COVID-19 or Russia-Ukraine conflict: which is informative in defining the dynamic relationship between Bitcoin and major energy commodities?

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Abstract

This paper examines an essential methodology to evaluate the influence of the COVID-19 and Russia-Ukraine conflict surprises and conception statements employed for the dynamic conditional correlation between returns and volatilities of energy commodity indices and Bitcoin. To assess analytically the unexpected component of COVID-19 and Russia-Ukraine conflict surprises, we use GARCH-DCC (1,1) model as established by Engle (2002) by incorporating a dummy variable which measures the surprise factor during the period of study from January 04, 2016, to April 04, 2022. The experimental outcomes of this paper suggest significant and considerable dynamic conditional correlation between energy commodities indices and Bitcoin if COVID-19 pandemic and Russia-Ukraine conflict shocks are incorporated in variance assessments. Additionally, these outcomes demonstrate the financialization phenomena of energy commodities indices and Bitcoin. We find that the dynamic conditional correlation between energy commodities indices and Bitcoin start to respond considerably more in the situation of Russia-Ukraine conflict shocks than COVID-19 surprises. Our outcomes contribute and improve to the research in financial and economic impacts of the recent epidemic and war between Russia and Ukraine with offering an experimental impervious that COVID-19 and Russia-Ukraine conflict give a bidirectional spillover effect on energy commodities and cryptocurrencies assets. This investigation has an essential and considerable concern for the officials and legislators and the portfolio risk administrators and executives.

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1. Introduction

Financial markets are strongly feeling the effects of global crises, and this is nothing new. Climate disasters, pandemics, political unrest, and military conflicts can compromise our security, health, infrastructure and international relations. These sweeping changes are also hurting businesses and the global economy. They cause considerable uncertainty, which poses a significant threat to investments in financial markets.

The COVID-19 pandemic, unfortunately, fits this picture, harming countries' economies and threatening entire stock markets. In Canada and the United States, stock markets quickly lost more than 30%, erasing most of the gains made in recent years. As the progression of the COVID-19 outbreak in these two countries has not yet peaked, it is unclear what is likely to happen in the coming weeks. The COVID-19 pandemic has thrown financial markets into a whirlwind, the uniqueness of this crisis and how business leaders and government officials can support the economy during this particularly intense time.

The COVID-19 pandemic is unprecedented in its scope and global impact, posing challenges to policy makers and the empirical analysis of its direct and indirect effects within the interconnected global economy. The outbreak of COVID-19 in December 2019, the global economy began to feel the pressure of the outbreak of violence that gripped the planet without any immunization for a year or more, organizations, governments and businesses are wondering how best to prepare for likely business and operational disruptions, as are expanding business and the legitimate ramifications of overseeing such a wellness emergency.

With the invasion of Ukraine by Russia on Thursday, February 24, the conflict between the two nations turned into a real war. This could also have serious economic consequences.

11th world power in terms of gross domestic product (GDP), Russia is one of the world's leading exporters of natural gas. It also supplies petroleum, cereals, such as wheat and rapeseed, and industrial metals, such as nickel and aluminum. In this context, one of the first consequences of the war in Ukraine should be an increase in the price of energy and certain raw materials.

On 24 February alone, the price of natural gas rose by more than 25% on the TTF market, a platform located in the Netherlands and considered a benchmark in Europe.

Several factors explain these pressures on energy and commodity prices. First, Russia could voluntarily reduce its offer, in order to exert pressure on the countries, in particular European, likely to impose the heaviest economic sanctions on it. According to a classic market mechanism, with unchanged demand, the price of a good increases when the quantities supplied decrease. On the other hand, in the face of sanctions taken by the United States and Europe, Russia could find itself increasingly isolated and reduce its participation in trade, which would lead other countries to seek alternative sources of energy and therefore more expensive. Finally, the war unleashed in Ukraine could lead to the deterioration of the infrastructures necessary for the export of goods: ports, gas pipelines, oil pipelines, etc.

In France, as in many countries, the mechanisms for setting gas and gasoline prices are complex and only partly depend on natural gas and oil prices. Rising prices on international energy and commodity markets should, however, cause the acceleration of inflation which made a comeback in the United States and Europe last year.

This acceleration in inflation could have two major consequences:

- First, it should weigh on purchasing power, i.e., the ability of households to buy goods and services with their income. If inflation is higher than the increase in household income, then purchasing power declines. This is also the scenario forecast by the National Institute of Statistics and Economic Studies (INSEE) for the year 2022. According to forecasts by the Institute published last December, the purchasing power of households should fall in France by 0.2% in 2022. The "additional" inflation generated by the war in Ukraine should aggravate this phenomenon.
- The acceleration of inflation could then encourage central banks, including the European Central Bank (ECB) for the euro zone and the Federal Reserve (FED) in the United States, to further tighten monetary policies. To limit inflation, they have already announced the forthcoming end of the quantitative easing programs implemented at the start of the Covid-19 crisis, such as the PEPP in Europe, and increases interest rate futures. Due to the war in Ukraine, central banks could accelerate the implementation of these strategies to the detriment of economic activity.

Finally, Russia's invasion of Ukraine has caused turbulence in international financial markets. Most stock markets in the United States and Europe closed lower. Unsurprisingly, the stocks most affected are those most exposed to the Russian market. For France, it is, for example, banking establishments.

On the Paris Stock Exchange, the CAC 40 index fell by nearly 3.8% during the session on Thursday, February 24.

In recent years, Russia, for its part, has tried to reduce its exposure to the international financial system, by considerably reducing the amount of its public debt and by building up foreign exchange reserves. If the United States and European countries were to completely exclude Russia from the international financial system through their sanctions, Russia's economy could collapse.

This paper is very directly connected to the recent financial and economic literature in the response of the correlation among the returns of Bitcoin and the energy commodities (Crude Oil West Texas Intermediate, Brent Oil, and Natural Gas) to the COVID-19 surprises and Russia-Ukraine conflict through the used period of study since January 04, 2016, to April 04, 2022. Therefore, it is crucial to consider a fundamental connection amongst the heathy crisis and the war conflict surprises and the volatility of financial stock market indices returns, particularly, energy commodities and Bitcoin returns.

Therefore, we study in our article the coronavirus and Russia-Ukraine conflict as a possible factor of the volatility of energy commodities and Bitcoin returns is significant specified used period of rapid catastrophe of the international financial stock market indices and the main role of the healthy and war crises actions on the financial asset values. In this research, we investigate empirically the moment-varying connections amongst strategic commodities including segment of energy (Crude Oil West Texas Intermediate, Brent Oil, and Natural Gas) and Bitcoin, through the period of study since January 04, 2016, to April 04, 2022. Econometrically, we employ the GARCH-DCC (1.1) approach with integrating of the coronavirus and Russia-Ukraine conflict which measured by the dummy variables.

The empirical findings of this paper validate a considerable correlation among Bitcoin and energy commodity indices if coronavirus and Russia-Ukraine conflict surprises are included in variance estimations. These findings demonstrate the existence of the financialization of energy commodity markets and Bitcoin and external factors especially, in the case of health, politic and social. Additionally, the empirical findings associated to the degree of the tenacity of the volatility, are susceptible in the existence of healthy crisis and Russia-Ukraine conflict shocks into the employed GARCH-DCC (1,1) methodology. The dynamic conditional correlation (DCC) among Bitcoin and selected energy commodity indices emerge to react significantly additional in the case of coronavirus surprises than the Russia-Ukraine conflict surprises.

Finally, this research is structured as follows: in the second section, we present a literature review. Section 3 describes the econometric procedure employed in this paper. In the section 4, we present the dataset utilized in our investigation. The section 5 exposes the empirical outcomes relative to the influence of coronavirus confirmed cases in USA and in China on the association amongst energy commodity and Bitcoin. Finally, in section 6, we conclude, and we present some important policy implications of this study.

2. Introduction

For the sudden incidents, comprising the terrorist assaults, wars, financial coverage news, and wholesome crisis, will result surprise, panic and worry among the worldwide traders and outcome withinside the short panic-promoting response (Burch et al., 2016; Derbali et al., 2020a; Derbali et al., 2020b; Derbali et al., 2012a, Derbali et al., 2021b). A growing grouping of monetary and economic framework, along with the research of Carter and Simkins (2004), Chen and Siems (2004), Nikkinen et al. (2008), Kollias et al. (2011), Derbali and Jamel (2019), and Papakyriakou et al. (2019), which has forwarded the effect of the terrorist attacks on the worldwide economic inventory marketplace indices.

Guidolin and La Ferrara (2010), Hudson and Urquhart (2015) and Gu et al. (2012) study the impact of each violent and non-violent international activities on worldwide inventory markets. Jamel and Derbali (2019) display that terrorism elements is a giant and vital aspect in clarifying the estimate volatilities of the inventory marketplace returns withinside the situation of the DSEWI (Damascus Securities Exchange Weighted Index), which ought to be accredited into rationalization after assessing volatility.

Also, Ye and Karali (2016) hire an intraday dataset to analyze the response of the crude oil returns and volatilities to deliver bulletins via the Energy Information Administration (EIA) and the American Petroleum Institute (API) at some point of the use of duration of observe from August 01, 2012, to December 31, 2013. From their empirical findings, they expect that deliver surprises in collectively API and EIA bulletins have a right of way inverted affect at the returns and a giant and wonderful affect at the volatility.

