Time-varying correlation between commodity price under Russian-Ukrainian War with DCC-GARCH Models

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1 Introduction

Correlation between commodity futures and financial markets is important, influencing risk evaluation, portfolio management, and strategic investment decisions. Commodity markets are particularly susceptible to volatility and large changes in correlation structures brought about by geopolitical happenings. The beginning of the Russian-Ukrainian War in February 2022 is one example of one of these events, which could alter the dynamics of the global commodities markets for metals, energy resources, and agricultural products.

This research aims to examine the correlations between significant commodity futures before and following the conflict between Russia and Ukraine. The primary focus will be on testing the temporal and long-term effects of the war on the interdependencies of the commodities.

A key component of this research will be the application of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with Dynamic Conditional Correlation (DCC). Recognized for its proficiency in predicting time-varying correlations in financial time series data, the DCC-GARCH model is a perfect instrument for representing the dynamic interactions between commodities futures in reaction to global conflicts.

2 Related Works

2.1 Impact of the Russian-Ukrainian War on Commodities

The escalation of the Russian-Ukrainian war has had a profound effect on global commodity markets, impacting not only market dynamics but also the interrelationships between different sectors. Fang and Shao (2022) provided an insightful analysis of how conflict escalation enhances market volatility, identifying wheat, nickel, aluminum, heating oil, and diesel oil as the top five commodities most affected by the war. Their study highlighted a high risk of contagion between the metal market and the energy market, underlining the complex interdependencies that exacerbate risk across sectors. (Fang & Shao, 2022)

Further expanding on the theme of market interrelationships, Manelli, Pace, and Leone (2024) utilized Quantile Vector Autoregressive (QVAR) analysis to explore the impacts across various commodity classes. Their findings revealed that raw materials, agricultural products, and energy sectors were disproportionately affected, with wheat and TTF gas futures exhibiting strong positive correlations with the Eurostoxx 50 index. This study underscores the broad economic repercussions of geopolitical conflicts on commodity-dependent industries. (Manelli, Pace, & Leone, 2024)

2.2 DCC-GARCH Models on Commodity Prices

The use of Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) models has provided key insights into market dynamics. Shiferaw (2019) demonstrated that oil prices are pivotal in driving the prices of agricultural commodities in South Africa.(Shiferaw, 2019) Jiang et al. (2019) observed a strong volatility spillover from global oil prices to China's commodities, emphasizing China's reliance on imported oil. (Jiang, Jiang, Nie, & Mo, 2019) Sadiq et al. (2022) analyzed the heightened volatility in metals like titanium, platinum, gold, and silver during the COVID-19 pandemic, highlighting their significant contributions to market fluctuations.(Sadiq et al., 2022) These studies illustrate the effectiveness of DCC-GARCH models in deciphering complex market behaviors, particularly during periods of global economic stress.

3 Research Design & Methods

3.1 Data

In this study, daily price data of gold futures, crude oil futures, and corn futures in the Chicago Mercantile Exchange for 2019-05-02 to 2024-05-02 will be utilized. These three commodities represent precious metal, energy, and agriculture since they are the most liquid futures contracts within their types. Analysis of the mentioned period will be done, and it will be done in two parts: before and after the conflict between Russia and

Ukraine started in February of 2022. This division permits an analysis of the correlation structures before and following the conflict.

3.2 Model

To analyze the dynamic correlation among the commodity futures, the study will employ the Dynamic Conditional Correlation (DCC) GARCH model. The model is an extension of the standard GARCH model that allows for time-varying correlations. Before estimating the DCC-GARCH model, the first step is to test for stationarity and autocorrelation of the returns. If autocorrelation of lag terms proves to exist significantly, it can be eliminated by fitting an autoregressive model and taking the residuals. The residuals are then fitted to a GARCH model and get the standardized residuals and finally put into the DCC-GARCH model.

After fitting the DCC-GARCH model, the conditional covariance will be calculated and tested for structural breaks to examine the temporal effects of the war. The whole time horizon would also be divided into pre-war and since-war and fit into the DCC-GARCH model separately. The unconditional correlation for each model would be calculated to examine the long-term effects on commodity markets of the war.

3.2.1 Model Specification:

1. **Autoregressive Model**: An autoregressive (AR) model is a representation of a type of random process. The notation for an AR model of order p (denoted as AR(p)) is as follows:

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t$$

   In this study, the residuals of gold after AR(11) model and crude oil after AR(4) model can pass the Ljung-Box test for 22 lags with a p-value higher than 0.1. The returns of corn futures pass the same Ljung-Box test without an AR model.

2. **Univariate GARCH Model**: Each commodity future's returns will be modeled

individually using a GARCH(1,1) process. This step involves estimating the conditional variance of each series, capturing the volatility dynamics inherent to each commodity.

$$r_t = \mu + \epsilon_t, \quad \epsilon_t = \sigma_t z_t, \quad z_t \sim N(0,1)$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

In this study, the distribution of z_t is chosen to be the student's t distribution to minimize BIC.

