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Do cryptocurrencies provide better hedging? Evidence from major equity markets during COVID-19 pandemic

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ABSTRACT

Using the five-minute interval price data of two cryptocurrencies and eight stock market indices, we examine the risk spillover and hedging effectiveness between these two assets. Our approach provides a comparative assessment encompassing the pre-COVID-19 and COVID-19 sample periods. We employ copula models to assess the dependence and risk spillover from Bitcoin and Ethereum to stock market returns during both the pre-COVID-19 and COVID-19 periods. Notably, the COVID-19 pandemic has increased the risk spillover from Bitcoin and Ethereum to stock market returns. The findings vis-a-vis portfolio weights and hedge effectiveness highlight hedging gains; however, optimal investments in Bitcoin and Ethereum have reduced during the COVID-19 pandemic, while the cost of hedging has increased during this period. The findings also confirm that cryptocurrencies cannot provide incremental gains by hedging stock market risk during the COVID-19 pandemic.

1. Introduction

The worldwide spread of COVID-19 has not only caused massive impairment to the socioeconomic status of the world population, but also wreaked havoc on the entire financial system across the globe. Since early March 2020, the global spread of COVID-19 has led to a sharp decline in economic growth, and as per recent estimates, the annual GDP growth of major world economies could be negative during 2020 (OECD, 2020a). To contain the spread of COVID-19 and losses of lives, most governments across the world have resorted to economy-wide lockdowns, resulting in the temporary shutdown of businesses and factories. Thus, the anticipated loss in business has resulted in financial market turmoil and intensified economic uncertainty. For example, stock markets have fallen by 30\%, credit spreads of risky bonds have increased, and implied volatilities of stocks and oil have jumped to a new level (OECD, 2020b). The impacts have further created panic among investors, leading them to start to “risk-off” their positions to minimize losses. The excessive selling off has caused stock markets to plummet heavily. For example, the UK’s benchmark index plunged by 10\%, equivalent to £160.4 billion, thus witnessing the worst fall since the 1987 market crash. Other European markets, such as France and...
Germany, have also dipped by 12% (BBC, 2020). Similarly, S&P 500 and Nasdaq have also suffered from steep falls of 9.5% and 9.4%, respectively. The contagion, which has percolated to the credit markets, has also adversely affected firm solvency, especially for firms with higher corporate debts.

Recent studies that have examined the impact of the COVID-19 pandemic on financial markets include financial market contagion (Akhtaruzzaman et al., 2020; Ashraf, 2020; Salisu and Vo, 2020; Topcu and Gulal, 2019; Azimli, 2019; Goodell and Goutte, 2020; Baker et al., 2020), portfolio diversification opportunities (Corbet et al., 2020; Conlon and McGee, 2020; Akhtaruzzaman et al., 2020; Yoshino et al., 2020), and co-movements among cryptocurrencies (Yarovaya et al., 2020), among others. The high economic uncertainties associated with the spread of the pandemic and its resultant shock in financial markets induce investors to search for alternative assets that can offer safe hedging opportunities. Given the notion that cryptocurrencies may offer hedging benefits against stock market fall (Baur et al., 2018; Al-Yahyaee et al., 2019), until recently, these digital currencies have attracted the attention of many investors. For instance, Bitcoin, being uncorrelated with other traditional assets (Baur et al., 2018; Al-Yahyaee et al., 2019) and uninfluenced by the monetary policy environment (Narayan et al., 2019), can decrease portfolio risk while offering hedging benefits during financial market turmoil (Gil-Alana et al., 2020; Pal and Mitra, 2019; Al-Yahyaee et al., 2019). Conversely, owing to the higher volatility level of Bitcoin, managing its risk is intrinsically challenging for investors (Yermack, 2013), and thus, it may not be an ideal candidate to be considered as a safe haven asset (Bouri et al., 2017; Shahzad et al., 2019). Existing studies seemingly show inconclusive evidence concerning the role of cryptocurrencies, that is, whether they can offer safe hedging opportunities or are merely diversifiers.

In the context of the COVID-19 spread, Conlon and McGee (2020) noted that Bitcoin is not found to hedge against the extreme market fall of S&P 500; instead, it aggravates the downside risk of the portfolio. Similarly, Corbet et al. (2020) documented that gold performs much better than Bitcoin in hedging Chinese financial market risk. However, Goodell and Goutte (2020) stated that a strong negative co-movement exists between Bitcoin prices and COVID-19, suggesting that Bitcoin can be a potential hedger. Understandably, the nature of risk-sharing and role of cryptocurrencies as a hedge or safe haven have not yet been settled. Undoubtedly, conducting further investigations to determine whether risk sharing between cryptocurrencies and stock markets has increased (decreased) during the COVID-19 period relative to the pre-COVID-19 era is essential. As the magnitude of the pandemic shock on financial markets differs across countries, it is expected that the cryptocurrency–stock market relationship may be nonuniform across a broad set of financial markets, including the US, UK, European, and Asian equity markets.

In a recent study by Melki and Nefzi (2022), Ripple was found to act as a weak safe haven for the forex market during the pandemic-induced crisis. Interestingly, Bitcoin and Ripple neither show any safe haven properties nor any hedge characteristics for stock markets; however, they behave as safe havens for the commodity and forex markets. This study indicates that besides Bitcoin, other cryptocurrencies, such as Ripple and Ethereum, prove to be better safe havens. Thus, portfolio investors may not remain dependent on Bitcoin as representative of cryptocurrencies, as Bitcoin has lost its shine as a safe haven during the pandemic-engendered crisis.