Similarly, Halova et al. (2014) reveal at an intraday dataset to evaluate the impact of the unanticipated aspect withinside the EIA's crude oil accounting bulletins on collectively the go back and the volatility. Halova et al. (2014) display that the electricity returns react similarly appreciably to unanticipated changes withinside the deliver levels at some point of the insertion duration than throughout the elimination progression. The pandemic propagation will genuinely have the same affect.

Nippani and Washer (2004) deal with the inventory marketplace indices of eight truly encouraged economies via the SARS epidemic propagation and finish that the SARS pandemic had no unwanted and awful impact at the economic inventory markets of the encouraged international locations with the exemption of China and Vietnam. In the identical context, Chen et al. (2007) study the impact of the SARS epidemic at the profitability of the lodge shares in exchanges of Taiwan and the Chinese mainland and finish sizable and terrible affect.

He et al. (2020) attempt to research and examine the direct affects and spillovers of the COVID-19 at the economic inventory markets of eight nations. By using a traditional t-exams and a non-parametric Mann–Whitney assessments, He et al. (2020) inspect empirically each day go back dataset from the economic inventory marketplace in China, Japan, South Korea, Germany, Spain, Italy, France, and USA. Their empirical findings reveal that the COVID-19 pandemic has a poor and sizeable however in short-time period have an impact on at the economic inventory markets of the prompted nations. Also, they discover that the impact of the COVID-19 pandemic at the economic inventory marketplace indices of decided on nations has bidirectional spillover affects amongst Asian economies and European and American economies.

Sansa (2020) commences to look at the have an impact on of the propagation of the COVID-19 at the economic inventory markets in China and in USA thru the duration of look at since March 01, 2020, to March 25, 2020. Additionally, Sansa (2020) shows the lifestyles of effective and large connection among the unfold of the COVID-19 pandemic instances and complete the used global economic inventory marketplace indices (Such as, New York Dow Jones and Shanghai inventory exchange) at some point of the duration of look at because March 01, 2020, to March 25, 2020, in USA and in China. Then, those findings mean that the COVID-19 pandemic had a large have an impact on global economic inventory marketplace indices since March 01, 2020, to March 25, 2020, in China and in USA.

3. Methods

The econometric method applied in our studies which is going to evaluate returns and volatilities of the power commodities and Bitcoin responses to the COVID-19 epidemic shocks and Russia-Ukraine conflict surprises the DCC multivariate specification (Engle, 2002).

The Dynamic Conditional Correlation (DCC) method has the pliancy of univariate specification of GARCH model (generalized autoregressive conditional heteroskedasticity) but does now no longer allow in view that the ‘expletive of dimensionality’ of a multivariate GARCH representations (generalized autoregressive conditional heteroskedasticity). The evaluation of GARCH-DCC specs calls for of steps. We evaluate, withinside the initial moment, the conditional suggests of returns and the conditional suggest of variance of all indices hired in our studies. In the section 2, we hire a reliable regression residual hooked up withinside the section 1 to assess the conditional connections amongst power commodity indices and Bitcoin during the COVID-19 epidemic shocks and Russia-Ukraine conflict surprises.

Then, to gain the response of major energy commodities returns associated with bitcoin simply at the surprise element, we make use of the following model: GARCH (1,1) model (generalized autoregressive conditional heteroskedasticity) is conducted with the assistance of using the equivalent (1):

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (1)$$

Where, the measurements ω, α and β correlate to the factors that require to will be measured. The estimate conditional relationship matrix R_t of the consistent disruptions ε_t which is recommended with the following equal:

$$R_t = \begin{bmatrix} 1 & q_{12t} \\ q_{21t} & 1 \end{bmatrix} \qquad (2)$$

Where, $\varepsilon_t = D_t^{-1} r_t$ and the estimate matrix R_t can be attained in the following equation:

$$R_t = Q_t^{*\ -1} Q_t Q_t^{*\ -1} \qquad (3)$$

Where, Q_t symbolizes the time-varying covariance matrix of ε_t and $Q_t^{*\ -1}$ signifies the upturned diagonal matrix along through the square root of the diagonal basics of Q_t. Besides, by showing that $Q_t^{*\ -1}$ is equivalent to the subsequent equation:

$$Q_t^{*\ -1} = \begin{bmatrix} \frac{1}{\sqrt{q_{11t}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{22t}}} \end{bmatrix} \qquad (4)$$

Consequently, the arrangement GARCH-DCC (1,1) is attained by the subsequent equation:

$$Q_t = \omega + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} \qquad (5)$$

With, $\omega = (1 - \alpha - \beta)\bar{Q}$, where $\bar{Q}$ signifies the unconditional covariance of the standardized disturbances mentioned by ε_t. ω, α, and β correspond to the determined measurements. Furthermore, this article provides some contributions to the economic and financial literature by the incorporating of a supplementary value in the arrangement GARCH-DCC (1,1) which assess the COVID-19 epidemic shocks and Russia-Ukraine conflict surprises. Consequently, our estimated models are presented by the subsequent equations:

$$Q_t = \omega + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} + \gamma COVID - 19_t \qquad (6)$$

$$Q_t = \omega + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} + \theta RUC_t \qquad (7)$$

With, $COVID - 19_t$ indicates the unexpected COVID-19 surprise pronouncements at moment t. This variable is a dummy variable which takes 0 before December 18, 2019 and takes 1 for each day beginning to this date. RUC_t indicates the unexpected Russia-Ukraine conflict surprise pronouncements at moment t. This variable is a dummy variable which takes 0 before February 21, 2022 and takes 1 for each day beginning to this date.

4. Data analysis

The database utilized in our research consist of everyday period collection at the returns and the conditional volatilities of Bitcoin and decided on energy commodities. Therefore, to research the immediate effect of the COVID-19 pandemic and Russia-Ukraine conflict surprises, we targeted withinside the expected and surprise factors withinside the COVID-19 instances alternate and Russia-Ukraine conflict surprises. Our facts pattern covers the duration of examine since January 04, 2016, to April 04, 2022. The dataset utilized on this article is collected from website such as, https://www.investing.com.

We notice that whole utilized stock price indices of Bitcoin and energy commodities are converted by the logarithm construction. We assess the logarithmic return formulation as $r_t = ln\left(\frac{p_t}{p_{t-1}}\right)$, with the indicator P_t symbolizes the stock market index at the period t and the indicator P_{t-1} corresponds to the stock market index at the period *t-1*.

In Table 1, we represent extremely significant descriptive statistics for the employed everyday returns of energy commodity indices and Bitcoin. We reveal that straight possible mean of daily return is equal to 0.000220 for the BRENT OIL but the higher probable mean of quotidian returns is equal to 0.000347 for the CRUDE OIL WTI escorted by BITCOIN with a daily return which equal to 0.000251 and the NATURAL GAS with a daily return which equal to 0.000280.

For the volatility of daily return of energy commodity indices and Bitcoin, which measured by the standard deviation, we can show that Natural Gas represents a high daily volatility equal to 0.014180 followed respectively by CRUDE OIL WTI with a quotidian volatility of 0.055769, Bitcoin with a daily volatility of 0.013363 and Brent Oil with a daily volatility of 0.013261.

Therefore, the coefficients of skewness statistic have a negative sign for the BRENT OIL variable. The distribution of the BRENT OIL index is asymmetrical in the left. Also, BITCOIN, CRUDE OIL WTI, and NATURAL GAS present a coefficient of skewness statistic with a positive sign. This outcome suggests that the distribution of BITCOIN, CRUDE OIL WTI, and NATURAL GAS are asymmetrical in the right. The presence of the identical make signs for these indicators supports the presence of a correlations amongst them.

Additionally, our outcomes prove that the assessed coefficients of the kurtosis indicator are greater than the 0. This result encourages the existence of a leptokurtic distribution. Furthermore, the leptokurticity is employed in the economic and financial information, especially with the stronger expansions than the standard distribution, requiring accompanying various abnormal assessments. Moreover, the approximate positive sign of the Jarque-Bera coefficient indicates that the null hypothesis of normal distribution of the indicators employed in our investigation can be reduced. Additionally, the higher-intensity significance of the Jarque-Bera measurement demonstrates that the employed financial period cycle is non-normally distributed.

Definitively, the assessed quantities of skewness, kurtosis and Jarque-Bera measurements of the numerous indices employed in this study suggest that the distribution of the assessed measurement of each indicator are not normally distributed. Consequently, we can eliminate the null assumption of the normality of the financial period cycle of the outputs at a degree of 1%.

Moreover, an examination of the causal association between Bitcoin and energy commodities necessitates stationarity tests to validate the request of integration of each indicator. The results of the Levin-Lin-Chu assessment, the Im-Pesaran-Shin assessment, the Augmented Dickey-Fuller assessment, and the Phillips Perron assessment utilized to the applied indicators are demonstrated in Table 2. Consequently, the recognition or elimination of the null hypothesis of the test is established on the significance of the probabilities and statistics concerning to the suggested assessments. These probabilities are matched to a level of 10%. If these probabilities are lesser to 10%, so we eliminate the null hypothesis which indicates that the utilized indicators are non-stationary and if these probabilities are superior to 10%, so we acknowledge the null hypothesis. In our case and based on Table 2, we observe that all utilized indicators are stationary in concentration corresponding to the Lin-Chu test, the Im-Pesaran-Shin test, the Augmented Dickey-Fuller test and the Phillips Perron test.

