PRICE AND VOLATILITY LINKAGES BETWEEN NATURAL GAS, FERTILIZER (UREA), CORN, AND WHEAT MARKETS USING A VAR-DCC-GARCH MODEL: UNCERTAINTIES DURING THE UKRAINE WAR

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ABSTRACT

Motivated by extreme commodity price fluctuations during the 2022 Ukraine war, this study examines price and volatility linkages among natural gas, fertilizer (urea), corn, and wheat markets from 2017 to 2025. It employs a VAR-DCC-GARCH model to capture dynamic spillovers and time-varying correlations, identifying shifting inter-market linkages under war-induced uncertainty. Results indicate that volatility linkages strengthened significantly after the war's onset in February 2022: cross-market volatility correlations increased, especially between corn and fertilizer prices, while wheat's volatility connections remained comparatively muted. Natural gas and fertilizer markets also became more tightly coupled post-2021, reflecting heightened integration amid geopolitical risk. War-driven uncertainty markedly amplified volatility spillovers across the energy–fertilizer–grain complex. These findings highlight the war's amplifying effect on commodity market linkages and carry critical implications for global food security and commodity market stability, underscoring the need for risk management strategies to safeguard supply chains under future crises.

BIOGRAPHICAL SKETCH

Bohua Duan is a candidate for the Master of Science in Applied Economics and Management at Cornell University's Charles H. Dyson School of Applied Economics and Management, graduating in May 2025.

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To my parents, whose unwavering love and encouragement made every step possible;

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Introduction

The Russia–Ukraine war, which erupted in February 2022, has led to unprecedented fluctuations in global fertilizer and energy prices. Natural gas, a critical feedstock for nitrogen fertilizer production, experienced extreme price spikes and volatility after the invasion. The war introduced immediate uncertainty around exports of key agricultural inputs: Russia accounted for a large share of internationally traded fertilizers, about 14% of urea, 11% of phosphates, and over 40% of potash jointly accounted with Belarus (Hebebrand & Glauber, 2024). Fears of supply shortfalls and post-invasion turmoil in natural gas markets, with gas prices skyrocketing, further contributed to turbulence in fertilizer prices (Rodziewicz & Cook, 2022).

At the same time, the war severely disrupted grain markets. Ukraine and Russia are major exporters of corn and wheat, and the conflict damaged production and blocked trade routes, causing global supply contractions. In less than two weeks after the invasion, futures prices for commodities like wheat soared (wheat spiked over 30% within March 2022 alone) (Kee & Zereyesus, 2023), and markets experienced extreme volatility amid the uncertainty (Hebebrand & Glauber, 2023). These developments have raised questions about how shocks propagate across energy, input, and food markets. In particular, understanding price and volatility transmission between natural gas, fertilizer, corn, and wheat has become crucial during the Ukraine war period, given the strong interdependencies among these commodities (Piesse & Thirtle, 2009).

Natural gas, fertilizer, corn, and wheat are deeply interconnected through both production and market linkages. Natural gas is the primary input for producing ammonia and urea – key nitrogen fertilizers, meaning gas prices heavily influence fertilizer supply costs (Huang, 2007). When gas prices rise sharply, as occurred in 2021–2022, fertilizer producers face higher costs, sometimes curtailing output, as evidenced by the U.S. annual aggregate supply of ammonia declining 17% from 2000–2006 when gas prices climbed (Huang, 2007). This translates into fertilizer price increases, which directly raise farm input costs. Corn is one of the most fertilizer-intensive crops; it requires substantial nitrogen application, so corn production costs and yields are especially sensitive to fertilizer price swings (Headey & Fan, 2008). Headey and Fan (2008) estimate that fertilizer expenses comprise over one-third of operating costs and about 15–20% of total costs in U.S. corn farming. Therefore, a surge in fertilizer prices can significantly erode profit margins and reduce optimal fertilizer use, curbing crop yields. If farmers cut fertilizer applications to save costs, corn output may fall, driving corn prices higher and potentially amplifying volatility.

Wheat, by contrast, is moderately less fertilizer-dependent than corn (Zhang et al., 2008). Depending on potential yield, the average nitrogen input for corn is about 100-250 pounds per acre, and it is 40-110 pounds per acre for wheat (Clark, 2023; Lentz et al., 2018). Farmers can often grow wheat with lower nitrogen inputs, making wheat production costs somewhat less sensitive to fertilizer price spikes. This difference implies that shocks in fertilizer markets might transmit more strongly to corn prices than to wheat prices. During the 2022 fertilizer price shock, many farmers and analysts noted incentives to shift some acreage from corn toward crops like wheat or soybeans, which require less nitrogen, as a cost-minimizing response to expensive fertilizer (Rodziewic & Cook, 2022).

The economic importance of these linkages is enormous: fertilizer price volatility affects food production and security worldwide. As Piesse and Thirtle (2009) observed after the 2007–08 price spike, the impact of fertilizer prices has not attracted the attention it warrants, even though such input cost surges likely contributed significantly to food price inflation. The Ukraine war's simultaneous impact on energy, fertilizer, and grain supplies can help us to examine how volatilities in one market can propagate across others, affecting global food prices, inflation, and even social stability.

Literature Review

A growing body of research examines price and volatility transmission among energy and agricultural commodity markets. Prior studies have frequently focused on linkages between crude oil (or biofuels) and food commodities. For instance, volatility spillovers between oil and staple crops have been documented in multiple contexts (Du et al., 2011). Du et al. (2011) found evidence of volatility spillover from crude oil to agricultural futures during the 2008 boom, and Gardebroek & Hernandez (2013) showed that energy prices (oil/ethanol) can stimulate grain price volatility. These studies typically employ multivariate GARCH models to assess how shocks in one market affect another. However, until recently, the role of fertilizers in commodity price dynamics had been largely overlooked. Fertilizer is a critical input to agriculture, yet few academic works had quantified how fertilizer price fluctuations are transmitted to crop markets (Etienne et al., 2016). The fertilizer market has unique characteristics, being influenced by both energy input costs and agricultural demand, which make its interactions with crop prices an important but complex topic.

