

# Effectiveness of Corn Futures as a Safe-Haven Asset During the Russia-Ukraine War

## Employing a DCC-GARCH and Wavelet Analysis Framework

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June 10, 2024

### Abstract

This study investigates the performance of corn futures as a safe-haven asset during the Russia-Ukraine War. Utilizing daily closing prices of corn futures and equity indices from China, Japan, and the United States across pre-conflict, conflict, and post-conflict periods, we employ an integrated methodology combining the Dynamic Conditional Correlation GARCH (DCC-GARCH) model with wavelet multi-resolution analysis. Our approach quantifies volatility spillovers between agricultural commodities and equity markets while characterizing scale-dependent hedging effectiveness.

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## 1 Research Background

On February 24, 2022, Russia launched a full-scale military offensive against Ukraine, an event that triggered significant political, economic, and social repercussions worldwide. The Russia-Ukraine war not only caused a severe humanitarian crisis but also had profound impacts on global financial and commodity markets. The outbreak of the war dramatically increased uncertainty in global markets, prompting investors to seek safe-haven assets to mitigate risks.

In financial markets, the study of safe-haven assets has always been a significant topic. Traditionally, gold, the US dollar, and government bonds are considered the primary safe-haven assets *Baur & Lucey, 2010*. However, as global economic uncertainties increase, other asset classes such as commodity futures are gradually gaining attention. Particularly, agricultural futures have become a focal point of research due to their close ties with food security and the energy market *Tang & Xiong, 2012*. During periods of financial stress, such as the 2008 global financial crisis, the European debt crisis, and the COVID-19 pandemic, investors and portfolio managers sought to hedge the equity market risks in their portfolios *Hemche et al., 2016; Khelifa et al., 2021*. To enhance portfolio performance and reduce portfolio risk, investors and portfolio

managers should select diverse assets that are not influenced by extreme market conditions. In most cases, crises affect asset price volatility and investment feasibility by triggering uncertainty in investor behavior *Adekoya et al., 2023*.

Multiple studies have explored the impact of the Russia-Ukraine war on global financial markets. The primary findings indicate that the conflict has had a significant negative effect on global stock markets. On the first day of the war, the S&P500 index dropped by 10% (*Boungou and Yatié, 2022*), while the MOEX Russia index fell by 9% in the first week (*Financial Times, 2022*). Conversely, it has been reported that the Russia-Ukraine conflict had a positive impact on the prices of key agricultural commodities such as wheat, rice, and corn (e.g., *Júnior et al., 2022; Mottaleb et al., 2022*).

The Russia-Ukraine conflict has had a significant impact on the prices of key agricultural commodities such as wheat, rice, and corn. The primary reasons include: Firstly, both Russia and Ukraine are major global producers and exporters of grain, particularly wheat and corn. The conflict has severely disrupted agricultural production and exports in these countries, leading to supply chain interruptions. Secondly, ports and transportation infrastructure in the conflict zone have been damaged or blockaded, hindering grain exports. Thirdly, the political and economic uncertainty brought about by the conflict has led to pessimistic market expectations regarding future grain supplies, increasing speculative activities. Speculators often hoard grain or raise price expectations, further driving up market prices. Fourthly, the Russia-Ukraine conflict has also caused a rise in energy prices, particularly oil and natural gas, directly affecting agricultural production costs (such as fuel for machinery and fertilizer production), thereby pushing up grain prices.

Based on this, the main contributions of this study are as follows: Firstly, it tests whether corn can serve as a new alternative candidate for a safe haven and hedging status during the Russia-Ukraine war. Secondly, by combining the DCC-GARCH model with wavelet analysis, this research not only dynamically captures the changes in the correlation between corn futures and stock indices but also reveals the characteristics of their volatility relationship in the time-frequency domain. This combined approach provides a more comprehensive and detailed analytical perspective. The findings not only offer guidance for investors in asset allocation under extreme market conditions but also provide empirical evidence for policymakers in addressing global agricultural market volatility.

## 2 Data and Descriptive Statistics

We utilized daily price data from three stock indices: the Shanghai Composite Index in China, the S&P 500 in the United States, and the Nikkei 225 in Japan, along with daily closing prices of corn futures from the Dalian Commodity Exchange, the Chicago Mercantile Exchange, and the Tokyo Grain Exchange. The time span covered from March 16, 2020, to December 30, 2022. To standardize units, we also collected daily exchange rates of USD to CNY and JPY to CNY from 2020 to 2022, and converted the corn futures prices to yuan (RMB) per ton for ease of calculation. We defined the period from March 16, 2020, to February 23, 2022, as the pre-war period, and from February 24, 2022, to December 30, 2022, as the war period. The daily return rate was calculated using the formula  $\frac{P_{it} - P_{i(t-1)}}{P_{i(t-1)}}$ , where  $P_{it}$  represents the daily closing price of asset  $i$  at time  $t$ , and  $P_{i(t-1)}$  represents the price at time  $t - 1$ .