Previous research has partially addressed these research questions. Moreover, there is conflicting evidence on the role of cryptocurrencies in diversifying equity market risk, especially during the pandemic crisis period. When creating effective portfolio allocations, investors are constantly concerned about cross-asset linkages (Antonakakis et al., 2018; Basher and Sadorsky, 2016; Sadorsky, 2014). With copula-based dependence analysis, investors can lower their risk exposure, especially when the market undergoes turmoil. The characteristics of specific cryptocurrencies that can be used to hedge portfolio risk with stocks can also be revealed through such an analysis. To create portfolios with less risk and choose alternative investment channels, understanding the differences in the nature and magnitude of risk spillovers can be helpful. Portfolio managers can create optimally balanced portfolios based on which cryptocurrency is more prone to market shocks regarding rising or falling stock prices. Moreover, knowledge of risk spillover during the upside and downside movements of stock markets better guides investors’ choices of risk-on and risk-off strategies. For instance, a higher downside risk spillover from cryptocurrencies to stocks during the pandemic crisis suggests that cryptocurrencies are unsuitable for hedging stock market risks during the pandemic period. This information encourages investors to abstain from taking higher long positions in assets, and this does not provide a better hedge during the markets’ downturn. Furthermore, given that the nature of Asian stock markets is different from the European and US equity markets, the nature of risk spillover and hedging analysis provide a lens through which investors can assess which cryptocurrencies are better for one market and which are more suitable for the other.

Motivated by the aforementioned reasons, we carry out an exhaustive analysis of the risk dependency between cryptocurrency and stock markets during the COVID-19 pandemic. Specifically, we add novelty to the extant literature by asking the following research questions:

Q1: What is the nature of the volatility or risk level in the cryptocurrency and stock markets during the pre-COVID-19 and COVID-19 periods?

Q2: What is the nature and extent of the dependency between cryptocurrencies and stock markets during the pre-COVID-19 and COVID-19 periods?

Q3: Is there any asymmetric tail risk transfer between cryptocurrencies and stock markets?

Q4: Is there a way to construct portfolios to minimize the tail risk in stock markets using cryptocurrencies during the pandemic crisis?

Armed with the aforementioned arguments, we examine the risk relationship between cryptocurrencies and stock market returns using five-minute interval data, including the pre-COVID-19 and COVID-19 periods. We begin by elucidating the volatility dynamics of the stock market and cryptocurrency returns, whereafter we employ copula models to assess the dependence between the two assets. This approach also allows us to find the best-fit copula to understand the risk spillover. This study considers two cryptocurrencies (Bitcoin and Ethereum) and eight stock markets. The choice of Bitcoin and Ethereum is based on the fact that they represent the two
major categories of cryptocurrencies. The market capitalization of Bitcoin and Ethereum accounted for 66 % and 8 % of the total market cap, respectively, in 2020.\footnote{This is based on the distribution of the market capitalization of leading cryptocurrencies in 2020. For details, see https://www.statista.com/statistics/730782/cryptocurrencies-market-capitalization/.} The stock market sample is chosen based on the number of cases as a proxy of COVID-19 spread.

Using copula-based VaR and CoVaR models, we evaluate the risk spillover from Bitcoin and Ethereum to stock market returns during both the pre-COVID-19 and COVID-19 periods. Furthermore, to test the hedging abilities of Bitcoin and Ethereum, especially during the crisis period, we apply optimal portfolio weights and hedge ratios and measure their hedging effectiveness.

Our results highlight the following four aspects. First, the highest negative return is exhibited by France during the COVID-19 period. Interestingly, Bitcoin and Ethereum have the lowest comparable returns between the pre-COVID-19 and COVID-19 periods. Conversely, for the stock markets, the minimum returns are multiple times higher during the COVID-19 period compared to the pre-COVID-19 era. Second, we observe that the persistence of the volatility for Bitcoin and stock markets in the UK, Germany, Japan, and China has increased during the COVID-19 period. Bitcoin shows a time-varying dependence on the stock markets of France and Germany. Ethereum and stock returns in the US are found to have increased during March–May 2020. Third, the COVID-19 pandemic has also increased the risk spillover from Bitcoin and Ethereum to stock market returns, as evident in the upside and downside CoVaR estimates, except in Japan. However, both the upside and downside stock market returns of Germany, Italy, Spain, and China exhibit fewer jumps in their sensitivities to the Bitcoin market risk during the COVID-19 pandemic. Interestingly, the results indicate a significant difference or asymmetry between VaR and CoVaR models for the risk spillover from cryptocurrencies to stock markets. The asymmetry is present both during the pre-COVID-19 and COVID-19 periods. Finally, the findings in connection to portfolio weights and hedge effectiveness highlight that diversifying stock portfolios with Bitcoin and Ethereum yields hedging gains; however, optimal investments in Bitcoin and Ethereum reduce during the COVID-19 period. This finding corroborates the results of risk spillovers that cryptocurrencies cannot provide incremental gains by hedging stock market risks during a market downturn (Glaser et al., 2014; Yermack, 2013; Bouri et al., 2017; Conlon and McGee, 2020).