A seminal contribution to filling this gap is the study by Etienne et al. (2016), which investigated price and volatility transmission between natural gas, fertilizer (ammonia), and U.S. corn markets over 1994–2014. Using a vector error-correction model (VECM) for prices and a BEKK multivariate GARCH model for volatility, they found strong interconnectedness between fertilizer and corn prices, but only a mild linkage between those markets and natural gas. In the short run, corn and ammonia prices moved positively together, and both responded to deviations from a long-run equilibrium relationship. Importantly, Etienne et al. (2016) documented bidirectional volatility spillovers between fertilizer and corn: increases in ammonia price volatility tended to increase volatility in corn, and vice versa. This implies that uncertainty in fertilizer markets can directly translate into uncertainty in crop markets. By contrast, natural gas showed only weak spillover effects – its volatility had little direct impact on corn or fertilizer volatility during that period. In fact, in a sub-period analysis (2006–2014, an era of abundant shale gas and relatively low U.S. gas prices), natural gas prices exhibited virtually no linkage with fertilizer or corn prices. Yet the fertilizer–corn connection remained robust, highlighting that fertilizer and agricultural prices can be tightly coupled even when energy prices are stable.

In response to recent volatility, Yang et al. (2022) revisited these inter-market dynamics with updated data. Their paper "Price and Volatility Transmissions among

Natural Gas, Fertilizer, and Corn Markets: A Revisit" extends the analysis to 2011–2021, a period that includes renewed turbulence in fertilizer and energy prices. Using a similar VECM-BEKK GARCH framework, Yang et al. confirm some of the earlier findings while revealing changes in the most recent years. Consistent with Etienne et al. (2016), they find that natural gas returns are significantly influenced by lagged corn and fertilizer market movements in the short-term. This suggests a degree of integration where corn market information can predict gas price movements and fertilizer market shocks also feed back into gas. However, Yang et al. report that the contemporaneous relationships among fertilizer, corn, and gas prices became insignificant during mid-2021, a period of extraordinary volatility, implying temporary decoupling or market-specific shocks. In terms of volatility, they found an interesting asymmetry: lagged corn price volatility affected natural gas volatility but not vice versa. This one-way spillover suggests that sudden swings in corn markets could transmit to energy markets, whereas gas volatility did not similarly feed into corn during that sample. Yang et al. (2022)'s update hinted that the established transmission mechanisms might be shifting under new market conditions, and they called for further examination, especially given the "recent enormous price volatility" in fertilizer and energy markets.

Notably, both of the above studies were completed just before the Ukraine war and therefore do not incorporate the effects of this major shock. It is unclear whether the previously mild gas–agriculture link might strengthen under such stress, or whether the fertilizer–corn relationship would intensify or change when fertilizer prices jump to unprecedented levels.

Research Gap and Hypotheses

Building on the literature, the present thesis addresses three key gaps. *First,* we include the Russia–Ukraine war period in the analysis. This allows us to directly observe how the war's disruptions altered price transmission patterns, something prior studies could only speculate on. *Second,* we expand the commodity set by incorporating wheat alongside corn, fertilizer, and natural gas. Wheat is introduced to provide a contrasting case: because wheat is generally less fertilizer-intensive than corn, comparing the two grains can yield insights into how fertilizer dependence affects volatility transmission. Including wheat also acknowledges its prominence in the Ukraine war context (Ukraine and Russia are among the top wheat exporters, so wheat markets were heavily impacted by the war). *Third,* we adopt a Dynamic Conditional Correlation multivariate GARCH (DCC-MGARCH) model instead of the BEKK-MGARCH specification used in earlier works. The shift in econometric approach is motivated by several advantages of DCC-MGARCH in this setting.

The DCC model is more flexible when handling a higher-dimensional system, four markets instead of three (Gabauer, 2020). As we add wheat, the number of parameters in a full BEKK model would increase substantially, risking over-parameterization. DCC-MGARCH, by separating the estimation of variances and time-varying correlations, offers improved computational efficiency and can better accommodate dynamic correlations among multiple assets. Moreover, DCC explicitly models the evolution of correlation over time, which is valuable for capturing how inter-market linkages might strengthen or weaken during crises like the war. In sum, this study differentiates itself by examining a more comprehensive market system through a period of extreme geopolitical uncertainty, using a methodology well-suited to detect time-varying relationships (Singhal & Ghosh, 2016).

To clarify research objectives, we outline the main hypotheses and expectations:

1. *Existence of Volatility Transmission:* We hypothesize that there are significant volatility transmission effects among natural gas, fertilizer, corn, and wheat markets. In other words, price shocks in one market will increase the volatility in others due to their economic linkages. This baseline hypothesis is supported by earlier findings of volatility spillovers between fertilizer and corn, and by general commodity market behavior where interconnected markets rarely move in isolation. We expect to confirm that volatility in fertilizer prices propagates to crop markets (at least for corn) and that grain market volatility can feed back into related markets.

2. *Higher Volatility in the Post-War Period:* We hypothesize that volatility levels and spillovers are greater in the post-invasion period compared to the pre-war period. The rationale is that the Ukraine war introduced extraordinary supply shocks and uncertainty across energy and food markets, likely elevating volatility. Empirical observations support this: commodity prices not only rose to record highs in early 2022 but also fluctuated wildly. We anticipate that our analysis will show a discernible jump in volatility measures for all four markets in the post-war period,

and possibly stronger cross-market volatility correlations consistent with the heightened uncertainty.