Figure 1 illustrates the return rates of all series during the sample period. In the return rate graphs of all assets, volatility clustering can be observed, where large fluctuations tend to follow large fluctuations, and small fluctuations tend to follow small fluctuations, justifying the use of the GARCH model to appropriately describe the dynamics of return volatility. Additionally, extreme return rate fluctuations can be observed in early 2020 and early 2022. These may be related to global economic events such as the COVID-19 pandemic and the Russia-Ukraine war. The impact of these extreme events on the market varies in intensity and duration across

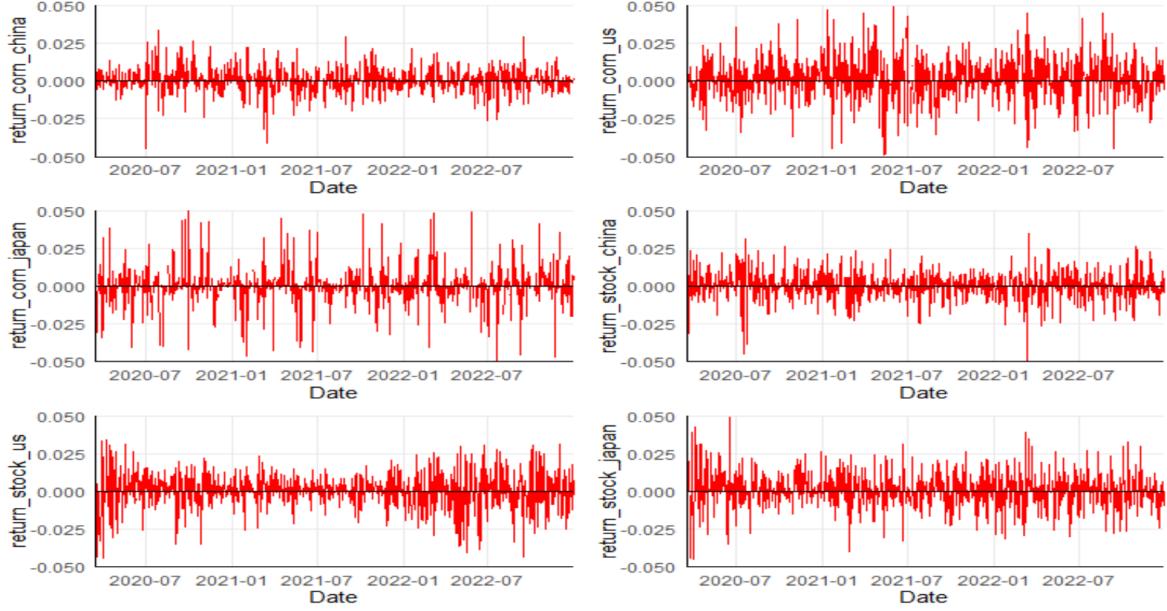


Figure 1: The yield chart of corn and the selected stock market

different assets and countries.

Descriptive statistics in Table 1 indicate that U.S. corn has the highest volatility (0.0159), while Japanese stocks have the lowest volatility (0.0109). The skewness is negative for most markets, indicating that the return distributions of most assets are left-skewed. The kurtosis of all assets is greater than three, meaning the return distributions have a leptokurtic and heavy-tailed characteristic, suggesting that these return distributions deviate from the normal distribution and have more extreme values. The Jarque-Bera test results show that the return distributions of all assets significantly deviate from the normal distribution. The ADF test results indicate that the return series of all assets are stationary.

Figure 2 illustrates the correlations among all assets before and during the war. Specifically, the pre-war correlation between corn futures and stock indices in the Chinese market was 0.12, which decreased to -0.01 post-war. In the U.S. market, the pre-war correlation was 0.04, dropping to -0.08 after the war. In the Japanese market, the pre-war correlation was 0.01, which fell to -0.12 post-war. This indicates a significant reduction in the correlation between corn futures and stock indices across various countries following the onset of the Russia-Ukraine war, suggesting a weakened linkage between the two.

### 3 Empirical method

#### 3.1 DCC-GARCH

This paper aims to provide investors with more investment advice and options. To achieve this goal, we first employ the Dynamic Conditional Correlation and Volatility model, namely the DCC-GARCH model (*Engle, 2002*), to estimate the dynamic conditional correlation between corn futures and stock indices. The DCC-GARCH model is a time series model widely used in financial markets, capable of capturing the dynamic correlations and volatility among variables. Through this model, we can more accurately estimate the correlation between corn futures and stock indices at different time points, thereby providing a basis for portfolio optimization.

After obtaining the dynamic conditional correlations, we further calculate the conditional covariance and conditional variance of corn futures and each stock index. Based on these estimates, we define the optimal portfolio weights for corn futures and each stock index. Specifically,