In light of the aforementioned discussion, the contributions of this study are threefold. First, given that cryptocurrencies are different from traditional assets, this study addresses an important concern related to the hedging effectiveness of cryptocurrencies as an alternative asset class during the global pandemic spread. Second, this study is perhaps the first to examine the risk dependence between cryptocurrencies and stock market returns with a focus on the intraday (five-minute interval) price dynamics of these two different assets. The five-minute interval allows us to have more observations to better examine risk sharing between cryptocurrencies and stock markets due to the COVID-19 pandemic. Third, we present a comparative analysis scenario using two different sample periods regarding the optimal portfolio for each cryptocurrency and stock market pair to hedge against extreme downward market movements due to the COVID-19 pandemic. Portfolio allocation strategies can illustrate the behavior of cryptocurrencies when there are any exogenous shocks, such as the COVID-19 pandemic.

The remainder of this paper is organized as follows: Section 2 theoretically discusses the relationship between cryptocurrencies and stock markets. Section 3 briefly reviews the relevant literature. Section 4 presents the empirical approach adopted in this study. Section 5 describes the characteristics of the data and provides a preliminary analysis. Section 6 presents the results and findings. Finally, Section 7 concludes the paper.

2. Theoretical channel

As argued by Schilling and Uhlig (2019), cryptocurrencies (Bitcoin) are nothing but worthless, storable, and non-dividend paying objects and can be a medium of exchange without any effects due to stabilization policies by the central bank. Thus, these characteristics make cryptocurrency a unique tool to diversify the risk of other traditional assets, such as stocks and bonds. Diversification benefits mostly arise because the returns of cryptocurrencies are not correlated with those of other asset classes (Shahzad et al., 2020). The theoretical argument indicates that there are three channels that motivate the inclusion of Bitcoin and equity markets.

In a recent study, Narayan et al. (2019) demonstrated how Bitcoin prices impacted an economy’s monetary system. Monetary aggregates, inflation, and exchange rates are the three channels through which Bitcoin affects the monetary system and financial markets. When Bitcoin is used instead of a traditional currency, it changes the function of money and slows down money circulation. Thus, the quantitative theory of money becomes redundant.

Cryptocurrencies’ unique characteristics not only set them apart from their traditional counterparts but also make them appealing for portfolio diversification with other assets such as stocks. Therefore, the fundamental variables that affect how cryptocurrency prices are formed differ. As a result, it is possible to anticipate that the cryptocurrency market’s business cycle will vary from that of other assets, such as equity markets, thus making these two assets worthy of portfolio diversification (Kang et al., 2019).

Behavioral theories can also be used to debate the connection between cryptocurrencies and stocks. The gradual information diffusion hypothesis and investor conservatism both explain price changes in one asset because of price movements in another (Narayan et al., 2019). According to these two theories, cryptocurrencies may behave differently from traditional stocks. The Hong and Stein (1999) information diffusion hypothesis can be applied to show that cryptocurrencies have different characteristics from traditional stocks and would therefore respond differently to changes in equity market prices.

Furthermore, investors in traditional markets are more conservative and exhibit under- or over-reactions to shocks to other assets based on investor conservatism (Narayan and Sharma, 2011). This hypothesis is underpinned by information asymmetry, which is more pronounced in traditional asset markets. Therefore, it is anticipated that this phenomenon will differ among cryptocurrency
investors, making these two assets suitable for portfolio diversification.

3. Literature review

Given the importance of alternative assets in diversifying traditional asset risks, both investors and academic researchers continuously pursue the investigation of cryptocurrencies. Lately, the literature on cryptocurrencies has grown considerably to cover two important facets of cryptocurrencies, namely, importance as an alternative investment asset (Bariviera et al., 2017) and risk and return transmission between cryptocurrencies and other traditional assets (Briere et al., 2015; Dyhrberg, 2016; Corbet et al., 2018, 2020; Salisu et al., 2019; Shahzad et al., 2019; Conlon and McGee, 2020; Yahyee et al., 2019; Goodell and Goutte, 2020). A few studies have recently examined the suitability of cryptocurrencies as an asset class to diversify the traditional stock market risk during the COVID-19 period. Consistent with this study’s objective, we focus on studies that investigate the relationship between cryptocurrencies and traditional asset markets.

Using weekly data over the 2010–2013 period, Briere et al. (2015) found that Bitcoin provided significant diversification benefits encompassing properties such as high average return, volatility, and low correlation with other traditional assets.

Similarly, Dyhrberg (2016), using the daily data of Bitcoin, dollar–euro, dollar–sterling, and FTSE returns, observed that Bitcoin clearly showed hedging capabilities against the FTSE index and US stocks.

Similarly, Bouri et al. (2017) and Baur et al. (2018) emphasized the suitability of Bitcoin as a risk diversifier. Using the DCC-GARCH model, Bouri et al. (2017) reported that Bitcoin could serve as a good hedge and safe haven for the world’s major stock markets. They also suggested that Bitcoin is capable of attenuating the risk of Asian stock markets during extreme downfall. Using the daily data of Bitcoin, treasury bill rate, US equity market returns, precious metals, energy, bonds, and currencies, Baur et al. (2018) reported that Bitcoin is uncorrelated with traditional assets and can provide diversification benefits during both normal and turbulent periods.

Similarly, Guesmi et al. (2018), employing the VARMA and DCC-GARCH models, observed that Bitcoin helps in portfolio management and can reduce the portfolio risk with other traditional assets, such as stocks, foreign exchange, CBOE VIX, and commodities.

In a follow-up study, Bouri et al. (2018) examined the time-varying nature of volatility spillovers between Bitcoin and other assets. They documented that Bitcoin has a stronger return spillover with other assets, and the return spillover heavily depends on market conditions. For example, there is a positive return spillover from Bitcoin to developed and emerging stocks during bullish market conditions, whereas it reverses when market conditions become bearish. However, Bitcoin continues to provide positive return spillovers to the global, emerging, and Chinese stock markets, even when markets are bearish.