3. *Differential Transmission to Corn vs. Wheat:* We hypothesize that wheat experiences a lower volatility transmission from fertilizer price shocks than corn does, owing to wheat's lower dependence on nitrogen fertilizer. Corn's yield and cost structure make it highly sensitive to fertilizer availability and price. Wheat, while still responsive to fertilizer, typically uses smaller fertilizer doses and can better tolerate reduced fertilizer without catastrophic yield loss. As a result, a spike in fertilizer prices should have a more pronounced effect on corn markets than on wheat. We expect the DCC-MGARCH results to reflect this: the correlation between fertilizer and corn volatility will be stronger than that between fertilizer and wheat volatility. Likewise, corn prices may show a greater increase than wheat in response to the war's fertilizer shock. This hypothesis aligns with anecdotal evidence during 2022 that some farmers shifted acreage toward wheat or other crops as fertilizer prices climbed, suggesting wheat is somewhat insulated relative to corn.

In addition to these hypotheses, this study generally seeks to verify whether previously documented relationships held up during the turmoil or if the war fundamentally altered the linkages.

Economic Framework

Understanding the price and volatility transmission mechanisms among natural gas, fertilizer, corn, and wheat requires a solid economic foundation. In this section, we outline the fundamental economic relationships linking these markets, drawing on production economics and market theory. We first consider how fertilizer fits into agricultural production through the lens of a production function, then examine the derived demand for fertilizer and farmers' cost-minimization behavior. Next, we discuss substitution effects between crops (corn and wheat) when input costs change. Finally, we connect these microeconomic principles to broader price and volatility transmission mechanisms in commodity markets. This framework builds on prior discussions such as the "How the fertilizer market relates to commodity prices" analysis by Etienne et al. (2016) and related theoretical expositions, as well as the economic foundations summarized by Debertin (2012).

Production Function: Agricultural output is commonly modeled by a production function that relates inputs (such as land, labor, capital, and fertilizer) to the quantity of crop produced. A convenient form is the Cobb-Douglas production function, which for a given crop (say corn or wheat) can be written conceptually as:

$$Q = A * L^{\alpha} * F^{\beta} * K^{\gamma}$$

where Q is crop output, L is labor, F is fertilizer, K is capital, and A is total factor productivity (Debertin, 2012). The exponents α, β, and γ represent the output elasticities of the inputs.

Fertilizer is a critical input influencing crop yields. A high value of β means fertilizer has a strong impact on output. From the Cobb-Douglas perspective, changes in fertilizer input (F) are caused by price or availability shifts will directly affect output (Q). If fertilizer becomes very expensive or scarce, farmers may use less of it, effectively reducing F.

<u>Derived Demands:</u> Farmers' demand for fertilizer is derived from the expected profitability of crop production. A farmer aiming to maximize profit will decide how much fertilizer to use based on the marginal value product of fertilizer versus its cost. The farmer's cost function can be written as:

$$C = p_L L + p_F F + p_K K$$

where p_L, p_F, p_K are the prices of labor, fertilizer, and capital, respectively.

The farmer faces a production function constraint $Q = f(L, F, K)$. Using the method of Lagrange multipliers, one can derive the input demand function for fertilizer by setting the marginal rate of technical substitution equal to the input price ratio. The first-order optimality condition for fertilizer is:

$$\frac{\partial f / \partial F}{\partial f / \partial L} = \frac{P_F}{P_L}$$

Simplified, the marginal value product of fertilizer (marginal gain in output times crop price) should equal its marginal cost. If the crop price is P_Q and the marginal physical product of fertilizer is MP_F, then profit maximization implies $MP_F * P_Q = P_F$.

Farmers will apply fertilizer up to the point where an additional unit of fertilizer yields a crop output worth just as much as that fertilizer costs.

From this condition, we can deduce how a change in the price of fertilizer P_F influences the optimal fertilizer use F^*. If P_F increases, then to restore equality, either MP_F must increase or the farmer reduces F until the marginal productivity of fertilizer rises to re-equate $MP_F * P_Q$ with the now-higher P_F. In practice, because of diminishing returns, reducing fertilizer use does increase the marginal productivity of the remaining fertilizer. Thus, higher fertilizer prices lead to a contraction in the quantity of fertilizer demanded.

The Cobb-Douglas relationship accentuates that any significant change in one input like fertilizer has tangible effects on agricultural output levels and can thereby influence equilibrium prices in crop markets.

<u>Substitution Effects:</u> When input costs change dramatically, farmers not only adjust the usage of that input for a given crop, but may also reconsider their crop mix and acreage allocation. This is especially relevant for crop substitution between corn and wheat in response to fertilizer market conditions. If fertilizer becomes very expensive, crops that require heavy fertilization (like corn) become relatively less attractive to plant compared to crops that require less (like wheat or soybeans). This is a form of substitution effect driven by cost considerations: farmers shift production towards the crop with a cost advantage.

The concept of cross-price elasticity between commodities can be invoked here. A high cross-price elasticity of supply between corn and wheat with respect to fertilizer price means that as fertilizer price rises, the supply of corn falls and the supply of wheat rises.

What does this mean for price transmission? If many farmers substitute away from corn, the reduced corn planting will tighten corn supply and thus push corn prices higher than they otherwise would be. Wheat supply might increase, which could moderate wheat's price increase relative to corn.

Another substitution to consider is between inputs within the crop production process. Farmers may try to substitute other inputs for fertilizer if possible. The marginal rate of technical substitution (MRTS) between fertilizer and other inputs like labor or land indicates how easily one input can replace another. If fertilizer becomes too expensive, a farmer might invest in more soil testing and targeted application to use fertilizer more efficiently. They might also rely on the residual soil fertility or plant lower-yielding varieties that need less fertilizer.

