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Investigating the Co-Volatility Spillover Effects between Cryptocurrencies and Currencies at Different Natures of Risk Events

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Abstract: This paper examines and confirms the varying volatility of the relationship between cryptocurrency and currency markets at different time periods, such as when the market encountered multiple risk events including the US–China trade war, COVID-19, and the Russian–Ukraine war. We employ the Diagonal BEKK model and find that the co-volatility spillover effects between the returns of cryptocurrencies and currencies, with the exception of Tether and the U.S. dollar index, evolved significantly. Furthermore, the co-volatility spillover effects between cryptocurrencies and EUR have the largest effects and fluctuations. Large-cap cryptocurrencies (Bitcoin and Ethereum) have greater co-volatility spillover effects between them and currencies. Regarding the ability of cryptocurrencies to act as safe-haven for currencies, we observe that Bitcoin, Ethereum, and Tether served as safe-havens during the US–China trade war, and Bitcoin was a safe-haven during COVID-19. During the 2022 Russian–Ukraine war, Bitcoin and Tether were safe-havens. Interestingly, our findings point out that Bitcoin provides a more consistent safe-haven function for currency markets. Overall, by including multiple global risk events and a comprehensive dataset, the results support our conjecture (and earlier studies) indicating that the capabilities of cryptocurrency are time-varying and related to market status and risk events with different natures.

Keywords: co-volatility spillover effects; cryptocurrency; diagonal BEKK model; exchange rates; global uncertainty

JEL Classifications: C32; G11; G14; G15

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1. Introduction

The foreign exchange market is by far the world's largest financial market with a daily turnover of USD 6.6 trillion in 2019 (an increase from USD 5.1 trillion in 2016), larger even than the stock market (Bank for International Settlements 2019). While foreign exchange trading is performed for practical purposes such as international trade, most currency trading is engaged in with the aim of earning a profit because of its high liquidity, around-the-clock trading and leverage (Hsu et al. 2021). The enormous volume of currency trade would make some currency prices extremely volatile, and many investors are attracted to the foreign exchange market due to the volatility and high returns (with risk).

Events around the world can influence exchange rates immediately due to the global interconnectedness of the foreign exchange market. For instance, the onset of the US–China trade war, begun when U.S. President Trump announced that the U.S. would impose tariffs on goods imported from China on 22 March 2018, reached a turning point on 15 January 2020 with the signing of the phase-one trade deal. As China becomes the U.S.'s top trading partner of over 120 countries and regions including the European Union, as well as Japan, the trade war is assuredly one of the most important events for the foreign exchange markets (Stensås et al. 2019; Xu and Lien 2020). Xu and Lien (2020) reported that the trade war caused heterogeneous effects on exchange rate dependence with the U.S. and China, and their trade partners can further affect the decisions of portfolio diversification, risk management, central bank interventions, and international trade.

The COVID-19 crisis is another event that had an enormous effect on exchange rates. It was declared a global public health emergency on 30 January 2020 and a pandemic on 11 March 2020 (by the World Health Organization). The ongoing COVID-19 crisis has not only had distressing health and social impacts worldwide but has also been pressuring the world economy and global growth (Congressional Research Service 2020). Li et al. (2021) and Jamal and Bhat (2022) reported that the COVID-19 pandemic has changed the expectations of market participants about the future value of exchange rates in the major COVID-19 hot spots. Specifically, the exchange rate is affected negatively (or weakened) due to the effect of COVID-19 cases and deaths in particular countries. The ongoing Russo–Ukrainian war has immensely influenced financial markets, gas and oil prices, and exchange rates since the beginning of the Russian invasion on 24 February 2022. This crisis has led to the rapid depreciation of the Russian ruble, which lost almost 50% of its value against the U.S. dollar at the end of February and the beginning of March 2022 (Lyócsa and Plíhal 2022), while the U.S. Dollar Index[1] reached an almost 20-year high in mid-May 2022, an increase of 9% since the Russian invasion of Ukraine (Capital.com 2022). In short, these phenomena of global uncertainty would force investors to look for alternative investment instruments such as cryptocurrency (Smutny et al. 2021), which can offer hedge or safe-haven advantages and mitigate asset risk exposure.

Cryptocurrency is decentralized digital money based on blockchain technology, the design of which possesses several key features of currencies such as being a medium of exchange, unit of account, and store of value (Yermack 2015; Baur and Dimpfl 2017; Baur et al. 2018b), and characteristics of gold, such as mining, finite supply, and decentralization (Dyhrberg 2016a, 2016b). Since the first decentralized cryptocurrency (Bitcoin) was developed in 2009, the popularity and applications of cryptocurrency have risen dramatically. As of 21 April 2022, the total number of cryptocurrencies has surpassed 19,000 with a total market capitalization of USD 1.9 trillion, with the top three highly capitalized cryptocurrencies (Bitcoin, Ethereum, and Tether) accounting for nearly 66.3% of the aggregate value (CoinMarketCap.com 2022). Evidently, cryptocurrency has quickly gained a lot of attention from market practitioners, scholars, regulators, and the financial press (Mikhaylov 2020).

Considering that the cryptocurrency's fundamental value, risk–return characteristics, and market environment exist outside of the traditional financial system, cryptocurrency seems to be less dependent on traditional economic systems and might be insulated from shocks pertaining to conventional financial markets (Kristoufek 2015; Feng et al. 2018; Shahzad et al. 2019; Smales 2019; Jeribi and Fakhfekh 2021). Some researchers and regulators suggest that cryptocurrency more closely resembles a speculative commodity than a currency (Baek and Elbeck 2015; Yermack 2015; Fry and Cheah 2016; Baur et al. 2018a; Stensås et al. 2019), and they find that a large majority of users treat their cryptocurrencies as an alternative investment instrument rather than as an alternative transaction system due to high volatility in the market (Glaser et al. 2014; Mikhaylov 2020). Moreover, the returns on financial assets usually exhibit a sizable unpredictable component, while Magner and Hardy (2022) report the evidence of predictability in cryptocurrencies and inferred that the cryptocurrency market exhibits arbitrage opportunities.