Later, Bouri et al. (2020a) observed that Bitcoin, Ethereum, and Litecoin are important assets for diversifying the risk of Asia-Pacific and Japanese stock markets. Using the daily data of eight cryptocurrencies and frequency domain causality tests, Bouri et al. (2020) noted that some unpopular cryptocurrencies, such as Stellar and Dash, should be included in the portfolio as they are segmented and have relatively stronger diversification benefits.

Yermack (2015), using a detailed examination of Bitcoin, observed that Bitcoin has zero correlation with US dollars and other prominent currencies, such as the euro, yen, and British pound and gold in the precious metals. Given the untethered characteristics of Bitcoin relative to other currencies, risk hedging is nearly impossible. Employing a cross-quantilogram approach, Shahzad et al. (2019) illustrated the similarities and differences in Bitcoin, gold, and commodities’ safe-haven properties, especially when the markets fell to extremes between July 2010 and February 2018. They found that the association between Bitcoin and stock markets is still weak, and Bitcoin needs more time to come into the shape of gold and other commodities. Bitcoin fails to deliver any safe haven property to investors in developed markets.

Studies that have examined the relationship between cryptocurrencies and stock markets during the pre-COVID-19 period have not provided conclusive answers to the debate over the effectiveness of cryptocurrencies as a safe haven asset. Accordingly, this issue remains unresolved in the literature.

Furthermore, in a COVID-19 context, using the daily data of Bitcoin and daily number of COVID-19-related deaths, Goodell and Goutte (2020) found that the levels of COVID-19 cause a rise in Bitcoin prices, especially after April 5, suggesting potential diversification benefits by Bitcoin. Conversely, there are studies by Shahzad et al. (2019), Yermack (2015), Colon and McGee (2020), and Corbet et al. (2020) that show contrarian evidence that Bitcoin barely hedges risks.

Colon and McGee (2020) observed that Bitcoin moved in lockstep with the S&P 500 market during the COVID-19 spread, and any allocation to Bitcoin in the diversified portfolio with stock increased the downside risk. Similarly, using hourly data from March 11, 2019, to March 20, 2020, and the DCC-GARCH model, Corbet et al. (2020) documented that during a time of serious economic and financial crisis, crypto-assets do not act as hedges or safe havens. Colon et al. (2020) also reported that cryptocurrencies were not found to act as safe havens for international equity markets during the spread of the pandemic.

Using 973 forms of cryptocurrencies and 30 international indices, Pengfei et al. (2019) suggested that cryptocurrencies are safe havens. However, there is no conclusive evidence of a hedge for most international equity markets. Interestingly, the safe haven property of cryptocurrencies is more visible for equity markets with larger capitalization and higher liquidity, especially in developed markets. Marorhée (2021) employed Bayesian structural vector autoregression to examine the susceptibility of cryptocurrencies to the COVID-19 pandemic. Hossain (2021), using a quasi-quantitative approach, conducted a synthesis analysis of the global cryptocurrency
market and examined the relevant distinguishing features of cryptocurrencies. The author documented that cryptocurrencies have emerged not only as a medium for digital cash systems, but also as a means of innovative investment. Shahzad et al. (2022) extended the scope of cryptocurrencies and examined whether conventional currencies were a hedge or safe haven for cryptocurrencies. They considered four cryptocurrencies: Bitcoin, Ethereum, Ripple, and Litecoin. They reported that the Japanese yen is the most consistent hedger for cryptocurrencies, followed by the Sterling and Chinese yuan. The euro, Japanese yen, and Chinese yuan are found to be safe havens during the downturn of the cryptocurrency market. Arif et al. (2021) investigated the dynamics of connectedness between conventional and green investments in fixed income, equity, and energy markets during the COVID-19 pandemic. They documented that only unidirectional spillovers existed from conventional bonds to green financial markets. The frequency-based analysis revealed that the connectedness between green and conventional markets is more pronounced in the short run.

The aforementioned studies demonstrate that interconnectedness and co-movements between equity markets and cryptocurrencies are important and investigate issues. However, there is inconclusive evidence on the role of cryptocurrencies in diversifying equity market risk. The abovementioned debate is more crucial, especially when financial markets tumble, as witnessed during the onset of the COVID-19 pandemic. Our study differs from the existing literature in three main ways. First, we consider a wide array of eight world major equity markets and two important cryptocurrencies, Bitcoin and Ethereum, to assess risk sharing between equity and cryptocurrency markets and the role of crypto-assets as hedges or safe havens. Second, the use of intraday, five-minute interval data can better illustrate the properties of risk dynamics between these two sets of assets. Moreover, we apply copula approaches to examine the nonlinear and asymmetric relationships between equity markets and cryptocurrencies. Unlike traditional methods, copula-based VaR and CoVaR models are more capable of disentangling the relationship between these two assets and lead to better allocation and decision-making. Third, portfolio allocation strategies, along with their hedge effectiveness, can extend the literature on the behavior of cryptocurrencies during exogenous shocks, such as the COVID-19 pandemic.

4. Methodology

In this section, we discuss the methodological approach used to estimate the risk dependence and portfolio implications. Section 4.1 discusses the marginal volatility model that we begin with to capture the volatility dynamics. Section 4.2 measures the best-fit copula for static and time-varying dependence between each cryptocurrency and stock market pair. Section 4.3 describes the method to quantify the risk of one asset with or without being conditional on the other asset. Section 4.4 explains the way to examine whether the hedging of stock markets with cryptocurrencies yields any gains.

