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Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions

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A R T I C L E I N F O

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A B S T R A C T

This paper applies a Diagonal BEKK model to investigate the risk spillovers of three major cryptocurrencies to ten leading traditional currencies and two gold prices (Spot Gold and Gold Futures). The daily data used are from 7 August 2015 to 15 June 2020. The dataset is analyzed in its entirety and is also subdivided into four distinct subsets in order to study and compare the patterns of spillover effects during economic turmoil, such as the 2018 cryptocurrency crash and the COVID-19 pandemic. The results reveal significant co-volatility spillover effects between cryptocurrency and traditional currency or gold markets, especially during the whole sample period and amid the uncertainty raised by COVID-19. The capabilities of cryptocurrency are time-varying and related to economic uncertainty or shocks. There are significant differences between normal and extreme markets with regard to the capabilities of cryptocurrency as a diversifier, a hedge or a safe haven. We find the significant co-volatility spillover effects are asymmetric in most cases especially during the COVID-19 pandemic period, which means the negative return shocks have larger impacts on co-volatility than positive return shocks of the same magnitude. Evidently, cryptocurrencies and traditional currencies or gold can be incorporated into financial portfolios for financial market participants who seek effective risk management and also for optimal dynamic hedging purposes against economic turmoil and downward movements.

1. Introduction

Over the past decade, blockchain technology has evolved rapidly and has provided a number of avenues through which technological innovation can advance. Cryptocurrency is one of the most publicized blockchain advancements that has taken place in the development of the financial market (Katsiampa et al., 2019a). Bitcoin is the first decentralized cryptocurrency proposed by Satoshi Nakamoto in 2009. Since Bitcoin's introduction, cryptocurrency markets have emerged rapidly, as evidenced by the total number of cryptocurrencies surpassing 5,700 by the middle of June 2020 (CoinMarketCap.com, as of 15 June 2020). The market capitalization of all cryptocurrencies has dramatically reached approximately 237.1 billion USD in 2019 from 10.62 billion USD in 2013 (Statista, 2019).

Cryptocurrency is a new digital currency and a peer-to-peer electronic cash system which allows any two willing parties to transact with each other on the web without passing through any trusted financial institution (Nakamoto, 2008). Cryptocurrency is designed to

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have features of traditional currencies such as being a medium of exchange, unit of account and store of value (Yermack, 2015; Baur & Dimpfl, 2017; Baur, Dimpfl, & et al., 2018). Moreover, cryptocurrency's design possesses key characteristics of gold, such as mining, finite supply (scarcity of supply), and decentralization (Dyhrberg, 2016a, 2016b). It is not controlled or backed by the government or laws, and it is traded globally 24 h a day, seven days per week (Baur, Hong, & et al., 2018). Selgin (2015) suggested that cryptocurrency is synthetic commodity money. It not only resembles fiat money (e.g., the US dollar and the euro) in having no intrinsic value, but also resembles commodity money (e.g., gold) in being contingently and absolutely scarce (Baur, Hong, & et al., 2018).

Cryptocurrency could be attractive to potential users because it has advantages such as low transaction costs, no central authority or control, and pseudo-anonymity (Baur, Dimpfl, & et al., 2018; Yi et al., 2018; Katsiampa, 2019a; Kristjanpoller & Bouri, 2019; Urquhart & Zhang, 2019). More and more offline businesses and organizations have started accepting cryptocurrency as payment for goods and services (including illegal ones) (Baur, Dimpfl, & et al., 2018; Katsiampa, 2019a). Even governments and central banks have strong interest in exploring the option of issuing central bank digital currencies (CBDCs), with payment efficiency, payment safety and financial inclusion (Bank for International Settlements, 2020). In addition, some have argued that cryptocurrency constitutes a new category of investment asset due to its price volatility, high average returns, and low correlation with major financial assets, which could be incorporated for the development of investment portfolios (Yermack, 2015; Baur & Dimpfl, 2017; Baur, Hong, & et al., 2018; Guesmi et al., 2019; Katsiampa, 2019a).

In summary, cryptocurrency has gained significant attention from market practitioners (policymakers, decision-makers, investors, portfolio managers, miners, and cryptocurrency users), scholars, regulators, and the financial press. However, while cryptocurrencies provide several potential benefits, there also exist sources of risk that could be detrimental to market participants due to their high price volatility (Baur, Dimpfl, & et al., 2018; Klein et al., 2018; Guesmi et al., 2019). As an example, the 2018 cryptocurrency crash was devastating for market participants. According to data from CoinMarketCap.com, the prices of major cryptocurrencies declined significantly from the market peak in January 2018 to December 2018, with such prices falling by 82% for Bitcoin, 92% for Ethereum, and 91% for Ripple. In addition, the market capitalization of all cryptocurrencies decreased considerably from $835 billion in January 2018 to $101 billion in December 2018 (down more than 80%). The economic upheaval caused by the COVID-19 outbreak is reported to be the most unrelenting since the Global Financial Crisis of 2007–2009. Obviously, the pandemic presents a different challenge to investors in developing a risk management portfolio that includes cryptocurrency.

In general, the literature has investigated the static and dynamic relationships between cryptocurrency and mainstream financial assets markets. Nonetheless, the risk spillover effects between cryptocurrency and foreign exchanges (traditional currencies) or gold markets have not been properly studied. For instance, previous studies focus primarily on Bitcoin as the representative of the cryptocurrency market,[1] while several altcoins (e.g., Ethereum and Ripple) that have gained substantial ground have not been considered in the research. Moreover, the interrelationships between leading cryptocurrencies and most traded traditional currencies and gold remain unexplored. Note that exploring and understanding the dynamic relationship of cryptocurrencies to traditional currencies and gold is essential for investors, portfolio managers, policymakers, and other market participants. The foreign exchange market is the largest and most active financial market in the world (Du, 2013), and it is a globally interconnected marketplace so that events around the world can have an immediate effect on exchange rates and currency values (Bank for International Settlements, 2019). Many investors (or traders) are attracted to the foreign exchange market with the aim of earning profit from its high liquidity, around-the-clock trading, and leverage. On the other hand, gold is widely regarded as a hedging instrument against stocks, bonds and the American dollar, in that it can be used as a tool to mitigate portfolio risk (Dyhrberg, 2016a, 2016b). As cryptocurrency, traditional currency and gold have many similarities, it is important to understand the comparable hedging capabilities of cryptocurrency. In particular, in states of economic turmoil (such as the COVID-19 pandemic), cryptocurrency could be considered as one of the fiat money or commodity money (gold) when investors want to hold cash or gold.

To fill this gap in the literature, this study intends to investigate the volatility spillover effects of cryptocurrency in order to build investment opportunities (diversifier, hedging, or safe haven) to facilitate risk management in cryptocurrency, traditional currency and gold markets. We propose to study the risk spillover effects of three major cryptocurrencies (Bitcoin, Ethereum, and Ripple) on the ten most traded traditional currencies and two gold prices. The ten most traded currencies, including the US dollar index (as a proxy for the US dollar), are the Euro, Japanese Yen, British Pound, Australian Dollar, Canadian Dollar, Swiss Franc, Chinese Yuan, Hong Kong Dollar, and New Zealand Dollar (Bank for International Settlements, 2019), and two gold prices, including Spot Gold and Gold Futures. In addition, this study uses the Diagonal BEKK multivariate conditional volatility model for empirical analysis. This model has appropriate regularity conditions and asymptotic statistical properties under appropriate parametric restrictions, so that we can more accurately capture the risk transmission effects or volatility spillover effects among financial assets (McAleer et al., 2008; Chang et al., 2018a, 2019). To the best of our knowledge, no previous study has used the Diagonal BEKK model to investigate the volatility spillover effects between cryptocurrencies and foreign exchanges or gold markets.

Overall, this study differs from previous literature in many aspects. First, we consider more selections of cryptocurrencies, traditional currencies and gold prices. Second, we use a most up-to-date and comprehensive dataset, including data from 7 August 2015 to 15 June 2020. To observe the impact of economic turmoil (e.g., the 2018 cryptocurrency crash and the Covid-19 pandemic), we divide the entire dataset or time period into four sub-periods for analysis: the pre-2018 cryptocurrency crash, the 2018 cryptocurrency crash, the post-2018 cryptocurrency crash, and the COVID-19 pandemic. Third, the use of a Diagonal BEKK multivariate conditional volatility

[1] Although Bitcoin is the dominant cryptocurrency, with 65% of the entire cryptocurrency market capitalization, several altcoins have gained substantial ground and became important segments of the cryptocurrency market (Kristjanpoller & Bouri, 2019). For instance, Ethereum and Ripple account for 13.08% of the total capitalization of the cryptocurrency market (CoinMarketCap.com, as of 15 June 2020).

model should be valuable for future empirical analyses of estimating and testing volatility spillover effects.

Our empirical findings reveal significant co-volatility spillover effects for all pairs of cryptocurrencies and traditional currencies, as well as of cryptocurrencies and gold for the whole sample period. However, cryptocurrency can be found as a hedge for few traditional currency markets, while there is no evidence of hedging opportunities between the cryptocurrency market and gold market. Moreover, the capabilities of cryptocurrency could be related to economic uncertainties. For instance, we find that there are different patterns of co-volatility spillover effects on the cryptocurrency market and the traditional currency market or gold market, during turbulent periods. Under the impact of the 2018 cryptocurrency crash, there are relatively few interconnections between cryptocurrencies and traditional currencies or gold. In contrast, during the COVID-19 pandemic, the interconnections increase significantly between cryptocurrencies and traditional currencies or gold. As the significant co-volatility spillover effects of cryptocurrencies to traditional currencies and gold are asymmetric (or negative) in most cases, suggesting cryptocurrencies could be considered as a safe haven to traditional currencies or gold. These empirical findings can serve as a valuable reference for market participants with better insights into behavioral dynamics in the financial markets and offer new hedging strategies in developing optimal financial portfolios.

The remainder of this paper is organized as follows. Section 2 presents an overview of the related literature. Section 3 discusses the research methodology, with a focus on the development of a Diagonal BEKK multivariate conditional volatility model. Section 4 describes the data and variables. Section 5 presents the analyses and empirical results, followed by the discussion and implications of the results in Section 6.

2. Literature review

As the literature on cryptocurrencies has rapidly emerged, there has been an increased interest in studying the transfer or spillover effects of price and risk of cryptocurrencies as well as the interactions between cryptocurrencies and various economic and financial assets. While investigating the aspect of cryptocurrencies' risk volatility, the extant research has found strong evidence of significant risk transfer or spillover effects among cryptocurrency markets which implies cross-products interdependent effects exist (Ciaian, Rajcaniova, & d'Artis, 2018; Katsiampa, 2019a,b; Katsiampa et al., 2019a,b; Koutmos, 2018; Kyriazis et al., 2019; Huynh et al., 2020; Wang et al., 2020). Numerous studies have examined the interactions between cryptocurrencies and various mainstream financial assets (e.g., gold, oil, stocks, bonds, traditional currencies, and futures) to understand the capability/role of cryptocurrency: a *diversifier*, a *hedging instrument,* or a *safe haven.*[2] Table 1 provides a structured review on how the extant literature addressed four critical components of research design in their studies: types of cryptocurrency, types of financial assets, research method, and the capability/role of cryptocurrency. The remainder of this section reviews the research design and findings of those studies and, accordingly, presents the research objectives of this study.

2.1. Capabilities of cryptocurrency

Previous studies have classified the capabilities of cryptocurrency into diversifier, hedge, or safe haven. First, several studies suggest cryptocurrency as a ***diversifier***. For instance, Briere et al. (2015) conduct spanning tests under the Ordinary Least Squares (OLS) regressions to check whether Bitcoin can be used to improve both traditional assets (stock indices, bonds, currencies (EUR and JPY)) and alternative investment opportunities (gold, oil, hedge funds, real estate). The results show that Bitcoin's correlation with other assets is remarkably low, but Bitcoin investments can offer significant diversification benefits to other assets and investments. Bouri, Gupta, & et al. (2017) use DCC model to examine the volatility co-movements between Bitcoin and financial assets (including major world stock indices, bonds, oil, gold, the general commodity index, and the US dollar index). They find that Bitcoin can be considered an effective diversifier in most cases. However, there is limited evidence of the hedging and safe haven properties of Bitcoin against or for other financial assets.

Maghyereh and Abdoh (2020) study the dynamic relationship between returns for Bitcoin and financial assets (stock indices, bonds, currency (EUR), commodity index, gold, oil, and silver) by using the quantile cross-spectral dependence approach. They find that Bitcoin does not granger-cause the returns of financial assets, but the financial assets can granger-cause Bitcoin returns, and Bitcoin can provide financial diversification opportunities. Zeng et al. (2020) use the VAR model to study the dynamic interdependence of returns between Bitcoin and conventional financial assets (stock indices, oil, and gold). They find that the connectedness between Bitcoin and conventional assets is limited and suggest that Bitcoin can serve as a diversification option for investors.

