Contagion Effects Among Commodity Markets and Securities Markets During the Conflict Between Russia and Ukraine: The Dynamic Conditional Correlation Approach

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Abstract. The continuation of the Russia-Ukraine war has led to an interest in examining the impacts of this war on the volatilities of various financial markets from February 2022 to May 2022 by using pre-war and wartime data covering the period from January 2010 to May 2022, The commodity and securities markets are considered, and the dynamic correlation between the volatilities of different financial markets is measured using the dynamic conditional correlation (DCC) based on the multivariate GARCH model. The DCC allows analysis of the extent of the impact. Results indicate that all return series display persistently high volatility at values greater than 0.80. Comparing the extent of pre-war and wartime impacts, following the start of the war there appears to be an increase in the conditional correlations but a decrease in the correlation between the volatilities of several financial market pairs, indicating that the impact between these markets exists. Moreover, some assets can serve as a safe haven for other assets.

Keywords: GARCH · DCC-GARCH · Russia-Ukraine · Safe haven

1   Introduction

Commodities are goods that are frequently used as raw materials in manufacturing and are known as products that must be used in large quantities continuously. Therefore, when trading, it is necessary to have futures contracts to hedge the risk as prices may change at any time. Since commodities have the same global standard, the direction of price changes is based on global supply and demand. In addition, commodities are assets for investment because their prices are generally positively correlated with inflation. Investing in commodities has the advantage of being able to adjust the value of an investment according to inflation, and their prices tend to react quickly to immediate events.

Decades of certainty are no longer valid following the COVID-19 outbreak, and then one of the greatest conflicts in the world came up. The conflict between Russia and Ukraine led to the war between the two countries. It not only endangers human life and property; it also raises the risks to the global economy and trade. The high degree of uncertainty in the situation can affect us in many ways. One of them is the commodity price. Oil and gas prices will increase due to the Western countries' sanctions with the purpose of increasing economic pressure on Russia to stop the war (Huther 2022), and the prices of related goods will also soar, e.g., wheat, soybeans, corn, etc. The increasing commodity prices lead to high inflation worldwide, directly affecting people's spending decisions. The globe is getting more complicated, risks and uncertainties increase, challenges become more complex, and the countries require faster and more consistent action to deal with the upcoming economic recession. Against this background, it is imperative to describe what can and must be learned from the current crisis (Fischedick 2022). This requires a technique that is based on a dynamic concept to provide a better understanding of the current situation.

Bitcoin is similar to commodities, and the analysis of Bitcoin prices can be generally learned from the analysis of resource commodities (Gronwald 2019). One study said that Bitcoin is not money but rather a digital commodity with value but no value-added because both the production of and the speculation with Bitcoin draw from the existing global pool of value-added (Rotta 2022). So, it can be said that Bitcoin is a commodity. Moreover, Bitcoin was used instead of the ruble during the Russia-Ukraine war in some transactions. One of the reasons is that the European Union banned some Russian banks from using the Society for Worldwide Interbank Financial Telecommunication (SWIFT) to put pressure on the Russian government during this war. And also, some Ukrainians are turning to Bitcoin as an alternative to Ukrainian financial institutions. In a scenario where governments are in chaos, relying on traditional banks is difficult, and there is fear of surveillance. So, a relatively anonymous system where no government is involved is appealing. Then, it is interesting to study Bitcoin as a commodity in this paper.

Volatility has no definitive outcome. This is because each fluctuation depends on the data and the computed model. In this paper, we focus on calculating the volatility errors in the relationship between the dominant securities in the financial markets and the commodities during the war between Russia and Ukraine. Since the volatilities are dynamic, the generalized autoregressive heteroscedasticity (GARCH) model is employed to describe them. The dynamic conditional correlation (DCC) model is used to describe the fluctuation of correlation.

In the time of conflict between Russia and Ukraine, the correlation between different financial and commodity markets' volatilities described in this paper can be applied as one of the academic insights that provide facts about the correlation and how the co-movement might change in these markets during the historically volatile period. This will be beneficial to policymakers as the existence of this correlation can be confirmed.

The rest of this paper is structured as follows: Sect. 2 presents the methodology, which mainly deals with the GARCH model. Section 3 reports the data and preliminary analysis. Section 4 reports the empirical findings. And Sect. 5 gives the conclusions.