In the meantime, a growing number of studies has been assessing the capabilities of cryptocurrency, such as being a diversifier, hedge, or safe-haven against financial assets during normal periods and times of global uncertainty (such as the COVID-19 pandemic), respectively. For instance, some studies suggest cryptocurrency acts as a diversifier (Briere et al. 2015; Bouri et al. 2017b; Maghyereh and Abdoh 2020; Zeng et al. 2020; Corbet et al. 2018; Kajtazi and Moro 2019; Gil-Alana et al. 2020; Charfeddine et al. 2020; Bakry et al. 2021; Joshi et al. 2022; Kumaran 2022). On the other hand, several studies show that cryptocurrency can offer new opportunities for a hedge investment (Dyhrberg 2016a, 2016b; Bouri et al. 2017a; Baur et al. 2018a; Demir et al. 2018; Klein et al. 2018; Guesmi et al. 2019; Naeem et al. 2020; Huynh et al. 2020). In contrast, some studies find that cryptocurrency can be regarded as a safe-haven (Shahzad et al. 2019, 2020; Stensås et al. 2019; Urquhart and Zhang 2019; Ji et al. 2020; Hsu et al. 2021; Mariana et al. 2021). Particularly, Tether, a stablecoin in the cryptocurrency market, is considered by many as a safe-haven (Conlon et al. 2020; Goodell and Goutte 2020; Hasan et al. 2021; Vukovic et al. 2021).

In summary, many of these studies present conflicting views about the capabilities of cryptocurrencies as financial assets. Specifically, cryptocurrency's capabilities of being a hedging or safe-haven seem to be time-varying and contingent on market types and status, as well as economic and environmental uncertainties or shocks (Kliber et al. 2019; Shahzad et al. 2019; Stensås et al. 2019; Urquhart and Zhang 2019; Charfeddine et al. 2020; Ji et al. 2020; Hasan et al. 2021; Hsu et al. 2021). Thus, it is imperative for market practitioners to understand the underlying features and driving forces of the nature of market turmoil when searching for hedging or safe-haven assets to mitigate downside market risk.

In addition, very few studies (Urquhart and Zhang 2019; Hsu et al. 2021; de Olde 2021) have examined the dynamic correlations and volatility spillovers between cryptocurrencies and currencies and considered their relevant asset volatility behavior. For example, Urquhart and Zhang (2019) examine the intraday interaction between Bitcoin and world currencies and find evidence that Bitcoin is a hedge for the CHF, EUR, and GBP, but acts as a diversifier for the AUD, CAD, and JPY. Moreover, they show that Bitcoin is a safe-haven during extreme periods of market turmoil for CAD, CHF, and GBP. Hsu et al. (2021) analyze co-volatility spillover effects between cryptocurrencies (Bitcoin, Ethereum, and Ripple) and the ten most traded currency and gold markets under different global economic conditions. They find that cryptocurrencies are difficult as a safe-haven when the cryptocurrency market suffers, while cryptocurrencies can be used as a safe-haven against several currencies and gold during the COVID-19 outbreak. de Olde (2021) examines the safe-haven properties of Bitcoin for currencies (GBP, USD, and CNY) during Brexit and the US–China trade war and finds Bitcoin functions as a weak safe-haven for any of those currencies.

Overall, despite numerous studies that have explored the different economic and financial aspects of cryptocurrencies, some important questions remain unexplored and need additional investigation. In particular, the dynamic correlations between cryptocurrencies and currencies have not been properly examined. Moreover, several studies have already reviewed the unique capabilities of cryptocurrency during one single risk event (Conlon et al. 2020; Goodell and Goutte 2020; Vukovic et al. 2021; Ji et al. 2020; Mariana et al. 2021). However, few studies have compared the capabilities of cryptocurrency for financial assets between multiple risk events with different natures (Stensås et al. 2019; Hasan et al. 2021; Hsu et al. 2021; de Olde 2021). As a cryptocurrency's hedging and safe-haven role can change from one crisis to another (Hasan et al. 2021; Hsu et al. 2021), it is important to assess, compare, and update the capabilities of cryptocurrency among different risk events.

To fill the gaps in the existing literature regarding the capabilities of cryptocurrencies, this study extends Hsu et al.'s (2021) study by incorporating three global risk events with different natures and the most up-to-date dataset to obtain more comprehensive information on the impact of the current events. Thus, the aim of this study is to examine the varying volatility relationship between cryptocurrency and currency markets and to decide whether cryptocurrencies are a better safe-haven, hedge, or diversification asset for currencies at risk events with different natures. To do so, we investigate the co-volatility spillover effects between major cryptocurrencies (Bitcoin, Ethereum, and Tether) and with six world currencies (US dollar index (as a proxy for the US dollar), Euro, Japanese Yen, British Pound, Chinese Yuan, and Russian Ruble). We then further explore capabilities by examining the diversifier, hedge, or safe-haven properties of cryptocurrencies to currencies in order to facilitate risk management in the cryptocurrency and foreign exchange markets. The data used for the empirical analyses are the daily closing prices of cryptocurrencies and the foreign exchange rates from 7 August 2015 to 22 April 2022, a period that includes three specific events: namely the US–China trade war, the COVID-19 pandemic, and the 2022 Russian–Ukraine war. In particular, this analysis focuses on the behavior of the time-varying dependence parameter, which is estimated using a diagonal BEKK multivariate conditional volatility model, as it is a multivariate conditional volatility model with known mathematical regularity conditions and valid asymptotic statistical properties (McAleer et al. 2008). To the best of our knowledge, this is the first study to analyze the capabilities of cryptocurrency to currency markets while taking into consideration different risk events such as economic and political events and public health concerns. Using a comprehensive dataset that covers three global events, this study expects to find evidence confirming the capabilities of cryptocurrency being time-varying in relation to the market status and nature of risk events. Previous studies have examined the timer-varying behavior with one single risk event; a study with multiple risk events would fully explore and confirm the nature of the capabilities of cryptocurrency. The results will provide guidance for market participants to fully benefit not only from developing and promoting central bank digital currencies and building the legal regulatory system for the digital currency industry, but also building investment opportunities, hedging strategies, or risk insurance for managing financial portfolios.