Table 3 summarizes major statistical attributes for the unconditional correlation matrix amongst Bitcoin and energy commodities. Founded on the unconditional correlation demonstrated in the table 3, we find that Bitcoin have a negative relationship with the BRENT OIL. Furthermore, we show that Bitcoin have a positive association with CRUDE OIL WTI and NATURAL GAS. This outcome confirms that COVID-19 pandemic and Russia-Ukraine conflict surprises can describes the spillover impacts of Bitcoin in energy commodities indices.

Figure 1 provides the progress of daily returns of employed stock market indices such as Bitcoin and energy commodities. For BRENT OIL, we notice that higher variability is observed in the first quarter of 2020. This period corresponds to the first important propagation of the COVID-19 cases in the world. Also, it can be noted that Bitcoin time series reveal numerous breaks in their projected return evolution across the period of study especially in January/March 2020 (first important propagation of COVID-19 pandemic) and January/March 2022 (Russia-Ukraine conflict). For the CRUDE OIL WTI, we find that their returns exhibit some important breaks in their progressions mostly, in two period such as, January to March 2020 in which the spread of COVID-19 epidemic is started in all countries in the world and throughout the Russia-Ukraine conflict in the first quarter of 2022. The NATURAL GAS index offers numerous significant break downs in their return progressions particularly in the third and fourth quarter of three years 2016, 2017, and 2018 (before the COVID-19) and in the third and fourth quarter of two years 2020 and 2021 (during the COVID-19) in which numerous countries have acknowledged that they have an significant total of COVID-19 confirmed cases and during the first quarter of 2022 which is coincided with the Russia-Ukraine conflict. Then, the pics detected in returns progressions of the chosen energy commodities can be justified by the significance of the impact of COVID-19 and Russia-Ukraine conflict shocks on the measured returns and volatilities of these indices.

Bitcoin presents many substantial pics in their return progressions mainly in the third and fourth quarter of three years 2016, 2017, and 2018 (before the COVID-19) and in the third and fourth quarter of two years 2020 and 2021 (during the COVID-19) in which several countries have recognized that they have an important total of COVID-19 confirmed cases and throughout the first quarter of 2022 which is coincided with the Russia-Ukraine conflict. Then, we can justify the impact of COVID-19 and Russia-Ukraine conflict shocks on the returns and volatilities of the Bitcoin.

Figures 2, 3, 4, and 5 present the progress of the conditional volatilities of returns for the energy commodities indices and Bitcoin. It can be noticed that Crude Oil WTI and Brent Oil accomplish the highest of their conditional volatility evolutions in two periods such as: the first quarter of 2020 which be consistent to the pronouncement of the COVID-19 confirmed incidents in all regions in the world and the first quarter of 2022 which coincided with the Russia-Ukraine conflict. For Bitcoin, we see that the conditional volatility of this asset achieves its highest in the first and the second quarter of all used years; 2016, 2017, 2018, 2019, 2020, 2021, and 2022. Then, we can presume that COVID-19 and Russia-Ukraine conflict surprises show an important influence on Bitcoin. Finally, For Natural Gas, we remark that their conditional volatility attains its greatest value in the third and the fourth quarter of all employed years; 2016, 2017, 2018, 2019, 2020, and 2021, and the first quarter of 2022. Then, we can presume that COVID-19 and Russia-Ukraine conflict surprises show an important influence on Bitcoin. The principal finding validates that COVID-19 and Russia-Ukraine conflict (RUC) shocks have a fundamental and significant impact on the energy commodities indices and Bitcoin.

Table 1. The descriptive statistics

	BITCOIN	BRENT OIL	CRUDE OIL WTI	NATURAL GAS	COVID-19	RUC
Mean	0.000251	0.000220	0.000347	0.000280	0.380827	0.021668
Median	0.000000	0.001017	0.000944	0.000000	0.000000	0.000000
Max	0.085984	0.082852	0.138815	0.085984	1.000000	1.000000
Min	-0.078410	-0.121499	-0.122561	-0.078410	0.000000	0.000000
Std. Dev.	0.013261	0.011310	0.013363	0.014180	0.485750	0.145644
Skewness	0.308453	-1.443906	0.082833	0.175982	0.490836	6.570667
Kurtosis	7.648065	25.35915	32.02592	7.257419	1.240920	44.17366
Jarque-Bera	1395.136	32254.04	53465.65	1158.082	257.5166	118538.0
Prob.	0.000000*	0.000000*	0.000000*	0.000000*	0.000000*	0.000000*
Obs.	1523	1523	1523	1523	1523	1523

Note: *Table recaps descriptive statistics of quotidian returns for Energy commodities indices and Bitcoin, such as Crude Oil West Texas Intermediate, Brent Oil, and Natural Gas. The period of study is since January 04, 2016, to April 04, 2022. The significance at the 1% threshold is denoted by *.*

Source: *Elaborated by authors*

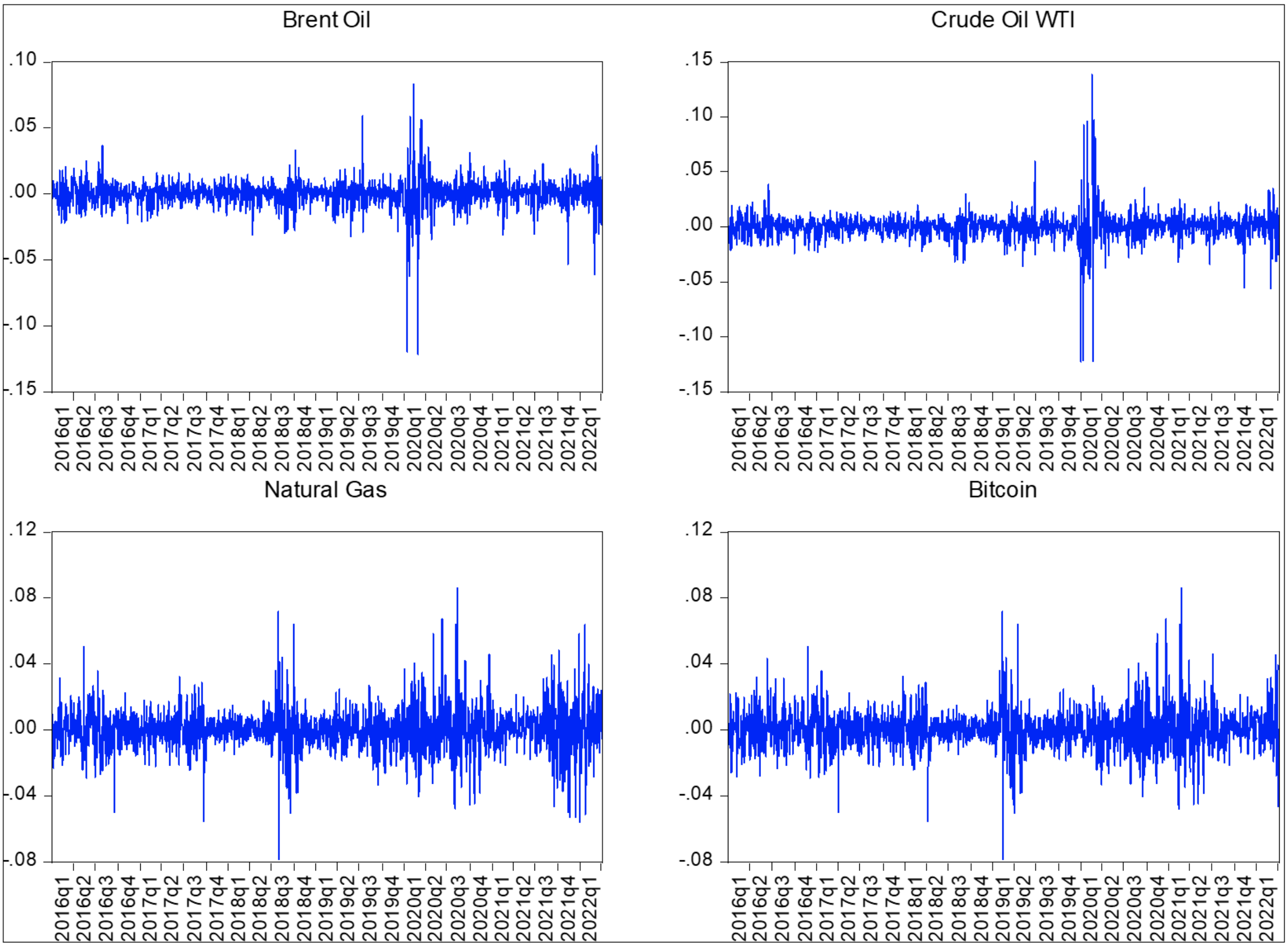

Figure 1. Daily returns of energy commodity indices and Bitcoin over the period of study since January 04, 2016, to April 04, 2022