2   Methodology

The DCC-GARCH model consists of two parts: the volatility model (GARCH process) and the dynamic conditional correlation (DCC) model. This study employs three GARCH-like models, including GARCH, GJR-GARCH, and CS-GARCH, to capture financial market volatility. These models are helpful in studying volatility, assuming that variability is dynamic rather than stable. These models have several advantages because they provide reliable results by eliminating the autocorrelation and heterogeneity common in time series data. For greater flexibility, this section uses the DCC model to explain the correlation with a better dynamic concept when the correlation changes over time.

2.1   GARCH Models

The standard model comprises mean and variance equations. The first equation is the mean equation written as

$$r_{i,t} = \mu_i + \varepsilon_{i,t}, \quad i = 1, 2, \ldots, n, \tag{1}$$

and

$$\varepsilon_{i,t} = \sqrt{h_{i,t}} z_{i,t}, \tag{2}$$

The stock i 's return at time t is represented by $r_{i,t}$, μ_i is the return's average which is a constant term, and the residual term is $\varepsilon_{i,t}$. $z_{i,t}$ is a standardized residual. Both $\varepsilon_{i,t}$ and $z_{i,t}$ are Independent and identically distributed (i.i.d.) random variables, with the property of i.i.d., $E(z_{i,t}) = 0$ and $E(z_t z_i^T) = I$, where z_t is a vector consisting of the values $z_{i,t}$ for different i.

Under the GARCH(1,1) process, the below equation describes conditional variance $h_{i,t}$ of return at time t is

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \tag{3}$$

In the variance equation, all parameters, including $\omega_i, \alpha_i, \beta_i > 0$ have to be positive. α captures ARCH effect on volatility. The GARCH effect is presented by β, showing the stackability of $h_{i,t}$ from its own past value. In the other words, ARCH and GARCH effects reveal the existence and persistence of the volatility, respectively. To extend more, ARCH shows the persistence in residual and GARCH shows the persistence in conditional variance.

2.2   Glosten-Jagannathan-Runkle-GARCH (GJR-GARCH)

The GJR-GARCH is an alternative GARCH model providing leverage term γ_i. The leverage term helps capture the volatility's bad news and good news. When the error $\varepsilon_{i,t-1}$ is negative, $I_{i,t-1}$ equals to one, otherwise, it is zero.

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \gamma_i I_{i,t-1} h_{i,t-1}, \tag{4}$$

where

$$I_{i,t-1} = \begin{cases} 1 \text{ if } \varepsilon_{i,t-1} < 0 \\ 0 \text{ if } \varepsilon_{i,t-1} \geq 0 \end{cases}, \tag{5}$$

2.3   Component GARCH (COGARCH)

The Component GARCH model provides a leverage term using $q_{i,t}$, which is an additional ARCH(1) quantity. The COGARCH(1,1) can be shown as follows

$$h_{i,t} = q_{i,t} + \alpha_i \left(\varepsilon_{i,t-1}^2 - q_{i,t-1} \right) + \beta_i \left(h_{i,t-1} - q_{i,t-1} \right), \tag{6}$$

$$q_{i,t} = v + \delta q_{i,t-1} + \phi \left(\varepsilon_{i,t-1}^2 - h_{i,t-1} \right), \tag{7}$$

where v, δ and ϕ are the estimated parameters.

2.4   Dynamic Conditional Correlation (DCC)

The DCC model is more realistic than the static correlation methods, such as Pearson and Spearman correlations which can not measure the time-varying correlation between the random variables. Engle (2002) suggested that the correlation could not be constant and there might exist structural change in the correlation series. In the other words, the behavior of the variables has been changing over time, thus, the interaction between variables could be also changed. To measure this time-varying correlation, Engle (2002) suggested the DCC process predicts the correlation at time t. In the DCC model, the correlation matrix is R_t, and the covariance, H_t. The covariance is affected by its own past at $t-1$, which is called the conditional covariance, $H_{,t} = E\left[r_t r_t' \mid \Psi_{t-1}\right]$ where Ψ_{t-1} is a set of past innovations (Engle 2002), or it is the past value of return in our case. The covariance matrix can be computed by using

$$H_t = D_t R_t D_t, \tag{8}$$

where D_t is a diagonal matrix of the time-varying conditional standard deviation of the error $\varepsilon_{1,t}$ under the GARCH(1,1) process. The matrix of D_t with the $n \times n$ dimension can be shown as follows

$$D_t = \begin{bmatrix} \sqrt{h_{1,t}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2,t}} & 0 & \cdots & 0 \\ 0 & 0 & \sqrt{h_{3,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sqrt{h_{n,t}} \end{bmatrix}, \tag{9}$$