4.1. Marginal distribution function

To examine the risk dependence between cryptocurrencies and stock market returns, we begin by estimating the marginal model. We employ the ARMA-GARCH model to investigate the volatility dynamics of two different asset returns during the pre-COVID-19 and COVID-19 periods. The volatility using a GARCH (1,1) process is expressed as:

\[ \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \]

where \( \sigma^2 \) refers to variance, and \( \varepsilon \) is the error term in the regression given by.

\[ r_i = a_{i0} + \beta r_{i-1} + \gamma \theta_{i-1}^{} + \varepsilon_{i,t} \]

where \( r_i \) and \( r_{i-1} \) are the returns of the current and past periods, respectively.

4.2. Copula model

To understand the dependence structure of returns between cryptocurrencies and stock markets, we apply copula models. Copula models can identify the risk spillover from one asset to another during extreme market movements, both upward and downward. Based on Sklar’s theorem, the copula function can be estimated as \( C(u, v) \), which is used as the joint distribution function of two continuous variables (e.g., \( x \) and \( y \)). The joint distribution function \( F_{xy}(x, y) \), is derived from the variable’s marginal distributions, \( F_x(x), F_y(y) \), and the bivariate copula. \( C(u, v) \) represents the bivariate copula function of marginal distributions from two series: cryptocurrency and stock returns. Thus, the bivariate copula allows the estimation of the joint probability density function:

\[ F_{xy}(x, y) = C(u, v)F_x(x)F_y(y) \]

We apply a family of bivariate copula models, while considering the static and time-varying parameters. Copula models are broadly employed owing to their symmetric and asymmetric properties. For example, the Normal, Frank, Student-\( t \), Plackett, and symmetrized Joe–Clayton (SJC) copulas consider symmetric tail dependence, whereas the Gumbel and Clayton copulas estimate dependence in either of the tails.\(^2\)

To estimate the time-varying dependence using copula functions, we specify the linear dependence parameter as \( \rho_t \) following an

\(^2\) The Gumbel copula captures lower tail dependence, while the rotated Gumbel considers upper tail dependence. On the contrary, the Clayton copula assesses the upper tail dependence and the rotated Clayton copula identifies lower tail dependence. For details, please see Mensi et al. (2017).
ARMA (1,q) process:
\[ \rho_t = \Lambda(\varphi_0 + \varphi_1 \rho_{t-1} + \varphi_2 \sum_{i=1}^{q} \omega^{-1}(u_{t-i}) \omega^{-1}(v_{t-i}) ) \]  
(4) 

where \( \Lambda(x) \) is the modified logistic transformation to ensure that \( \rho_t \) lies between \(-1\) and \(+1\). Eq.(4) estimates the linear dependence of the Normal and Student-t copulas. \( \varphi_0 \) is an autoregressive coefficient and \( \varphi_2 \) represents the average product of two transformed variables over the lag length of \( q \). We obtain the Student-t copula dependence parameters by replacing \( \omega^{-1}(u_{t-i}) \) and \( \omega^{-1}(v_{t-i}) \) with \( t_i^{-1}u_{t-i} \) and \( t_i^{-1}v_{t-i} \), respectively. The time-varying Gumbel and rotated Gumbel copula dependence parameters (\( \vartheta_i \)) are estimated by considering the ARMA (1,q) process as follows:
\[ \vartheta_i = \alpha + \tau_i \rho_{t-1} + \gamma \sum_{i=1}^{q} \mid u_{t-i} - v_{t-i} \mid \]  
(5) 

The time-varying dependence parameters for the SJC copula are estimated based on Eqs. (6) and (7).
\[ \vartheta_i^U = \Delta(\vartheta_0 + \tau_i \theta_{t-1} + \gamma \sum_{i=1}^{q} \mid u_{t-i} - v_{t-i} \mid) \]  
(6) 
\[ \vartheta_i^D = \Delta(\vartheta_0 + \tau_i \theta_{t-1} + \gamma \sum_{i=1}^{q} \mid u_{t-i} - v_{t-i} \mid) \]  
(7) 

where \( \Delta(x) \), considering logistic transformation, keeps \( \vartheta_i^U \) and \( \vartheta_i^D \) between 0 and 1.

4.3. VaR and CoVaR estimations

Notably, VaR and CoVaR are two approaches to assess the nature and amount of risk in a particular asset market. In VaR, an investor evaluates the risk of losing an asset or portfolio’s value over a particular period for a given confidence level. The VaR for long (short) positions evaluates the downside (upside) risk. However, the CoVaR quantifies the amount of risk conditional on the risk of another asset. Thus, the CoVaR estimates the VaR of one asset or market returns conditional on the VaR of the other asset or market returns. Considering the VaR, we estimate both the upside and downside risks of cryptocurrency and stock returns. The downside and upside VaR measures are expressed as follows:
\[ \text{VaR}_{\alpha}^{\text{Downside}} = r_t + t_i^{-1}(\alpha)\sigma_t \]  
(8) 
\[ \text{VaR}_{\alpha}^{\text{Upside}} = r_t + t_i^{-1}(1 - \alpha)\sigma_t \]  
(9) 