The remainder of the paper is organized as follows: Section 2 discusses the empirical models, followed by the description of data in Section 3. Section 4 provides an analysis of the empirical results, and concluding comments are presented in Section 5.

2. Methodology

To examine the dynamic relationship between cryptocurrency and currency markets and to explore the diversifier, hedge, and safe-haven capabilities of cryptocurrency against movements in currency markets, we follow the method used by Hsu et al. (2021). The diagonal BEKK multivariate conditional volatility model, with well-established regularity conditions and valid asymptotic statistical properties under appropriate parametric restrictions (McAleer et al. 2008; McAleer 2019), is allowed to calculate and test the partial co-volatility spillover effects (Chang et al. 2018). Consider the conditional mean equation of the price return series:

$$R_t = E(R_t | I_{t-1}) + \varepsilon_t \tag{1}$$

where R_t is the financial returns, $R_t = (R_{1t}, \ldots R_{mt})'$, I_{t-1} is the information set available at time $t-1$, and ε_t is the conditionally heteroskedastic error term (return shocks), $\varepsilon_t = (\varepsilon_{1t}, \ldots \varepsilon_{mt})'$.

We follow McAleer et al. (2008)'s derivation, the vector random coefficient autoregressive (VRCAR) process of order one underlying the return shocks, ε_t, to derive the conditional volatility specifications, which is given as:

$$\varepsilon_t = \Phi_t \varepsilon_{t-1} + \eta_t \tag{2}$$

where ε_t and η_t are $m \times 1$ vectors, η_t is a random residual, $\eta_t \sim iid(0, C)$, and C is an $m \times m$ matrix. The symbol Φ_t is a random coefficient autoregressive matrix, with an $m \times m$ matrix of random coefficients, $\Phi_t \sim iid(0, A)$.

Under A is restricted to be a diagonal matrix, $A = aI_m$, McAleer et al. (2008) show that the conditional covariance matrix of the diagonal BEKK model, H_t, is given as:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \tag{3}$$

where A and B are both diagonal matrices, C is an upper triangular matrix of parameters, and $\varepsilon_{t-1}\varepsilon'_{t-1}$ is an $m \times m$ matrix.

As highlighted by Chang et al. (2018), the diagonal BEKK model is allowed to calculate and test the partial co-volatility spillover effects. The partial co-volatility spillover measures the impact of the lagged return shock of financial asset i on the subsequent co-volatility between two financial assets i and j at current period t, is defined as follows:

$$\frac{\partial H_{ij,t}}{\partial \varepsilon_{i,t-1}} = a_{ii} \times a_{jj} \times \varepsilon_{j,t-1},\ i \neq j \tag{4}$$

where $H_{ij,t}$ is the conditional covariance matrix, a_{ii} and a_{jj} are the elements in matrix A of the diagonal BEKK model, and $\varepsilon_{j,t-1}$ is the average return shock of financial assets j at time $t-1$ over the sample period.

It is possible to verify the partial co-volatility spillover effects through testing by estimating the weight matrix A in the diagonal BEKK model. If null hypothesis (H_0 : $a_{ii}a_{jj} = 0$) is rejected, there is a non-zero spillover effect from the return shock of financial asset i at time $t-1$ ($\varepsilon_{i,t-1}$) to the co-volatility between financial assets i and j at time t ($H_{ij,t}$). Different sizes of the weighting matrix A in the diagonal BEKK model and the average return shock could cause the different pattern of co-volatility spillover effects, and the signs of co-volatility spillover effects can be either positive or negative (Chang et al. 2019).

The nature of the interaction between cryptocurrencies and currencies and their co-volatility spillover effects are considered when analyzing the capabilities of cryptocurrency to act as a diversified, a hedge or a safe-haven against currency markets. We apply the definition of capabilities of an asset given in Hsu et al. (2021), which extends the framework proposed by Baur and Lucey (2010) and Baur and McDermott (2010). A diversifier is defined as an asset that has positive co-volatility spillover effects (positive correlation) with another asset or portfolio. A hedge is an asset that has negative co-volatility spillover effects (negative correlation) with another asset or portfolio. Negative co-volatility spillover effects between two assets in times of market stress or turmoil could be regarded as a safe-haven.

3. Data

The data used for this study were scoured from Yahoo Finance and included daily closing prices from 7 August 2015 to 22 April 2022 of cryptocurrencies and foreign exchange rates, with 1689 observations. The prices are listed in USD. We focus on the top three most highly capitalized cryptocurrencies and most widely traded cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), and Tether (USDT). Samples of six foreign exchange rates were selected, representing the main traded currencies by value: American Dollar (U.S. dollar index (DXY) is used as a proxy (Bouri et al. 2017b; Hsu et al. 2021)); Euro (EUR); Japanese Yen (JPY); British Pound (GBP); Chinese Yuan (CNY); and Russian Ruble (RUB). The daily price return is calculated as $R_t = \ln(P_t/P_{t-1}) \times 100$, where P_t and P_{t-1} are the daily closing price at time periods t and $t-1$, respectively.

The daily closing price and returns evolution of cryptocurrencies and exchange rates are shown in Figures 1 and 2. As shown in Figure 1, the prices of BTC and ETH seem to follow a similar pattern: the trend of the cryptocurrency price exhibits the presence of several periods of sharp increases and decreases. In particular, during the 2018 cryptocurrency crash (also known as the Bitcoin crash and the Great crypto crash) period, the prices of cryptocurrencies markedly decrease from the beginning of 2018 after an unprecedented boom in 2017, with such prices falling by 82% for BTC and 92% for ETH from market peak in January 2018 to December 2018. As the digital currency exchange Coinbase went public in April 2021 and China widened its crackdown on crypto mining, the prices of cryptocurrencies have significant increases and decreases in 2021. Moreover, prices of cryptocurrency showed a slight increase due to U.S. President Biden signing a sweeping executive order on cryptocurrency on 9 March 2022. As USDT is a stablecoin, which has successfully maintained a 1:1 ratio with the value of the U.S. dollar, the price of USDT is relatively stable even during market turmoil.