Table 1: Descriptive Statistics

return of	corn_china	corn_us	corn_japan	stock_china	stock_us	stock_japan
Pre-Russia-Ukraine war period						
Mean	0.0005	0.0009	0.0012	0.0003	0.0009	0.0007
Max	0.0699	0.0730	0.4334	0.0571	0.0938	0.0804
Min	-0.0646	-0.1747	-0.3081	-0.0540	-0.0589	-0.0451
Std. Dev.	0.0082	0.0156	0.0313	0.0082	0.0111	0.0111
Obs.	709	709	709	709	709	709
Russia-Ukraine war period						
Mean	0.0001	0.0003	0.0007	-0.0002	0.0003	0.0001
Max	0.0293	0.0605	0.2993	0.0348	0.0554	0.0394
Min	-0.0264	-0.1460	-0.2502	-0.0252	-0.0432	-0.0260
Std. Dev.	0.0066	0.0156	0.0310	0.0069	0.0103	0.0084
Obs.	310	310	310	310	310	310
General view						
Mean	0.0004	0.0007	0.0010	0.0001	0.0007	0.0004
Max	0.0699	0.0730	0.4334	0.0571	0.0938	0.0804
Min	-0.0646	-0.1747	-0.3081	-0.0540	-0.0589	-0.0451
Std. Dev.	0.0082	0.0159	0.0310	0.0081	0.0110	0.0109
Skewness	-0.1435	-1.7338	1.2250	-0.2735	0.5144	0.6634
Kurtosis	17.632	23.510	61.3731	9.920	11.6867	9.3180
Jarque-Bera	8397	18000	14000	1589	349	1766
Obs.	1019	1019	1019	1019	1019	1019
ADF	-33.323***	-30.294***	-30.291***	-31.911***	-35.577***	-32.437***
Q(20)	28.9251	29.0166	26.4774	11.2972	77.9177***	26.2016
$Q^2_{(20)}$	128.9032***	35.365	5.1185	125.0737***	408.2374***	290.9641***

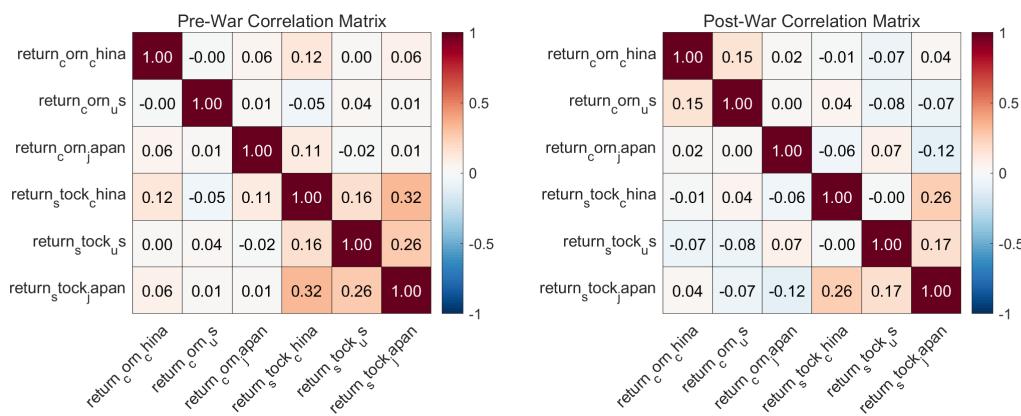


Figure 2: Comparison of Heat Maps Before and After the Start of the Russia-Ukraine Conflict War.

the formula for calculating the optimal weight of corn futures relative to each stock index is as follows:

$$w_t^{\text{corn/equity}} = \frac{h_t^{\text{equity}} - h_t^{\text{equity,corn}}}{h_t^{\text{equity}} - 2h_t^{\text{equity,corn}} + h_t^{\text{corn}}}$$

Here,  $h_t^{\text{equity}}$  and  $h_t^{\text{corn}}$  represent the conditional variances of each stock index and corn futures at time  $t$ , respectively, while  $h_t^{\text{equity,corn}}$  denotes the conditional covariance between the stock index and corn futures at time  $t$ . According to the research by *Kroner and Ng (1998)*, the optimal weight for the stock index lies between 0 and 1. A lower weight value (close to 0) suggests that investors should allocate more to the stock index, whereas a higher weight value (close to 1) indicates a preference for more corn futures. The calculation of this weight helps investors optimize their portfolios across different market conditions, thereby achieving risk minimization and return maximization.

To further analyze the effectiveness of corn futures as a hedging asset, we calculated the risk-minimizing hedge ratio  $b_t^{\text{corn/equity}}$ , which is given by the following formula:

$$b_t^{\text{corn/equity}} = \frac{h_t^{\text{equity,corn}}}{h_t^{\text{corn}}}$$

A positive value of  $b_t^{\text{corn/equity}}$  indicates a positive hedge ratio, while a negative value of  $b_t^{\text{corn/equity}}$  indicates a negative hedge ratio. The calculation of the hedge ratio helps investors to reasonably allocate the proportion of corn futures and stock indices in the face of market fluctuations, thereby reducing the overall risk of the investment portfolio.

Furthermore, drawing on the research of *Akhtaruzzaman et al. (2021)*, we employ the following regression model to verify the hedging ability of corn futures during wartime:

$$DCC_{ij,t} = \delta_0 + \delta_1 DCC_{ij,t-1} + \delta_2 D_{RUW} + \epsilon_{ij,t}$$

Here,  $D_{RUW}$  is a dummy variable for the war period (1 during the war, 0 otherwise). The negative value and significance of  $\delta_0$  indicate that corn futures serve as a hedging asset for stocks. The negative value and significance of  $\delta_2$  suggest the intensity of corn futures as a hedging asset during the war. Through the analysis of the regression model, we are able to quantify the hedging effectiveness of corn futures in different market environments, providing investors with more decision-making insights.