Source: *Elaborated by authors*

Table 2. The unit root test

Procedure	Statistic	Prob.**	Cross-sections	Obs
Null assumption: presumes common unit root method				
Levin, Lin & Chu (LLC) t* test	-38.1165	0.0000	4	1520
Null assumption: presumes individual unit root method				
Im, Pesaran and Shin (IPS) W-stat test	-35.0082	0.0000	4	1520
ADF – Fisher Chi-square test	571.380	0.0000	4	1520
PP – Fisher Chi-square test	573.091	0.0000	4	1521

Note: *Table 2 recaps unit root test of daily returns of Bitcoin and energy commodity indices. The data period is from January 04, 2016, to April 04, 2022*

Source: *Elaborated by authors*

Table 3. Unconditional correlation between Bitcoin and Energy commodities

	BRENT OIL	CRUDE OIL WTI	NATURAL GAS	BITCOIN	COVID-19	RUC
BRENT OIL	1.0000	0.0434	-0.0089	-0.0098	0.0102	0.0108
CRUDE OIL WTI	0.0434	1.0000	0.0837	0.0069	0.0285	0.0052
NATURAL GAS	-0.0089	0.0837	1.0000	0.0062	0.0375	0.0438
BITCOIN	-0.0098	0.0069	0.0062	1.0000	0.0274	0.0498
COVID-19	0.0102	0.0285	0.0375	0.0274	1.0000	0.1898
RUC	0.0108	0.0052	0.0438	0.0498	0.1898	1.0000

Note: *Table 3 recaps unconditional correlation matrix between quotidian returns of energy commodity indices and Bitcoin. The data period is from January 04, 2016, to April 04, 2022.*

Source: *Elaborated by authors*

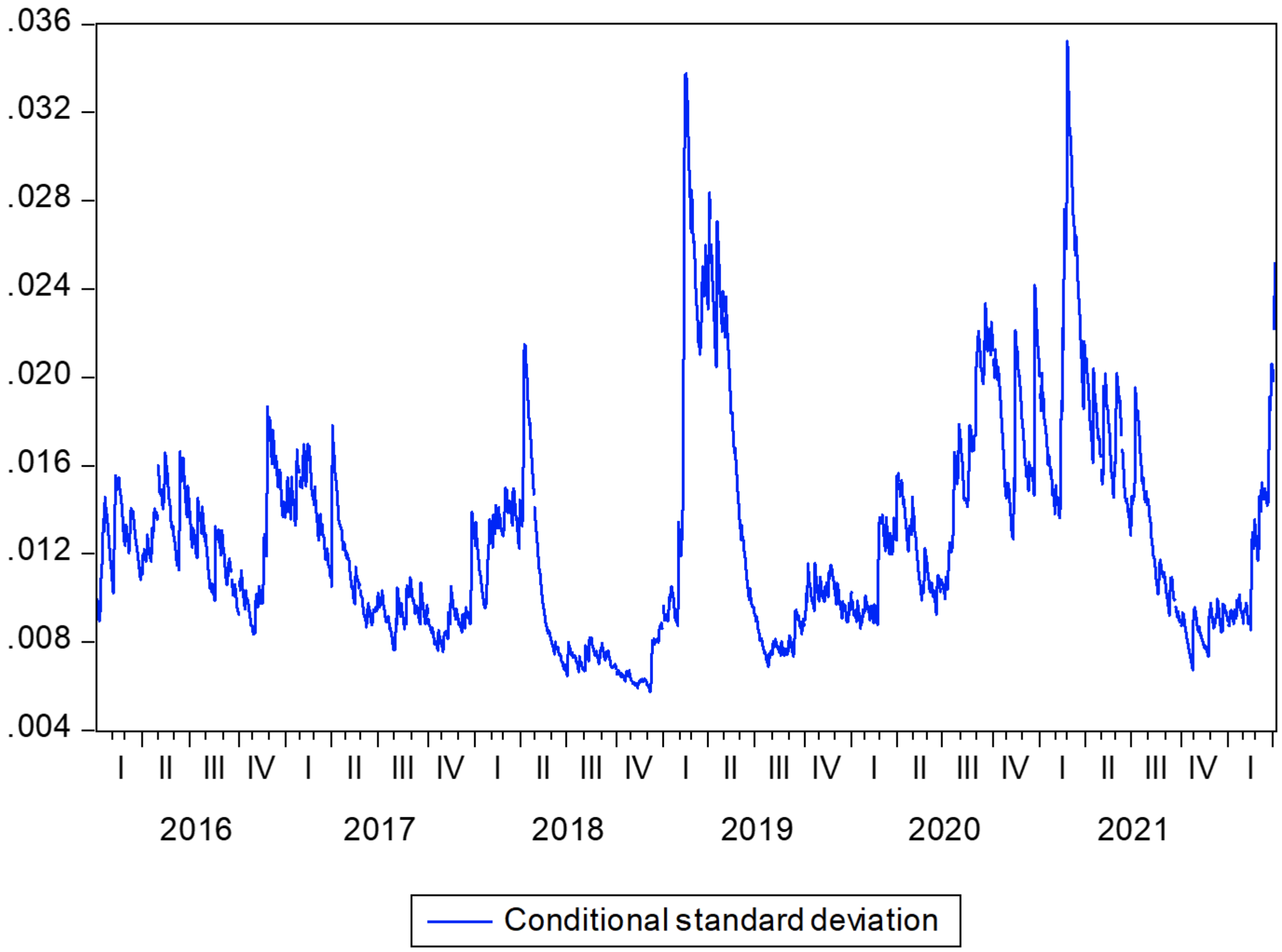

Figure 2. The daily conditional volatility of Bitcoin over the period of study since January 04, 2016, to April 04, 2022

Source: Elaborated by authors

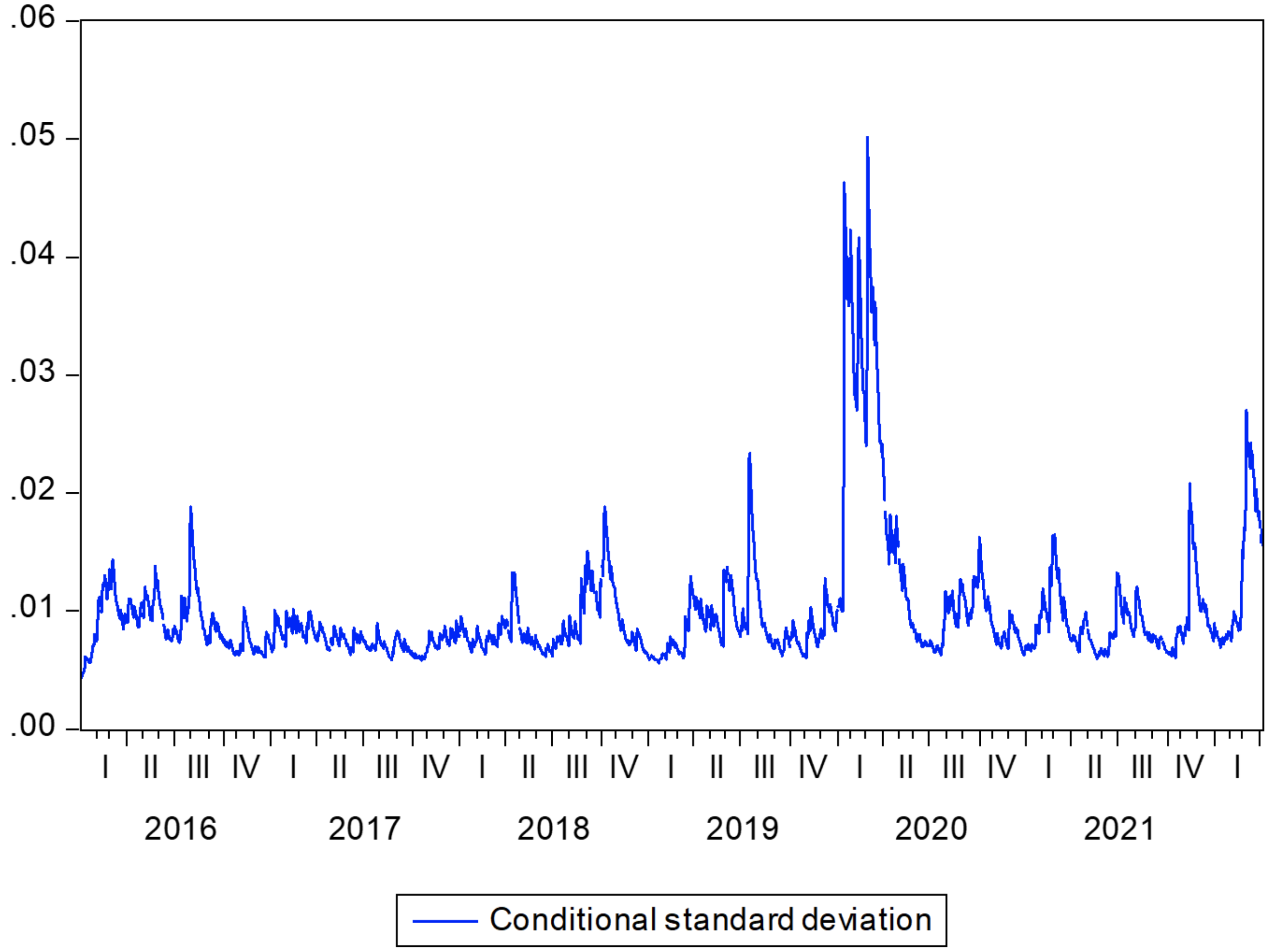

Figure 3. The daily conditional volatility of Brent Oil over the period of study since January 04, 2016, to April 04, 2022