The correlation matrix, R_t, is a symmetric positive semi-definite matrix, showing a correlation between asset i and $j, \rho_{ij}, i \neq j$

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1n,t} \\ \rho_{21,t} & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1,t} & \rho_{n2,t} & \cdots & 1 \end{bmatrix}, \tag{10}$$

The parameter set (Θ) can be computed using the DCC log-likelihood function as

$$L(\Theta) = -\frac{1}{2} \sum_{t=1}^{T} \left(n \log(2\pi) + \log |D_t| + \log |R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t \right). \tag{11}$$

where $|D_t|$ and $|R_t|$ are the determinant of the matrix D and R respectively. And the Maximum likelihood estimation is employed to find the best-explained parameters.

3 Data

We investigate the dynamic correlation between stock returns of the Dow Jones Industrial Average (DJI), the 10-Year Treasury Yield of the USA (TNX) of NY Mercantile, Wheat (WHT), Corn (CRN), Soybean (SOY), Sugar (SUG), NYMEX West Texas Intermediate crude oil (WTI), natural gas (NG), the gold price (GOLD) of COMEX, silver (SIL), copper (COP), and bitcoin (BTC). The data is collected by Yahoo Finance.com. The sample covers the period from January 4, 2010, to May 10, 2022, with 1845 observations. We include this range because we want to explore the dynamic correlations between commodity and securities markets before and during the war between Russia and Ukraine. This will give us a clearer understanding of the implications of this war. Table 1 and Table 2 show negative skewness and high kurtosis. The results show that the data are not normally distributed after finding the minimum Bayesian factor (MBF). Moreover, the extended Dickey-Fuller test (unit root) shows that all returns are stationary. Our goal is to examine the degree of contagion in financial markets.

Table 1. Descriptive statistics of returns (1)

	DJI	TNX	WHT	CRN	SOY	SUG
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.001	0.000	−0.000	0.001	0.001	0.000
Maximum	0.108	0.017	0.197	0.077	0.064	0.108
Minimum	−0.138	−0.015	−0.113	−0.191	−0.086	−0.078
Std. Dev.	0.012	0.003	0.019	0.016	0.012	0.019
Skewness	−1.054	−0.110	0.610	−0.930	−0.223	0.308
Kurtosis	23.548	2.295	7.673	13.176	3.537	1.895
Jarque-Bera	43,075*	410*	4,654*	13,648*	980*	306*
Unit root test (ADF)	−29.554*	−31.769*	−28.679*	−30.432*	−29.982*	−30.046*

Note: "*" denotes a strong rejection of the null hypothesis, according to Minimum Bayes Factor (MBF) (see, Maneejuk and Yamaka 2021)

Table 2. Descriptive statistics of returns (2)

	WTI	NG	GOLD	SIL	COP	BTC
Mean	0.001	0.001	0.000	0.000	0.000	0.003
Median	0.002	0.000	0.000	0.000	0.000	0.002
Maximum	0.320	0.382	0.058	0.089	0.064	0.225
Minimum	−0.282	−0.301	−0.051	−0.124	−0.069	−0.465
Std. Dev.	0.031	0.035	0.009	0.018	0.014	0.047
Skewness	0.123	0.436	−0.120	−0.732	−0.077	−0.655
Kurtosis	21.988	12.931	4.472	7.074	1.408	8.785
Jarque-Bera	37,262*	12,946*	1,547*	4,023*	155*	6,082*
Unit root test (ADF)	−30.582*	−32.695*	−30.780*	−29.076*	−31.304*	−30.240*

Note: "*" denotes a strong rejection of the null hypothesis, according to Minimum Bayes Factor (MBF) (see, Maneejuk and Yamaka 2021)

4   Estimation Results

Before figuring out what the results mean for volatility and correlation, we look at different DCC-GARCH models with four different distributional assumptions: Student's t, Student's skewed, normal, and normally skewed. Table 3 shows that the normally distributed GARCH (1,1) has the lowest value of the Bayesian Information Criterion (BIC) and is thus the best model for explaining the properties of the data.