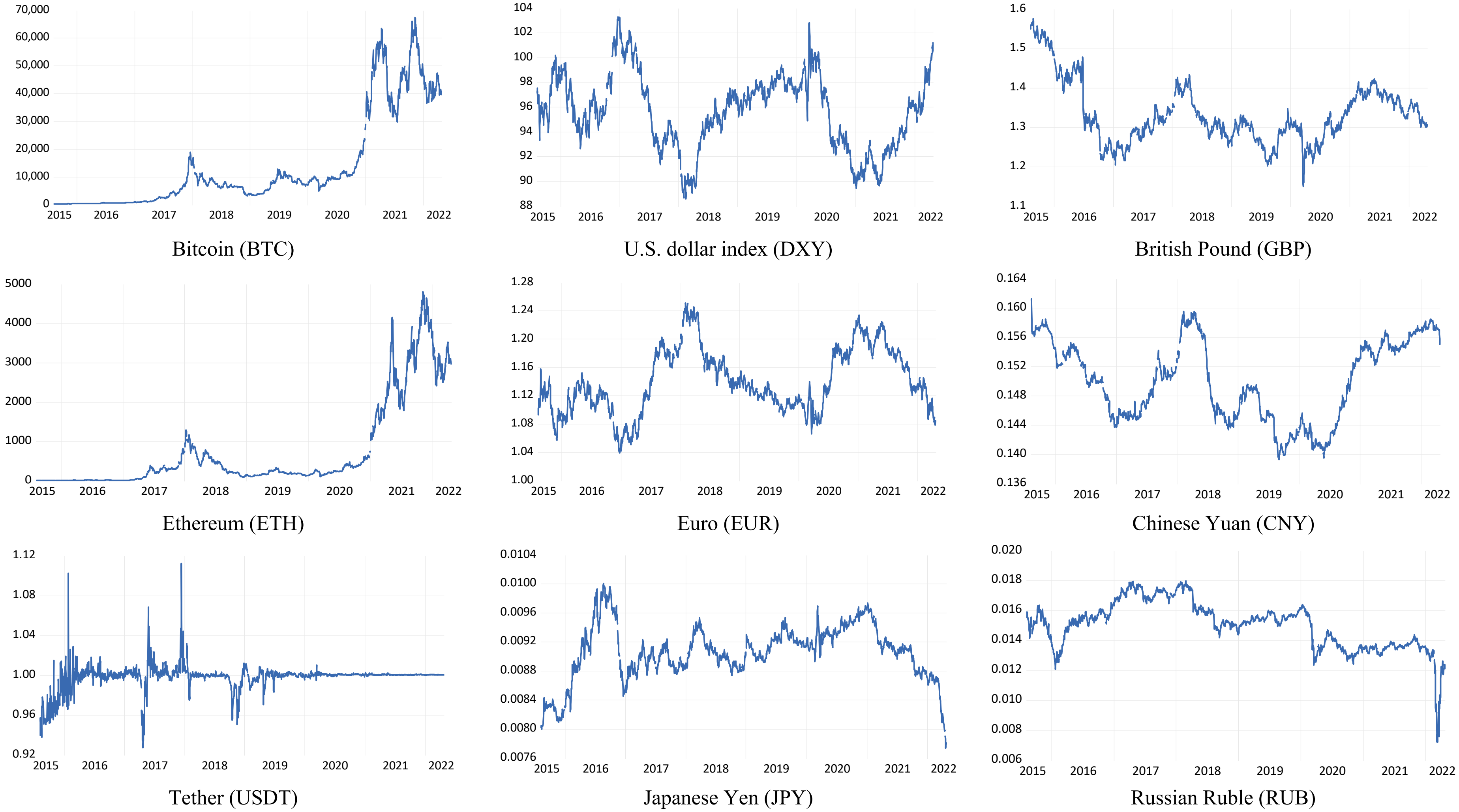

Figure 1. Daily Closing Price of Cryptocurrencies and Currencies (in US Dollars) from 7 August 2015 to 22 April 2022.