Investigating the relationships among multiple cryptocurrencies and other financial assets, several studies also find that cryptocurrencies could be considered diversifiers. Corbet et al. (2018) employ the generalized variance decomposition method to explore the volatility spillover effects between three major cryptocurrencies (Bitcoin, Ripple, and Litecoin) and financial assets (including stock indices, gold, bonds, and US$ Broad exchange rates). They find there is little evidence of volatility spillovers between cryptocurrencies and other financial assets. This suggests that cryptocurrencies are difficult to hedge against other financial assets but are suitable as diversifiers for investors with short investment horizons. Gil-Alana et al. (2020) use the ARFIMA model to examine the dynamic relationship between cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Tether) and six stock indices. The results reveal

[2] Following Baur and Lucey (2010) and Baur and McDermott (2010), a diversifier is defined as an asset that has a positive correlation (but not perfectly correlated) with another asset or portfolio on average. A weak (strong) hedge is an asset that is consistently uncorrelated (negatively correlated) with another asset or portfolio on average. A weak (strong) safe haven is an asset that is consistently uncorrelated (negatively correlated) with another asset or portfolio on average during times of market turmoil.

Table 1
Literature review: capability of cryptocurrency, financial assets, research method.

Source	Cryptocurrencies	Financial assets	Methods
Diversifier			
Briere et al. (2015)	Bitcoin	stock indices, bonds, gold, oil, currencies, hedge funds, and real estate	OLS model with spanning tests
Bouri, Gupta, and et al. (2017)	Bitcoin	stock indices, bonds, gold, oil, and the general commodity index, and the US dollar index	DCC model
Maghyereh and Abdoh (2020)	Bitcoin	stock indices, bond, currency, commodity index, gold, oil, and silver	Quantile cross-spectral dependence approach
Zeng et al. (2020)	Bitcoin	stock indices, gold, and oil	VAR model
Corbet et al. (2018)	Bitcoin, Ripple, and Litecoin	stock indices, bonds, gold, and US$ broad exchange rate	Generalized variance decomposition method
Gil-Alana et al. (2020)	Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Tether	stock indices	ARFIMA model
Charfeddine et al. (2020)	Bitcoin and Ethereum	stock index, gold, and oil	Copula methods and DCC model
Hedge instrument			
Dyhrberg (2016a)	Bitcoin	gold, currencies, and stock index	GARCH and EGARCH models
Dyhrberg (2016b)	Bitcoin	gold, currencies, and stock index	GJR model
Bouri, Molnár, and et al. (2017)	Bitcoin	global uncertainty (VIXs)	Wavelet-based quantile-in-quantile regression approach
Demir et al. (2018)	Bitcoin	economic policy uncertainty (EPU)	BGSVAR model, OLS and the QQ estimations
Guesmi et al. (2019)	Bitcoin	stock indices, gold, oil, currencies, and VIX	VARMA(1,1)-DCC-GJR-GARCH model
Naeem et al. (2020)	Bitcoin	gold, market capitalization (small or big), and other stock attributes	AGDCC-GARCH model
Huynh et al. (2020)[1]	14 cryptocurrencies	gold	Transfer entropy approach
Baur, Hong, and et al. (2018)[2]	Bitcoin	gold, currencies, and stock index	GJR model
Klein et al. (2018)[2]	Bitcoin	gold, silver, oil, and stock indices	BEKK-GARCH model
Safe haven			
Shahzad et al. (2019)	Bitcoin	stock indices	Bivariate cross-quantilogram approach
Shahzad et al. (2020)	Bitcoin	stock indices	AGDCC-GARCH model
Stensås et al. (2019)	Bitcoin	stock indices, oil, gold, cotton, corn, coffee and all wheat	DCC model
Urquhart and Zhang (2019)[3]	Bitcoin	currencies	DCC model
Conlon and McGee (2020)[2]	Bitcoin	stock index	Downside risk measurement (value at risk and conditional value at risk)
Conlon et al. (2020)	Bitcoin, Ethereum and Tether	stock indices	Downside risk measurement (value at risk and conditional value at risk)
Goodell and Goutte (2020)	Bitcoin, Bitcoin Futures, Ethereum, Litecoin, Tether, XRP, and EOS	stock indices and VIX	Wavelet coherence, copula principal component, and neural network analyses
Kristoufek (2020)[2]	Bitcoin	stock index and VIX	Quantile correlations analysis
Grobys (2020)[2]	Bitcoin	stock indices	Realized dynamic correlation analysis
Corbet et al. (2020)[2]	Bitcoin	Chinese stock markets (Shanghai SE, Shenzhen SE)	GARCH model and DCC model
Mariana et al. (2021)	Bitcoin and Ethereum	stock index	DCC and cDCC models

Note: [1] Gold could be a hedging instrument for cryptocurrencies. [2] There is no evidence for Bitcoin as a hedging instrument or safe haven. [3] Urquhart and Zhang (2019) find Bitcoin can be considered as diversified (AUD, CAD and JPY), hedging (CHF, EUR and GBP) and safe haven (CAD, CHF and GBP).

no cointegration between cryptocurrencies and the stock market indices, and cryptocurrencies can provide financial diversification for investors. Charfeddine et al. (2020) use a battery of time-varying copula methods and DCC models to investigate the dynamic relationship between cryptocurrencies (Bitcoin and Ethereum) and conventional assets (S&P 500, gold and oil). They conclude that the cross-correlation with financial assets is changeable over time, depending on economic shocks, and cryptocurrencies can be suitable for financial diversification but work poorly as hedging instruments.

Second, another group of researchers favors cryptocurrency being a ***hedge investment***. For instance, Dyhrberg (2016a) employs the

GARCH and EGARCH models to investigate the similarities and dynamic relationships among Bitcoin, gold, currencies (EUR and GBP), and the UK stock market (FTSE index), and find Bitcoin shares hedging capabilities similar to those of gold and has advantages as a medium of exchange to the US dollar. A related study done by Dyhrberg (2016b) using the GJR model, suggests Bitcoin can be used as a hedge against the FTSE Index and has a short-term hedging capability against the US dollar. However, Baur et al. (2018b) argue that Dyhrberg's (2016a) and Dyhrberg's (2016b) models are mis-specified, in both econometric and economic terms. They replicate both studies using the GJR model and fail to support Bitcoin as a hedging instrument against gold, currencies, or the UK stock market. Klein et al. (2018) employ the BEKK-GARCH model to estimate the interconnectedness of Bitcoin to gold, silver, the WTI oil price, and three stock indices. They find that gold can be a hedge for other assets, but there is no support for the hedging capabilities of Bitcoin.

Bouri, Molnár, and et al. (2017) and Demir et al. (2018) suggest that Bitcoin can be considered a hedging instrument against uncertainty. More specifically, Bouri, Molnár, and et al. (2017) investigate the relationship between Bitcoin and global uncertainty (the Volatility Indices of 14 developed and developing stock markets) by employing the wavelet-based quantile-in-quantile regression approach. They find that Bitcoin can serve as a hedge against global uncertainty at short investment horizons, and at both lower and upper ends of Bitcoin returns and global uncertainty. Demir et al. (2018) examine the predictive power of economic policy uncertainty (EPU) on the daily Bitcoin returns by using the BGSVAR model, as well as the OLS and the QQ estimations, and they find Bitcoin returns are negatively associated with changes in the EPU. Accordingly, the authors suggest Bitcoin can be used as a hedging instrument extreme times of extreme uncertainty.

Guesmi et al. (2019) explore the volatility spillover effects between Bitcoin and financial assets (stock indices, currencies (EUR and CNY), gold, oil and the implied volatility index (VIX)) by using the VARMA(1,1)-DCC-GJR-GARCH model. The results reveal a short position in the Bitcoin market allows hedging against all different financial assets. In addition, the authors find the portfolio of gold, oil, VIX and Bitcoin can reduce risks significantly. Naeem et al. (2020) use the AGDCC-GARCH model to compare the hedging, safe-haven, and diversification potential of gold and Bitcoin for different investment decisions and industry portfolios in the United States. The results show gold offers hedging potential for large-cap portfolios, while Bitcoin can be hedging for the noncyclical industries. However, they find that gold is a superior hedging instrument compared with Bitcoin.

Huynh et al. (2020) employed a transfer entropy approach to investigate the spillover effects among 14 cryptocurrencies and their linkages with gold prices. The authors find that there are spillover effects among cryptocurrencies. Bitcoin is the most appropriate instrument for hedging, and the small coins are more likely to be shock creators in the cryptocurrency market. Moreover, they find significant interactions between cryptocurrency and gold, and gold could be a good hedging instrument for cryptocurrencies due to its independence.

Finally, another group of authors consider cryptocurrency as a ***safe haven***. Shahzad et al. (2019) use a bivariate cross-quantilogram approach to investigate the properties of Bitcoin during extreme market conditions and whether such a capability is similar to those of gold and the general commodity index. They find that the safe haven capabilities of Bitcoin, gold, and commodities are time-varying and differ across the stock market indices, among which Bitcoin can be regarded as a weak safe-haven in the China stock market. Shahzad et al. (2020) employ the AGDCC-GARCH model and conclude that gold acts as a safe haven and hedge for several G7 stock indices, whereas Bitcoin possesses these two capabilities in Canada stock market.

Stensås et al. (2019) investigate the interrelationship of Bitcoin to major developed and developing stock market indices and commodities (oil, gold, cotton, corn, coffee and all wheat) by using the DCC model. The results reveal that Bitcoin can be considered as a hedge in most of the developing countries, but only as a diversifier in developed countries and for commodities. Moreover, the authors find Bitcoin can be regarded as a safe haven during the US election in 2016, Brexit referendum in 2016, and the burst of Chinese market bubble in 2015. Urquhart and Zhang (2019) also employ the DCC model to investigate the dynamic relationship between Bitcoin and traditional currencies (EUR, JPY, GBP, AUD, and CHF). The results reveal that Bitcoin can be used as an intraday hedge for the CHF, EUR and GBP, and as a diversifier for the AUD, CAD and JPY. They also find that Bitcoin can be classified as a safe haven for the CAD, CHF and GBP during periods of extreme market turmoil.

Several studies also review the dynamic relationship between cryptocurrencies and other financial assets during the COVID-19 turmoil and explore the safe haven properties of cryptocurrencies for market practitioners. For instance, by calculating value at risk (VaR) and conditional value at risk (CVaR), Conlon and McGee (2020) find Bitcoin cannot be considered a safe haven for S&P 500 since it could increase portfolio risk during COVID-19. Kristoufek (2020) studies the quantile correlations of Bitcoin and S&P500 and VIX Index during the COVID-19 pandemic and finds that Bitcoin cannot be considered a safe haven while gold can serve as a much better safe haven in the pandemic period. Grobys (2020) employs the realized dynamic correlation analysis to explore the hedging abilities of Bitcoin in the early wake of the COVID-19 outbreak. The findings suggest that Bitcoin cannot serve as a safe haven for hedging this extraordinary tail risk in U.S. stocks. Corbet et al. (2020) use GARCH model and DCC model to investigate the volatility relationship associated with the onset of the COVID-2019 pandemic between Chinese stock markets (Shanghai SE, Shenzhen SE) and Bitcoin. The results show that, in times of serious financial and economic disruption, Bitcoin does not act as hedges, or safe havens, but rather as amplifiers of contagion. Overall, those studies suggest that Bitcoin cannot be considered as a safe haven during the COVID-19 pandemic.

Conlon et al. (2020) examine the safe haven properties of cryptocurrencies (Bitcoin, Ethereum and Tether) for six international equity markets by using two-moment value at risk. The authors find Bitcoin and Ethereum are not a safe haven for the majority of international equity markets, but Tether acts as a safe haven for all of the international indices during the COVID-19 turmoil. Goodell and Goutte (2020) use the wavelet coherence, copula principal component, and neural network analyses to investigate the co-movements of cryptocurrencies (Bitcoin, Bitcoin futures, Ethereum, Litecoin, Tether, XRP, and EOS) to fourteen equity indices and the VIX. The results reveal that some cryptocurrencies (Ethereum, Litecoin, XRP, and EOS) cannot regard as a safe haven during the COVID-19 crisis, however, Bitcoin futures and Tether are safe havens for equities. Mariana et al. (2021) use DCC and cDCC models to test Bitcoin and Ethereum as safe havens for S&P500 during the COVID-19 pandemic. The results show that both Bitcoin and Ethereum are suitable as short-term safe havens during the extreme stock market plunges. Moreover, Ethereum might be a better safe haven than Bitcoin during the pandemic, but Ethereum exhibits higher daily return volatility than Bitcoin.