Table 3. BIC estimates for multivariate GARCH (1,1) under four distributions

	Std	Sstd	Norm	Snorm
GJR-GARCH	−70.519	−70.470	−70.565	−70.517
GARCH	−70.524	−70.478	−70.583	−70.533
CSGARCH	−70.475	−70.422	−70.537	−70.484

In Table 4, we show only the best estimation results of the GARCH (1,1) obtained from the previous step. According to Table 4, a high level of volatility persistence is measured by $\alpha_i + \beta_i$, in all markets as the values along our sample period are higher than 0.8. Table 4 also shows that copper is the least volatile asset (0.8507). On the other hand, natural gas is the most volatile (0.9990). In addition, the results also provide the DCC parameters (a and b). A dynamic conditional correlation can be interpreted as persistent if the sum between these parameters is close to 1.

Table 4. Results of the DCC-GARCH model

		DJI	TNX	WHT	CRN	SOY	SUG	WTI	NG	GOLD	SIL	COP	BTC
Mean Eq.	μ_i	0.001*	−0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	−0.000	0.000	0.003*
GARCH	ω_i	0.000	0.000	0.000*	0.000	0.000	0.000	0.000*	0.000	0.000	0.000	0.000	0.000*
	α_i	0.220*	0.058*	0.092*	0.077	0.070*	0.050	0.139*	0.100*	0.023	0.033*	0.073	0.144*
	β_i	0.744*	0.919*	0.823*	0.903*	0.909*	0.874*	0.835*	0.899*	0.970*	0.961*	0.777*	0.801*
	a	0.009*											
	b	0.944*											

Note: "*" denotes a strong rejection of the null hypothesis, according to Minimum Bayes Factor (MBF) (see, Maneejuk and Yamaka 2021)

The result shows that conditional volatility increased after the war between Russia and Ukraine arose. Since then, it has shown a decline in many markets. Except for NG, which suddenly rises and then falls. Before the war, NG, WHT, and WTI were the top three markets showing a great reaction to the war, with highs of 0.025, 0.005, and 0.004, respectively. The degree of correlation between financial markets was found to mostly increase during this war, linked to the potential impact of the war.

According to the result, TNX is always an alternative investment that reduces volatility or is a safe haven asset for WTI, COP, and DJI, as a negative correlation is shown in Fig. 1. However, TNX only served as a safe-haven asset for WHT, CRN, SOY, and SUG prior to the war. But when the war began, TNX was no longer a safe haven for WHT, CRN, SOY, and SUG. This differs from NG in that TNX gradually became a safe-haven asset for it after the war began, as shown by the correlation in Fig. 2.
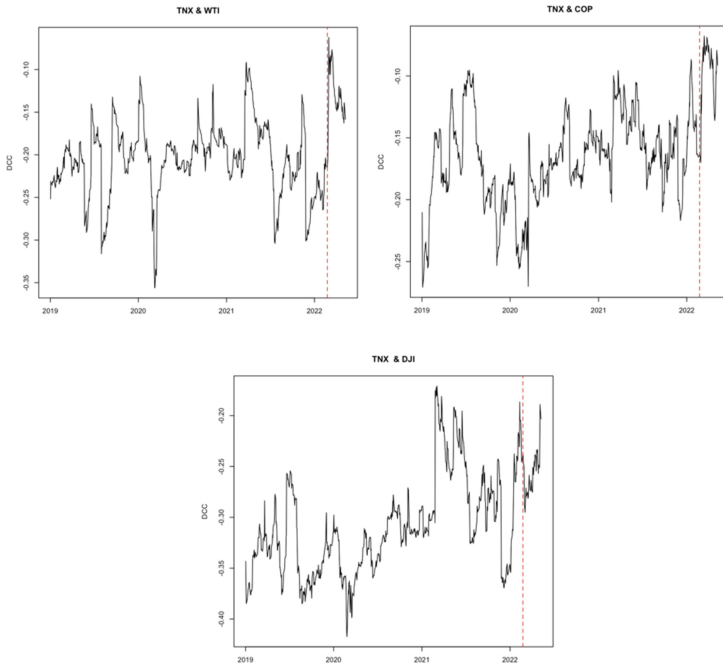
Fig. 1. Dynamic conditional correlation: TNX - WTI, COP, and DJI. The vertical red dashed line is the date the Russian-Ukrainian conflict started (February 24, 2022).