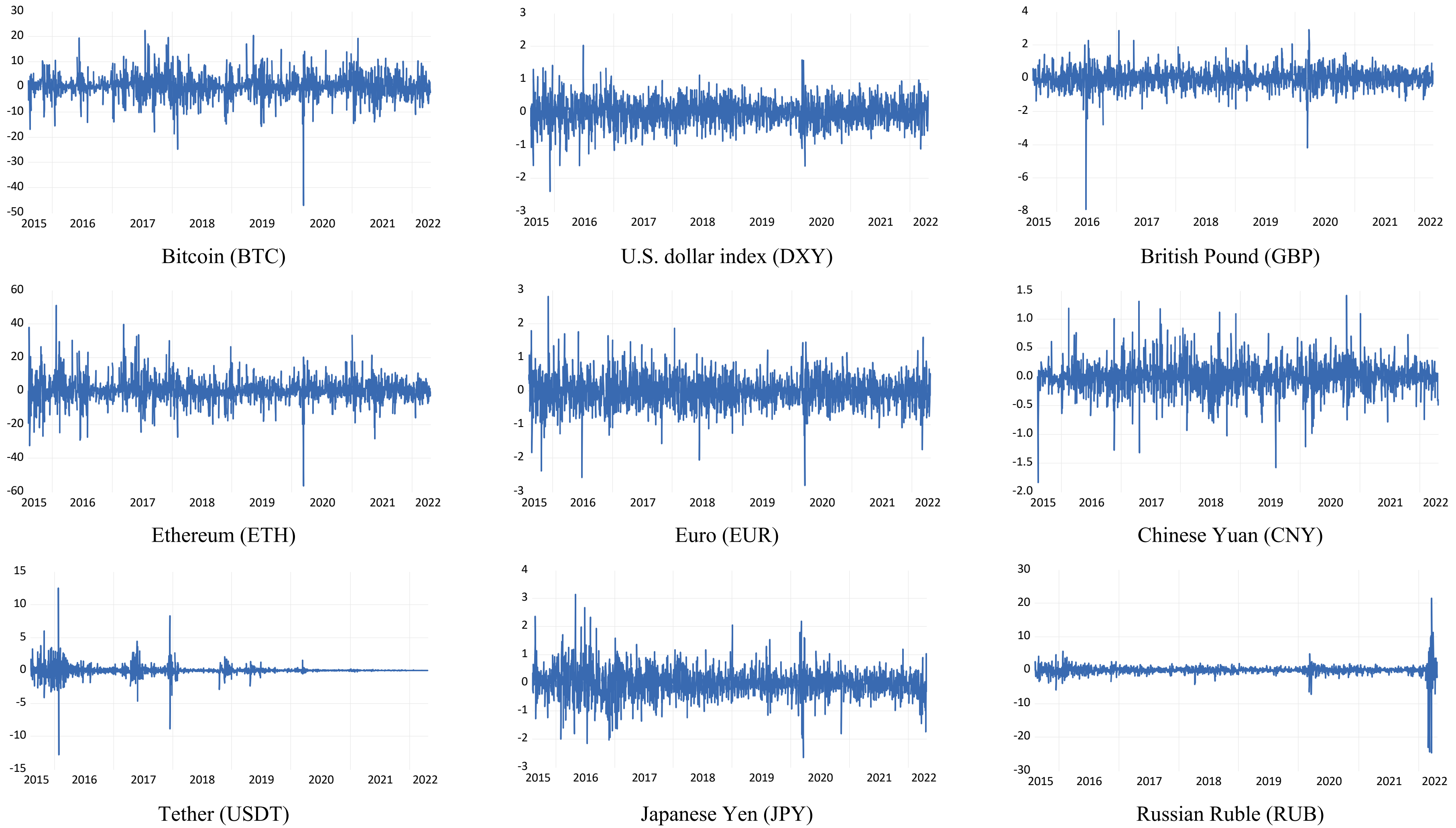

Figure 2. Daily Closing Price Returns of Cryptocurrencies and Currencies (in US Dollars) from 7 August 2015 to 22 April 2022.

For the time-series plot of exchange rates in Figure 1, the DXY is generally upward from the first quarter of 2018 (the US–China trade war) but rebounded from the first quarter of 2020 (the COVID-19 pandemic) and exhibits sharp increases during the Russian–Ukraine war period, contrary to the trend of EUR, JPY, GBP, CNY, and RUB. As displayed in Figure 2, fluctuations in both cryptocurrency returns and exchange rate returns show well-known financial stylized facts, such as the presence of volatility clustering and asymmetry behavior. However, cryptocurrency returns are clearly more volatile than exchange rate returns.

The descriptive statistics for the returns of cryptocurrencies and exchange rates in this study are given in Table 1. The average daily return is extremely high for the BTC and ETH, while it is quite small and close to zero for six currencies as well as USDT. The standard deviation shows that the degrees of dispersion in cryptocurrency returns (BTC and ETH) are greater than those of USDT and exchange rate returns. All returns series experience positive skewness except the EHT, USDT, and JPY, and all variables have a kurtosis statistic greater than three indicating a leptokurtic distribution. The Jarque–Bera statistic shows that none of these return series match the normal distribution. Additionally, the results of the ARCH Lagrange Multiplier (ARCH-LM) test of Engle (1982) for conditional heteroskedasticity suggest autocorrelation in the returns and their volatility. Finally, the results of applying the three unit root tests (ADF, PP, and KPSS)[2] show that the sequences R_t, for the daily data on all cryptocurrency returns and exchange rate returns exhibit stationarity properties.

Table 1. Descriptive Statistics.

	R_{BTC}	R_{ETH}	R_{USDT}	R_{DXY}	R_{EUR}	R_{JPY}	R_{GBP}	R_{CNY}	R_{RUB}
Mean	0.294	0.463	0.004	0.002	−0.001	−0.002	−0.010	−0.002	−0.013
Max	22.405	51.098	12.515	2.032	2.815	3.140	2.906	1.416	21.425
Min	−47.056	−56.561	−12.846	−2.399	−2.814	−2.669	−7.909	−1.841	−24.780
SD	4.646	7.371	0.856	0.403	0.467	0.517	0.600	0.264	1.643
Skew.	−0.635	0.228	0.003	−0.024	−0.039	0.155	−1.402	−0.203	−3.899
Kurt.	11.940	9.606	76.040	5.065	6.136	6.488	23.161	8.447	105.935
J-B	5734.2 ***	3083.5 ***	375,212.0 ***	300.0 ***	692.1 ***	862.7 ***	29,141.1 ***	2098.4 ***	749,496.7 ***
ARCH (5)	6.248 ***	11.459 ***	45.119 ***	18.136 ***	6.446 ***	21.980 ***	3.316 ***	6.003 ***	70.836 ***
ADF	−41.932 ***	−40.376 ***	−21.483 ***	−40.003 ***	−40.669 ***	−40.969 ***	−39.298 ***	−45.419 ***	−11.640 ***
PP	−42.050 ***	−40.473 ***	−148.399 ***	−40.211 ***	−40.886 ***	−40.973 ***	−39.324 ***	−45.179 ***	−46.579 ***
KPSS	0.122	0.222	0.224	0.126	0.123	0.435	0.161	0.380	0.033

Note: ARCH (5) is the test for heteroscedasticity for the 5th-order ARCH. The ADF and PP results of the unit root tests correspond to the case of unit with intercept but without trend. *** denotes significance at the 1% level.