Price and Volatility Transmission Mechanisms: With the above microeconomic foundations, we can interpret how price and volatility transmission occurs among the natural gas, fertilizer, corn, and wheat markets. Price transmission refers to how a shock or price change in one market leads to a response in another market. Volatility transmission (or spillover) refers to how uncertainty or variability in one market affects the variability in another. The production and substitution framework provides channels for both types of transmission.

If natural gas prices surge due to a geopolitical event, fertilizer production costs rise, leading to higher fertilizer prices. Farmers react by reducing fertilizer usage and potentially planting less corn. This reduction in expected corn output puts upward pressure on corn prices. If the shock persists, corn and fertilizer may find a new equilibrium at higher prices. The extent of price transmission depends on elasticities: for instance, if fertilizer supply is inelastic in the short run, then increased fertilizer demand from a corn price boom will mainly result in higher fertilizer prices, rather than much more quantity, thus transmitting the price signal strongly.

Beyond average price levels, shocks often increase uncertainty and cause volatility. Volatility transmission can occur due to both fundamental linkages and market sentiment. Fundamentally, if one market becomes more volatile, the planning and expectations for related markets are also destabilized. Fertilizer producers facing volatile gas prices might delay decisions or change pricing frequently, translating into more volatile fertilizer price quotes. Farmers dealing with volatile fertilizer costs may change planting decisions last minute or become uncertain about yield projections, which can make crop prices more erratic as well.

Data

We analyze four key commodity price series, all obtained from Yahoo Finance, to investigate linkages in prices and volatility. The data include Corn Futures (ticker ZC=F), which are traded on the Chicago Board of Trade (CBOT) and represent corn prices, and U.S. Wheat Futures (ticker ZWK5), which represent CBOT wheat futures prices. We also use Henry Hub Natural Gas Futures, the benchmark for U.S. natural gas prices (NYMEX Henry Hub), and Urea Granular FOB Middle East Futures, used as a proxy for fertilizer prices. Urea is a major nitrogen fertilizer whose production cost is closely tied to natural gas. Using a fertilizer-based futures contract provides a more direct measure of fertilizer market conditions than equity proxies. Prior literature has used alternative proxies – for example, Liao et al. (2016) employ ammonia prices as a fertilizer variable, while Yang et al. (2023) use a fertilizer/ potash ETF index – but Urea futures capture price movements in a widely traded fertilizer commodity that responds rapidly to gas-driven costs.

All series are daily closing prices spanning June 28, 2017 through January 24, 2025. This period provides a long history of commodity market conditions, encompassing various global events and business cycles. To facilitate analysis of the impact of the Ukraine war, we split the sample into three segments: the full period, a "pre-war" period, and a "post-war" period. We designate December 1, 2021 as the cutoff between pre-war and post-war sub-samples. This date is chosen because by early December 2021, U.S. intelligence warnings had emerged about a likely Russian invasion of Ukraine in the near future. In particular, Western officials warned in Dec 2021 that Russia was planning a major military offensive against Ukraine as soon as early 2022 (Lomas, 2022). These warnings signaled a significant geopolitical risk on the horizon. The war formally began in late February 2022, but commodity markets likely began pricing in risk once credible warnings surfaced; hence December 2021 serves as a reasonable boundary separating the "pre-war" vs. "post-war" periods.

Figure 1 displays the price evolution of corn, wheat, natural gas, and urea over the entire sample, with a vertical red line marking December 2021. Overall, commodity price trends were volatile and co-moved during certain episodes. Notably, all four series experienced a sharp increase around late 2021 into 2022 (to the right of the red line), coinciding with the escalation of Russia–Ukraine tensions and the outbreak of war. In the earlier years before mid-2020, all four series experienced moderate fluctuations but started an upward trend after 2021. Natural gas prices hit multi-year lows in 2020 amid the COVID-19 pandemic. Urea price remained moderate through mid-2020, then started rising in 2021. For corn, natural gas, and urea, together with the spike after the outbreak of the war, the series showed two spikes, indicating excessive market turbulence during the period.

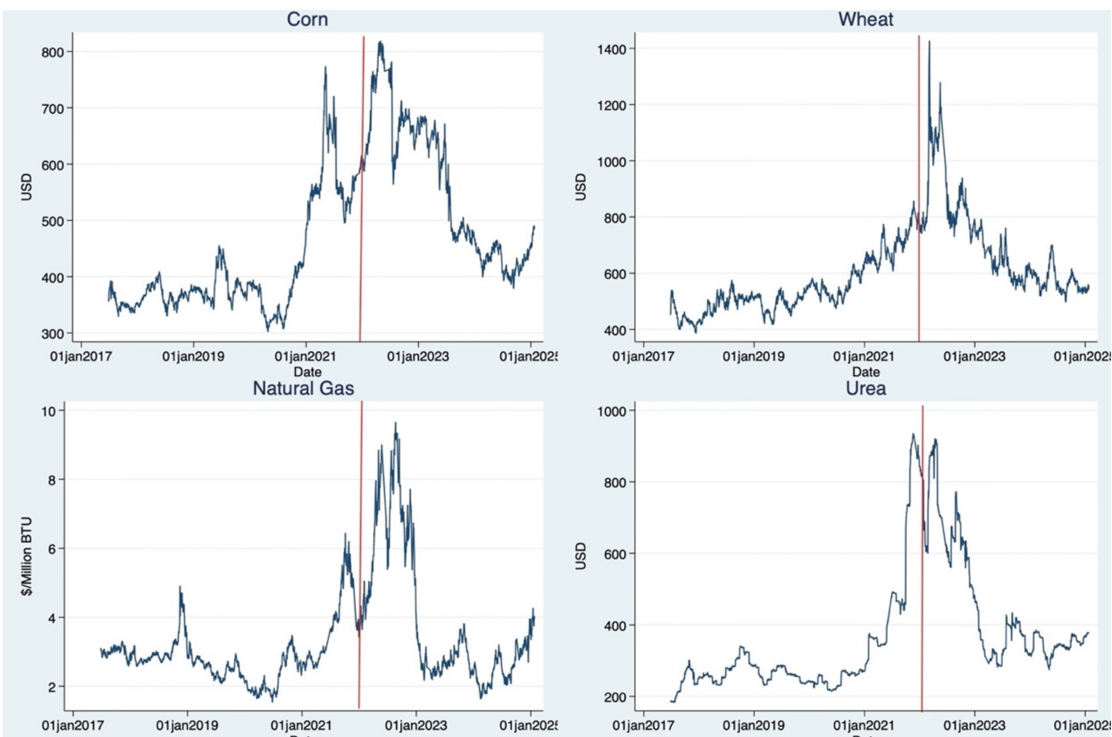

Figure 1: Historical Prices of Commodities. Source: Yahoo Finance.