3. **DCC Model**: Following the estimation of univariate GARCH models, the DCC-GARCH model parameters will be estimated using the standardized residuals from the GARCH model. The DCC-GARCH model is specified as follows:

$$Q_t = (1 - a - b)\bar{Q} + a(z_{t-1}z'_{t-1}) + bQ_{t-1}$$

where $\bar{Q}$ is the unconditional covariance matrix of the standardized residuals z_t.

4 Results

The coefficient a in the DCC-GARCH model when fitted to complete data is not significant as shown in Table 1. Hence, we cannot prove that conditional correlation is indeed dynamic in the whole period. However, when the pre-war period and the since-war period were fitted separately, the coefficient was significant at a 5% significance level, which proves that the conditional correlation has been dynamic since the war began. A possible explanation for this is that before the war, the market participants traded on various information channels, which relied less on the commodity returns on the last trading day. However, they now heavily rely on the latest news of the war to trade, which is more correlated with the last trading day's return.

The results from the models show both the temporal and long-term effects of the Russian-Ukrainian War on commodity correlations exist. First, from the plots of conditional correlation shown in Figure 2 to Figure 4, all the conditional correlations of the commodity pairs peaked around late February 2022. For gold & corn and gold & crude oil, the correlation in late February 2022 is the highest within the time horizon of the data. For crude oil & corn, the correlation in late February 2022 is almost as high as the maximum in late 2019. The conditional covariances were tested for structural breaks using the Bai-Perron Test. As shown in Figure 5, All three commodities pairs show structural breaks around the 708th observation, which marks the start of the war. This further proves a temporal effect of the war on commodity interdependencies.

The unconditional correlations are shown in Table 2 for the pre-war period and Table 3 for the since-war period. There is a significant change in the unconditional correlation between crude oil & gold and gold& corn. This indicates that the temporal increase in commodity correlations proved above could potentially be long-lasting.

5 Discussion

Though the choice of the commodities is based on how liquid the commodity is, it is still interesting to explore other commodities that seem to have a more direct relationship with the war, for example, natural gas. The Russian-Ukrainian war has significantly changed natural gas prices not only in Europe but also around the world. Its price movements could potentially indicate information about the war and thus correlate with other commodities more than before. This relationship should be explored in future studies.

References

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Attachments

	Parameter	Estimate	S.D	t-stats	p-value
Complete Data	**a**	0.00916	0.008128	1.13135	0.257909
	b	0.959218	0.047749	20.8868	0.00000
Pre-War	**a**	0.011902	0.017560	0.67778	0.497914
	b	0.781516	0.165725	4.71573	0.000002
Since-War	**a**	0.010572	0.004637	2.27944	0.022623
	b	0.977622	0.010057	97.20897	0.00000

Table 1: DCC-GARCH Model Parameters by Condition

	Crude Oil	Gold	Corn
Crude Oil	1.0000	0.0343	0.1848
Gold	0.0343	1.0000	0.0627
Corn	0.1848	0.0627	1.0000

Table 2: Unconditional Correlation matrix (Pre-war)

	Crude Oil	Gold	Corn
Crude Oil	1.0000	0.1993	0.1878
Gold	0.1993	1.0000	0.0906
Corn	0.1878	0.0906	1.0000

Table 3: Unconditional Correlation matrix (After-war)