### 3.2 Wavelet Analysis

To more comprehensively analyze the relationship between corn futures and stock indices, we rely on wavelet technology, performing continuous wavelet transform and wavelet coherence analysis. Wavelet analysis is a tool capable of analyzing in both the time and frequency domains simultaneously, particularly suitable for processing non-stationary time series data. Through wavelet transform, we can capture the correlation and co-movement between corn futures and stock indices at different time scales.

First, we employ the continuous wavelet transform technique, projecting the wavelet function  $\psi(t)$  using the following formula:

$$W_X(r, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \psi^* \left( \frac{t-r}{s} \right) dt$$

Here,  $\psi$  is influenced by four factors: time  $t$ , position  $r$ , scale expansion  $s$ , and the normalization factor  $\frac{1}{\sqrt{s}}$ . Through continuous wavelet transform, we can capture the local characteristics of the time series at different times and frequencies, thereby gaining a better understanding of the dynamic relationship between corn futures and stock indices.

Next, we proceed with wavelet coherence analysis to quantify the co-movement between corn futures and stock indices. The wavelet coherence analysis is calculated using the following formula:

$$W_{XY}(r, s) = W_X(r, s)W_Y(r, s)$$

Among them,  $W_X(r, s)$  and  $W_Y(r, s)$  represent the continuous transforms of the time series  $x(t)$  and  $y(t)$ , respectively. This method reveals the local covariance between the two time series in the time-frequency domain. The wavelet coherence measure can be expressed as:

$$R_{xy}^2(r, s) = \frac{|S(W_{xy}(r, s))|^2}{S(|W_x(r, s)|^2) \cdot S(|W_y(r, s)|^2)}$$

Here,  $S$  denotes the smoothing operation, and the value of  $R_{xy}^2(r, s)$  ranges between 0 and 1, indicating the degree of co-movement between two time series at time  $r$  and scale  $s$ . A lower value of  $R_{xy}^2(r, s)$  suggests weaker co-movement, while a higher value indicates stronger co-movement.

Additionally, we calculated the phase difference between the two time series to further understand their relationship. The phase difference can be expressed as:

$$\phi_{xy}^r = \tan^{-1} \left( \frac{\text{Im}(S(W_{xy}(r, s)))}{\text{Re}(S(W_{xy}(r, s)))} \right)$$

Here,  $\text{Im}$  and  $\text{Re}$  denote the imaginary and real parts, respectively. The direction of the phase difference is indicated by arrows, with black arrows representing a phase difference of zero. If the arrow points to the right, it indicates that the two time series are in phase; if it points to the left, it signifies that the two time series are out of phase. The magnitude and direction of the phase difference provide information about the time delay and causal relationship between the two time series.

Through the wavelet analysis method described above, we can comprehensively understand the dynamic relationship between corn futures and stock indices, particularly in terms of their co-movement and phase differences across different time scales and frequencies. These analytical results will offer investors deeper insights, aiding them in making more rational investment decisions under varying market conditions.

## 4 Empirical results

Our presentation and discussion of empirical findings commence with Figure 3, which illustrates the time-varying conditional correlations between corn and the stock indices of China, the United States, and Japan.<sup>1</sup> We observe that throughout the entire sample period, the correlations between corn and each stock index fluctuate between positive and negative levels, suggesting that investors should frequently adjust their portfolio strategies. Since the outbreak of the Russia-Ukraine war in February 2022, correlations have significantly declined, particularly in the initial months of the conflict. At the onset of the war, the negative correlation between corn and stock market indices indicated that these two markets were moving in opposite directions. The war in Ukraine and the new sanctions imposed on Russia led to an increase in corn prices while stock prices fell. During this period, the negative correlation between corn and the Japanese stock index was most pronounced, indicating that the Japanese market was particularly sensitive to the war. This suggests that corn can serve as a safe haven for the stock market during wartime.

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<sup>1</sup>To facilitate a unified display of the trends in dynamic correlation coefficients across the three countries before and after the war, standardization has been applied here.