2.2. Types of Cryptocurrency, financial assets, research method

In addition to debating the capabilities of cryptocurrency, previous studies differ in three other important research design components: the type of cryptocurrency studied, the financial assets studied, and research method employed. First, most of the studies focus solely on Bitcoin, with only a few studies including other cryptocurrencies (Corbet et al., 2018; Charfeddine et al., 2020; Conlon et al., 2020; Gil-Alana et al., 2020; Goodell & Goutte, 2020; Huynh et al., 2020; Mariana et al., 2021). Second, while the literature recognizes traditional currency as one of financial assets, several important traditional currencies, such as the American Dollar, Canadian Dollar, Hong Kong Dollar, and New Zealand Dollar are not examined. Third, some studies discuss the relationship between cryptocurrencies and other financial assets (stock market) during the COVID-19 turmoil (Conlon & McGee, 2020; Conlon et al., 2020; Corbet et al., 2020; Goodell & Goutte, 2020; Grobys, 2020; Kristoufek, 2020; Mariana et al., 2021). However, no previous study has explored the dynamic relationship of leading cryptocurrencies to major traditional currencies and gold during economic turmoil, such as the 2018 cryptocurrency crash and the COVID-19 pandemic. Consequently, it is difficult to gain a comprehensive understanding of the volatility behavior and interconnection between cryptocurrency and traditional currency or gold markets and to determine whether there is a hedging opportunity both in normal and extreme markets.

Many studies adopted multivariate conditional volatility models to examine the capabilities of cryptocurrency. Multivariate conditional volatility models are initially applied in the finance literature and have been used in cryptocurrency literature (such as Bouri, Gupta, & et al., 2017; Klein et al., 2018; Guesmi et al., 2019; Urquhart & Zhang, 2019; Stensås et al., 2019; Charfeddine et al., 2020; Corbet et al., 2020; Shahzad et al., 2020; Naeem et al., 2020; Mariana et al., 2021), in which they discuss the risk transfer among different assets. Risk transmission (also referred to as the risk spillover effect) is critical to enable market participants to develop suitable dynamic hedging strategies for risk management (Chang et al., 2018a). Unfortunately, the multivariate conditional volatility models suffer from some common theoretical shortcomings (McAleer, 2005; Chang, Li, & et al., 2018). For instance, the constant conditional correlational (CCC) model (Bollerslev, 1990), the Vector ARMA-GARCH (VARMA-GARCH) model (Ling & McAleer, 2003), and the Vector ARMA-asymmetric GARCH (VARMA-AGARCH) model (McAleer et al., 2009) have static conditional covariances and correlations, which implies that accommodating volatility spillovers is not possible (McAleer et al., 2008). Additionally, the Full BEKK multivariate conditional volatility model (Baba et al., 1985; Engle & Kroner, 1995) and the dynamic conditional correlation (DCC) model (Engle, 2002) fail to establish the internal consistency and asymptotic normality of the estimated parameters. Overall, those multivariate conditional volatility models lack statistical properties of consistency and asymptotic normality (Chang & McAleer, 2019; McAleer, 2019a, 2019b). Namely, previous studies using those models have reached their conclusions about spillover effects based on invalid statistical inferences.

In summary, this literature review suggests that the interrelationships between three major cryptocurrencies and two important financial assets (traditional currency and gold) have not been properly studied. Therefore, this study extends the literature by including three major cryptocurrencies (Bitcoin, Ethereum, Ripple), ten most traded traditional currencies, and two gold prices to study the spillover effects among these assets. The data used for analysis include both stable and unstable economic conditions. Additionally, this study proposes the use of the Diagonal BEKK model to better capture the statistical properties.

3. Methodology

Risk spillover effects are frequently implemented in research in empirical finance and cognate disciplines to measure the risks transmitted among different financial assets, thereby helping market practitioners to forecast their returns, vis-a-vis risk, and construct optimal dynamic hedging strategies. As distinct from the previous studies, this study employs the Diagonal BEKK multivariate conditional volatility model, with known mathematical regularity conditions and valid asymptotic statistical properties, to analyze the risk spillover effects between the cryptocurrency market and financial asset (traditional currency and gold) markets. This study also uses Chang, Li, and et al.'s definition (2018) to test and calculate the co-volatility spillover effects between cryptocurrency returns and foreign exchange rate returns, as well as cryptocurrency returns and gold returns.

3.1. Diagonal BEKK model

The Diagonal BEKK model is the special case of the unrestrictive Baba, Engle, Kraft, and Kroner (BEKK) model, which was proposed by Baba et al. (1985) and Engle and Kroner (1995), and it has several advantages over the Full BEKK model. Specifically, the Diagonal BEKK model addresses the "curse of dimensionality[3]" issue. It decreases the number of parameters to be estimated and guarantees the positive definiteness of the conditional covariance matrix (Terrell & Fomby, 2006; Chang et al., 2018a). In addition, the Diagonal BEKK model has an underlying stochastic process that leads to its specification (with appropriate regularity conditions) so that the standard statistical inference for the hypotheses test is valid because the QMLE of the parameters can be established as consistent and

[3] The "curse of dimensionality" implies that the number of parameters to be estimated is excessively large, and thus the convergence of any estimation algorithm somewhat problematic and less reliable (Chang et al., 2018a).

asymptotically normal (McAleer et al., 2008; McAleer, 2019b).

Following Chang et al. (2020), we use a simple specification for the conditional mean equation of the financial return series, as given below:

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

where R_t is financial returns, $R_t = (R_{1t}, \cdots R_{mt})^{'}$, I_{t-1} is the information set available at time t −1, and ε_t is the shocks on returns, $\varepsilon_t = (\varepsilon_{1t}, \cdots \varepsilon_{mt})^{'}$.

In order to derive the Diagonal BEKK model, we follow McAleer et al.'s (2008) derivation, the vector random coefficient autoregressive (VRCAR) process of order one, 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, η_t $iid(0, C)$, and C is an $\mathrm{m} \times \mathrm{m}$ matrix. Φ_t is a random coefficient autoregressive matrix, with an $m \times m$ matrix of random coefficients, Φ_t $iid(0, A)$, and A is restricted to be a diagonal matrix, $\mathrm{A} = \mathrm{a}I_m$.

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, and $\varepsilon_{t-1}\varepsilon_{t-1}^{'}$ is an $m \times m$ matrix. The matrices C, A and B, respectively, are given as:

$$\mathrm{C} = \begin{bmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & c_{mm} \end{bmatrix}, \mathrm{A} = \begin{bmatrix} a_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_{mm} \end{bmatrix}, B = \begin{bmatrix} b_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & b_{mm} \end{bmatrix} \tag{4}$$

3.2. Co-volatility spillovers

According to Chang, Li, and et al. (2018), the Diagonal BEKK model allows testing of the co-volatility spillover effects, which is the impact of the return shock of financial asset *i* at time t −1 on the subsequent co-volatility between two financial assets *i* and *j* at time t. The definition of the co-volatility spillover effect can be presented as:

$$\frac{\partial H_{ij,t}}{\partial \varepsilon_{i,t-1}} = a_{ii} \times a_{jj} \times \varepsilon_{j,t-1}, i \neq j \tag{5}$$

where a_{ii} and a_{jj} are the elements in matrix A of the Diagonal BEKK model, and $\varepsilon_{j,t-1}$ is the return shock of financial assets *j* at time t −1.

The null hypothesis (H_0) and the alternative hypothesis (H_1) are as follows:

$$H_0 : a_{ii}a_{jj} = 0$$

$$H_1 : a_{ii}a_{jj} \neq 0 \tag{6}$$

If H_0 is rejected, the spillover effect will exist, from the return shock of financial asset *i* at time t −1 to the co-volatility between financial assets *i* and *j* at time t, which depends only on the return shock of financial asset j at time t −1. This indicates that $\varepsilon_{i,t-1}$ does not affect the spillover effect of financial asset *i* at time t −1 on the co-volatility between financial assets *i* and *j*. Furthermore, spillovers can be different for each observation at time t −1, so that an average of the co-volatility spillovers will be presented in the empirical results, based on the average return shock over the sample period (Chang, Li, & et al., 2018).

The Diagonal BEKK model with different sizes of the weighting matrix A and the average return shock at time t −1 are likely to cause the co-volatility spillover effects from financial assets *i* and *j* to be different (Chang et al., 2019). The signs of co-volatility spillover effects can both be either positive or negative, or one positive and another negative. In order to explore and identify the capabilities of cryptocurrencies, we extend the definition of the capabilities of an asset, proposed in Baur and Lucey (2010) and Baur and McDermott (2010), and differentiate testable definitions of a diversifier, hedge and safe haven asset. Specifically, positive co-volatility spillover effects (positive covariances and correlations among financial assets) indicate that two assets can be taken as diversifiers, as the positive performance of one asset could neutralize the negative performance of another to smooth out unsystematic risk events in a portfolio (on condition that the assets are not perfectly correlated) (Kliber et al., 2019). Negative co-volatility spillover effects (negative covariances and correlations among financial assets) suggest two assets be taken as hedging instruments in an optimal financial portfolio because of ensuring large losses in one financial asset are mitigated by positive returns with another asset (Joy, 2011; Bouri, Gupta, & et al., 2017; Chang et al., 2018a). The asymmetric co-volatility spillover effects (if one sign is positive and another is negative, or either financial asset *i* positive and financial asset *j* negative, or the reverse) imply that these two assets might be considered as a hedging portfolio, as their co-volatility spillover effects are moving in different directions (Chang et al., 2018b; Chang, Liu, & McAleer, 2019). Moreover, negative or asymmetric co-volatility spillover effects between two assets in times of market stress or turmoil could be considered as a safe haven.

4. Data and variables

The dataset used in the empirical analysis consists of the closing price for cryptocurrencies, foreign exchange rates and gold from 7 August 2015 (the earliest data available for Ethereum) to 15 June 2020, giving 1,267 daily observations obtained from CoinMarketCap[4] and Bloomberg, and the prices are listed in US Dollars.

We focus on the top three highly capitalized cryptocurrencies also mostly widely traded cryptocurrencies, ten foreign exchange rates representing the ten most traded currencies by value (Bank for International Settlements, 2019) and two gold prices. Specifically, the variables we use are three major cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), Ripple (XRP). The market share of those cryptocurrencies is around 79.7% by the middle of June 2020 (CoinMarketCap.com). The ten most traded traditional currencies chosen are American Dollar (US dollar index (DXY) is used as a proxy (Bouri, Gupta, & et al., 2017)), Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Chinese Yuan (CNY), Hong Kong Dollar (HKD), and New Zealand Dollar (NZD) (Bank for International Settlements, 2019). Two gold prices selected are the gold bullion in USD per troy ounce (Spot Gold) and the CMX Gold Futures 100-ounce in US dollar (Gold Futures).

The formula used to calculate closing price returns is the first difference in log prices, defined as$R_t = \ln(P_t/P_{t-1}) \times 100$, where P_t and P_{t-1} are the daily closing prices at time periods t and t −1, respectively. The definition of variables is presented in Table 2.

Fig. 1 depicts the daily closing price trends of cryptocurrencies, exchange rates and gold. All closing prices of cryptocurrencies present a significant increase from the end of the first quarter of 2017, while all prices dramatically decreased from the beginning of 2018, likely the outcome of the 2018 cryptocurrency crash. During the COVID-19 pandemic (beginning mid-February 2020), the closing price of cryptocurrencies shows a slight decrease, while all prices rebounded from mid-March 2020. It can be seen that all prices of cryptocurrencies seem to follow a similar pattern and could be correlated.

In addition, the closing price of the US dollar index and HKD/USD decreased from the fourth quarter of 2016 but climbed back from the end of the first quarter of 2018. The closing prices of EUR/USD, JPY/USD, GBP/USD, AUD/USD, CAD/USD, CHF/USD, CNY/USD, and NZD/USD have been declining steadily since the end of the first quarter of 2018. The trends of exchange rates are similar to those of cryptocurrencies, with evidence that closing prices decreased slightly during the COVID-19 pandemic (from mid-February to mid-March 2020). Moreover, the closing prices of Stop Gold and Gold Futures increased markedly from the third quarter of 2018, especially case during the COVID-19 pandemic.

Fig. 2 displays the trend of the daily closing price returns of cryptocurrency, exchange rate and gold. The trend of cryptocurrency returns in Fig. 1 is consistent with that in Fig. 2, suggesting that the volatility continues to increase significantly during the fourth quarter of 2017 and the beginning of the first quarter of 2018. Moreover, as shown in Fig. 2, the volatility trend of all series continues significantly higher during the COVID-19 pandemic. In addition, fluctuations in cryptocurrency returns, exchange rate returns, and gold returns have a persistent volatility clustering effect. Cryptocurrency returns are, however, more volatile than exchange rate returns and gold returns.