Table 2 reports the correlation matrix between different cryptocurrency returns and exchange rate returns. Consistent with Yermack (2015) and Baur and Dimpfl (2017), it is evident that cryptocurrencies' returns are not correlated with most of the exchange rate returns examined. Bitcoin has a significant negative correlation with GBP and CNY while they have only a slight correlation. Ethereum has a slightly negative correlation with DXY and CNY. Tether has a positive correlation with DXY, as Tether is backed 1-to-1 by U.S. dollars. Overall, we conclude that cryptocurrencies are different from those currencies investigated in this study, and it can be inferred that cryptocurrency and currency are independent.

Table 2. Correlation Matrix.

	R_{BTC}	R_{ETH}	R_{USDT}	R_{DXY}	R_{EUR}	R_{JPY}	R_{GBP}	R_{CNY}	R_{RUB}
R_{BTC}	1.000								
R_{ETH}	0.554 ***	1.000							
R_{USDT}	0.051 *	0.044 *	1.000						
R_{DXY}	−0.037	−0.042 *	0.042 *	1.000					
R_{EUR}	−0.021	0.000	0.036	−0.101 ***	1.000				
R_{JPY}	−0.027	0.018	0.025	−0.039	0.419 ***	1.000			
R_{GBP}	−0.061 **	−0.033	−0.010	−0.067 ***	0.539 ***	0.140 ***	1.000		
R_{CNY}	−0.068 ***	−0.044 *	0.019	−0.044 *	0.286 ***	0.127 ***	0.258 ***	1.000	
R_{RUB}	0.026	0.018	−0.011	−0.072 ***	0.073 ***	−0.047 *	0.131 ***	0.112 ***	1.000

Note: ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

4. Empirical Results

This study pays particular attention to the different patterns of co-volatility spillover effects between cryptocurrency and currency markets under different global economic conditions and current events. We use the Diagonal BEKK model, in which the co-volatility spillover effect is a function of the diagonal elements of matrix A and the average return shock of asset j at time $t-1$ (i.e., $a_{ii} \times a_{jj} \times \varepsilon_{j,t-1}$).

A 7×7 matrix that includes all the variables is estimated for the Diagonal BEKK model consisting of one cryptocurrency return (R_{BTC}, R_{ETH} or R_{USDT}) and six exchange rate returns (R_{DXY}, R_{EUR}, R_{JPY}, R_{GBP}, R_{CNY}, and R_{RUB}). The empirical results of the estimates of matrix A of the Diagonal BEKK model are given in Table 3. All the coefficients in matrix A are statistically significant at the 1% level, except USDT and DXY. This implies that there are spillover effects from the impact of the returns shock of exchange rate (i) at the prior period to the co-volatility between cryptocurrency returns (j) and exchange rate returns (i) at the current period.

Table 3. Estimation of Diagonal Elements of A in the Diagonal BEKK Model for Cryptocurrency Returns and Exchange Rate Returns.

Bitcoin (BTC)		Ethereum (ETH)		Tether (USDT)	
Variables	**A**	**Variables**	**A**	**Variables**	**A**
R_{BTC}	0.213 ***	R_{ETH}	0.248 ***	R_{XRP}	0.464 ***
R_{DXY}	0.043 ***	R_{DXY}	0.040 ***	R_{DXY}	0.013
R_{EUR}	0.481 ***	R_{EUR}	0.376 ***	R_{EUR}	0.392 ***
R_{JPY}	0.174 ***	R_{JPY}	0.172 ***	R_{JPY}	0.173 ***
R_{GBP}	0.275 ***	R_{GBP}	0.292 ***	R_{GBP}	0.143 ***
R_{CNY}	0.160 ***	R_{CNY}	0.184 ***	R_{CNY}	0.234 ***
R_{RUB}	0.352 ***	R_{RUB}	0.347 ***	R_{RUB}	0.326 ***

Note: *** denotes significance at the 1% level.

In order to understand the capabilities of cryptocurrencies against currencies under the different times of market turmoil, the empirical analysis is conducted in its entire period and also subdivided into four sub-periods: (i) whole sample, from 7 August 2015 to 15 July 2021; (ii) US–China trade war, from 22 May 2018 to 15 January 2020; (iii) COVID-19 pandemic, from 30 January 2020 to 23 February 2022; and (iv) Russia–Ukraine war, from 24 February 2022 to 22 April 2022. The numbers of observations for each period are 1689, 458, 522, and 41. Table 4 shows the average return shocks and co-volatility spillover effects for both the whole sample period and for the three sub-periods, and the results of four time periods will be described in detail below.

Table 4. Co-volatility Spillover Effects.

Variables	Average Return Shocks	Partial Co-Volatility Spillover Effects					
		R_{DXY}	R_{EUR}	R_{JPY}	R_{GBP}	R_{CNY}	R_{RUB}
Group 1: Whole Sample (7 August 2015 to 22 April 2022)							
R_{BTC}	0.0174	0.00016 (0.04226)	0.00177 (0.47562)	0.00064 (0.17167)	0.00102 (0.27234)	0.00059 (0.15798)	0.00130 (0.34825)
R_{ETH}	0.1146	0.00115 (0.07402)	0.01070 (0.68991)	0.00491 (0.31637)	0.00830 (0.53546)	0.00524 (0.33816)	0.00987 (0.63652)
R_{USDT}	0.0037	-	0.00068 (0.14189)	0.00030 (0.06242)	0.00025 (0.05168)	0.00040 (0.08479)	0.00056 (0.11783)