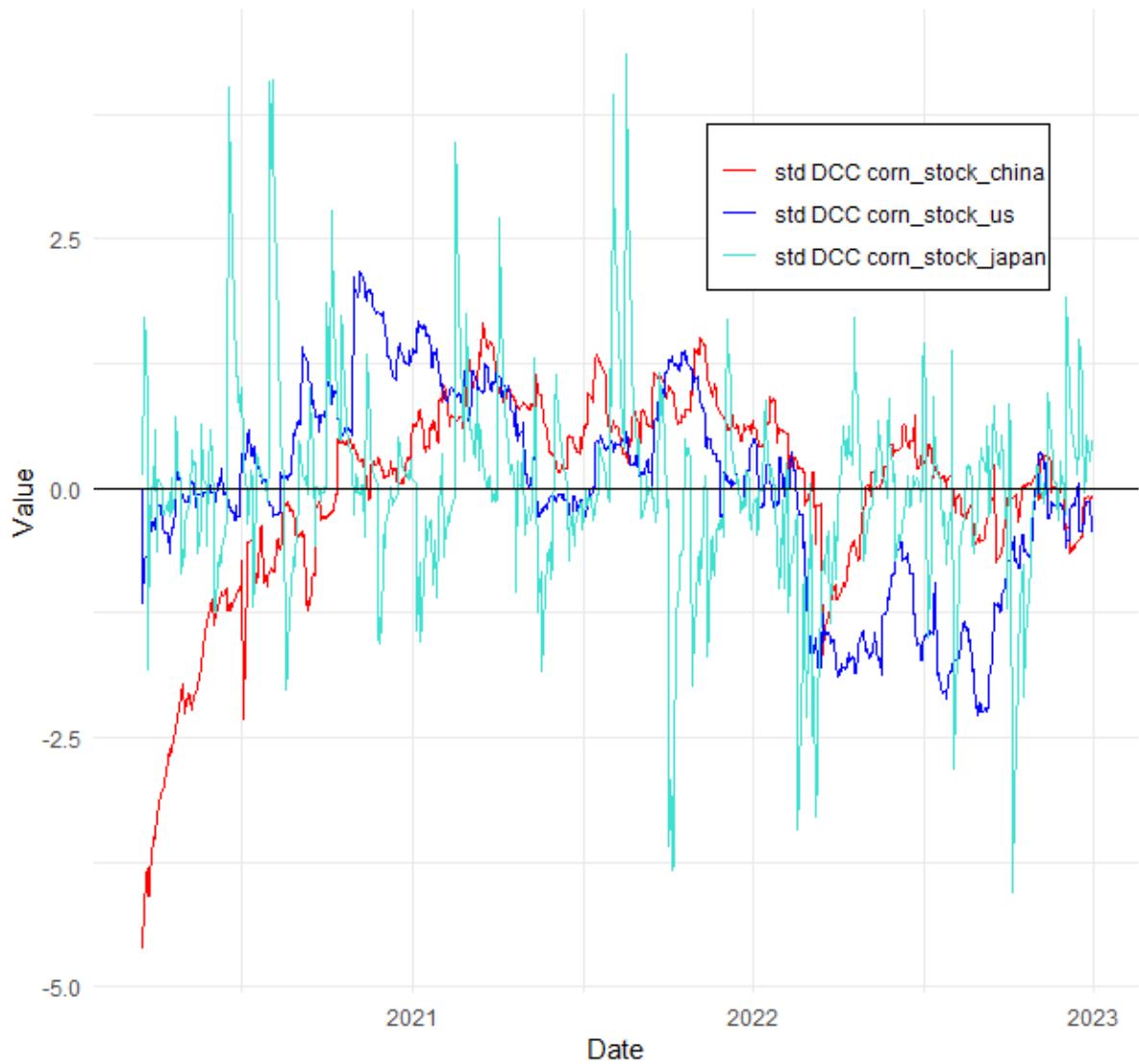


Figure 3: Dynamic Correlation Coefficient Graph

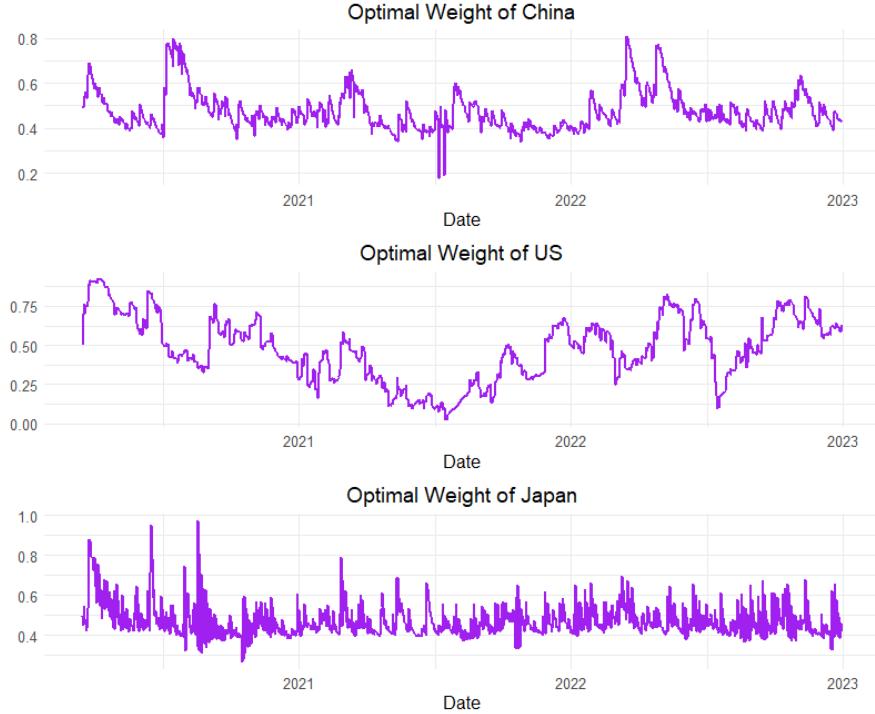


Figure 4: Optimal weights

Figure 4 illustrates the optimal weights of corn futures relative to the stock indices of China, the United States, and Japan. Throughout the sample period, the optimal weights of corn in relation to the stock indices of these three countries exhibited significant fluctuations across different timeframes, indicating that investors need to continuously adjust the proportion of corn in their portfolios based on market conditions. Since the outbreak of the Russia-Ukraine war in February 2022, the optimal weight of corn has increased, suggesting that corn futures provided investors with opportunities for portfolio diversification during the war. In the Chinese market (top panel), the optimal weights of corn futures and the stock index showed considerable volatility during the sample period, particularly increasing significantly during the early stages of the COVID-19 pandemic and the onset of the Russia-Ukraine war. This indicates that during these uncertain times, investors were more inclined to increase the proportion of corn in their portfolios. In the U.S. market (middle panel), the increase in the optimal weights of corn futures and the stock index during the Russia-Ukraine war was relatively modest. Over the entire sample period, the optimal weight of corn exhibited cyclical fluctuations. In the Japanese market (bottom panel), despite the significant volatility in corn futures and the stock index, the overall trend showed an increase in the optimal weight of corn during periods of uncertainty.

Table 2 presents the estimation results of corn's role as a safe haven. The results show that for all assets, the coefficients of the war dummy variable are negative and insignificant. These negative coefficients imply that during the war, corn served as a weak safe haven in the Chinese, U.S., and Japanese markets. For the Chinese and Japanese markets, the coefficients of  $\delta_0$  are positive and significant, indicating that corn acted as a weak hedge in these markets. In contrast, in the U.S. market, the coefficient of  $\delta_0$  is positive but insignificant, suggesting that corn's hedging effect in the U.S. market is not significant. Across all three markets,  $\delta_1$  is positive and significant, indicating that corn futures generally possess strong safe-haven attributes.

Figure 5 illustrates the time-varying optimal hedge ratios between corn and the stock indices of China, the United States, and Japan. The results show that the hedge ratios for all assets fluctuate significantly, oscillating between negative and positive values. Positive values indicate

Table 2: The hedging attribute of corn

Variable	China	US	Japan
$\delta_0$	0.00167***	0.00005	0.00274
$\delta_1 DCC_{t-1}$	0.98052***	0.98089***	0.85149***
$\delta_2 D_{RUW}$	-0.00020	-0.00017	-0.00492

*Note:* This table reports the estimated results of assets as hedging and safe-haven instruments during the Russia-Ukraine war. A significantly (or insignificantly) negative coefficient ( $\delta_0$ ) indicates a strong (or weak) hedge on average, while a significantly (or insignificantly) negative coefficient ( $\delta_1$ ) indicates a strong (or weak) safe-haven instrument during the Russia-Ukraine war.