In order to enable a greater understanding of the relationship between cryptocurrencies and traditional currencies or gold during turbulent periods, the empirical analyses are made for its entire period as well as for four sub-periods: (i) whole sample (2015/8/7 to 2020/6/15); (ii) pre-2018 cryptocurrency crash (2015/8/7 to 2017/12/31); (iii) 2018 cryptocurrency crash (2018/1/1 to 2018/12/31); (iv) post-2018 cryptocurrency crash (2019/1/1 to 2019/12/30); (v) COVID-19 pandemic (2019/12/31 to 2020/6/15). The numbers of observations for each period are 1267, 626, 262, 261, and 121, respectively. The descriptive statistics, unit root tests and ARCH test for cryptocurrency returns, exchange rate returns, and gold returns for five time periods (four sub-periods and the entire period) are presented in Table 3. The mean returns for the exchange rate and gold are rather small. All series present negative mean returns during the 2018 cryptocurrency crash period, except DXY and JPY. Cryptocurrency returns display a greater standard deviation than exchange rate returns and gold returns for all periods, indicating that cryptocurrency markets are more volatile than financial asset (traditional currency and gold) markets. Moreover, as expected, all the variables have higher standard deviations during the COVID-19 pandemic.

The skewness coefficient is negative, which means that the series has a longer left tail (extreme losses) than right tail (extreme gains), and vice versa. The returns have different degrees of skewness for all periods. The closing price returns of Bitcoin, Ethereum, EUR, and AUD are skewed to the left (negative skewness) during the 2018 cryptocurrency crash, which means more extreme losses occurred than extreme gains. In addition, we find the skewness for most of the series (except DXY, HKD, and Gold Futures) is negative during the COVID-19 pandemic. All return series have a kurtosis statistic higher than 3, indicating that the distribution has an extremely narrow peak, with higher probabilities of extreme market movements.

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) tests for the existence of a unit root are shown in the Table 3. The results of unit root tests indicate that the returns of all variables are stationary. The ARCH Lagrange Multiplier (ARCH-LM) test of Engle (1982) along 1–7 lags are used for checking whether there are any ARCH effects, as shown in the last column of Table 3. The returns of all series of whole period and pre-2018 cryptocurrency crash period display significant ARCH effects. As expected, a few tests are insignificant for the other three periods, due to their low number of samples (McClain et al., 1996).

[4] https://coinmarketcap.com/coins/.

Table 2
Definitions of Variables.

Variables	Definition
Cryptocurrencies	
R_{BTC}	Returns of changes in daily closing prices of the Bitcoin (BTC) in the US dollar.
R_{ETH}	Returns of changes in daily closing prices of the Ethereum (ETH) in the US dollar.
R_{XRP}	Returns of changes in daily closing prices of the Ripple (XRP) in the US dollar.
Foreign Exchange Rates	
R_{DXY}	Returns of changes in daily closing prices of the US dollar index (DXY).
R_{EUR}	Returns of changes in daily closing prices of the exchange rate of the Euro (EUR) to the US dollar.
R_{JPY}	Returns of changes in daily closing prices of the exchange rate of the Japanese Yen (JPY) to the US dollar.
R_{GBP}	Returns of changes in daily closing prices of the exchange rate of the British Pound (GBP) to the US dollar.
R_{AUD}	Returns of changes in daily closing prices of the exchange rate of the Australian Dollar (AUD) to the US dollar.
R_{CAD}	Returns of changes in daily closing prices of the exchange rate of the Canadian dollar (CAD) to the US dollar.
R_{CHF}	Returns of changes in daily closing prices of the exchange rate of the Swiss Franc (CHF) to the US dollar.
R_{CNY}	Returns of changes in daily closing prices of the exchange rate of the Chinese Yuan (CNY) to the US dollar.
R_{HKD}	Returns of changes in daily closing prices of the exchange rate of the Hong Kong Dollar (HKD) to the US dollar.
R_{NZD}	Returns of changes in daily closing prices of the exchange rate of the New Zealand dollar (NZD) to the US dollar.
Gold	
R_{GOLDS}	Returns of changes in daily closing prices of the gold bullion in USD per troy ounce (Spot Gold).
R_{GOLDf}	Returns of changes in daily closing prices of the CMX Gold Futures 100-ounce in US dollar (Gold Futures).

5. Empirical results

In the empirical analysis, we select three cryptocurrencies, ten exchange rates and two gold prices, from which to analyze all 180 possible pairwise combinations/cases of risk spillover effects based on the Diagonal BEKK multivariate condition volatility model for each asset, both for the whole time period and for each of the four sub-periods.

Table 4 presents the empirical results of the estimates of matrix A of the Diagonal BEKK model for five periods, with various dimensions for the cryptocurrency, traditional currency, and gold markets. The estimated coefficients in matrix A of the Diagonal BEKK model can be interpreted as the weights that each asset has on the co-volatility spillover effect. Table 5 reports the average return shocks for each asset, for five periods. Table 6 shows the empirical results of average co-volatility spillovers, which are calculated by using Chang et al.'s (2018b) definition of co-volatility spillover effects. Specifically, three cryptocurrency returns (R_{BTC}, R_{ETH}, and R_{XRP}) are tested with ten exchange rate returns (R_{DXY}, R_{EUR}, R_{JPY}, R_{GBP}, R_{AUD}, R_{CAD}, R_{CHF}, R_{CNY}, R_{HKD}, and R_{NZD}) and two gold returns (R_{GOLDS} and R_{GOLDF}), respectively. Thus, for each period, there are 36 pairwise combinations/cases of average co-volatility spillovers. Moreover, the patterns of every combination pair are summarized, and the capabilities (a diversifier, a hedge, or a safe haven) of cryptocurrencies to traditional currencies or gold are summarized in Table 7 based on the results presented in Table 6. The remainder of this section presents the results of five time periods, respectively.

5.1. Whole sample (Entire Period: 2015/8/7 to 2020/6/15)

From the results of the estimates in matrix A of the Diagonal BEKK model for the whole sample period in Table 4, all estimated coefficients are significantly different from zero at the 1% significance level. The results suggest that the respective impacts of the returns of change in daily closing prices in the previous period on the current period, whether the cryptocurrencies (Bitcoin, Ethereum, and Ripple) or financial assets (ten exchange rates and two gold), exhibit significant co-volatility spillover effects.

With the significance of all the estimated parameters of matrix A, we use the formula from Chang, Li, and et al.'s (2018) framework (i.e.,$a_{ii} \times a_{jj} \times \varepsilon_{j,t-1}$) to calculate the average co-volatility spillover effects. Table 6 displays the results of average co-volatility spillover effects. For example, for the whole sample period, the co-volatility spillover effect of R_{BTC} on (R_{BTC} and R_{DXY}) is 0.00003, while the co-volatility spillover effect of R_{DXY} on (R_{BTC} and R_{DXY}) is 0.001, and so on. In general, it is found that in all cases, co-volatility spillover effects between cryptocurrency returns and exchange rate returns, as well as between cryptocurrency returns and gold returns, are statistically significant. That implies that each of the variables has significant impacts on its co-volatility with the corresponding variable. The detail about three cryptocurrencies are presented below.

In the Bitcoin group, there are positive co-volatility spillover effects between Bitcoin and financial assets (namely the US dollar index, Euro, Japanese Yen, Hong Kong Dollar, New Zealand dollar, Spot Gold, and Gold Futures), while there are negative co-volatility spillover effects between Bitcoin and British Pound. The co-volatility spillover effects are asymmetric between Bitcoin and Australian Dollar, Bitcoin and Canadian Dollar, Bitcoin and Swiss France, and Bitcoin and Chinese Yuan.

In the Ethereum group, the positive co-volatility spillover effects are found between Ethereum and Euro, Ethereum and Japanese Yen, Ethereum and British Pound, Ethereum and Australian Dollar, Ethereum and Swiss France, Ethereum and Hong Kong Dollar, Ethereum and New Zealand dollar, Ethereum and Spot Gold, and Ethereum and Gold Futures. There are asymmetric co-volatility spillover effects between Ethereum and the US dollar index, Ethereum and Canadian Dollar, and Ethereum and Chinese Yuan.

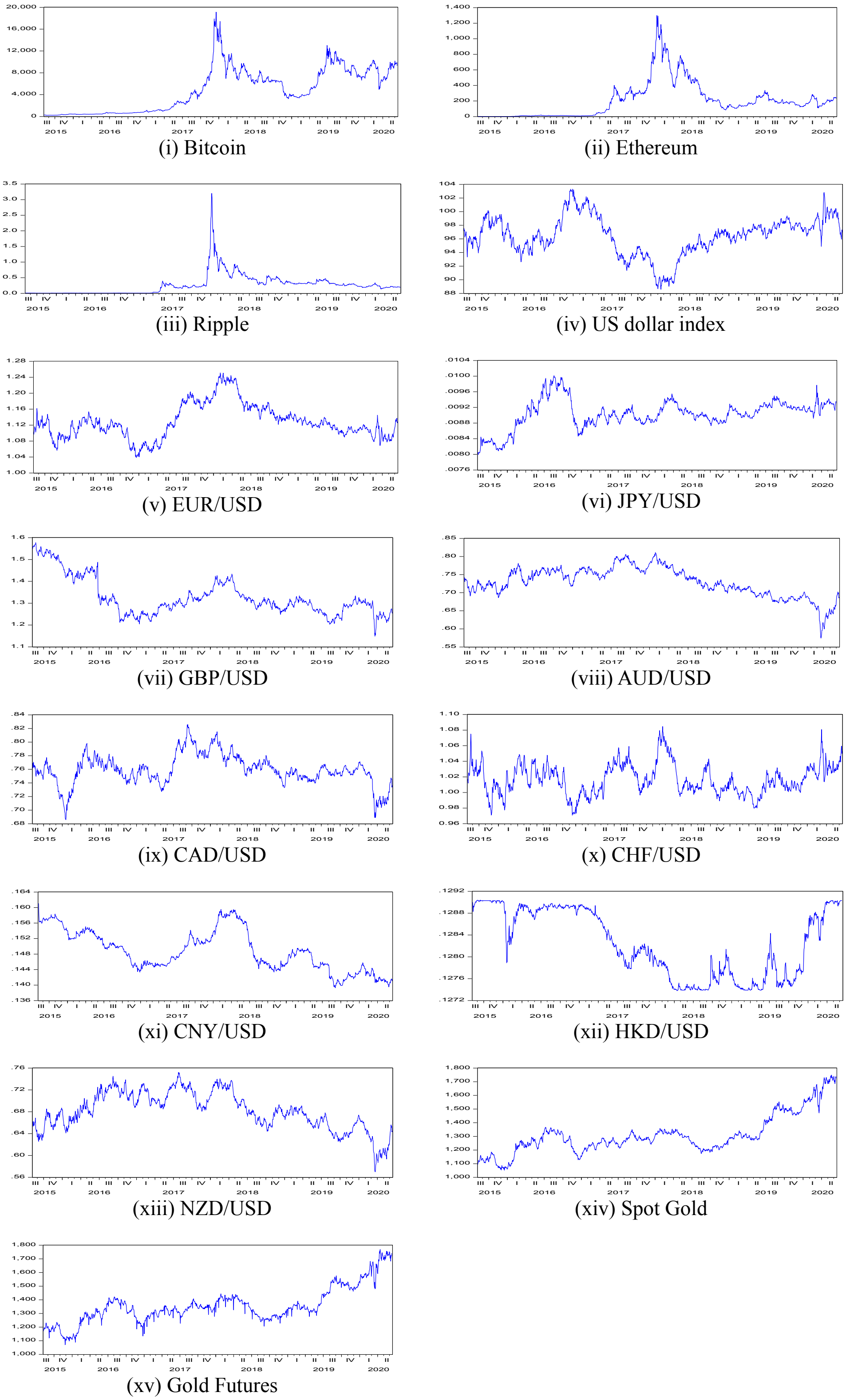

Fig. 1. Daily Closing Price of Select Series from 2015/8/7 to 2020/6/15.