Source: Elaborated by authors

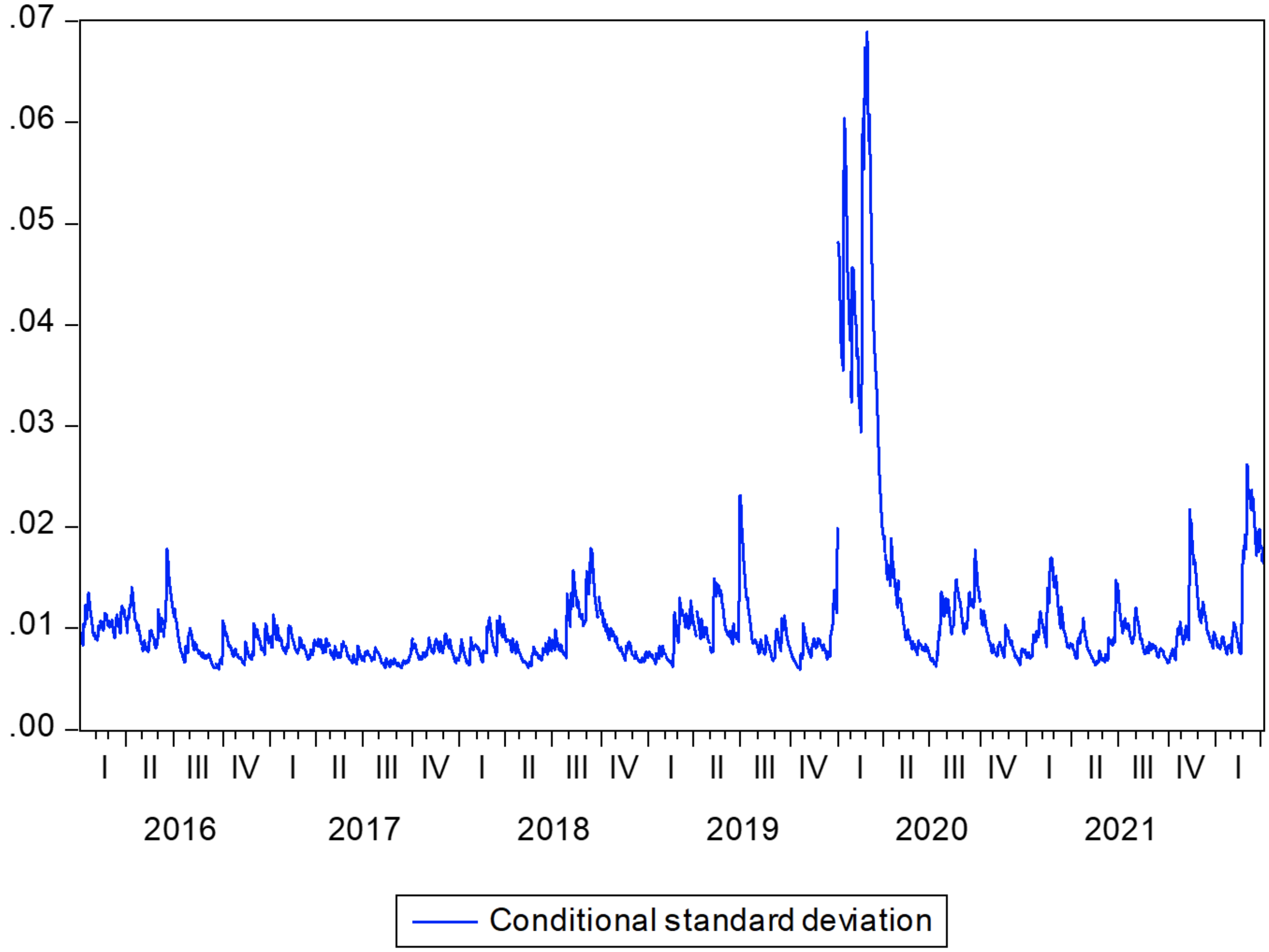

Figure 4. The daily conditional volatility of Crude Oil WTI over the period of study since January 04, 2016, to April 04, 2022

Source: Elaborated by authors

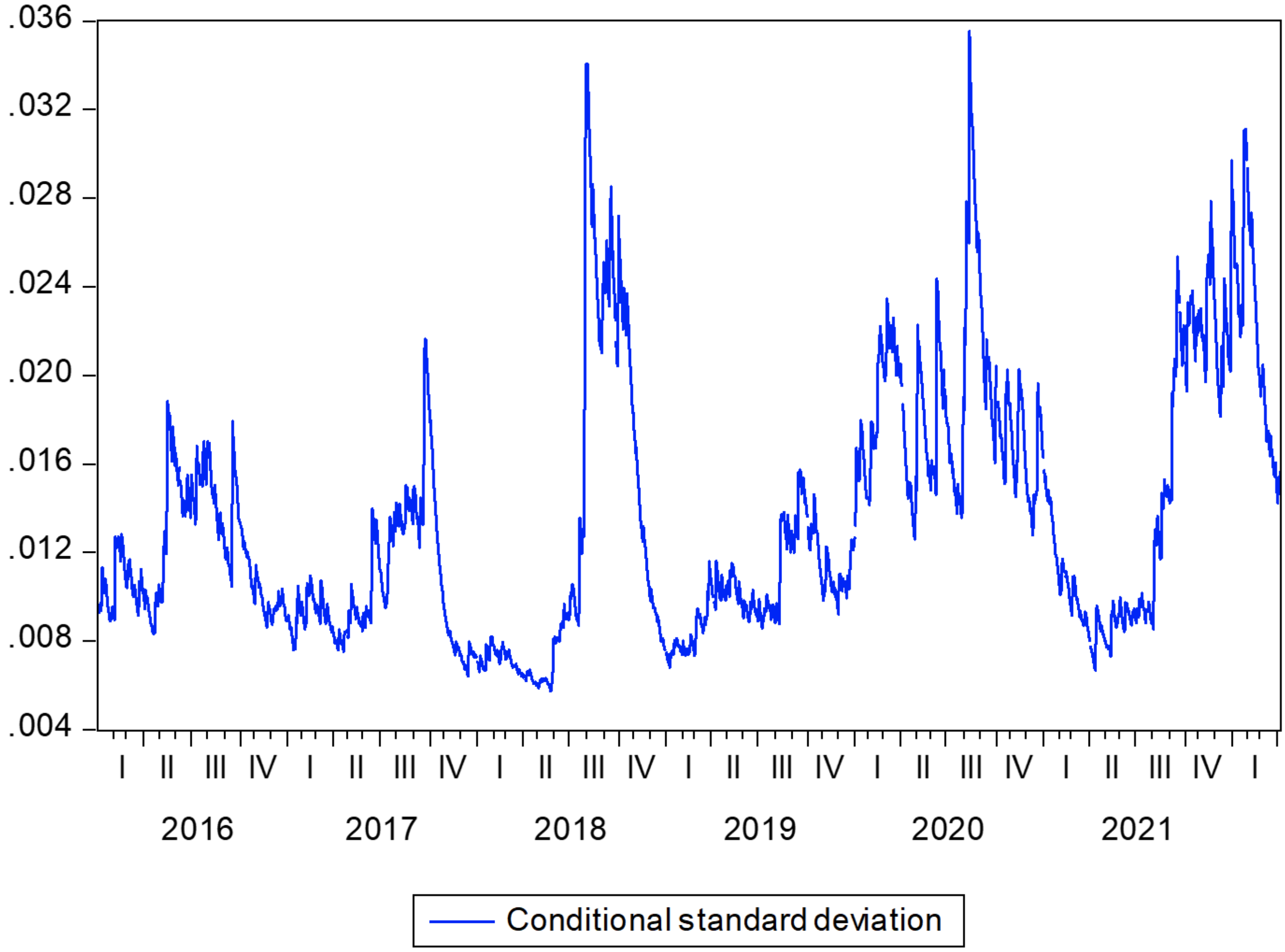

Figure 5. The daily conditional volatility of Natural Gas over the period of study since January 04, 2016, to April 04, 2022

Source: Elaborated by authors

5. Empirical results

In our empirical examination of this study, we investigate the influence of the COVID-19 pronouncements and the Russia-Ukraine conflict surprises on the dynamic relationship amongst the returns of energy commodities indices and Bitcoin. The econometric approach utilized in our research is the GARCH-DCC (1,1) model introduced by Engle (2002). The data sample passes across the period of analysis through January 04, 2016, to April 04, 2022. Furthermore, the chosen energy commodity indices are the Crude Oil West Texas Intermediate, the Brent Oil, and the Natural Gas. Additionally, we integrate a dummy variable in the GARCH-DCC (1,1) specification which measure the COVID-19 pronouncements and the Russia-Ukraine conflict shocks.