\*\*\* denotes statistical significance at the 1% level.

that investors should take opposite positions (e.g., long in one asset and short in the other), while negative values suggest that investors should take the same position (e.g., both long or both short). Although the hedge ratio for the United States notably shifted from positive to negative during the Russia-Ukraine war, implying that investors in the U.S. stock market needed to hedge their positions with corn in the same direction during the conflict, the hedge ratios for China and Japan did not exhibit a clear downward trend. The reason may lie in the different measures taken by governments in response to changes in the international situation. As the Russia-Ukraine conflict continues to escalate, the United States has gradually revealed a strategic intent to exhaust and weaken Russia through proxy wars and to drag China into the conflict, while China remains committed to the principle of neutrality and continues to make efforts to de-escalate the situation. This may have led to increased risk aversion in the U.S. market, while the Chinese government's economic policies and market interventions in the face of international conflicts may have stabilized the domestic market, reducing the demand for commodities as a hedge. Meanwhile, Japan's economic structure and market characteristics may cause its response to international conflicts to differ from other markets, particularly in terms of demand for commodities and reactions to price fluctuations.

Figure 6, as a continuous wavelet transform diagram, illustrates the situation of all indices. This figure demonstrates the local variance of each index in the frequency-time domain. The horizontal axis represents the time period, while the vertical axis represents frequency, divided into three levels: short-term (high frequency), medium-term, and long-term (low frequency). The color coding indicates the level of volatility, with blue representing low volatility and red representing high volatility. Figure 6 reveals that the volatility of corn futures and the stock market exhibits a certain degree of synchronicity over time. All assets show regions of high volatility during the Russia-Ukraine war, with the corn futures market seemingly experiencing even higher volatility during this period.

Wavelet coherence analysis simultaneously addresses the frequency and time dimensions of two variables to detect specific characteristics where assets exhibit safe-haven properties across different investment horizons. We explored the co-movement between corn futures and each stock index to determine the safe-haven attributes of corn futures across various investment horizons. In the Chinese market: within the range of approximately 64 to 128 days, coherence is relatively high, particularly around 800 days. The corn market lags behind the stock market (arrows mostly pointing to the upper left ), which may reflect the stock market's quicker response to macroeconomic information, while the agricultural market (e.g., the corn market) may require more time to reflect these changes. Therefore, during significant fluctuations in the stock market, investors can hedge potential market risks by adjusting corn futures positions. In the Japanese market: within the period of around 64 days, corn prices and the stock market also