where \( r_t \) and \( \sigma_t \) are the conditional mean and standard deviation of the return series, respectively, as estimated by the ARMA-GARCH model. \( t_i^{-1}(\alpha) \) represents \( \alpha \) percent (5%) quantile of the skewed Student’s t distributions. However, VaR is not capable of examining the risk of stock markets, given the risk flows from cryptocurrency markets. To overcome this limitation, we estimate CoVaR (Adrian and Brunnermeier, 2011), whereby we measure the VaR of stock market returns conditional on the VaR of Bitcoin and Ethereum returns. Thus, the upside and downside CoVaR measures for stock market returns can be written as:
\[ \text{Pr} \left( r_t^U \geq \text{CoVaR}_{\beta}^{\text{Upside}} \mid r_t^L \geq \text{VaR}_{\alpha}^{\text{Downside}} \right) = \beta \]  
(10) 
\[ \text{Pr} \left( r_t^L \leq \text{CoVaR}_{\beta}^{\text{Downside}} \mid r_t^U \leq \text{VaR}_{\alpha}^{\text{Upside}} \right) = \beta \]  
(11) 

where \( r_t^U \) and \( r_t^L \) denote the stock returns and cryptocurrency returns, respectively. Eqs. (10) and (11) estimate the upside and downside CoVaR measures of stock market returns for the \( \beta \) quantile (1 - \( \beta \) confidence level) of the conditional distributions of \( r_t^L \). \( r_t^L \geq \text{VaR}_{1 - \alpha}^{\text{Upside}} \) represents the VaR of cryptocurrency returns at the 1-\( \alpha \) confidence level for ‘t’ time period.

The best-fit copula estimated in Section 3.2 is applied to estimate the CoVaR with the copula. The estimation is performed in two steps. First, \( F_{r_t} \left( \text{CoVaR}_{\beta}^{\text{Upside}} \right) \) is estimated at the quantiles of VaR and CoVaR and a particular bivariate copula function. \( F_{r_t} \left( \text{CoVaR}_{\beta}^{\text{Upside}} \right) \) is estimated as follows:
\[ 1 - F_{r_t} \left( \text{CoVaR}_{\beta}^{\text{Downside}} \right) = C \left( F_{r_t} \left( \text{CoVaR}_{\beta}^{\text{Upside}} \right), F_{r_t} \left( \text{VaR}_{\alpha}^{\text{Downside}} \right) \right) = \alpha \beta \]  
(12)

Second, using the distribution functions for stock and cryptocurrency returns (Eqs. (1) and (2)), the CoVaR for stock returns is estimated as \( F_{r_t} \left( \text{CoVaR}_{\beta}^{\text{Upside}} \right) \). To assess whether upside/downside CoVaR is equal to upside and downside VaR, we employ the KS
Interestingly, China Bitcoin, Ethereum, and stock market indices in March 2020 due to the sudden outbreak of the COVID-19 pandemic worldwide. The UK (FTSE 100), the US (S&P 500), the UK (FTSE 100), Europe, and Asia responded to the second crash of the Shanghai Stock Index. However, unlike the stock market, cryptocurrencies (Bitcoin and Ethereum) and eight stock market indices. The stock markets considered in this study are S&P 500 of the US, FTSE 100 of the UK, CAC40 of France, DAX30 of Germany, FTSE MIB of Italy, IBEX35 of Spain, Nikkei 225 of Japan, and SSE composite index of China. We consider five-minute interval sample data in the study covering the pre-COVID-19 and COVID-19 periods. The countries selected are based on the impact of the COVID-19 pandemic, as noted in April 2020. We measure the impact of the COVID-19 pandemic based on the number of cases.

4.4. Portfolio estimations

In this section, we discuss the methods used to estimate hedge ratios, optimal portfolio weights, and hedge effectiveness. Following Kroner and Sultan (1993) and Kroner and Ng (1998), we use conditional variance estimates (DCC-GARCH) to construct hedge ratios and optimal portfolio weights. We calculate the optimal weights and hedge ratios based on the conjecture that investors are willing to take a long (short) position in Bitcoin and Ethereum (stock markets). The hedge ratio between cryptocurrencies and stock markets can be measured as follows:

\[ \beta_{\text{crypto,stock}} = \frac{h_{\text{crypto,stock}}}{h_{\text{stock,stock}}} \]  

(14)

where \( \beta \) is a hedge ratio with a one-dollar long position in cryptocurrency and a one-dollar short position in stock. \( h_{\text{crypto,stock}} \) is the conditional covariance between the cryptocurrencies and stocks. \( h_{\text{stock,stock}} \) is the conditional variance of stock returns. One asset (e.g., cryptocurrency) is a cheap hedge for another asset (stock market) when the associated hedge ratio is close to zero.

We also calculate the optimal weights for investment in cryptocurrencies and stock markets by minimizing the risk of the portfolio without offsetting the expected return. The optimal portfolio weights are estimated as:

\[ w_{\text{crypto,stock}} = \frac{h_{\text{crypto,stock}} - h_{\text{crypto,stock}}}{h_{\text{crypto,stock}} - 2h_{\text{crypto,stock}} + h_{\text{stock}} - h_{\text{crypto,stock}}} \]  

(15)

where \( w_{\text{crypto,stock}} \) is the weight of the stock in a one-dollar portfolio of cryptocurrency and the stock market at time \( t \). The hedge effectiveness (HE) to examine the effectiveness in minimizing the risk by following the optimal portfolio weights between cryptocurrency and stock can be expressed as follows:

\[ \text{HE} = \frac{h_{\text{unhedged}} - h_{\text{crypto,stock,stock}}}{h_{\text{unhedged}}} \]  

(16)

where \( h_{\text{unhedged}} \) is the variance of stock returns when it is not hedged with cryptocurrency and \( h_{\text{crypto,stock,stock}} \) denotes the hedged portfolio variance with optimal investment in cryptocurrency and stocks.