Figures 6, 7, and 8 indicate the evolution of the dynamic conditional correlation between energy commodities indices and

Bitcoin. It can be observed that the DCC among Bitcoin and Natural Gas and between Bitcoin and Brent Oil accomplish the maximum of their dynamic conditional correlation in two periods such as: in 2020 which be consistent to the pronouncement of the COVID-19 confirmed cases in all regions in the world and the first quarter of 2022 which coincided with the Russia-Ukraine conflict. It can be observed that the DCC among Bitcoin and Natural Gas and between Bitcoin and Brent Oil accomplish the maximum of their dynamic conditional correlation in two periods such as: in 2020 which be consistent to the pronouncement of the COVID-19 confirmed cases in all regions in the world and the first quarter of 2022 which coincided with the Russia-Ukraine conflict. Then, we can presume that COVID-19 and Russia-Ukraine conflict surprises show an important influence on the dynamic conditional correlation between energy commodities indices and Bitcoin. This result corroborates that COVID-19 and Russia-Ukraine conflict surprises have an important and considerable influence on the dynamic conditional correlation between energy commodities indices and Bitcoin.

The Table 4 describes the most important descriptive statistics relative to the estimated dynamic conditional correlation between energy commodities indices and Bitcoin in without integration of the COVID-19 pronouncements and the Russia-Ukraine conflict surprises in the estimated model. Based on this table, we find that in the maximum the bigger DCC is between Bitcoin and NATURAL GAS (0.70243) and among Bitcoin and BRENT OIL (0.716724). Therefore, these outcomes suggest the significant implication of the two energy commodity indices such as Natural Gas and Brent Oil in the financial stock markets. Furthermore, these findings validate a significant dynamic conditional correlation between energy commodities indices and Bitcoin principally during the period with the presence of unanticipated shocks. Also, we remark the importance impact of the unanticipated surprises in financial stock markets particularly, for the return and volatility of the energy commodity classes.

In addition, Table 5 recap the descriptive statistics for the estimated DCC among energy commodities indices and Bitcoin in the presence of COVID-19 shocks. Based on this Table, we demonstrate that in the maximum, the larger dynamic conditional correlation is between Bitcoin and NATURAL GAS (0.679185) and amongst BRENT OIL and Bitcoin (0.794847). These findings suggest the importance of the two energy commodity indices such as Natural Gas and Brent Oil in the international financial markets. Additionally, this outcome explains the great implication of the dynamic conditional correlation among energy commodities indices and Bitcoin mainly throughout the existence of the COVID-19 shocks.

Finally, based on the Table 6 which summarizes the descriptive statistics for the estimated dynamic conditional correlation between energy commodities indices and Bitcoin in the existence of Russia-Ukraine conflict surprises, we assume that this conflict in is more important than COVID-19 shocks, principally in operation of financial stock markets. Furthermore, we observe the presence of a significant linkage between the Russia-Ukraine conflict surprises and the international financial market indices, principally in the case of energy commodities and cryptocurrencies assets.

Moreover, and seeing at the daily moment, we can corroborate that surprise elements in Russia-Ukraine conflict shocks have accomplished a fundamental purpose in the enhancements of the volatility of extremely crucial energy commodities assets. These outcomes are not surprising. The unique possible explanation and probable is to offer the indispensable consequence of the Russia-Ukraine conflict shocks and financial market on the international financial markets and the worldwide economy, and the declarations associated to the fluctuations in Russia-Ukraine conflict shocks may noticeably influence the outside economic fundamentals and subsequently the significant volatility of the energy commodity indices and cryptocurrencies assets such as Bitcoin. Additionally, the considerable influence of Russia-Ukraine conflict surprises in financial stock market can be justified by the role of Russia in exportation of oil and natural gas.

Consequently, the effect of COVID-19 surprises is encouraged by the importance of this epidemic to dominate the global financial stock market indices and the worldwide economic organization. Furthermore, COVID-19 surprises have a significant impact on the uncertainties of the extremely significant and highly uncertain energy commodities.

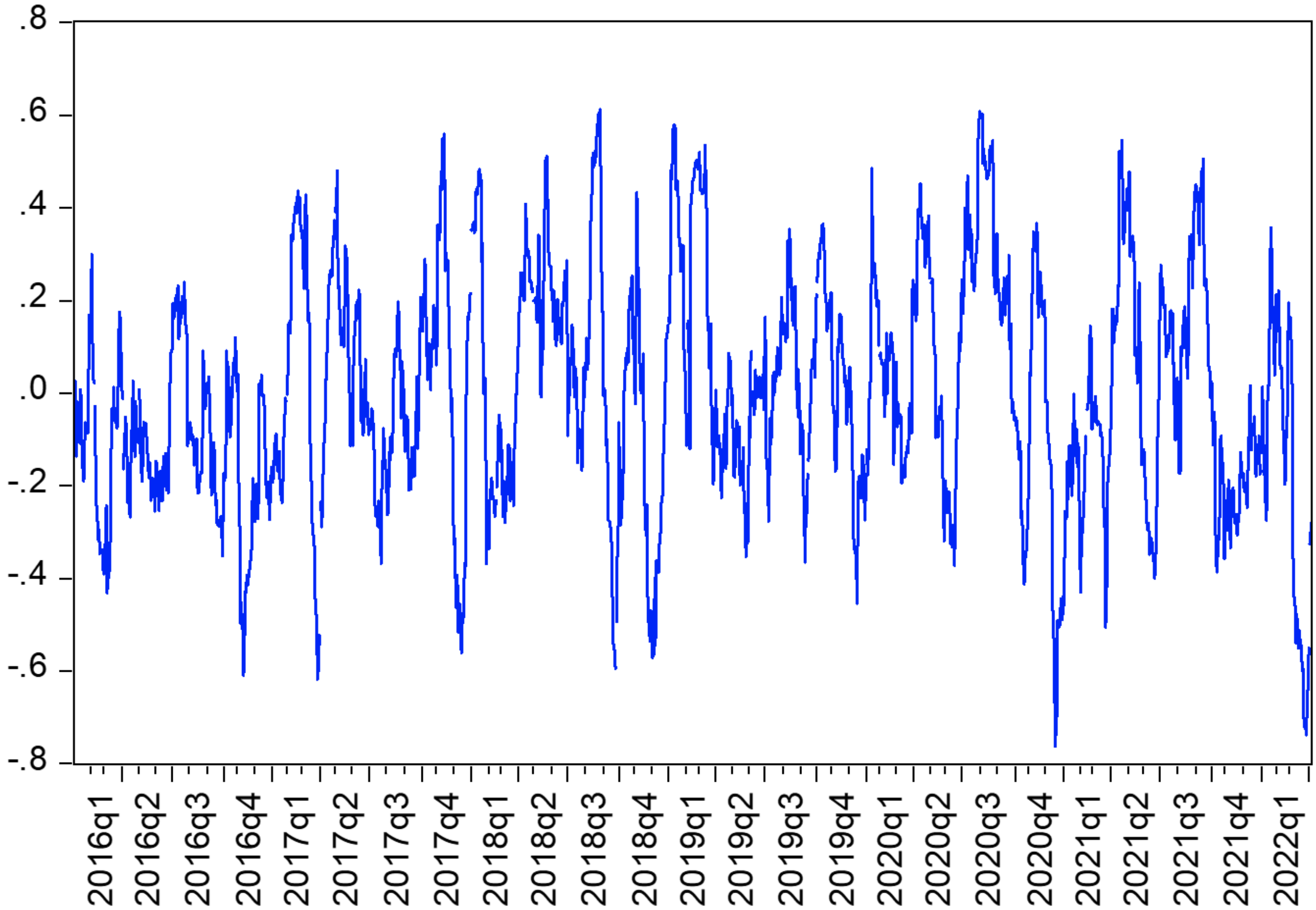

Figure 6. The dynamic conditional correlation between Bitcoin and Brent Oil over the period of study since January 04, 2016, to April 04, 2022
Source: *Elaborated by authors*