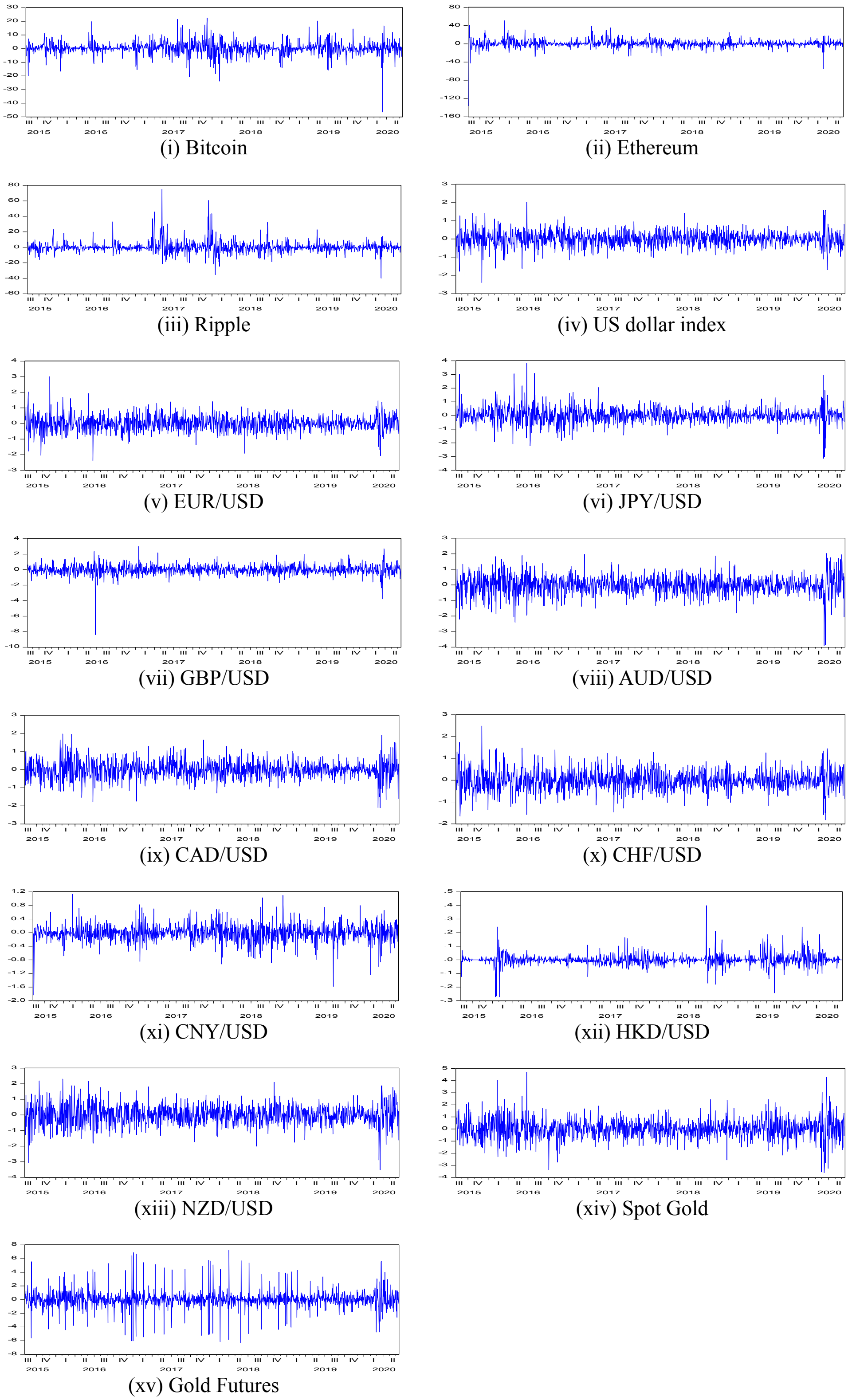

Fig. 2. Daily Closing Returns of Select Series from 2015/8/7 to 2020/6/15.

Table 3
Descriptive Statistics, Unit Root Tests and ARCH Test for the Closing Price Returns.

Variables	Descriptive Statistics						Unit Roots Tests			ARCH test
	Mean	Max	Min	SD	Skewness	Kurtosis	ADF	PP	KPSS	LM(1–7)
Whole Sample: 2015/8/7 to 2020/6/15 (1266 observations)										
R_{BTC}	0.278	22.512	−46.473	4.681	−0.830	14.137	−35.807*	−35.818*	0.215	8.489*
R_{ETH}	0.349	51.083	−136.353	8.535	−2.942	58.925	−40.119*	−39.474*	0.299	10.311*
R_{XRP}	0.250	75.083	−39.897	7.387	2.313	21.656	−21.054*	−32.816*	0.178	52.449*
R_{DXY}	−0.0004	2.031	−2.401	0.414	−0.067	5.633	−34.767*	−35.140*	0.059	45.650*
R_{EUR}	0.002	3.016	−2.382	0.479	0.118	5.810	−35.005*	−35.329*	0.073	8.174*
R_{JPY}	0.012	3.811	−3.141	0.561	0.413	9.356	−36.569*	−36.562*	0.101	51.634*
R_{GBP}	−0.017	3.001	−8.395	0.639	−1.802	28.271	−33.603*	−33.638*	0.121	36.488*
R_{AUD}	−0.006	2.035	−3.900	0.613	−0.520	6.190	−23.219*	−34.791*	0.048	7.468*
R_{CAD}	−0.003	1.976	−2.110	0.482	0.035	4.677	−35.287*	−35.287*	0.038	16.236*
R_{CHF}	0.003	2.484	−1.817	0.457	0.186	4.620	−34.374*	−34.505*	0.035	18.086*
R_{CNY}	−0.010	1.131	−1.836	0.252	−0.523	8.423	−36.736*	−36.780*	0.126	25.939*
R_{HKD}	0.00002	0.399	−0.273	0.042	0.648	18.785	−33.658*	−33.637*	0.299	11.014*
R_{NZD}	−0.002	2.306	−3.526	0.636	−0.183	4.782	−35.094*	−35.095*	0.080	6.435*
R_{GOLDS}	0.036	4.693	−3.609	0.826	0.187	6.155	−35.369*	−35.376*	0.117	19.111*
R_{GOLDf}	0.031	7.226	−6.309	1.370	0.174	10.384	−31.851*	−54.125*	0.101	210.790*
Pre-2018 Cryptocurrency Crash: 2015/8/7 to 2017/12/31 (625 observations)										
R_{BTC}	0.633	22.512	−20.753	4.451	0.140	8.333	−24.024*	−24.010*	0.559	23.193*
R_{ETH}	0.897	51.083	−136.353	10.404	−3.134	52.956	−29.386*	−29.386*	0.250	4.888*
R_{XRP}	0.896	75.083	−21.370	8.395	3.235	22.328	−13.719*	−21.947*	0.503	25.077*
R_{DXY}	−0.009	2.031	−2.401	0.448	−0.238	5.600	−25.122*	−25.133*	0.113	5.512*
R_{EUR}	0.014	3.016	−2.382	0.531	0.269	5.746	−25.042*	−25.049*	0.120	1.667*
R_{JPY}	0.016	3.811	−2.216	0.645	0.727	7.378	−24.819*	−24.820*	0.205	5.460*
R_{GBP}	−0.022	3.001	−8.395	0.695	−2.765	37.304	−24.449*	−24.488*	0.269	5.460*
R_{AUD}	0.008	1.965	−2.402	0.627	−0.380	3.982	−26.339*	−26.325*	0.036	10.612*
R_{CAD}	0.007	1.976	−1.791	0.521	0.175	3.852	−25.026*	−25.026*	0.075	4.039*
R_{CHF}	0.002	2.484	−1.648	0.505	0.293	4.417	−24.237*	−24.254*	0.023	8.515*
R_{CNY}	−0.008	1.131	−1.836	0.223	−0.523	12.378	−23.494*	−23.496*	0.735	19.697*
R_{HKD}	−0.001	0.242	−0.273	0.037	−1.021	20.131	−23.410*	−23.461*	0.078	5.898*
R_{NZD}	0.011	2.306	−3.068	0.691	−0.037	3.704	−25.879*	−25.900*	0.043	13.705*
R_{GOLDS}	0.028	4.693	−3.384	0.830	0.364	5.734	−24.908*	−24.943*	0.072	13.010*
R_{GOLDf}	0.026	6.869	−6.039	1.428	0.189	9.939	−23.685*	−37.033*	0.050	105.172*
Variables	Descriptive Statistics						Unit Roots Tests			ARCH test
	Mean	Max	Min	SD	Skewness	Kurtosis	ADF	PP	KPSS	LM(1–7)
During 2018 Cryptocurrency Crash: 2018/1/1 to 2018/12/31 (261 observations)										
R_{BTC}	−0.523	12.413	−23.874	4.883	−0.700	5.526	−16.755*	−16.776*	0.056	11.836*
R_{ETH}	−0.663	24.743	−27.163	6.681	−0.174	4.694	−16.277*	−16.349*	0.083	1.839
R_{XRP}	−0.703	32.201	−35.328	7.766	0.069	6.031	−10.157*	−15.192*	0.149	14.713*
R_{DXY}	0.016	1.417	−1.024	0.378	0.055	3.219	−16.894*	−16.925*	0.116	2.139
R_{EUR}	−0.018	1.403	−1.909	0.447	−0.181	3.628	−16.162*	−16.302*	0.109	0.329
R_{JPY}	0.011	1.087	−1.432	0.401	0.043	3.361	−15.969*	−15.969*	0.186	0.761
R_{GBP}	−0.022	1.909	−1.692	0.511	0.154	4.054	−16.454*	−16.457*	0.121	0.117
R_{AUD}	−0.039	1.863	−1.370	0.536	−0.048	3.114	−17.013*	−17.024*	0.038	0.576
R_{CAD}	−0.031	1.299	−1.296	0.428	0.166	3.091	−16.109*	−16.154*	0.070	0.999
R_{CHF}	−0.003	1.275	−1.170	0.399	0.025	3.120	−16.300*	−16.300*	0.110	12.150*
R_{CNY}	−0.021	1.094	−0.926	0.302	0.081	4.325	−17.975*	−17.944*	0.389	5.901*
R_{HKD}	−0.001	0.399	−0.180	0.044	2.989	32.698	−16.531*	−16.543*	0.149	1.376
R_{NZD}	−0.021	2.095	−2.006	0.536	0.076	3.926	−16.378*	−16.384*	0.097	0.639
R_{GOLDS}	−0.006	2.443	−2.556	0.649	0.144	5.031	−19.017*	−19.602*	0.306	6.123*
R_{GOLDf}	−0.013	7.226	−6.309	1.484	0.064	11.627	−13.491*	−32.980*	0.191	48.504*
Post-2018 Cryptocurrency Crash: 2019/1/1 to 2019/12/30 (260 observations)										
R_{BTC}	0.257	20.305	−15.903	4.210	0.424	7.494	−15.644*	−15.640*	0.335	3.992*
R_{ETH}	−0.002	17.945	−18.429	4.706	−0.151	6.117	−14.962*	−14.956*	0.239	3.501

(*continued on next page*)

Table 3 (*continued*)

Variables	Descriptive Statistics						Unit Roots Tests			ARCH test
	Mean	Max	Min	SD	Skewness	Kurtosis	ADF	PP	KPSS	LM(1–7)
R_{XRP}	−0.229	22.858	−13.418	4.209	0.576	7.288	−15.106*	−15.189*	0.144	11.248*
R_{DXY}	0.002	0.816	−0.839	0.280	0.015	3.366	−16.970*	−16.958*	0.083	0.372
R_{EUR}	−0.009	0.898	−1.061	0.311	−0.056	3.880	−16.693*	−16.703*	0.097	0.101
R_{JPY}	0.003	1.318	−1.346	0.346	0.427	4.804	−16.523*	−16.575*	0.077	7.935*
R_{GBP}	0.011	1.992	−1.519	0.510	0.722	4.879	−15.880*	−15.880*	0.156	4.396*
R_{AUD}	−0.003	1.516	−1.799	0.430	−0.082	4.217	−16.013*	−16.013*	0.097	1.152
R_{CAD}	0.016	1.023	−0.913	0.315	0.162	3.625	−15.459*	−15.451*	0.068	0.124
R_{CHF}	0.005	1.255	−1.168	0.345	0.226	3.997	−15.332*	−15.311*	0.156	17.050*
R_{CNY}	−0.006	0.799	−1.581	0.242	−1.105	10.694	−9.513*	−16.612*	0.164	1.892
R_{HKD}	0.002	0.242	−0.243	0.048	0.665	9.790	−14.745*	−14.773*	0.239	8.394*
R_{NZD}	0.001	1.256	−1.755	0.463	−0.269	3.742	−15.389*	−15.403*	0.196	11.560*
R_{GOLDS}	0.064	2.436	−2.165	0.718	0.056	3.899	−16.420*	−16.432*	0.096	0.731
R_{GOLDf}	0.054	4.288	−4.049	0.963	0.275	8.198	−21.121*	−21.132*	0.100	28.022*
Variables	Descriptive Statistics						Unit Roots Tests			ARCH test
	Mean	Max	Min	SD	Skewness	Kurtosis	ADF	PP	KPSS	LM(1–7)
COVID-19 pandemic: 2019/12/31 to 2020/6/15 (120 observations)										
R_{BTC}	0.216	16.710	−46.473	6.022	−3.842	32.108	−12.951*	−12.780*	0.079	0.113
R_{ETH}	0.459	17.427	−55.071	7.550	−3.281	26.568	−13.538*	−13.232*	0.087	0.590
R_{XRP}	−0.006	14.263	−39.897	5.956	−2.576	19.224	−13.270*	−13.082*	0.099	0.620
R_{DXY}	0.002	1.588	−1.695	0.533	0.414	4.752	−8.318*	−8.297*	0.110	31.286*
R_{EUR}	0.006	1.460	−2.064	0.554	−0.350	4.656	−9.078*	−9.149*	0.165	17.635*
R_{JPY}	0.012	2.940	−3.141	0.746	−0.744	9.216	−12.938*	−12.765*	0.033	18.448*
R_{GBP}	−0.036	2.699	−3.779	0.821	−0.638	7.014	−8.047*	−8.227*	0.062	9.065*
R_{AUD}	−0.016	2.035	−3.900	0.948	−0.892	6.472	−8.263*	−8.498*	0.266	33.160*
R_{CAD}	−0.033	1.905	−2.110	0.651	−0.396	4.874	−10.581*	−10.588*	0.213	7.876*
R_{CHF}	0.017	1.446	−1.817	0.531	−0.228	4.534	−9.690*	−9.733*	0.059	6.553*
R_{CNY}	−0.012	0.657	−1.242	0.294	−1.042	5.766	−12.620*	−12.535*	0.066	0.146
R_{HKD}	0.004	0.187	−0.117	0.044	0.549	5.832	−9.748*	−9.727*	0.070	17.669*
R_{NZD}	−0.035	1.879	−3.526	0.836	−0.691	5.688	−8.869*	−8.943*	0.327	30.202*
R_{GOLDS}	0.108	4.297	−3.609	1.261	−0.168	4.824	−9.537*	−9.544*	0.031	5.101*
R_{GOLDf}	0.101	5.601	−4.746	1.552	0.273	5.812	−10.104*	−10.077*	0.031	11.538*

Notes: * denotes significance at the 1% level.