5. Data and preliminary analysis

5.1. Data

We study the volatility dynamics and risk dependence between cryptocurrencies and stock markets. Our sample consists of two cryptocurrencies (Bitcoin and Ethereum) and eight stock market indices. The stock markets considered in this study are S&P 500 of the US, FTSE 100 of the UK, CAC40 of France, DAX30 of Germany, FTSE MIB of Italy, IBEX35 of Spain, Nikkei 225 of Japan, and SSE composite index of China. We consider five-minute interval sample data in the study covering the pre-COVID-19 and COVID-19 periods. The countries selected are based on the impact of the COVID-19 pandemic, as noted in April 2020. We measure the impact of the COVID-19 pandemic based on the number of cases.\(^3\) The sample period spans from August 1, 2019, to May 29, 2020. The pre-COVID-19 period is considered until November 2019. The COVID-19 period includes samples from December 2019 to May 2020. We source the intraday stock market data from Portara CQG\(^4\) and cryptocurrency price data from Kaiko.\(^5\)

5.2. Preliminary analysis

Fig. 1 shows the price movements of cryptocurrencies and stock market indices. We noticed that there was a sharp decline in the Bitcoin, Ethereum, and stock market indices in March 2020 due to the sudden outbreak of the COVID-19 pandemic worldwide. Interestingly, China’s stock market (SSE Index) shows two crashes in February and March 2020. The other markets of the US (S&P 500), the UK (FTSE 100), Europe, and Asia responded to the second crash of the Shanghai Stock Index. However, unlike the stock

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\(^3\) The data on number of cases are collected from the European Centre for Disease Prevention and Control (https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide).

\(^4\) The Portara CQG (https://www.cqg.com) provides data solutions for financial and commodity market data. They were judged the best market data provider at the HFM European Technology Awards 2018.

\(^5\) Kaiko (https://www.kaiko.com) is a market data provider of cryptocurrencies, dealing with blockchain-based digital assets.
markets, Bitcoin and Ethereum showed a consistent upward trend in April and May 2020, whereas the stock market indices did not adjust at a similar rate. The pricing trends of Bitcoin and Ethereum suggest possible hedging benefits for stock markets.

Table 1 reports the summary statistics of the mean returns, standard deviation, skewness, kurtosis, and other important characteristics of cryptocurrency prices and stock market indices. In Panel (A), we notice differences in returns, risk, skewness, and kurtosis between the pre-COVID-19 and COVID-19 periods. Bitcoin and Ethereum show negative average returns during the pre-COVID-19 period, whereas their intraday, five-minute interval, and average returns are positive during the COVID-19 period. Conversely, during the COVID-19 period, all the stock markets yielded higher negative returns. CAC40 exhibited the highest negative returns during the COVID-19 period. We note that for Bitcoin and Ethereum, the lowest returns during the pre-COVID-19 and COVID-19 periods are close to each other. However, the minimum returns of the stock markets are multiple times higher during the COVID-19 period than during the pre-COVID-19 period. The UK (FTSE 100), Germany (DAX 30), and China (SSE index) witnessed a higher fall than other markets. Similar to returns, the intraday standard deviation increased during the COVID-19 pandemic for both Bitcoin and Ethereum. Unlike cryptocurrencies, stock markets demonstrate higher jumps in risk. Interestingly, Bitcoin flips from positive to negative skewness during the COVID-19 period. Contrariwise to Bitcoin, Ethereum shows positive skewness, suggesting a longer tail on the right-hand side, with many positive returns. Among the stock markets, the SSE Index displays the highest negative skewness during the COVID-19 period. Both the cryptocurrency and stock markets show fat tails, indicating a leptokurtic distribution. The high value of the Jarque–Bera statistics suggests nonnormality in the returns.

Panel (B) shows the unconditional correlations between cryptocurrencies and the stock markets. We find that both Bitcoin and Ethereum have significantly positive and negative correlations with the US market (S&P 500). Ethereum shows higher significantly negative and positive correlations with Germany’s and Japan’s stock markets during the COVID-19 period, respectively. Similarly, significantly positive correlations are observed between the Bitcoin–CAC40 and Bitcoin–Spain compositions.

Panel (C) shows stationarity in the return series. We find that all return series are stationary, as the ADF and PP tests are found to be significant. We also estimate the serial correlations in the residuals and squared residuals up to the 20th lag using Ljung–Box statistics. Ljung–Box tests indicate that there are autocorrelations. Moreover, the ARCH–LM test also suggests that squared residuals are serially correlated; this implies that conditional volatility models, such as GARCH, are required to estimate marginal models for cryptocurrency and stock market returns.

6. Results and discussion

6.1. Estimation of marginal model

Tables 2a and 2b show the estimates of the mean model (Panel A), volatility model (Panel B), and diagnostic checks of residuals (Panel C) during the pre-COVID-19 and COVID-19 periods, respectively. The mean model estimated with a 1-lag for ARMA indicates that the present returns carry past returns. Almost all series of cryptocurrencies and stock markets have positive significant autoregressive coefficients during the COVID-19 period, except FTSE 100 and FTSE MIB. However, the AR coefficients of these two indices are significant during the pre-COVID-19 period (Table 2a). Similarly, the moving average coefficients are also significant during the COVID-19 period, except for the UK (FTSE 100), Germany (DAX30), and Italy (FTSE MIB). We find that the moving average coefficients are negative, except for China.