Table 4. *Cont.*

Variables	Average Return Shocks	Partial Co-Volatility Spillover Effects					
		R_{DXY}	R_{EUR}	R_{JPY}	R_{GBP}	R_{CNY}	R_{RUB}
Group 2: US–China Trade War (22 March 2018 to 15 January 2020)							
R_{BTC}	−0.2480	−0.00225 (0.03983)	−0.02535 (0.44826)	−0.00915 (0.16179)	−0.01452 (0.25668)	−0.00842 (0.14889)	−0.01856 (0.32822)
R_{ETH}	−0.5446	−0.00545 (0.05762)	−0.05084 (0.53707)	−0.02331 (0.24628)	−0.03946 (0.41684)	−0.02492 (0.26324)	−0.04691 (0.49551)
R_{USDT}	−0.0007	-	−0.00012 (0.07142)	−0.00005 (0.03142)	−0.00004 (0.02601)	−0.00007 (0.04268)	−0.00010 (0.05931)
Group 3: COVID-19 Pandemic (30 January 2020 to 23 February 2022)							
R_{BTC}	−0.0312	−0.00028 (0.04436)	−0.00319 (0.49924)	−0.00115 (0.18019)	−0.00183 (0.28587)	−0.00106 (0.16582)	−0.00234 (0.36555)
R_{ETH}	0.1501	0.00150 (0.06647)	0.01401 (0.61959)	0.00643 (0.28412)	0.01087 (0.48089)	0.00687 (0.30369)	0.01293 (0.57164)
R_{USDT}	0.0002	-	0.00004 (0.01750)	0.00002 (0.00770)	0.00002 (0.00637)	0.00003 (0.01046)	0.00003 (0.01453)
Group 4: Russian–Ukraine War (24 February 2022 to 22 April 2022)							
R_{BTC}	−0.0883	−0.00080 (0.03173)	−0.00902 (0.35713)	−0.00326 (0.12890)	−0.00517 (0.20449)	−0.00300 (0.11862)	−0.00661 (0.26149)
R_{ETH}	0.0542	0.00054 (0.03649)	0.00506 (0.34010)	0.00232 (0.15596)	0.00393 (0.26396)	0.00248 (0.16670)	0.00467 (0.31378)
R_{USDT}	−0.0012	-	−0.00021 (0.00206)	−0.00009 (0.00091)	−0.00008 (0.00075)	−0.00013 (0.00123)	−0.00018 (0.00171)

Note: Partial co-volatility spillover effect is from currency market *i* to cryptocurrency market *j*. Standard deviations are in parentheses.

(1) Group 1: Whole sample

During the whole sample period, it is found that in all cases (except USDT and DXY), co-volatility spillover effects between cryptocurrency returns and exchange rate returns are statistically significant and positive (the first row of Table 4). It means that a return shock in the exchange rate returns at time $t-1$ leads to a positive effect between co-volatility (or on the relationship between the volatility) of cryptocurrency returns and exchange rate returns at time t. For example, the co-volatility spillover effects of R_{DXY} on (R_{BTC} and R_{DXY}) is 0.00016, and so on. The empirical results reveal that cryptocurrencies can be suitable as a financial diversifier for currencies but work poorly as hedging instruments.

According to the magnitude of the co-volatility spillover effects between cryptocurrency returns and exchange rate returns, EUR (0.00177, 0.01070, 0.00068) shows the strongest effects, followed by RUB (0.00130, 0.00987, 0.00056), GBP (0.00102, 0.00830, 0.00025), JPY (0.00064, 0.00491, 0.00030), CNY (0.00059, 0.00524, 0.00040), and DXY (0.00016, 0.00115). The standard deviation of co-volatility spillover effects shows that the degree of dispersion in EUR is larger than other exchange rates, which indicates co-volatility spillover effects between cryptocurrencies and EUR fluctuate greatly. Moreover, we can see that the impact of the shocks caused by Ethereum on the co-volatility spillover effects is much greater than the shocks of Bitcoin and Tether on these relations.

(2) Group 2: The US–China trade war

As shown in the second row of Table 4, during the US–China trade war period, there are significant negative co-volatility spillover effects between three cryptocurrency markets and currency markets (except USDT and DXY). Consequently, the findings affirm that Bitcoin, Ethereum, and Tether can be considered safe-havens for currencies.

For the magnitude of the co-volatility spillover effects between cryptocurrency returns and exchange rate returns, the empirical results again show that EUR (−0.02535, −0.05084, −0.00012) is the largest, followed by RUB (−0.01856, −0.04691, −0.00010), GBP (−0.01452, −0.03946, −0.00004), JPY (−0.00915, −0.02331, −0.00005), CNY (−0.00842, −0.02492, −0.00007), and DXY (−0.00225, −0.00545). The standard deviation of co-volatility spillover effects for EUR is larger than other currencies. In addition, the effect of the shocks caused by the returns of Ethereum on the co-volatility spillover effects of Ethereum and exchange rates is greater than the shocks caused by Bitcoin and Tether on said relations.

(3) Group 3: The COVID-19 pandemic

During the COVID-19 pandemic period, there are negative co-volatility spillover effects between Bitcoin returns and exchange rate returns, while there are positive co-volatility spillover effects between Ethereum returns and exchange rate returns, as well as Tether returns and exchange rate returns (except USDT and DXY), as shown in the third row of Table 4. This implies that Bitcoin can act as a safe-haven for currencies, and Ethereum and Ripple can only be considered as diversifier assets.

According to the magnitude, EUR (−0.00319, 0.01401, 0.00004) have the largest co-volatility spillover effects with cryptocurrencies, followed by RUB (−0.00234, 0.01293, 0.00003), GBP (−0.00183, 0.01087, 0.00002), JPY (−0.00115, 0.00643, 0.00002), CNY (−0.00106, 0.00687, 0.00003), and DXY (−0.00028, 0.00150). In addition, the standard deviation of co-volatility spillover effects for EUR and GBP are larger than for other currencies. Comparing the absolute value of co-volatility spillover effects, the impact caused by Ethereum has a greater effect on the relationship between it and exchange rates volatility, followed by the shocks of Bitcoin and Tether.

(4) Group 4: Russian–Ukraine war

During the Russian–Ukraine war period, there are negative co-volatility spillover effects between Bitcoin returns and exchange rate returns, as well as between Tether returns and exchange rate returns (except USDT and DXY), while there are positive co-volatility spillover effects between Ethereum returns and exchange rate returns (the last column of Table 4). Therefore, Bitcoin and Tether act as safe-havens for currencies, and Ethereum is the only effective diversifier for currencies.