Entering 2021, we see all commodities trending upward: recovering demand and supply bottlenecks drove broad commodity inflation. When the red line is crossed (Dec 2021 onward), the plots show an acceleration: natural gas prices skyrocketed in early 2022, and grain prices (corn and wheat) also jumped to multi-year highs. For example, wheat spiked dramatically in March 2022 as the war jeopardized Black Sea grain exports, while corn climbed to its highest levels since 2012 (Tertre et al., 2023). These visual trends already suggest that the war was a common shock that pushed these markets up together. After mid-2022, prices moderated somewhat – natural gas fell back sharply by 2023 (helped by a mild winter and adjustments in gas supply), and wheat retreated as partial export routes reopened. Corn and fertilizer(urea) prices also came off their war-driven peaks but remained above pre-2021 averages. Overall, Figure 1 illustrates that the post-Dec 2021 period was characterized by heightened price levels and volatility across all four markets, in contrast to more divergent or idiosyncratic movements pre-2021.

Table 1 provides summary metrics for the logarithmic returns of the commodities. Logarithmic returns of commodities are calculated as $log\ (P_t/P_{t-1}) * 100$. Key statistics include the mean and standard deviation, as well as measures of distribution shape (skewness and kurtosis) and tests for autocorrelation. All log return series display positive skewness, especially natural gas and urea, which indicates occasional price spikes. Kurtosis is significantly above 3 for all series, indicating heavy tails, so large log return moves are more common than a normal distribution would predict. These high skewness and kurtosis values suggest the distributions of commodity prices are far from normal, which is also evidenced by the high Jarque-Bera test statistics, with extreme events occurring more frequently.

Table 1: Descriptive Statistics

	Corn	**Wheat**	**Natural Gas**	**Urea**
No. of Obs.	1,842	1,842	1,842	1,842
Mean	0.0155827	0.0096674	0.0119326	0.0379716
SD	1.722264	2.121654	3.74649	2.186168
Min	-19.09974	-15.76556	-30.7297	-19.04339
Max	7.657359	19.70139	21.02685	31.46594
Skewness	-1.615326	0.3252833	-0.2576194	3.069645
Kurtosis	21.54648	10.09189	9.664968	54.1168
Jarque-Bera	876.74***	300.37***	278.12***	1497.20***
Ljung-Box	53.6181*	59.3029**	53.8922*	80.6780***
ADF	-18.261***	-17.776***	-24.672***	-13.423***

Note: Log returns are calculated as $log\ (P_t/P_{t-1}) * 100$. The t-statistics are denoted as ***p < 0.01, **p < 0.05, *p < 0.1.

To formally examine the time-series properties, we conducted unit root tests (Augmented Dickey-Fuller, ADF) on each price series. The ADF tests indicated that the four commodities price series are non-stationary in levels. Working with non-stationary prices in regression models can lead to spurious results, so we transform the data to achieve stationarity. Specifically, we take logarithmic returns – i.e. first differences of the natural log of prices. Using daily log returns stabilizes the mean and variance. The ADF tests on the log return series overwhelmingly reject the unit root null, confirming that returns are stationary. This is a common practice in financial econometrics: by analyzing returns, we focus on short-term fluctuations around the changing trend, which is essential for modeling volatility and correlations properly. We also report the Ljung–Box Q-test statistics for autocorrelation in returns over multiple lags. Ljung–Box test rejects the null of no autocorrelation. This indicates a substantial serial correlation in volatility: large returns tend to be followed by large returns and small by small.

Additionally, ARCH tests on each return series detect significant ARCH effects in the three time periods, confirming time-varying heteroskedasticity. These characteristics motivate the use of a VAR-DCC-GARCH framework to capture both mean relationships and dynamic volatility linkages in these markets.

Econometric Methods

To analyze the linkage between these markets, we employ a two-step econometric approach: a Vector Autoregression (VAR) model for the conditional mean, combined with a Dynamic Conditional Correlation Multivariate GARCH (DCC-GARCH) model for the conditional variance-covariance structure. This VAR-DCC-GARCH methodology allows us to investigate both price spillovers (how past price changes in one market affect others) and volatility spillovers (how uncertainty or volatility is transmitted across markets) in a unified framework.

We begin by modeling the mean equations with a VAR model. In a VAR, each variable's current value is regressed on past values of all variables in the system. Let

$y_t = (r_{corn,t}, r_{wheat,t}, r_{gas,t}, r_{fertilizer,t})'$ be the vector of log returns at time t for corn, wheat, natural gas, and fertilizer, respectively. A VAR(p) model can be written as:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \varepsilon_t,$$

where Φ_0 is a vector of intercepts, Φ_i are 4×4 coefficient matrices for lag i, and ε_t is the vector of residuals at time t. We determine the lag order p based on Akaike information criterion (AIC). The VAR captures relationships in mean: for instance, it can tell us if past natural gas returns have a statistically significant impact on corn returns, etc. The inclusion of multiple lags allows flexibility to account for delayed effects as it might take a few days for a shock in fertilizer markets to reflect in corn prices. By estimating the VAR, we can formally test for price spillovers.