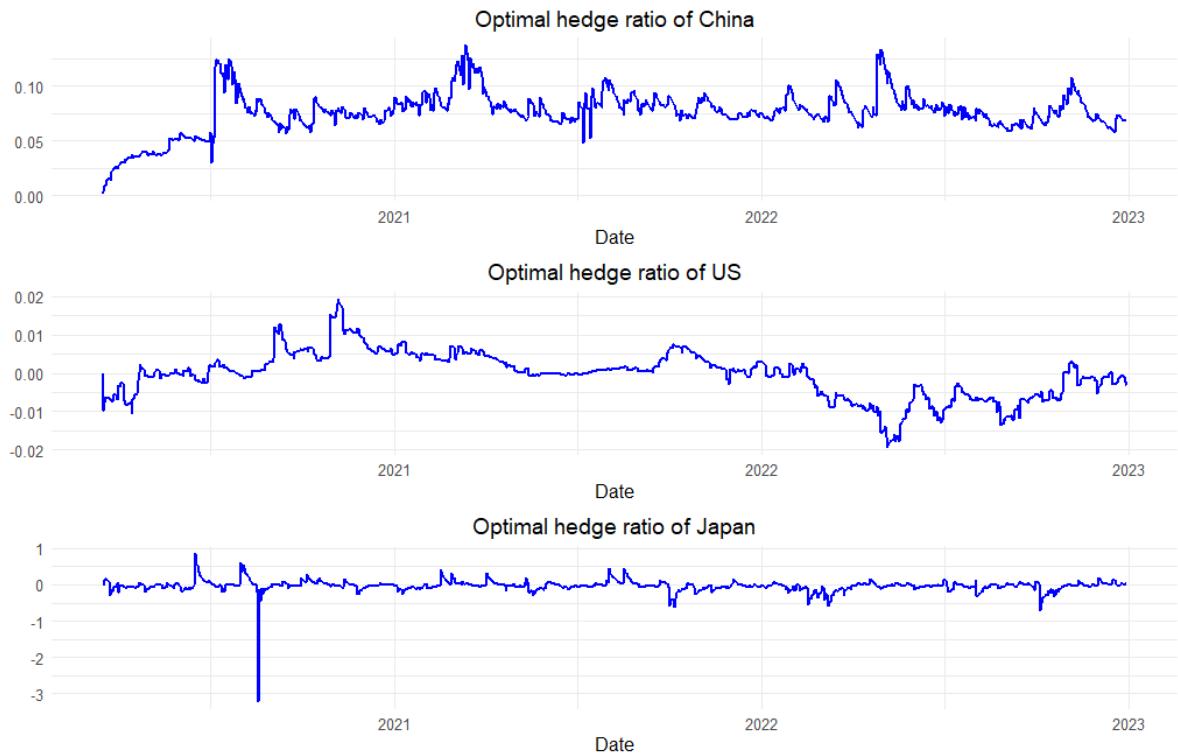


Figure 5: Optimal Hedge Ratio

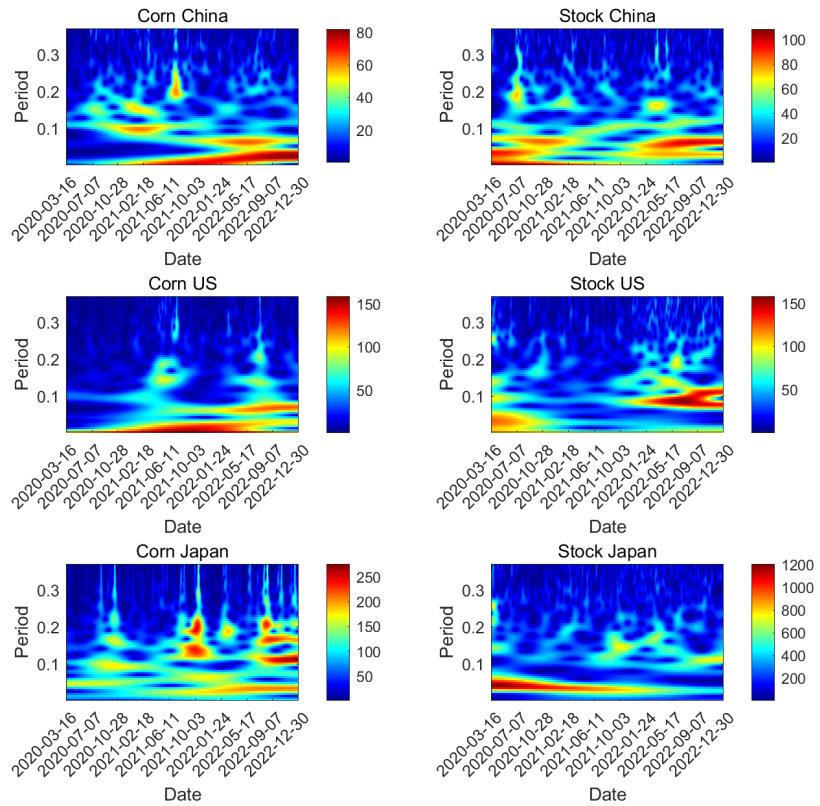


Figure 6: Wavelet spectrogram

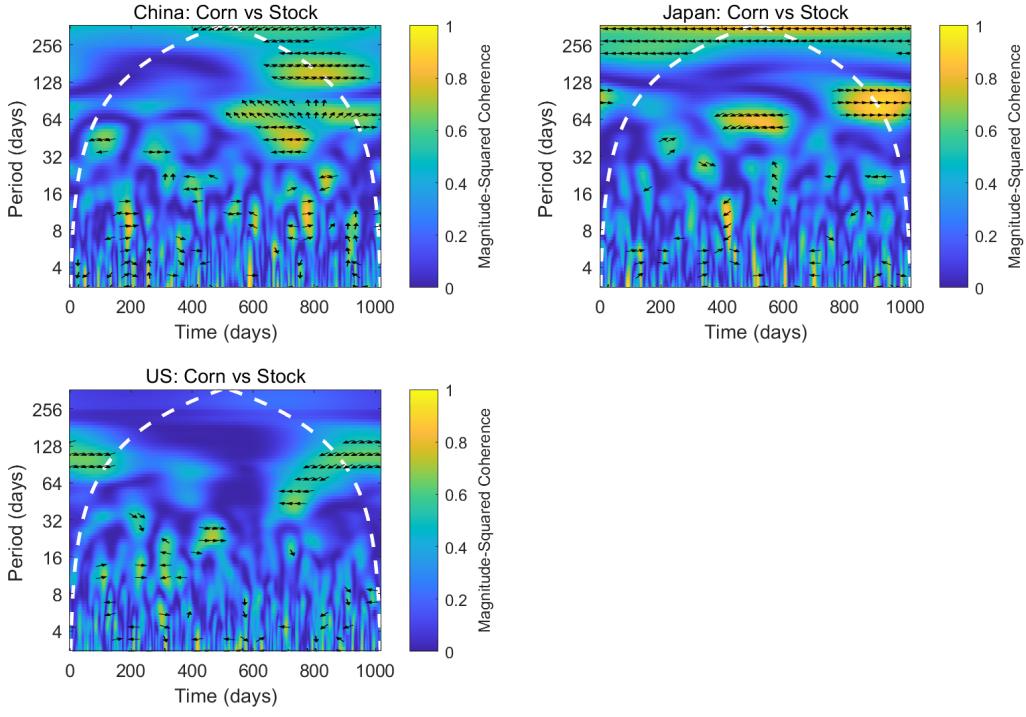


Figure 7: Wavelet coherence plot

show synchronous changes, with corn prices slightly leading the stock market (arrows partially pointing to the upper right ), indicating that in the medium to long term, corn futures can serve as a potential leading indicator for the stock market, providing some hedging function. Investors can use price movements in corn futures to predict stock market trends, enabling effective risk management. In the U.S. market: within the period between 32 and 128 days, the corn market leads the stock market (arrows mostly pointing to the lower left ), but the leading relationship between the two is not significant. This suggests they may be influenced by common economic factors without a clear causal relationship. Thus, the effectiveness of corn futures as a hedging tool in the U.S. market may be weaker. Although both are influenced by common economic factors, investors should exercise caution when using corn futures for hedging and may need to combine other market indicators for comprehensive analysis.

## 5 Research findings

Amid various crises such as the global financial crisis, the European debt crisis, the COVID-19 pandemic, and the Russia-Ukraine war, financial markets tend to become more volatile, increasing the complexity of international investments. To mitigate risks, investors often turn to traditional safe-haven assets. This paper investigates whether corn futures can serve as an alternative safe-haven asset and a hedging tool against stock market risks during political crises like the Russia-Ukraine war. The results indicate that the effectiveness of corn futures as a safe-haven