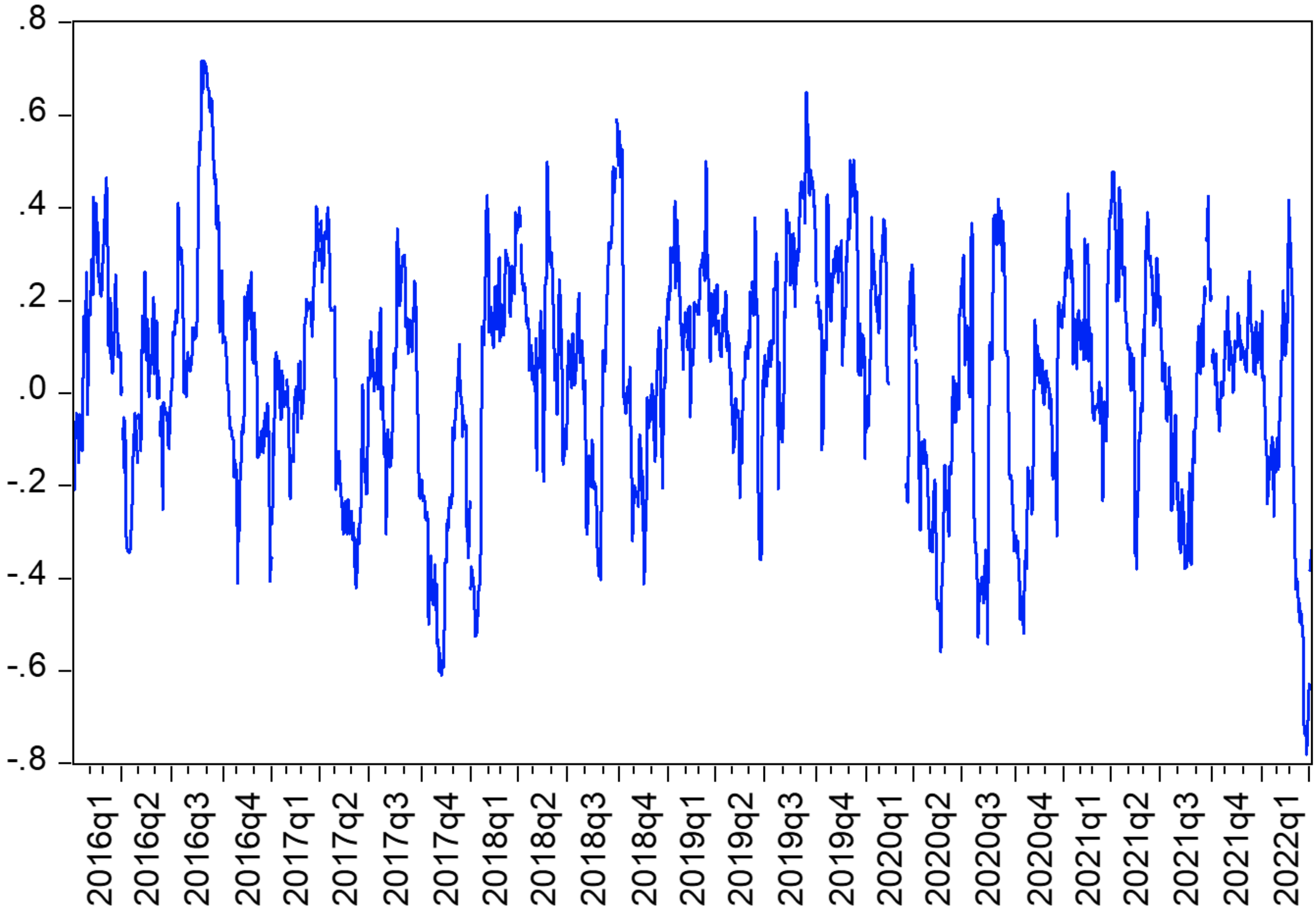

Figure 7. The dynamic conditional correlation between Bitcoin and Natural Gas over the period of study since January 04, 2016, to April 04, 2022

Source: *Elaborated by authors*

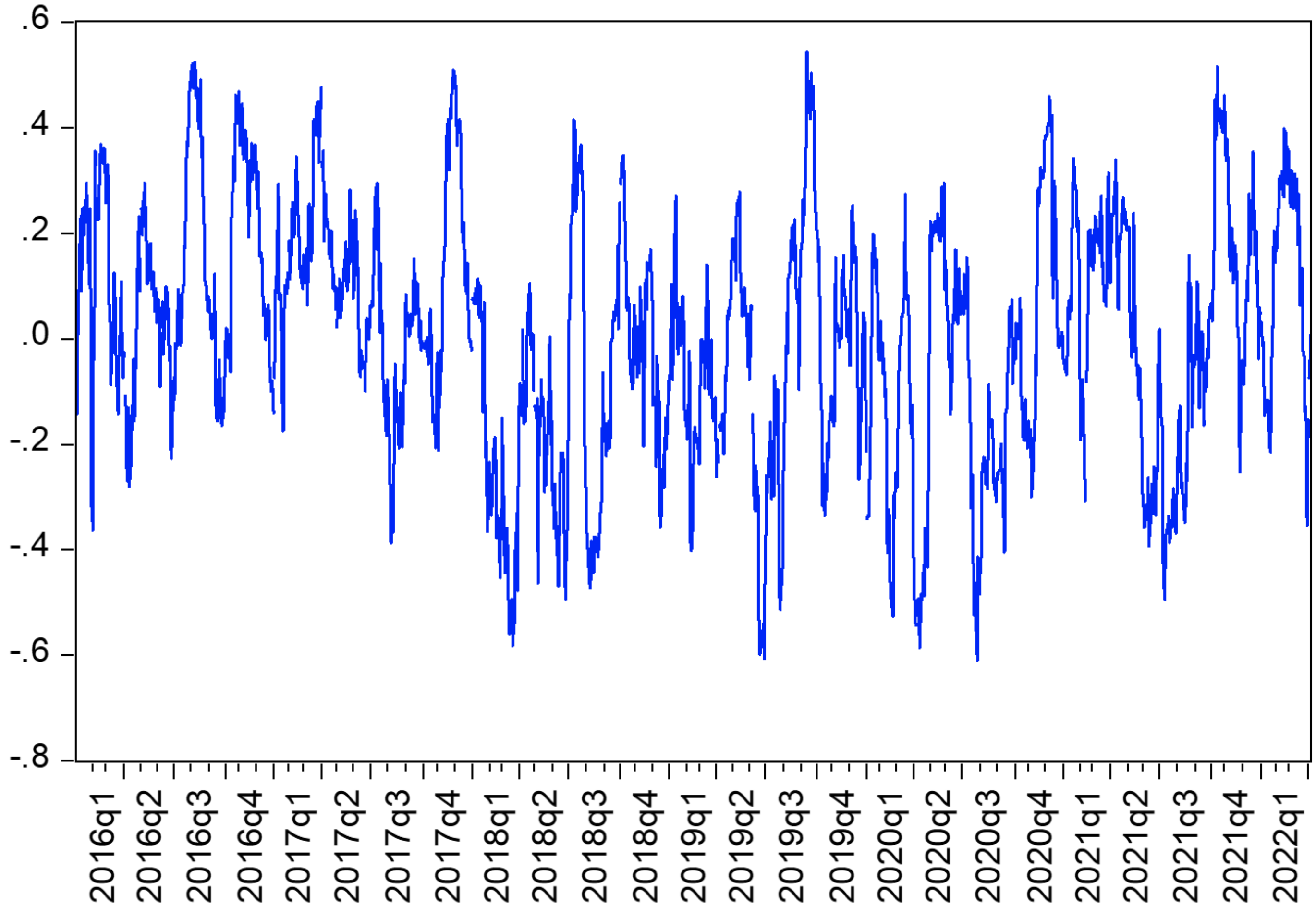

Figure 8. The dynamic conditional correlation between Bitcoin and Crude Oil WTI over the period of study since January 04, 2016, to April 04, 2022

Source: *Elaborated by authors*

Table 4. Descriptive statistics for DCC among Energy commodity indices and Bitcoin without COVID-19 and RUC shocks

	Dynamic correlation among Bitcoin and		
	BRENT OIL	**NATURAL GAS**	**CRUDE OIL WTI**
Mean	3.63E-05	0.041963	0.008375
Median	-0.01145	0.068923	0.024053
Max	0.70243	0.716724	0.543701
Min	-0.76363	-0.7805	-0.60983
Std. Dev.	0.258854	0.245634	0.236122
Skewness	-0.00317	-0.29286	-0.18399
Kurtosis	2.673652	3.026085	2.545567
Jarque-Bera	6.672273	21.52758	21.41275
Prob.	0.035574	0.000021	0.000022
Obs.	1503	1503	1503

Notes: *The table 5 gives brief statistics of correlation among Energy commodity indices and Bitcoin, specifically the Crude Oil West Texas Intermediate, the Brent Oil, and the Natural Gas in existence of the COVID-19 shocks in China. The used period is from January 04, 2016, to April 04, 2022. The variable significant at the (1%) threshold is characterized by (*).*

Source: *Elaborated by authors*

Table 5. Descriptive statistics for DCC among Energy commodity indices and Bitcoin with COVID-19 shocks

	Dynamic correlation among Bitcoin and		
	BRENT OIL	**NATURAL GAS**	**CRUDE OIL WTI**
Mean	4.03E-05	0.046537	0.009288
Median	-0.01269	0.076436	0.026675
Max	0.679185	0.794847	0.602964
Min	-0.84687	-0.86557	-0.6763
Std. Dev.	0.287069	0.272408	0.261859
Skewness	-0.00351	-0.32478	-0.20405
Kurtosis	2.96508	3.355928	2.823034
Jarque-Bera	7.399551	23.87409	23.74674
Prob.	0.039452	2.33E-05	2.44E-05
Obs.	1503	1503	1503

Notes: *The table 5 gives brief statistics of correlation among Energy commodity indices and Bitcoin, specifically the Crude Oil West Texas Intermediate, the Brent Oil, and the Natural Gas in existence of the COVID-19 shocks in China. The used period is from January 04, 2016, to April 04, 2022. The variable significant at the (1%) threshold is characterized by (*).*

Source: *Elaborated by authors*

Table 6. Descriptive statistics for DCC among Energy commodity indices and Bitcoin with RUC shocks

	Dynamic correlation among Bitcoin and		
	BRENT OIL	NATURAL GAS	CRUDE OIL WTI
Mean	4.14E-05	0.047838	0.009548
Median	-0.01305	0.078572	0.02742
Max	0.69817	0.817065	0.619819
Min	-0.87054	-0.88977	-0.69521
Std. Dev.	0.295094	0.280023	0.269179
Skewness	-0.00361	-0.33386	-0.20975
Kurtosis	3.047963	3.449737	2.901946
Jarque-Bera	7.606391	24.54144	24.41054
Prob.	0.040554	2.39E-05	2.51E-05
Obs.	1503	1503	1503

Notes: *The table 5 gives brief statistics of correlation among Energy commodity indices and Bitcoin, specifically the Crude Oil West Texas Intermediate, the Brent Oil, and the Natural Gas in existence of the COVID-19 shocks in China. The used period is from January 04, 2016, to April 04, 2022. The variable significant at the (1%) threshold is characterized by (*).*
Source: *Elaborated by authors*

Table 7 presents the empirical results relative to the Estimation of GARCH-DCC (1,1) model amongst energy commodity indices and Bitcoin in existence of the COVID-19 shocks and Russia-Ukraine conflict shocks and without these factors. Several significant conclusions appear from this empirical examination. First, we exhibit that COVID-19 surprises and Russia-Ukraine conflict shocks influence the dynamic conditional correlation between energy commodity indices and Bitcoin. The negative sign of the coefficients of the COVID-19 surprises and Russia-Ukraine conflict shocks indicates that the fluctuations on health and war crisis decrease the average concentration of volatility of energy commodities indices and the cryptocurrencies assets (Bitcoin).