We proceed to model the volatility and correlation of the VAR residuals using a DCC-GARCH model. The DCC-GARCH, introduced by Engle (2002), is a two-stage multivariate volatility model that is well-suited for capturing time-varying correlations between asset returns. In the first stage, each series is fitted with a univariate GARCH model to capture its own volatility dynamics. In the second stage, the standardized residuals are used to estimate a time-varying correlation matrix. This approach is much more parsimonious than an unrestricted multivariate GARCH, like BEKK and thus feasible even for a four-dimensional system. Specifically, for each series i (corn, wheat, gas, fertilizer) we assume a GARCH(1,1) process for its variance:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1},$$

where $\varepsilon_{i,t-1}$ is the residual from the VAR for series i at time $t-1$ and $h_{i,t-1}$ is the conditional variance. The α_i (ARCH term) captures the impact of a new shock on volatility, while β_i (GARCH term) captures the persistence of volatility. We expect $\alpha_i > 0$ and $\beta_i > 0$ and typically $\alpha_i + \beta_i < 1$ for stability.

The DCC model (Engle, 2002) extends the constant conditional correlation (CCC) model by allowing the correlation matrix to vary over time. Let H_t represent the time-varying covariance matrix of the residuals, which can be decomposed as:

$$H_t = D_t R_t D_t,$$

where D_t is a diagonal matrix of conditional standard deviations from the univariate GARCH models: $D_t = diag(\sqrt{h_{1,t}}, \sqrt{h_{2,t}}, \sqrt{h_{3,t}}, \sqrt{h_{4,t}})$; R_t is the time-varying correlation matrix.

The core of the DCC model is modeling the time-varying correlation matrix Q_t. Let Q_t be the time-varying covariance matrix of the standardized residuals$= D_t^{-1}\varepsilon_t$. In the DCC(1,1) model, the correlation matrix is updated as follows:

$$Q_t = (1 - \lambda_1 - \lambda_2)\overline{Q} + \lambda_1(z_{t-1}z'_{t-1}) + \lambda_2 Q_{t-1},$$

where $\overline{Q}$ is the unconditional covariance matrix of the standardized residuals; λ_1 and λ_2 non-negative scalar parameters that measure the sensitivity of correlations to new shocks and persistence of dynamic correlations, respectively. $\lambda_1 + \lambda_2 < 1$ is required for model statistical stability.

The time-varying conditional correlation matrix is obtained by normalizing Q_t:

$$R_t = diag(Q_t)^{-1/2}\, Q_t\, diag(Q_t)^{-1/2}$$

This normalization ensures that the diagonal elements of R_t are equal to one, preserving the interpretation of R_t as a correlation matrix.

Estimation Results

VAR Model Results

We first discuss the VAR estimation results on the four return series to capture mean spillovers. An 8-lag VAR was selected by information criteria to allow for short-term dynamics. The full-sample VAR coefficients are shown in Table 2. In general, we find weak mean spillovers: most off-diagonal lagged coefficients are statistically insignificant, indicating that each market's returns are largely driven by its own past shocks rather than others'. For example, lagged natural gas returns have negligible coefficients in the corn and wheat equations, and none are significant. This implies that yesterday's gas price changes have virtually no immediate predictive power for today's corn or wheat returns. Similarly, lagged corn or wheat returns do not significantly predict urea returns the next day, suggesting that agricultural commodity price shocks do not feed back strongly into fertilizer prices on a daily basis.

Nonetheless, a few notable linkages appear in the VAR results. Most importantly, the one-day lag of the urea return has a significant positive effect on next-day corn. In other words, when urea prices rise sharply today, corn prices tend to rise slightly tomorrow. We also find that lagged urea return affects the wheat return positively and significantly at the 5% level. For example, 1 % increase in urea price yesterday will raise corn return today by 0.0457% (holding all other lags constant). These results suggest a short-run connection from fertilizer to grain prices: higher fertilizer prices today coincide with higher grain prices shortly after. This is consistent with the intuition and previous findings that fertilizer cost shocks can feed through to crop price levels. Etienne et al. (2016), for instance, documented a positive relationship between ammonia and corn prices in short-run dynamics, a pattern we observe here with urea. By contrast, other potential mean spillovers are nearly absent. For example, we see no strong mean effect of corn or wheat on each other, nor of natural gas on the grains, reinforcing the conclusion that daily price shocks in one market rarely "spill over" into the mean returns of the others. Overall, the VAR results indicate mostly isolated mean dynamics, with only a modest positive fertilizer-to-corn (and to a lesser extent wheat) effect among the significant coefficients.

To ensure the VAR was specified adequately, we performed diagnostic checks on the residuals. The Ljung-Box tests on VAR residuals showed no significant autocorrelation up to 12 lags for each equation, suggesting the VAR captured the linear dependencies in the mean. We then tested for ARCH effects on the residuals of each equation. The ARCH tests were strongly significant for all four series' residuals, confirming the presence of conditional heteroskedasticity. The tests are performed on all three time periods. In other words, while the mean equations are well-specified, the residuals still exhibit time-varying volatility. This is an important precondition for applying the DCC-GARCH model. It implies that there are volatility dynamics and possible volatility spillovers left to model – exactly what we address next with the MGARCH framework.