asset varies significantly across different markets during the war, but overall performance is favorable. In times of political conflict and uncertainty, corn futures can effectively reduce the risk of stock portfolios. This provides recommendations for investors in markets such as China, Japan, and the United States to incorporate corn futures into their portfolios for risk hedging purposes.

## References

- [1] Said, A., & Ouerfelli, C. (2022). Downside risk in Dow Jones equity markets: hedging and portfolio management during COVID-19 pandemic and the Russia–Ukraine war. IHECSO, Sousse, Tunisia.
- [2] Mahran, H. A. (2022). The impact of the Russia–Ukraine conflict (2022) on volatility connectedness between the Egyptian stock market sectors: evidence from the DCC-GARCH-CONNECTEDNESS approach. Department of Statistics, Mathematics, and Insurance, Faculty of Business, Ain Shams University, Cairo, Egypt.
- [3] Ghorbali, B., Kaabia, O., Naoui, K., Urom, C., & Ben Slimane, I. (2022). Wheat as a hedge and safe haven for equity investors during the Russia–Ukraine war.
- [4] Chancharat, S., & Sinlapates, P. (2022). Dependences and dynamic spillovers across the crude oil and stock markets throughout the COVID-19 pandemic and Russia-Ukraine conflict: Evidence from the ASEAN+6.
- [5] Adekoya, O. B., Asl, M. G., Oliyide, J. A., & Izadi, P. (2023). Multifractality and cross-correlation between the crude oil and the European and non-European stock markets during the Russia-Ukraine war. Resour. Policy, 80, 103134.
- [6] Akhtaruzzaman, M., Boubaker, S., Lucey, B. M., & Sensoy, A. (2021). Is gold a hedge or a safe-haven asset in the COVID-19 crisis? Econ. Model., 102, 105588.
- [7] Boungou, W., & Yatié, A. (2022). The impact of the Ukraine-Russia war on world stock market returns. Econom. Lett., 215, 110516.