In the Ripple group, there are positive co-volatility spillover effects between Ripple and financial assets (namely Euro, Japanese Yen, Australian Dollar, Hong Kong Dollar, New Zealand dollar, Spot Gold, and Gold Futures). The asymmetric co-volatility spillover effects are found between Ripple and the US dollar index, Ripple and British Pound, Ripple and Canadian Dollar, Ripple and Swiss France, Ripple and Chinese Yuan.

In summary, as Table 7 presents, during the whole sample period, Bitcoin is a diversifier for the US dollar index, Euro, Japanese Yen, Hong Kong Dollar, New Zealand dollar, Spot Gold, and Gold Futures. Ethereum can be regarded as a diversifier for Euro, Japanese Yen, British Pound, Australian Dollar, Swiss France, Hong Kong Dollar, New Zealand dollar, Spot Gold, and Gold Futures. Ripple appears as a diversifier for Euro, Japanese Yen, Australian Dollar, Hong Kong Dollar, New Zealand dollar, Spot Gold, and Gold Futures. As for hedging capabilities, we find statistical evidence of Bitcoin being a hedge for British Pound, Australian Dollar, Canadian Dollar, Swiss France, and Chinese Yuan. Ethereum acts only as hedge for the US dollar index, Canadian Dollar, and Chinese Yuan. Ripple can be regarded as a hedge for the US dollar index, British Pound, Canadian Dollar, Swiss France, Chinese Yuan. Overall, these findings suggest that hedging opportunities can only be found between the cryptocurrency market and few traditional currency markets, while there is no evidence of hedging opportunities between the cryptocurrency market and gold market. However, cryptocurrencies can be suitable as a financial diversifier for most of traditional currencies and gold.

5.2. Pre-2018 cryptocurrency crash (2015/8/7 to 2017/12/31)

During pre-2018 cryptocurrency crash period, not all the estimates of the diagonal matrix A are significantly different from zero at the 1% significance level (Table 4). The results indicate that some of the combinations between cryptocurrency returns and exchange rate returns or gold returns do not have significant co-volatility spillover effects.

First, as Table 6 indicates, in the Bitcoin group, nine of twelve combinations have significant co-volatility spillover effects. More specifically, there are positive co-volatility spillover effects between Bitcoin and the Japanese Yen, Bitcoin and the British Pound,

Table 4
Estimation of Diagonal Elements of A in the Diagonal BEKK Model.

Bitcoin (BTC)						Ethereum (ETH)						Ripple (XRP)					
Asset	All	2018 Cryptocurrency Crash			COVID 19	Asset	All	2018 Cryptocurrency Crash			COVID 19	Asset	All	2018 Cryptocurrency Crash			COVID 19
		Pre	During	Post				Pre	During	Post				Pre	During	Post	
R_{BTC}	0.401*	0.429*	0.245*	0.599*	0.926*	R_{ETH}	0.401*	0.454*	0.294*	0.308*	0.929*	R_{XRP}	0.525*	0.872*	0.450*	0.521*	−0.458*
R_{DXY}	0.149*	−0.210*	−0.053	0.090	0.457*	R_{DXY}	0.159*	0.012	−0.024	0.098	0.435*	R_{DXY}	0.154*	−0.011	−0.034	0.021	0.448*
R_{BTC}	0.399*	0.425*	0.249*	0.608*	1.091*	R_{ETH}	0.422*	0.465*	0.273*	0.299*	1.017*	R_{XRP}	0.527*	0.707*	0.453*	0.527*	−0.397*
R_{EUR}	0.128*	−0.024	−0.021	0.058	0.352*	R_{EUR}	0.137*	0.004	−0.050	0.054	0.350*	R_{EUR}	0.135*	−0.009	−0.061	−0.026	0.325*
R_{BTC}	0.381*	0.439*	0.236*	0.541*	0.613*	R_{ETH}	0.368*	0.425*	0.307*	0.300*	0.863*	R_{XRP}	0.476*	0.688*	0.471*	0.536*	0.547*
R_{JPY}	0.277*	0.158*	−0.125	0.115	0.539*	R_{JPY}	0.271*	0.190*	−0.147	0.163*	0.515*	R_{JPY}	0.274*	0.182*	−0.020	−0.170*	0.606*
R_{BTC}	0.395*	0.417*	0.242*	0.537*	0.715*	R_{ETH}	0.386*	0.399*	−0.143*	0.294*	1.037*	R_{XRP}	0.533*	0.700*	0.339*	0.518*	1.033*
R_{GBP}	0.357*	0.378*	−0.134*	0.342*	0.505*	R_{GBP}	0.376*	0.461*	−0.127	0.354*	0.493*	R_{GBP}	0.345*	0.389*	−0.173*	0.329*	0.484*
R_{BTC}	0.402*	0.415*	0.223*	0.589*	0.403*	R_{ETH}	0.400*	0.443*	0.232*	0.323*	0.879*	R_{XRP}	0.529*	1.010*	0.447*	0.521*	0.360*
R_{AUD}	0.198*	−0.040	0.065	0.013	0.702*	R_{AUD}	0.195*	−0.010	0.065	−0.017	0.422*	R_{AUD}	0.191*	−0.007	0.048	−0.033	0.403*
R_{BTC}	0.413*	0.423*	0.239*	0.569*	0.710*	R_{ETH}	0.396*	0.427*	0.300*	0.317*	0.661*	R_{XRP}	0.533*	0.871*	0.490*	0.513*	0.475*
R_{CAD}	0.149*	0.134*	−0.022	−0.025	0.174*	R_{CAD}	0.173*	0.219*	0.172	0.002	0.205*	R_{CAD}	0.167*	0.122*	−0.009	−0.006	0.030
R_{BTC}	0.400*	0.427*	0.216*	0.626*	0.982*	R_{ETH}	0.400*	0.440*	−0.043	0.313*	0.936*	R_{XRP}	0.525*	0.705*	0.346*	0.505*	0.659*
R_{CHF}	0.096*	−0.004	0.207*	0.263*	0.333*	R_{CHF}	0.152*	0.022	0.228*	0.270*	0.347*	R_{CHF}	0.082*	−0.021	−0.159*	0.237*	0.371*
R_{BTC}	0.394*	0.438*	0.213*	0.652*	0.561*	R_{ETH}	0.381*	0.399*	0.222*	0.263*	0.571*	R_{XRP}	0.493*	0.664*	0.330*	0.394*	0.425*
R_{CNY}	0.325*	−0.287*	0.288*	0.465*	−0.116	R_{CNY}	0.349*	0.306*	0.373*	0.438*	−0.112	R_{CNY}	0.301*	0.285*	0.300*	0.375*	−0.089
R_{BTC}	0.338*	0.368*	0.212*	0.533*	0.510*	R_{ETH}	0.329*	0.372*	0.045*	0.284*	0.522*	R_{XRP}	0.381*	0.614*	0.090*	0.502*	0.373*
R_{HKD}	0.680*	0.588*	1.109*	0.305*	0.453*	R_{HKD}	0.663*	0.481*	1.107*	0.300*	0.476*	R_{HKD}	0.691*	0.541*	1.078*	0.312*	0.454*
R_{BTC}	0.405*	0.428*	0.233*	0.618*	0.820*	R_{ETH}	0.407*	0.407*	0.256*	0.343*	0.747*	R_{XRP}	0.552*	0.963*	0.338*	0.528*	0.509*
R_{NZD}	0.146*	−0.093*	0.026	0.033	0.423*	R_{NZD}	0.145*	0.293*	0.056	0.011	0.057	R_{NZD}	0.138*	−0.021	0.011	−0.007	0.073
R_{BTC}	0.387*	0.419*	0.304*	0.571*	0.612*	R_{ETH}	0.399*	0.434*	0.338*	0.283*	0.700*	R_{XRP}	0.528*	0.731*	0.473*	0.510*	0.477*
R_{GOLDS}	0.191*	0.104*	−0.020	0.182*	0.355*	R_{GOLDS}	0.187*	0.009	−0.122*	0.193*	0.378*	R_{GOLDS}	0.178*	−0.101*	−0.014	0.180*	0.388*
R_{BTC}	0.398*	0.410*	0.248*	0.553*	0.569*	R_{ETH}	0.386*	0.396*	0.238*	0.182*	0.627*	R_{XRP}	0.453*	0.602*	0.247*	0.465*	0.455*
R_{GOLDF}	0.509*	0.528*	0.573*	0.042	0.415*	R_{GOLDF}	0.495*	0.532*	0.497*	0.475*	0.400*	R_{GOLDF}	0.474*	0.494*	0.528*	0.459*	0.387*

Notes: * denotes significance at the 1% level.

Table 5
Average Return Shock.

Bitcoin (BTC)

Asset	All	2018 Cryptocurrency Crash			COVID 19
		Pre	During	Post	
R_{BTC}	0.018	0.270	−0.058	0.139	−0.380
R_{DXY}	0.001	−0.006	−0.001	−0.002	−0.037
R_{BTC}	0.015	0.268	−0.035	0.157	−0.337
R_{EUR}	0.002	−0.0001	−0.002	0.001	0.045
R_{BTC}	0.028	0.263	−0.096	0.158	−0.263
R_{JPY}	0.014	0.003	0.004	0.009	0.021
R_{BTC}	−0.022	0.261	−0.003	0.120	−0.667
R_{GBP}	−0.002	0.0005	0.010	0.001	−0.013
R_{BTC}	0.036	0.249	−0.023	0.155	0.050
R_{AUD}	−0.005	−0.001	−0.015	0.001	−0.326
R_{BTC}	0.031	0.240	−0.044	0.160	−0.454
R_{CAD}	−0.004	−0.0005	−0.002	0.001	0.004
R_{BTC}	0.018	0.266	−0.065	0.225	−0.658
R_{CHF}	−0.0004	−0.0004	0.004	0.006	0.024
R_{BTC}	0.060	0.247	−0.042	0.266	−0.317
R_{CNY}	−0.007	−0.006	0.001	−0.014	−0.006
R_{BTC}	0.056	0.208	0.044	0.178	−0.337
R_{HKD}	0.001	−0.001	0.001	0.001	0.003
R_{BTC}	0.035	0.247	−0.051	0.177	−0.413
R_{NZD}	0.003	0.003	−0.004	−0.001	0.070
R_{BTC}	0.040	0.242	−0.032	0.119	−0.316
R_{GOLDS}	0.011	0.003	−0.017	0.028	0.027
R_{BTC}	0.007	0.233	−0.078	0.114	−0.373
R_{GOLDF}	0.079	0.072	0.178	0.014	0.046

Ethereum (ETH)

