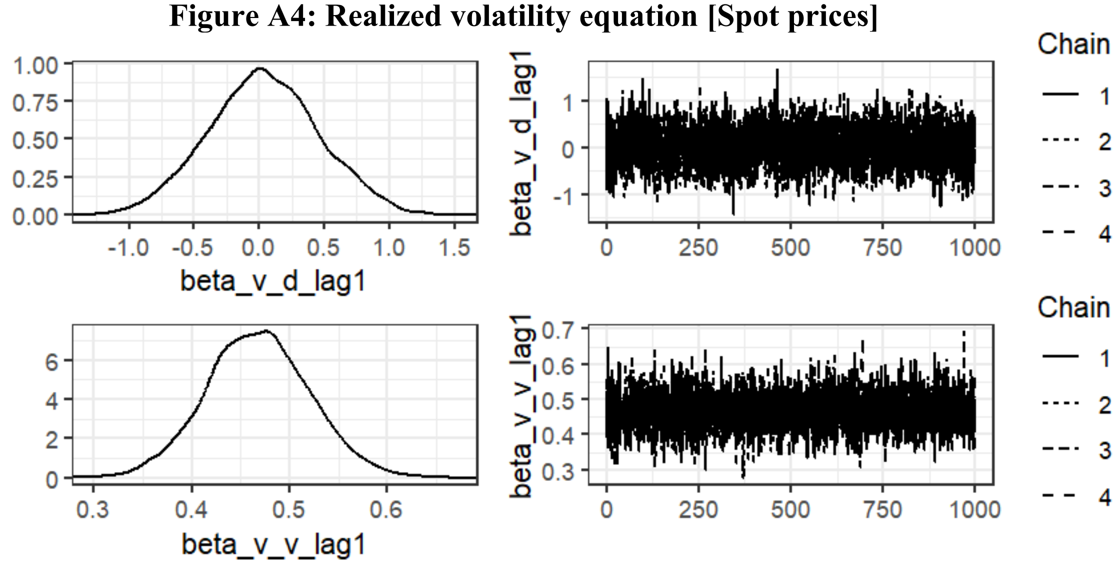
Source: Authors' own work

Figure A3: US-China tension equation [Futures prices]



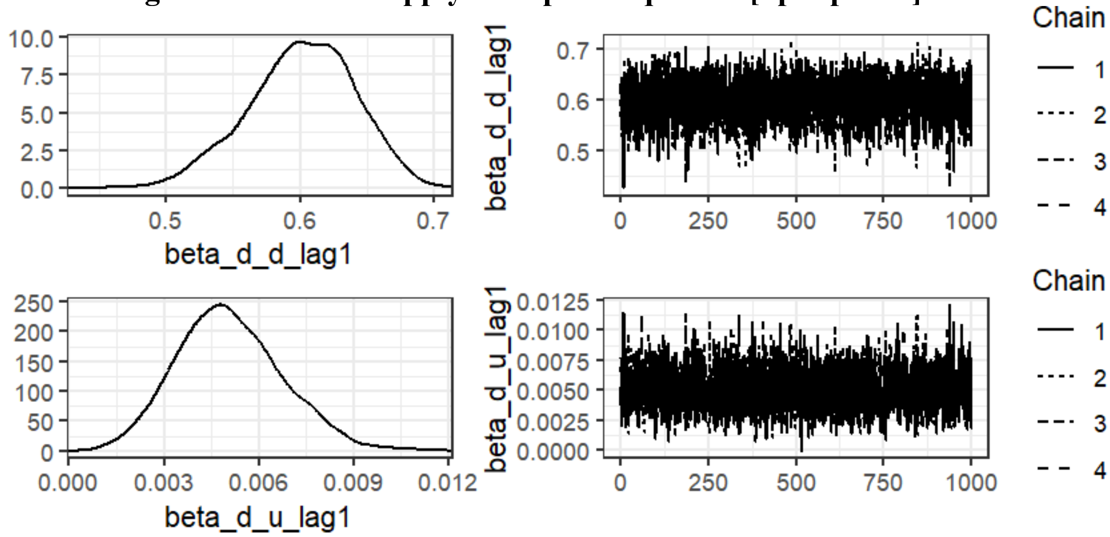
Source: Authors' own work

Figure A4: Realized volatility equation [Spot prices]



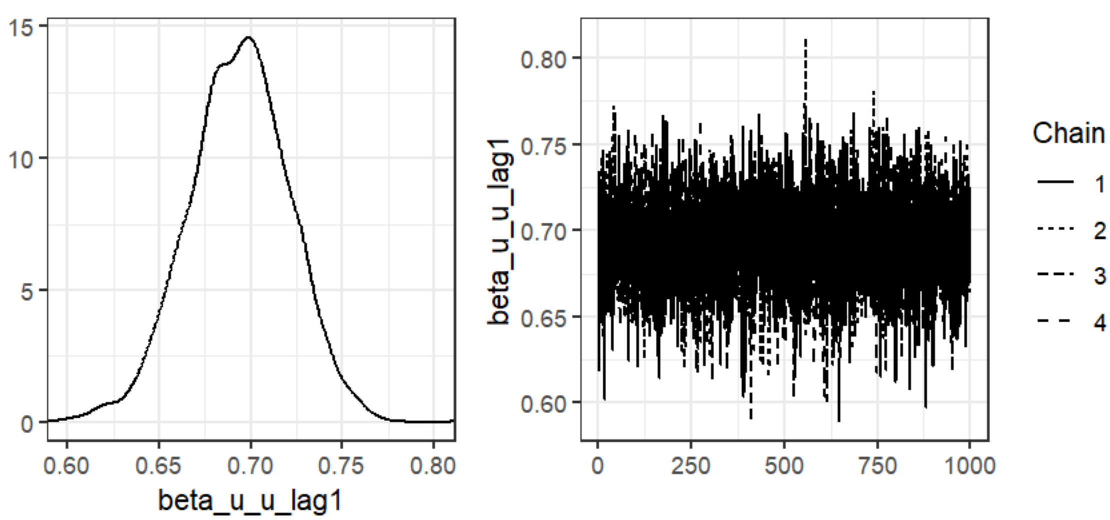
Source: Authors' own work

Figure A5: Global supply disruption equation [Spot prices]



Source: Authors' own work

Figure A6: US-China tension equation [Spot prices]



Source: Authors' own work