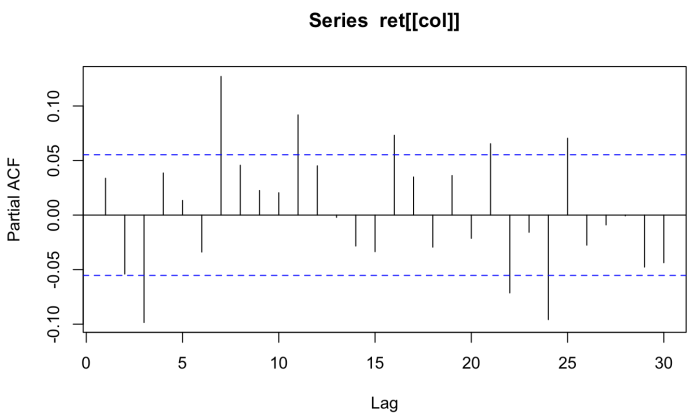

Figure 1: Example of Autocorrelation Test on Gold Futures

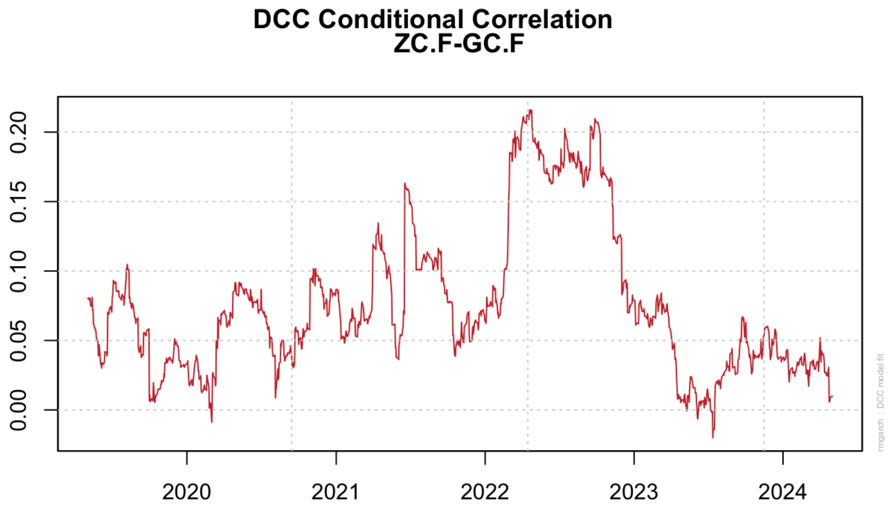

Figure 2: Conditional Correlations for Gold & Corn

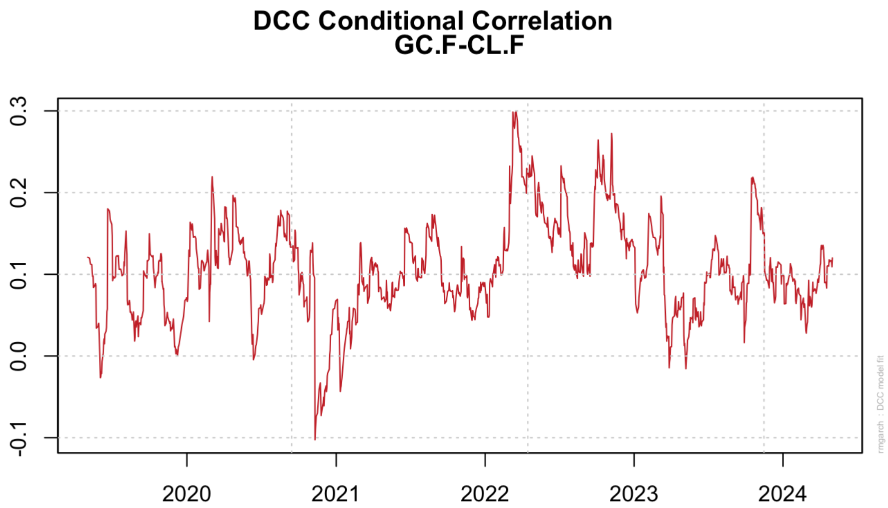

Figure 3: Conditional Correlations for Gold & Crude Oil

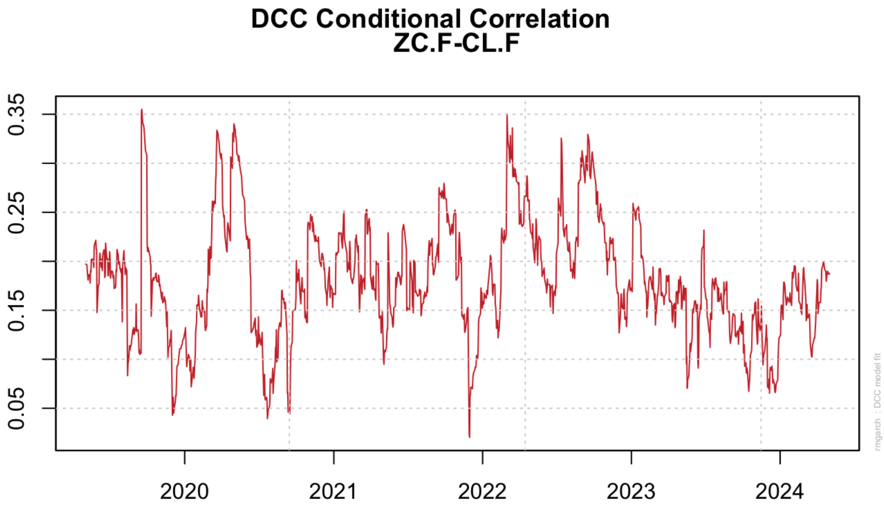

Figure 4: Conditional Correlations for Crude Oil & Corn

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         Optimal 5-segment partition:

Call:
breakpoints.formula(formula = ccov[i, j, ] ~ 1)

Breakpoints at observation number:
195 383 711 912

Corresponding to breakdates:
0.1552548 0.3049363 0.5660828 0.7261146

         Optimal 5-segment partition:

Call:
breakpoints.formula(formula = ccov[i, j, ] ~ 1)

Breakpoints at observation number:
207 395 709 897

Corresponding to breakdates:
0.1648089 0.3144904 0.5644904 0.714172

         Optimal 4-segment partition:

Call:
breakpoints.formula(formula = ccov[i, j, ] ~ 1)

Breakpoints at observation number:
217 700 888

Corresponding to breakdates:
0.1727707 0.5573248 0.7070064
```

Figure 5: Results of Bai-Perron Test on Conditional Covariances