Asset	All	2018 Cryptocurrency Crash			COVID 19
		Pre	During	Post	
R_{ETH}	0.331	0.580	0.233	0.007	−0.857
R_{DXY}	−0.001	0.003	−0.001	0.0003	−0.029
R_{ETH}	0.325	0.580	0.254	0.006	−0.976
R_{EUR}	0.004	0.001	0.001	−0.001	0.035
R_{ETH}	0.348	0.538	0.185	0.052	−0.988
R_{JPY}	0.012	0.005	0.003	0.006	0.029
R_{ETH}	0.338	0.580	0.215	0.015	−1.117
R_{GBP}	0.003	0.009	0.009	−0.006	−0.031
R_{ETH}	0.334	0.544	0.295	−0.008	−0.881
R_{AUD}	0.003	−0.0005	−0.010	0.003	0.029
R_{ETH}	0.311	0.528	0.299	0.009	−1.131
R_{CAD}	−0.001	0.001	−0.004	0.001	0.013
R_{ETH}	0.320	0.568	0.110	0.078	−0.941
R_{CHF}	0.002	0.002	0.006	0.001	0.018
R_{ETH}	0.300	0.466	0.247	0.014	−0.905
R_{CNY}	−0.005	−0.005	−0.00003	−0.010	−0.005
R_{ETH}	0.373	0.590	0.251	0.053	−0.782
R_{HKD}	0.001	−0.001	0.001	0.001	0.004
R_{ETH}	0.338	0.524	0.277	−0.001	−1.117
R_{NZD}	0.005	0.001	−0.004	0.001	0.072
R_{ETH}	0.343	0.549	0.187	0.035	−0.859
R_{GOLDS}	0.016	0.005	0.005	0.015	0.035
R_{ETH}	0.289	0.467	0.254	−0.020	−0.851
R_{GOLDF}	0.090	0.089	0.171	0.039	0.058

Ripple (XRP)

Asset	All	2018 Cryptocurrency Crash			COVID 19
		Pre	During	Post	
R_{XRP}	0.525	1.389	0.189	0.089	−0.554
R_{DXY}	−0.0003	0.006	0.001	−0.001	−0.022
R_{XRP}	0.518	1.189	0.201	0.090	−0.503
R_{EUR}	0.003	−0.001	−0.002	−0.0002	0.020
R_{XRP}	0.497	1.150	0.229	0.043	−0.188
R_{JPY}	0.012	0.006	−0.001	0.006	0.005
R_{XRP}	0.503	1.178	0.124	0.079	−0.509
R_{GBP}	−0.001	−0.001	0.009	−0.005	−0.034
R_{XRP}	0.550	1.388	0.204	0.059	−0.383
R_{AUD}	0.004	0.004	−0.013	0.004	0.046
R_{XRP}	0.543	1.369	0.220	0.070	−0.445
R_{CAD}	−0.001	0.001	−0.002	−0.001	0.028
R_{XRP}	0.525	1.168	0.103	0.121	−0.614
R_{CHF}	−0.00002	0.001	0.002	−0.001	0.022
R_{XRP}	0.492	1.110	0.047	0.057	−0.331
R_{CNY}	−0.005	−0.008	0.003	−0.012	−0.006
R_{XRP}	0.527	0.954	0.028	0.100	−0.095
R_{HKD}	0.001	−0.001	0.001	0.001	0.005
R_{XRP}	0.563	1.343	0.079	0.069	−0.353
R_{NZD}	0.004	0.006	−0.005	0.002	0.095
R_{XRP}	0.553	1.181	0.017	0.132	−0.440
R_{GOLDS}	0.013	0.018	−0.159	0.014	0.025
R_{XRP}	0.477	1.050	0.052	0.016	−0.342
R_{GOLDF}	0.082	0.082	0.170	0.026	0.048

Table 6
Average Co-volatility Spillovers.

Bitcoin (BTC)						Ethereum (ETH)						Ripple (XRP)					
Asset	All	2018 Cryptocurrency Crash			COVID 19	Asset	All	2018 Cryptocurrency Crash			COVID 19	Asset	All	2018 Cryptocurrency Crash			COVID 19
		Pre	During	Post				Pre	During	Post				Pre	During	Post	
R_{BTC}	0.00003	0.0006	–	–	−0.0159	R_{ETH}	−0.0001	–	–	–	−0.0116	R_{XRP}	−0.00002	–	–	–	0.0044
R_{DXY}	0.0010	−0.0243	–	–	−0.1609	R_{DXY}	0.0211	–	–	–	−0.3461	R_{DXY}	0.0424	–	–	–	0.1136
R_{BTC}	0.0001	–	–	–	0.0172	R_{ETH}	0.0003	–	–	–	0.0125	R_{XRP}	0.0002	–	–	–	−0.0026
R_{EUR}	0.0008	–	–	–	−0.1296	R_{EUR}	0.0188	–	–	–	−0.3477	R_{EUR}	0.0370	–	–	–	0.0649
R_{BTC}	0.0015	0.0002	–	–	0.0070	R_{ETH}	0.0012	0.0004	–	0.0003	0.0128	R_{XRP}	0.0016	0.0008	–	−0.0005	0.0018
R_{JPY}	0.0030	0.0182	–	–	−0.0869	R_{JPY}	0.0347	0.0435	–	0.0025	−0.4391	R_{JPY}	0.0648	0.1442	–	−0.0039	−0.0624
R_{BTC}	−0.0002	0.0001	−0.0003	0.0001	−0.0047	R_{ETH}	0.0005	0.0017	–	−0.0007	−0.0158	R_{XRP}	−0.0002	−0.0003	−0.0005	−0.0008	−0.0170
R_{GBP}	−0.0031	0.0411	0.0001	0.0220	−0.2411	R_{GBP}	0.0491	0.1066	–	0.0015	−0.5712	R_{GBP}	0.0926	0.3206	−0.0072	0.0134	−0.2545
R_{BTC}	−0.0004	–	–	–	−0.0920	R_{ETH}	0.0002	–	–	–	0.0106	R_{XRP}	0.0004	–	–	–	0.0066
R_{AUD}	0.0029	–	–	–	0.0141	R_{AUD}	0.0260	–	–	–	−0.3263	R_{AUD}	0.0554	–	–	–	−0.0555
R_{BTC}	−0.0003	−0.00003	–	–	0.0005	R_{ETH}	−0.0001	0.0001	–	–	0.0017	R_{XRP}	−0.00004	0.0002	–	–	–
R_{CAD}	0.0019	0.0136	–	–	−0.0560	R_{CAD}	0.0214	0.0493	–	–	−0.1534	R_{CAD}	0.0483	0.1451	–	–	–
R_{BTC}	−0.00002	–	0.0002	0.0011	0.0078	R_{ETH}	0.0001	–	–	0.0001	0.0058	R_{XRP}	−0.000001	–	−0.0001	−0.0002	0.0053
R_{CHF}	0.0007	–	−0.0029	0.0371	−0.2153	R_{CHF}	0.0194	–	–	0.0066	−0.3055	R_{CHF}	0.0225	–	−0.0057	0.0145	−0.1503
R_{BTC}	−0.0009	0.0007	0.0001	−0.0044	–	R_{ETH}	−0.0006	−0.0007	0.0000	−0.0011	–	R_{XRP}	−0.0008	−0.0014	0.0003	−0.0018	–
R_{CNY}	0.0077	−0.0310	−0.0026	0.0806	–	R_{CNY}	0.0399	0.0570	0.0205	0.0016	–	R_{CNY}	0.0729	0.2101	0.0046	0.0085	–
R_{BTC}	0.0002	−0.0003	0.0002	0.0001	0.0008	R_{ETH}	0.0002	−0.0002	0.0001	0.0001	0.0010	R_{XRP}	0.0002	−0.0003	0.0001	0.0001	0.0008
R_{HKD}	0.0130	0.0452	0.0103	0.0289	−0.0779	R_{HKD}	0.0811	0.1055	0.0125	0.0045	−0.1945	R_{HKD}	0.1388	0.3166	0.0027	0.0156	−0.0161
R_{BTC}	0.0002	−0.0001	–	–	0.0243	R_{ETH}	0.0003	0.0001	–	–	–	R_{XRP}	0.0003	–	–	–	–
R_{NZD}	0.0021	−0.0098	–	–	−0.1432	R_{NZD}	0.0200	0.0625	–	–	–	R_{NZD}	0.0429	–	–	–	–
R_{BTC}	0.0008	0.0001	–	0.0030	0.0059	R_{ETH}	0.0012	–	−0.0002	0.0008	0.0093	R_{XRP}	0.0012	−0.0013	–	0.0013	0.0047
R_{GOLDS}	0.0030	0.0105	–	0.0123	−0.0686	R_{GOLDS}	0.0255	–	−0.0077	0.0019	−0.2270	R_{GOLDS}	0.0520	−0.0869	–	0.0121	−0.0816
R_{BTC}	0.0161	0.0157	0.0253	–	0.0108	R_{ETH}	0.0172	0.0187	0.0203	0.0034	0.0146	R_{XRP}	0.0175	0.0244	0.0221	0.0055	0.0084
R_{GOLDF}	0.0014	0.0505	−0.0111	–	−0.0881	R_{GOLDF}	0.0553	0.0983	0.0301	−0.0017	−0.2132	R_{GOLDF}	0.1023	0.3122	0.0068	0.0035	−0.0603

Notes: 1. Average co-volatility spillover $= \frac{\partial H_{ij,t}}{\partial \varepsilon_{j,t-1}} = a_{ii} \times a_{jj} \times \varepsilon_{j,t-1}, \, , i \neq j$. 2. – denotes insignificant.

Table 7
Capabilities of Cryptocurrencies: to Traditional Currencies or Gold.

Asset			Diversifier[1]	Hedge[2]	Safe haven[3]
All		BTC	DXY, EUR, JPY, HKD, NZD, GOLDS, GOLDF	GBP, AUD, CAD, CHF, CNY	
		ETH	EUR, JPY, GBP, AUD, CHF, HKD, NZD, GOLDS, GOLDF	DXY, CAD, CNY	
		XRP	EUR, JPY, AUD, HKD, NZD, GOLDS, GOLDF	DXY, GBP, CAD, CHF, CNY	
2018 Cryptocurrency Crash	Pre	BTC	JPY, GBP, GOLDS, GOLDF	DXY, CAD, CNY, HKD, NZD	
		ETH	JPY, GBP, CAD, NZD, GOLDF	CNY, HKD	
		XRP	JPY, CAD, GOLDF	GBP, CNY, HKD, GOLDS	
	During	BTC	HKD		GBP, CHF, CNY, GOLDF
		ETH	CNY, HKD, GOLDF		GOLDS
		XRP	CNY, HKD, GOLDF		GBP, CHF
	Post	BTC	GBP, CHF, HKD, GOLDS	CNY	
		ETH	JPY, CHF, HKD, GOLDS	GBP, CNY, GOLDF	
		XRP	HKD, GOLDS, GOLDF	JPY, GBP, CHF, CNY	
COVID 19		BTC			DXY, EUR, JPY, GBP, AUD, CAD, CHF, HKD, NZD, GOLDS, GOLDF
		ETH			DXY, EUR ,JPY, GBP, AUD, CAD, CHF, HKD, GOLDS, GOLDF
		XRP	DXY		EUR, JPY, GBP, AUD, CHF, HKD, GOLDS, GOLDF

[1]Diversifier: co-volatility spillover effects between two assets is positive.
[2]Hedge: co-volatility spillover effects between two assets being negative or asymmetric.
[3]Safe haven: negative or asymmetric co-volatility spillover effects between two assets in times of market stress or turmoil (such as the 2018 cryptocurrency crash and COVID-19).

Bitcoin and Spot Gold, and Bitcoin and Gold Futures, while there are negative co-volatility spillover effects between Bitcoin and the New Zealand dollar. The asymmetric co-volatility spillover effects are found between Bitcoin and financial assets (namely the US dollar index, Canadian dollar, Chinese Yuan, and Hong Kong dollar).

In the Ethereum group, seven of twelve combinations have significant co-volatility spillover effects. Positive co-volatility spillover effects are found between Ethereum and the Japanese Yen, Ethereum and the British Pound, Ethereum and the Canadian dollar, Ethereum and the New Zealand dollar, and Ethereum and Gold Futures. There are asymmetric co-volatility spillover effects between Ethereum and the Chinese Yuan, and Ethereum and the Hong Kong dollar.

In the Ripple group, seven of twelve combinations have significant co-volatility spillover effects. There are positive co-volatility spillover effects between Ripple and the Japanese Yen, Ripple and the Canadian dollar, and Ripple and Gold Futures, while there are negative co-volatility spillover effects between Ripple and Spot Gold. The co-volatility spillover effects between Ripple and the British Pound, Ripple and the Chinese Yuan, Ripple and the Hong Kong dollar are asymmetric.