Table 2: VAR Output for the Whole Period

	(1) Corn	(2) Wheat	(3) Natural Gas	(4) Urea
L.corn	0.0060	-0.0246	-0.0924	-0.0186
L2.corn	-0.0276	-0.0055	-0.0221	-0.0029
L3.corn	0.0065	0.0124	-0.0174	0.0406
L4.corn	-0.0432	-0.0036	-0.0051	0.0516
L5.corn	-0.0034	0.0173	-0.0412	-0.0025
L6.corn	-0.0155	-0.0255	-0.0499	0.0243
L7.corn	0.0416	0.0526	-0.0572	0.0126
L8.corn	0.0504*	0.0243	0.0591	-0.0307
L.wheat	-0.0112	0.0424	0.1388***	0.0307
L2.wheat	-0.0086	0.0153	-0.0310	0.0390
L3.wheat	0.0277	-0.0036	-0.0433	0.0161
L4.wheat	-0.0140	-0.0603**	0.0081	0.0179
L5.wheat	-0.0181	-0.0353	0.0600	-0.0220
L6.wheat	0.0268	0.0448*	0.0341	0.0211
L7.wheat	-0.0477**	-0.0196	0.0502	0.0235
L8.wheat	0.0077	0.0020	-0.0558	-0.0036
L.natural gas	0.0064	0.0190	-0.0472**	0.0037
L2.natural gas	0.0128	0.0046	-0.0146	-0.0066
L3.natural gas	-0.0052	0.0018	0.0323	0.0279**
L4.natural gas	-0.0145	-0.0148	-0.0001	0.0148
L5.natural gas	-0.0046	-0.0027	-0.0320	0.0056
L6.natural gas	-0.0140	0.0013	-0.0069	0.0136
L7.natural gas	0.0119	0.0102	-0.0010	0.0252*
L8.natural gas	-0.0065	-0.0024	0.0112	-0.0041
L.urea	0.0457**	0.0446**	0.0309	0.0849***
L2.urea	-0.0134	-0.0486**	0.0618	0.0026
L3.urea	0.0151	0.0138	-0.0581	-0.0176
L4.urea	-0.0053	0.0098	0.0147	0.0050
L5.urea	-0.0055	-0.0008	0.0486	0.0443*
L6.urea	0.0099	0.0202	0.0293	0.0566**
L7.urea	-0.0227	-0.0248	-0.0588	-0.0045
L8.urea	-0.0060	-0.0126	0.0731*	0.0117
Constant	0.0103	-0.0001	0.0125	0.0289

***p < 0.01, **p < 0.05, *p < 0.1

In summary, Hypothesis 1 is only weakly supported in the mean. This suggests that any strong relationships between these markets are unlikely to be in the mean; instead, they may manifest in volatility and co-movement, which is what we explore with the DCC-GARCH results. The weak mean spillovers are convenient for interpretation: since returns don't predict each other strongly, any correlation we detect in the volatility phase can be more confidently attributed to contemporaneous shocks and volatility transmission rather than delayed price reactions.

DCC-GARCH Results

The core results of our study come from the DCC-MGARCH model, which captures the volatility interactions and time-varying correlations among the four markets. Table 3 presents the estimated parameters of the DCC-GARCH model.

The ARCH (L1) coefficient α captures the "news" or shock effect (a large positive return shock $\varepsilon_{i,t-1}^2$ immediately raises tomorrow's conditional variance by $\alpha_i\varepsilon_{i,t-1}^2$). The GARCH (L1) coefficient β captures volatility persistence (If yesterday's variance $h_{i,t-1}$ was high, today's variance remains elevated by $\beta_i h_{i,t-1}$). The closer $\alpha + \beta$ is to 1, the more persistent the volatility is. For example, ARCH (L1) for corn is 0.1165, meaning a 1-unit squared return shock yesterday raises today's conditional variance by 11.65 %. GARCH (L1) is 0.8597, meaning 85.97 % of yesterday's variance carries over to today – volatility is highly persistent. GARCH-L1 ≈ 0.86–0.93 for corn, wheat, gas; ARCH-L1 modest (0.05–0.12). These values imply that volatility is highly persistent – a shock to volatility today will have a long-lasting effect, with a life of several days.

The estimated unconditional covariance matrix ($\overline{Q}$) in DCC model allows us to extract the time series of conditional correlations for each pair of markets. We computed the correlation for each pair in the pre-war period and in the post-war period, and the contrast is striking. In the pre-war period, correlations were generally moderate. The corn-urea and wheat-urea volatility correlation coefficients are not statistically significant. The natural gas correlation with urea was also quite low in pre-war years, essentially near zero and insignificant. This is consistent with earlier findings that energy and food markets were not strongly intertwined prior to 2022.

The negative and significant corn–urea correlation during the post-war period can be rationalized by input constraints and asymmetric transmission. A shock in urea increases corn production costs and volatility, but corn can only use so much fertilizer – farmers cannot infinitely raise urea usage when corn prices spike. Evidence by Heady et al. (1972), agronomic data and the fitted production functions both demonstrate upper boundaries (where extra fertilizer no longer pays and may cut yields) and lower boundaries (below which nutrient deficiency limits growth). Sound fertilizer management, therefore, means staying inside this window rather than "More is always better." Thus, volatility "from corn back to urea" is dampened by this boundary, yielding an overall negative relative volatility correlation. In plain terms, urea shocks push corn volatility, but corn's feedback to urea is limited, so the net DCC correlation is negative. This asymmetric mechanism was also noted by Etienne et al.

(2016), which explains the negative coefficient. Before the war, the corn–urea volatility correlation was near zero and not significant; after the war, it became more negative and significant.