According to the influence of COVID-19 surprises and Russia-Ukraine conflict shocks on the dynamic conditional correlation amongst Bitcoin and selected energy commodities indices in our study, the experimental results presented in the Table 7 signify that the 1% growth in COVID-19 shocks entrains a reduction of 0.0524688 percent in the dynamic conditional correlation amongst returns of BRENT OIL and Bitcoin, and similarly, 0.0254351 and 0.0635542 for the dynamic conditional correlation between the returns of Bitcoin and CRUDE OIL WTI and NATURAL GAS.

Besides, we show that 1 percent elevation in Russia-Ukraine conflict shocks causes a diminution of 0.0152623 percent in the dynamic conditional correlation amongst the returns of BRENT OIL and Bitcoin, and consistently, 0.0536263 and 0.0637212 for the dynamic conditional correlation between the returns of Bitcoin and with CRUDE OIL WTI and NATURAL GAS. In the identical framework, we observe that the considerable difference among COVID-19 surprises and Russia-Ukraine conflict shocks and their influence on the dynamic conditional correlation amongst energy commodity indices and Bitcoin. Our experimental outcomes explain that Russia-Ukraine conflict shocks and COVID-19 surprises has a significant and negative but short-term impact on the international financial stock markets. Additionally, we discover that the influence of the Russia-Ukraine conflict shocks and COVID-19 surprises on the stock market indices has a bidirectional spillover impacts amongst energy commodity indices and Bitcoin.

Furthermore, we confirm an explanation that the sum of the assessed volatility coefficients (+) is very contiguous to the unity (1). For the state of the assessed dynamic conditional correlation between energy commodity indices and Bitcoin as showing, we show a preeminent tenacity and persistence of the volatility amongst COVID-19 surprises and Russia-Ukraine conflict shocks and energy commodity markets and cryptocurrencies assets. Formerly, we can validate the presence of one possible clarification which establishes that a significant perseverance drives laterally through the phenomena of financialization of the international financial stock market indices, the cryptocurrencies assets, political crisis and conflicts, war, and health epidemic spread, such as energy commodity indices, Bitcoin, COVID-19 epidemic, and Russia-Ukraine conflict (Creti et al., 2013; Chebbi and Derbali, 2015; Chebbi and Derbali, 2016a; Chebbi and Derbali, 2016b; Derbali and Jouini, 2019; Derbali and Bouzgarrou, 2020; Derbali et al., 2020a; Derbali et al., 2020b; Derbali et al., 2021a; Derbali et al., 2021b). The empirical outcomes of our study emphasize the implication of employing the GARCH-DCC (1,1) measurement in determining the crucial time-varying of the dynamic conditional correlations amongst energy commodity indices and Bitcoin in the existence of the health epidemic (COVID-19) and political crisis and war (Russia-Ukraine conflict).

Table 7. Estimation results of GARCH-DCC (1,1) among Energy Commodityindices and Bitcoin

Coefficients	ωi	α_i	β_i	Without shocks		With COVID-19 shocks	With RUC shocks
BITCOIN and BRENT OIL	0.0488971 (2.14)**	0.1193374 (9.89)*	0.8726311 (82.13)*	-			
	0.0611273 (2.13)**	0.1073621 (9.91)*	0.8836282 (67.09)*			-0.0328112 (-6.78)*	
	0.0218734 (2.01)**	0.0911263 (9.78)*	0.9022872 (81.08)*				-0.0152623 (-9.71)*
BITCOIN and CRUDE OIL WTI	0.0585273 (2.09)**	0.0926312 (9.45)*	0.9028372 (63.12)*	-			
	0.0429576 (2.14)**	0.1023643 (9.07)*	0.8812535 (83.44)*			-0.0254351 (-7.88)*	
	0.0418478 (2.18)**	0.1102934 (8.48)*	0.8836452 (71.32)*				-0.0536263 (-9.65)*
BITCOIN and NATURAL GAS	0.0477238 (2.90)*	0.1293993 (8.92)*	0.8635423 (82.09)*	-			
	0.0319450 (2.83)*	0.1023645 (8.83)*	0.8825361 (51.87)*			-0.0635542 (-7.94)*	
	0.0482564 (2.04)**	0.0922442 (9.17)*	0.8836421 (83.12)*				-0.0637212 (-9.32)*

Notes: *Table 7 summarizes the estimated parameters from the GARCH-DCC (1,1) specification. To estimate this specification, the authors employ the daily volatility series of the returns for Energy commodity indices and Bitcoin, specifically the Crude Oil WTI, the Brent Oil, and the Natural Gas during the period used in our study since January 04, 2016, to April 04, 2022. The variable significant at the 1%, 5% and 10% points are characterized by *, ** and ***, correspondingly. The statistics in parentheses expose the estimated t-Student.*

6. Conclusion

Commonly, the associations between energy commodity indices and Bitcoin have understood important literature through the preceding two decades. Various significant developments have been produced to improve the estimated outcomes. Among these improvements, we perceive a presence of the monetary policy surprises in the estimated volatility specifications, the political instabilities surprises, war shocks (Russia-Ukraine conflict), and the health crisis surprises (COVID-19). These groups of surprises in the volatility probably will be influenced by the country-detailed financial and economic proceedings, regional and global financial and economic influences (for example, the 2007-2008 financial crisis surprises, the European sovereign-debt crisis surprises in 2010, the 2011 Arab Spring surprises, the FOMC monetary policy surprises, the ECB monetary policy surprises, COVID-19 pandemic surprises, and Russia-Ukraine conflict surprises).

In our paper, we investigate the dynamic conditional correlations amongst Bitcoin and crucial commodities which covering the sector of energy (Crude Oil WTI, Brent Oil, and Natural Gas), during the period of examination since January 04, 2016, to April 04, 2022. Then, we utilize the GARCH-DCC (1.1) methodology with incorporating of COVID-19 surprises and Russia-Ukraine conflict shocks as a dummy variables. Our experimental outcomes in this research paper suggest fantastic significant dynamic conditional correlations between energy commodity indices and Bitcoin if COVID-19 and Russia-Ukraine conflict shocks are incorporated in the expected variance equivalence. Our conclusions prove the existence of the financialization phenomena of energy commodity indices and Bitcoin. Furthermore, our assessment outcomes correlated with the concentration of the persistence of the volatility, are susceptible in the presence of the COVID-19 and Russia-Ukraine conflict shocks in GARCH-DCC (1,1) model. The dynamic conditional correlations amongst energy commodity indices and Bitcoin emerge to react considerably additional in the existence of the Russia-Ukraine conflict shocks in China than the COVID-19 shocks. Additionally, our outcomes suppose that the performance of the energy commodity indices incorporating Bitcoin elasticities, recommend the suggestion that the energy commodity indices cannot generate a consistent and homogeneous portfolio class.

Completely, the impact of the COVID-19 and war (Russia-Ukraine conflict) shocks on the global financial stock markets exhibit a bidirectional spillover influence among energy commodity indices and Bitcoin. Also, the significant propagation of the coronavirus in the world and Russia-Ukraine conflict shocks negatively affected the connection amongst energy commodity indices and Bitcoin.

Our findings contribute and add to the investigation in financial and economic consequences of the recent epidemic and Russia-Ukraine conflict with providing an experimental confirmation that COVID-19 and recent war between Russia and Ukraine cause a bidirectional spillover influence on energy commodities and cryptocurrencies assets. Our investigation has a significant and considerable concern for the policymakers and the portfolio risk directors and supervisors. Additionally, and from a policy-making viewpoint, receiving straightforward an investigational explanation of the approximation volatility spillovers between worldwide financial stock markets is an imperative and vital phase in creating convenient monetary policy pronouncements and decisions and healthy strategies and policies, and political decisions and plans. For the viewpoint of portfolio risk managers and administrators, the consequences of our study are consistent to the suggestion of the cross-market hedging.

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Declaration of conflict interests

The authors proclaim no possible conflicts of interest regarding the investigation, authorship and/or publication of this paper.

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