Table 7 shows that in the pre-2018 cryptocurrency crash period, Bitcoin is a diversifier for the Japanese Yen, British Pound, Spot Gold, and Gold Futures. Ethereum can act as a diversifier for the Japanese Yen, British Pound, Canadian dollar, New Zealand dollar, and Gold Futures. Ripple appears as a diversifier for the Japanese Yen, Canadian dollar, and Gold Futures. Additionally, Bitcoin was a hedge for the US dollar index, Canadian dollar, Chinese Yuan, Hong Kong dollar, and the New Zealand dollar. In the meantime, Ethereum can be considered a hedge for the Chinese Yuan, and Hong Kong dollar. Ripple can be regarded as a hedge for the British Pound, Chinese Yuan, Hong Kong dollar, and Spot Gold.

5.3. 2018 Cryptocurrency crash (2018/1/1 to 2018/12/31)

During the 2018 cryptocurrency crash, a small number of the estimated coefficients in matrix A of Diagonal BEKK model are statistically significant at the 1% level (Table 4), which implies the co-volatility spillover effects only exist in a few cases. In what follows, the empirical results regarding the average co-volatility spillover effects for each of the three groups, namely Bitcoin, Ethereum, and Ripple during the 2018 cryptocurrency crash period are presented in Table 6.

In the Bitcoin group, five of twelve combinations display significant co-volatility spillover effects. The co-volatility spillover effects between Bitcoin and the Hong Kong dollar are positive. There are asymmetric co-volatility spillover effects between Bitcoin and the British Pound, Bitcoin and the Swiss Franc, Bitcoin and the Chinese Yuan, and Bitcoin and Gold Futures.

In the Ethereum group, only four of twelve combinations have significant co-volatility spillover effects. Specifically, in each of the cases involving the co-volatility between Ethereum and financial assets (namely Chinese Yuan, Hong Kong dollar, and Gold Futures), positive co-volatility is found. The co-volatility spillover effects between Ethereum and Spot Gold are asymmetric.

The results in the Ripple group are similar to those of Bitcoin. In detail, there are positive co-volatility spillover effects between Ripple and the Chinese Yuan, Ripple and the Hong Kong dollar, and Ripple and Gold Futures. The negative co-volatility spillover effects are found between Ripple and the British Pound, and Ripple and the Swiss Franc.

Table 7 summarizes that, during the 2018 cryptocurrency crash period, Bitcoin acts as a safe haven for the British Pound, Swiss Franc, Chinese Yuan, and Gold Futures. Ethereum is a safe haven only for Spot Gold. Ripple can be considered a safe haven for the British Pound and Swiss Franc. Moreover, we find evidence of Bitcoin being a diversifier for the Hong Kong dollar, and Ethereum and Ripple can be considered diversifiers for the Chinese Yuan, Hong Kong dollar, and Gold Futures.

5.4. Post-2018 cryptocurrency crash (2019/1/1 to 2019/12/30)

Not all the estimates of the diagonal matrix A are significantly different from zero at the 1% significance level in the post-2018 cryptocurrency crash period (Table 4). The results are similar to those of the pre-2018 cryptocurrency crash period (Ethereum group and Ripple group) and the 2018 cryptocurrency crash period (Bitcoin group). The average co-volatility spillover effects for each of the three groups, namely Bitcoin, Ethereum, and Ripple for the Post-2018 Cryptocurrency Crash period in Table 6 are discussed sequentially.

In the Bitcoin group, five of twelve combinations have significant co-volatility spillover effects. Specifically, there are positive co-volatility spillover effects between Bitcoin and the British Pound, Bitcoin and the Swiss Franc, Bitcoin and the Hong Kong dollar, and Bitcoin and Spot Gold, while the co-volatility spillover effects between Bitcoin and the Chinese Yuan are asymmetric.

In the Ethereum group, seven of twelve combinations display significant co-volatility spillover effects. Namely, there are positive co-volatility spillover effects between Ethereum and the Japanese Yen, Ethereum and the Swiss Franc, Ethereum and the Hong Kong dollar, and Ethereum and Spot Gold. The asymmetric co-volatility spillover effects are found between Ethereum and the British Pound, Ethereum and the Chinese Yuan, and Ethereum and Gold Futures.

In the Ripple group, seven of twelve combinations have significant co-volatility spillover effects, Specifically, there are positive co-volatility spillover effects between Ripple and the Hong Kong dollar, Ripple and Spot Gold, and Ripple and Gold Futures, while there are negative co-volatility spillover effects between Ripple and the Japanese Yen. The co-volatility spillover effects between Ripple and the British Pound, Ripple and the Swiss Franc, and Ripple and the Chinese Yuan are asymmetric.

As shown in Table 7, in the post-2018 cryptocurrency crash period, we find statistical evidence of Bitcoin being a diversifier for the British Pound, Swiss Franc, Hong Kong dollar, and Spot Gold. Ethereum can be a diversifier for the Japanese Yen, Swiss Franc, Hong Kong dollar, and Spot Gold. Ripple can be considered a diversifier for the Hong Kong dollar, Spot Gold, and Gold Futures. Moreover, as for hedging capability, Bitcoin acts as a hedge only for the Chinese Yuan. Ethereum can be regarded as a hedge for the British Pound, Chinese Yuan and Gold Futures. Ripple appears as a hedge for the Japanese Yen, British Pound, Swiss Franc, and Chinese Yuan.

5.5. COVID-19 pandemic (2019/12/31 to 2020/6/15)

During the COVID-19 pandemic period, most of the estimates of the diagonal matrix A are significantly different from zero at the 1% significance level (Table 4), indicating co-volatility spillover effects exist between cryptocurrency and traditional currency markets, as well as between cryptocurrency and gold markets.

In the Bitcoin group, there are significant co-volatility spillover effects in all combinations, except Bitcoin and the Chinese Yuan (Table 6). More specifically, the co-volatility spillover effects are asymmetric between Bitcoin and financial assets (the US dollar index, Euro, Japanese Yen, Australian Dollar, Canadian Dollar, Swiss France, Hong Kong Dollar, New Zealand dollar, Spot Gold, and Gold Futures). Only the co-volatility spillover effects between Bitcoin and the British Pound are negative.

In the Ethereum group, ten of twelve combinations have significant co-volatility spillover effects. To go a step further, there are negative co-volatility spillover effects between Ethereum and the US dollar index, and Ethereum and the British Pound. The co-volatility spillover effects for most combinations between Ethereum and other financial assets are asymmetric, namely Ethereum and the Euro, Ethereum and the Japanese Yen, Ethereum and the Australian Dollar, Ethereum and the Canadian Dollar, Ethereum and the Swiss Franc, Ethereum and the Hong Kong Dollar, Ethereum and Spot Gold, and Ethereum and Gold Futures.

In the Ripple group, nine of twelve combinations have significant co-volatility spillover effects. There are positive co-volatility spillover effects between Ripple and the US dollar index, while there are negative co-volatility spillover effects between Ripple and the British Pound. The asymmetric co-volatility spillover effects are found between Ripple and the Euro, Ripple and the Japanese Yen, Ripple and the Australian Dollar, Ripple and the Swiss Franc, Ripple and the Hong Kong dollar, Ripple and Spot Gold, and Ripple and Gold Futures.

Table 7 shows that during the COVID-19 pandemic period, Ripple is a diversifier for the US dollar index. Moreover, with the exception of a few insignificant cases, cryptocurrencies (Bitcoin, Ethereum and, Ripple) can be considered a safe haven for exchange rates or gold. These findings suggest that market practitioners can treat cryptocurrencies as an alternative investment instrument in an optimal portfolio for the sake of effective risk management and optimal dynamic hedging in times of extreme market turmoil and uncertainty, such as the COVID-19 pandemic.

The next section highlights the key findings of the analyses on how the spillover effects change in those five time periods. Research and practical implications are then derived to support the research objectives.

6. Conclusion

The primary purpose of this study is to understand and explain the risk volatility spillover effects between three major cryptocurrencies and ten leading exchange rates or two gold prices in order to facilitate risk management in the cryptocurrency, traditional currency and gold markets. The data used in the empirical analysis are the daily closing price of cryptocurrencies, exchange rates and gold from 7 August 2015 to 15 June 2020, with 1,267 observations. The dataset is analyzed in its entirety and also four divided time periods: pre-2018 cryptocurrency crash, 2018 cryptocurrency crash, post-2018 cryptocurrency crash, and COVID-19 pandemic. A Diagonal BEKK multivariate conditional volatility model, with well-established regularity conditions and valid asymptotic statistical properties under appropriate parametric restrictions, is used to analyze the co-volatility spillover effects.

The empirical results reveal significant co-volatility spillover effects for every pair of cryptocurrencies and exchange rates or gold for the whole sample period. The patterns of spillover effects, and thus the capabilities of cryptocurrencies, changed due to the economic shocks. For instance, the co-volatility spillover effects have similar patterns before and after the 2018 cryptocurrency crash. Namely, there are no co-volatility spillover effects for some pairs of cryptocurrencies and exchange rates or gold, such as the combination pairs for all three cryptocurrencies and the Euro or the Australian Dollar. During the 2018 cryptocurrency crash, the pattern of spillover effects changed dramatically with only a few cases displaying significant co-volatility spillover effects. However, significant spillover patterns are found between cryptocurrencies and exchange rates or gold during the COVID-19 pandemic except for a few insignificant cases. Interestingly, asymmetric co-volatility spillover effects are found in most cases of five periods which means the negative return shocks have larger impacts on co-volatility than positive return shocks. In other words, the impacts of the exchange rates and gold on co-volatility spillover effects are greater than those of cryptocurrency. Thus, hedging or safe haven opportunities can be found between the cryptocurrency market and traditional currency market, as well as between the cryptocurrency market and gold market.

In conclusion, the capabilities of cryptocurrency seem to be related to economic and environmental uncertainties, a result which mirrors the findings of prior studies showing that the capabilities of cryptocurrency are time-varying and related to economic uncertainty or shocks (Corbet et al., 2018; Shahzad et al., 2019; Charfeddine et al., 2020). However, unlike previous studies, the Diagonal BEKK model that provides more accurate estimates of spillover effects was developed for the analysis (McAleer et al., 2008; Chang et al., 2018a; McAleer, 2019b). Using more comprehensive sets of data and variables, this study finds evidence of significant differences between normal and extreme markets with regard to the capabilities of cryptocurrency as a diversifier, hedge or safe haven, against or for tractional currencies and gold. For the whole sample period (in the long run), cryptocurrencies can be considered as a hedge to some traditional currency markets, but only as an effective diversifier for market participants in Spot Gold and Gold Futures. We also find that cryptocurrencies can be a safe haven for only a few traditional currencies and gold when the cryptocurrency market suffers (i.e., 2018 cryptocurrency crash period). Comparably, during the COVID-19 pandemic period, cryptocurrencies can be used as a safe haven for market practitioners, in most cases, against traditional currencies and gold. Additionally, the hedging opportunities between cryptocurrencies and traditional currencies or gold in the post-2018 cryptocurrency crash period are fewer than those in the pre-2018 cryptocurrency crash period. The results suggest that cryptocurrencies are highly suitable as a safe haven asset in a period of high uncertainty. Some recent studies discuss the relationship between cryptocurrencies and stock markets during the COVID-19 turmoil, and most research document that cryptocurrencies (such as Bitcoin) cannot be considered as a safe haven during the pandemic (Conlon & McGee, 2020; Goodell & Goutte, 2020; Grobys, 2020; Kristoufek, 2020). However, Bitcoin futures and Tether are safe havens for stock indices (Conlon et al., 2020; Corbet et al., 2020) and Bitcoin and Ethereum are suitable as short-term safe havens for S&P500 (Mariana et al., 2021). Therefore, our study adds to the literature by examining the safe haven behavior of cryptocurrencies to traditional currencies and gold.

Overall, our empirical results suggest numerous opportunities for optimal dynamic hedging (or safe haven in times of market stress or turmoil) across the cryptocurrency and traditional currency or gold markets. The findings are valuable to market practitioners who seek protection from downward movements in traditional currency and gold markets. As such, governments and central banks can use the knowledge of risk transfer and spillover effects to develop and promote central bank digital currencies and build the legal regulatory system on the digital currency industry. For businesses, the information can be used to tailor payment methods or build asset portfolios to develop optimal risk management and hedging strategies. Investors and portfolio managers can use such information to build investment opportunities, hedging strategies, or risk insurance for managing financial portfolios.

Finally, the COVID-19 pandemic is still unfolding throughout the world, with wide-ranging and severe impacts upon the world's economies and financial markets. As an extension of this study, it would be helpful to follow up with the most up-to-date dataset to obtain more comprehensive information on the impact. Moreover, another possible research extension would be incorporating additional financial assets to aid in a more comprehensive understanding and modelling of the interrelationships between cryptocurrencies and financial assets.

CRediT authorship contribution statement

Shu-Han Hsu: Conceptualization, Data curation, Software, Formal analysis, Methodology, Writing - original draft. **Chwen Sheu:** Conceptualization, Supervision, Funding acquisition, Writing - review & editing. **Jiho Yoon:** Software, Validation, Writing - review & editing.

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