The United States of America is sensitive to the war between Russia and Ukraine, as the correlations with other market prices have obviously increased showing that the United States is not the best choice to invest in during a war if the investors want to take the lower risk. However, TNX seems to be the best place to park money with the lowest volatility. Moreover, COP and BTC have not increased in correlation compared to other stocks. This evidence allows us to conclude that financial markets are affected by the war. In addition, TNX negatively correlates with WTI, COP, DJI, NG, and SUG during the war, confirming that TNX is the safe haven for WTI, COP, DJI, NG, and SUG. Investors in these markets are encouraged to invest in the TNX market to mitigate the risk to their portfolios.
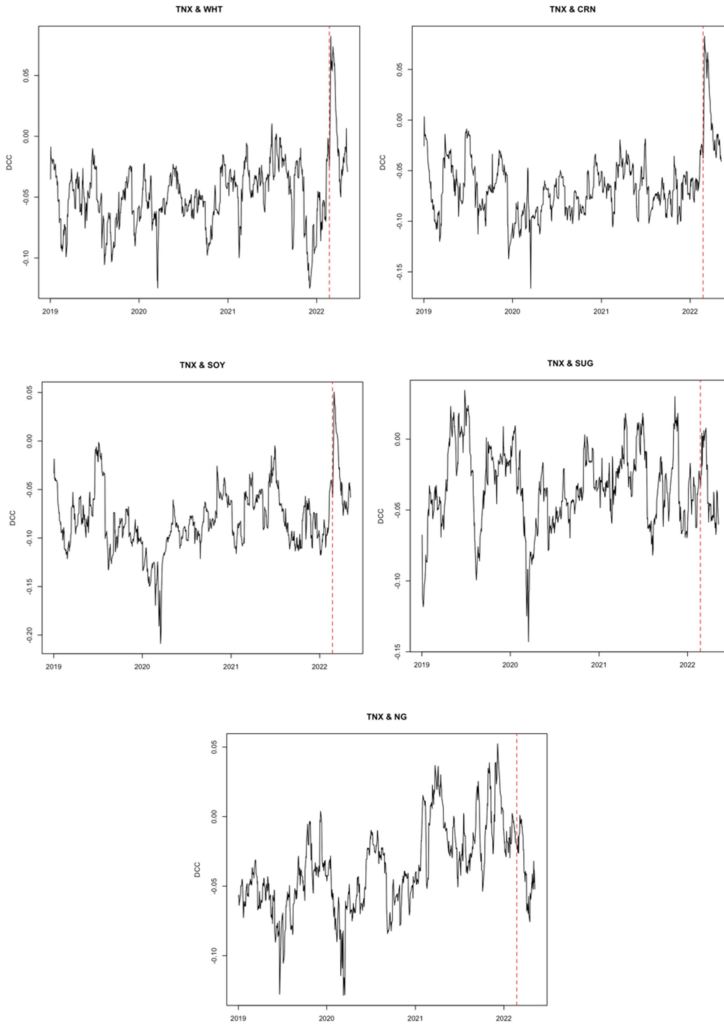
Fig. 2. Dynamic conditional correlation: TNX - WHT, CRN, SOY, SUG, and NG. The vertical red dashed line is the date the Russian-Ukrainian conflict started (February 24, 2022).

5   Conclusion

This paper aims to examine the correlation among financial markets by detecting the impact of the war between Russia and Ukraine. The correlation between different investments changes with time, so the relationship between the assets should not be fixed; thus, DCC-GARCH-type models are used to model the correlation. The data employed in this study was collected from January 4, 2010, to May 10, 2022, encompassing 1845 observations. The market data include

Dow Jones Industrial Average (DJI), 10-Year Treasury Yield of USA (TNX) of NY Mercantile, Wheat (WHT), Corn (CRN), Soybean (SOY), Sugar (SUG), NYMEX West Texas Intermediate crude oil (WTI), Natural gas (NG), Gold Price (Gold) of COMEX, Silver (SIL), Copper (COP) and Bitcoin (BTC). The model selection result indicates that the multivariate S-GARCH model outperforms other multivariate GARCH models. Furthermore, the result of the multivariate DCC-GARCH shows that some of the assets performed moderately after the war between Russia and Ukraine; however, the degree of volatility dropped later. The evidence is confirmed by the financial markets' low degree of volatility and persistence during this war situation.

In addition, the dynamic correlation results show that the correlation between the volatilities of different financial markets during the war was weaker than before, suggesting the occurrence of an impact. There is also evidence of the safe haven characteristic of the 10-Year Treasury Yield of the USA (TNX) of NY Mercantile. According to our findings, investors need to invest with special attention to the war between Russia and Ukraine and consider the US 10-year Treasury yield as one of their portfolio's assets.

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