Table 3: DCC-MGARCH Results

	Whole Period		Pre-War Period		Post-War Period	
	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
ARCH_e_corn						
ARCH L1	0.1165***	0.000	0.0632***	0.000	0.2160***	0.000
	(0.0155)		(0.0110)		(0.0422)	
GARCH L1	0.8597***	0.000	0.9273***	0.000	0.6792***	0.000
	(0.0185)		(0.0122)		(0.0615)	
ARCH_e_wheat						
ARCH L1	0.0805***	0.000	0.0489***	0.000	0.1024***	0.000
	(0.0135)		(0.0129)		(0.0207)	
GARCH L1	0.8919***	0.000	0.9173***	0.000	0.8513***	0.000
	(0.0201)		(0.0226)		(0.0336)	
ARCH_e_ng						
ARCH L1	0.0672***	0.000	0.0954***	0.000	0.0501	0.187
	(0.0091)		(0.0158)		(0.0380)	
GARCH L1	0.9363***	0.000	0.8955***	0.000	-0.3185	0.264
	(0.0077)		(0.0159)		(0.2849)	
ARCH_e_urea						
ARCH L1	1.0243***	0.000	0.7498***	0.000	0.9803***	0.000
	(0.1357)		(0.1320)		(0.1981)	
GARCH L1	-0.0057***	0.000	-0.0014	0.475	-0.0145***	0.000
	(0.0016)		(0.0020)		(0.0032)	
Correlations						
e_corn, e_wheat	0.5251***	0.000	0.5538***	0.000	0.4954***	0.000
	(0.0173)		(0.0238)		(0.0281)	
e_corn, e_ng	0.0538**	0.024	0.0408	0.224	0.0784**	0.034
	(0.0238)		(0.0359)		(0.0371)	
e_corn, e_urea	-0.0467**	0.048	-0.0066	0.843	-0.0763**	0.039
	(0.0236)		(0.0331)		(0.0370)	
e_wheat, e_ng	0.0565**	0.018	0.0067	0.841	0.1018***	0.006
	(0.0238)		(0.0336)		(0.0370)	
e_wheat, e_urea	0.0055	0.816	-0.0021	0.949	0.0062	0.869
	(0.0237)		(0.0331)		(0.0375)	
e_ng, e_urea	0.0640***	0.007	0.0340	0.305	0.0777**	0.035
	(0.0237)		(0.0333)		(0.0369)	
Adjustment						
Lambda1	0.0139	0.209	0.0212**	0.020	0.0155	0.502
	(0.0111)		(0.0092)		(0.0232)	
Lambda2	0.2551	0.578	0.7852***	0.000	0.0392	0.939
	(0.4580)		(0.0835)		(0.5098)	

***p < 0.01, **p < 0.05, *p < 0.1

Other volatility correlations evolve similarly: corn–wheat volatility remains strongly positive and high in all periods, reflecting the usual co-movement among grain markets. Natural gas correlations with corn and wheat are weak pre-war but grow modestly post-war. The gas–urea volatility correlation is significant in the full sample and also becomes stronger post-war. Overall, these results indicate that volatility spillovers across the energy-fertilizer-grains system intensified after late 2021. This evidence supports Hypothesis 2: volatility transmission became more pronounced after the war began. Intuitively, the Ukraine war created common shocks that hit multiple markets simultaneously, whereas in the pre-war period, each market's volatility was more driven by independent factors. The war effectively increased the coupling between energy, fertilizer, and food markets. As a concrete example, during 2022 we often observed days when natural gas, corn, and wheat prices all jumped together on news of escalations in Ukraine or export restrictions, a phenomenon less common before.

Finally, regarding Hypothesis 3 (wheat's volatility linkage with fertilizer is smaller than corn's), our results clearly confirm this. The what-urea correlation remains insignificant for both pre-war and post-war periods. Throughout the analysis, corn stands out as having a stronger connection to fertilizer. In the DCC correlations, corn–fertilizer is consistently higher and more statistically significant than wheat–fertilizer, especially in the post-war era. Our empirical results bear out that corn and fertilizer have a tight volatility nexus.

Conclusion

This study examines the price and volatility linkages between natural gas, fertilizer, corn, and wheat markets over 2017–2025, with a special focus on the turmoil around the 2022 Ukraine war. Using a VAR-DCC-GARCH approach, we provide evidence that these seemingly disparate markets become closely intertwined under certain conditions. Several findings emerge. First, while direct price spillovers in normal times are limited, there are significant volatility spillovers and dynamic correlations among natural gas, fertilizer, and grains. In particular, fertilizer prices play a pivotal role in corn markets – we find that both corn prices and corn volatility respond to shocks in fertilizer, underscoring the tight input-output relationship between these markets. This confirms the importance of fertilizer, an often overlooked factor, in agricultural commodity dynamics. Second, the Ukraine war acted as an integrative shock that strengthened the linkages across all four markets. Our pre-war vs. post-war analysis shows a marked increase in correlations after late 2021. Geopolitical risk thus elevated the co-movement: energy, fertilizer, and food prices, which historically had some independence, moved in concert when the crisis hit. This finding highlights how an extreme event can synchronize markets, an insight that aligns with the notion of "commodities as an asset class" during crises. Third, we establish that wheat's connections to fertilizer, though present, are weaker than corn's. This nuanced result suggests that not all crops are impacted equally by input cost volatility – corn, being more fertilizer-intensive, has a more pronounced linkage, whereas wheat's price is driven relatively more by land use competition and geopolitical supply factors than by fertilizer cost swings.

The findings have practical implications. Market participants, such as farmers, agribusinesses, traders, and investors, can benefit from understanding these interdependencies. For instance, a corn farmer or a food processing company should be aware that a spike in natural gas prices can drive up fertilizer costs, which in turn may lift corn prices and volatility.

The constantly changing geopolitical environment highlights the importance of the study's findings. As of late March 2025, Russia announced that the United States agreed to assist in lifting a range of Western sanctions affecting food, fertilizer, and shipping companies. This agreement aims to ensure safe navigation and eliminate the use of force in the Black Sea, facilitating the resumption of agricultural exports from the region (Faulconbridge, 2025). Geopolitical risk is a crucial factor in commodity markets – not only can it cause price spikes, but it can also alter the correlation structure and volatility transmission pathways. However, stabilizing natural-gas supply or subsidizing fertilizer can dampen downstream food-price volatility in future shocks. The lessons from the Ukraine war period may inform responses to future crises, be it conflicts or other shocks, ensuring more resilient food and energy systems in an interconnected global market.

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