For the magnitude of the co-volatility spillover effects between cryptocurrency returns and exchange rate returns, the empirical results again show that EUR (−0.00902, 0.00506, −0.00021) shows the strongest effects, followed by RUB (−0.00661, 0.00467, −0.00018), GBP (−0.00517, 0.00393, −0.00008), JPY (−0.00326, 0.00232, −0.00009), CNY (−0.00300, 0.00248, −0.00013), and DXY (−0.00080, 0.00054). The standard deviation of co-volatility spillover effects shows that the degree of dispersion in EUR is larger than other exchange rates. Moreover, the impact of the shocks caused by Bitcoin on the co-volatility spillover effects is much greater than the shocks of Ethereum and Tether on these relations.

When comparing the absolute value of co-volatility spillover effects with different periods, the effect of the shocks caused by Bitcoin and Ethereum in the US–China trade war period is stronger than those in the COVID-19 pandemic period and the Russian–Ukraine war period, while the impact and contagion of the shocks caused by Tether in the Russian–Ukraine war period have larger effects than the shocks of the US–China trade war period and the COVID-19 pandemic period. The next section highlights the key findings of the empirical results on how the co-volatility spillover effects change in their entirety and sub-periods. Implications for research and practice are then derived to support the research objectives.

5. Conclusions

This study adds and contributes to the emerging literature on cryptocurrency and its economic and financial benefits by investigating the dynamic relationship between cryptocurrencies and exchange rates under different global events, including economic and political events (the US–China trade war and the Russia–Ukraine war) and public health concern (the COVID-19 pandemic). In particular, we evaluate the financial capabilities of three leading traded cryptocurrencies (Bitcoin, Ethereum, and Tether) to six main exchange rates (U.S. dollar index, EUR, JPY, GBP, CNY, and RUB) to generate benefits for market practitioners from portfolio diversification, hedging, and safe-haven strategies.

There are five important findings that can be drawn from this study: First, the empirical results reveal that cryptocurrencies are not correlated with most of the analyzed exchange rates, which implies that cryptocurrencies and currencies may divide into two different categories of financial assets. This result is consistent with the findings from the studies of Baek and Elbeck (2015), Yermack (2015), Fry and Cheah (2016), Baur and Dimpfl (2017) and Baur et al. (2018a). Second, using the diagonal BEKK multivariate conditional volatility model, and with the exception of Tether and DXY, we find evidence in all periods of significant co-volatility spillover effects between the returns of cryptocurrencies and the exchange rates although there are differences in the magnitude. This finding implies that each of the assets has significant impacts on its co-volatility with the corresponding assets.

Third, using a more comprehensive dataset that covers three global events, this study finds evidence of significant differences in the nature of risk events with regard to the capabilities of cryptocurrency. During the US–China trade war sub-period, Bitcoin, Ethereum, and Tether can be considered as safe-havens against currencies. Bitcoin as a safe-haven effect during the COVID-19 pandemic, and Bitcoin and Tether as safe-havens during the Russian–Ukraine war. Surprisingly, only Bitcoin provides a more consistent safe-haven, reinforcing the result from de Olde (2021). However, there is no evidence of hedging opportunities between the cryptocurrency and exchange currency markets during the whole time period. Instead, cryptocurrencies can offer significant diversification benefits to currencies in the whole sample period (in the long run). This finding is thus in accordance with the studies of Urquhart and Zhang (2019), that cryptocurrencies do offer safe-haven benefits for currencies to market practitioners at specific periods of time.

Fourth, in all periods, the co-volatility spillover effects between cryptocurrencies and EUR have the largest effects and fluctuations, followed by the co-volatility spillover effects of cryptocurrencies and RUB, GBP, JPY, CNY, and DXY. That could be because the European Union is an organization spanning many different policy areas with high regional structural heterogeneity. Russia's ruble is one of the strongest currencies in the world due to Russia's role as the major exporter of natural gas and oil to world markets. In addition, the Brexit process has affected the UK economy that caused the rise in economic uncertainty. Finally, we discover that the magnitude of co-volatility spillover effects seems to be related to the market capitalization of cryptocurrencies. Large-cap cryptocurrencies, including Bitcoin and Ethereum, have greater co-volatility spillover effects between them and exchange rates. Additionally, the effects of the shocks caused by Bitcoin and Ethereum on the value of co-volatility spillover effects in the US–China trade war period are stronger than those in the COVID-19 pandemic period and the Russian–Ukraine war period. Conversely, the effect of the shocks caused by Tether in the Russian–Ukraine war period are larger than those in the US–China trade war period and the COVID-19 pandemic period.

Overall, these findings provide evidence, consistent with previous studies, that the capabilities of cryptocurrency as a diversifier, hedging, or safe-haven might change over time and be contingent on the nature of market states and types, uncertainties, shocks, and risk events (Kliber et al. 2019; Shahzad et al. 2019; Urquhart and Zhang 2019; Charfeddine et al. 2020; Ji et al. 2020; Hasan et al. 2021; Hsu et al. 2021). The results of this study can serve as a valuable reference for market practitioners. In addition to shedding light on the nature of cryptocurrencies, this study provides a more comprehensive representation of the dynamic relationship between cryptocurrencies and currencies under different times of global uncertainty, which can serve as valuable guidance for market practitioners. As such, investors and portfolio managers build investment plans and hedging strategies to minimize the risk to their portfolios. Governments and central banks build the legal regulatory system and develop and promote central bank digital currency.

For future research, it would be helpful to incorporate additional cryptocurrencies in the analysis to support market practitioners. Moreover, future study should dig deeper and add to a more comprehensive understanding and modeling of the interrelationships of cryptocurrencies and other financial assets. Finally, more studies should continue to monitor other global events to identify the behavior and capabilities of cryptocurrency.

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Notes

[1] The DXY index is a weighted average of the dollar's value against six major currencies, namely the Euro, Japanese yen, British pound, Canadian dollar, Swedish krona, and Swiss franc.

[2] The ADF, PP, and KPSS refer to the Augmented Dickey–Fuller (ADF) of Dickey and Fuller (1979), Phillips–Perron (PP) of Phillips and Perron (1988), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) of Kwiatkowski et al. (1992) unit root tests, respectively.

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