Panel (B) indicates the estimates of the variance model. We see that the persistence of volatility has increased during the COVID-19 period (Table 2b), as is evident in the GARCH terms for Bitcoin, FTSE 100, DAX30, Nikkei 225, and SSE Index. The overall volatility is highly persistent for Ethereum and SSE Index. Given the nature of the return series being asymmetric and leptokurtic, we add asymmetric and tail terms to the student’s t distributions. The tail term is significant for all return series; thus, it suggests the presence of fat tails and possible dependence on the tails of joint distributions (Rehman et al., 2020). The residual diagnostic tests imply that the ARMA-GARCH (1,1) model is sufficient to capture the serial correlations in the residuals and squared residuals (Panel C).

6.2. Copula models for dependence structure

In this subsection, we estimate copula models between cryptocurrencies and stock market returns. The best-fit copula is decided based on the lowest AIC value. The best-fit copula dependence allows us to examine whether the dependence structure between cryptocurrency and stock market returns is time-varying. The best-fit copula further reveals the presence of tail dependence, asymmetric tail dependence, and a linear relationship. We find that Bitcoin shows a time-invariant relationship with most stock market returns, except for CAC40 and DAX30 (see Table A1 in the appendix). On the contrary, Ethereum exhibits a time-varying relationship with stock market returns, except for FTSE 100 of the UK, FTSE MIB of Italy, and IBEX35 of Spain (see Table A2 in the appendix). The Student’s t copula between Bitcoin and stock returns of the S&P 500, FTSE 100, FTSE MIB, IBEX35, Nikkei 225, and the SSE index suggests symmetrical dependence during both bullish and bearish market conditions. On the one hand, Bitcoin has a tail-independent relationship with DAX30. This indicates a good pair for the portfolio between Bitcoin and Germany’s stock market, as there is no

6 In the interest of brevity, we did not include Table A1 in the main text.
Table 1
Descriptive statistics of intraday returns during the pre-COVID-19 and COVID-19 periods.

|                      | Bitcoin | Ethereum | S&P 500 (US) | FTSE 100 (UK) | CAC40 (France) | DAX30 (Germany) | FTSE MIB (Italy) | IBEX35 (Spain) | CAC40 (France) | DAX30 (Germany) | FTSE MIB (Italy) | IBEX35 (Spain) | Nikkei 225 (Japan) | SSE index (China) |
|----------------------|---------|----------|--------------|---------------|----------------|-----------------|------------------|----------------|----------------|-----------------|------------------|----------------|----------------------|------------------|
| Panel (A): Descriptive statistics |         |          |              |               |                |                 |                  |                |                |                 |                  |                |                      |                  |
| Mean (%)             | -0.0041 | -0.0047  | 0.0007       | -0.0003       | 0.0006         | 0.0007          | 0.0010           | 0.0005         | 0.0018         | -0.00046        |                  |                |                      |                  |
| Std. Dev (%)         | 0.469   | 0.470    | 0.091        | 0.073         | 0.090          | 0.068           | 0.087            | 0.081          | 0.120          | 0.110           |                  |                |                      |                  |
| Skewness             | 6.600   | 6.69     | 0.767        | 1.357         | 0.331          | 0.651           | 0.031            | 0.651          | 0.031          | -5.545          |                  |                |                      |                  |
| Kurtosis             | 574.413 | 317.461  | 67.855       | 45.132        | 50.341         | 32.167          | 64.124           | 32.167         | 50.341         | -20.636         |                  |                | (217.56)            |                  |
| Jarque-Bera          | 93,173  | 28,254   | 1,200        | 649           | 819            | 312             | 5,369            | 650            | 2090000000     |                  |                  |                | (19241927)          |                  |
| Panel (B): Unconditional correlations |          |          |              |               |                |                 |                  |                |                |                 |                  |                |                      |                  |
| BTC                  |         |          | -0.737***    | -0.144***     | -0.003         | 0.0002          | -0.022           | 0.003          | 0.011          | 0.0166          |                  |                |                      |                  |
| ETH                  |         |          | (0.834***     | (0.0956***     | (0.009)        | (0.026**)       | (0.019)         | (0.008)        | (0.029**)      | (0.023**)       |                  |                |                      |                  |
| Panel (C): Unit root tests |          |          |              |               |                |                 |                  |                |                |                 |                  |                |                      |                  |
| ADF                  | -83.19*** | -84.31*** | -82.96***    | -93.72***     | -83.83***      | -111.03***      | -94.95***        | -97.02***      | -71.52***      | -59.84***       |                  |                |                      |                  |
| PP                   | (-101.87*** | (-101.87*** | (-49.36***   | (-77.62***    | (-54.03***     | (-86.61***      | (-59.78***       | (-114.62***    | (-81.43***     | (-75.32***      |                  |                |                      |                  |
| Panel (D): Residual tests |          |          |              |               |                |                 |                  |                |                |                 |                  |                |                      |                  |
| Q(20)                | 85.925*** | 93.909*** | 267.03***    | 95.356***     | 383.85***      | 192.10***       | 162.27***        | 67.300***      | 20.875         |                  |                  |                |                      |                  |
| Q²(20)               | 406.23*** | 341.24*** | 216.17***    | 135.42***     | 1632.8***      | 296.90***       | 75.675***        | 1556.5***      | 128.15***      | 0.3786          |                  |                |                      |                  |
| ARCH(20)             | 16.2408*** | 14.1905*** | 8.9967***    | 5.2425***     | 57.3273***     | 13.4518***      | 5.7307***        | 48.6085***     | 5.1109***      | 0.0187          |                  |                |                      |                  |

Notes: Values with and without parentheses show estimates for the pre-COVID-19 and COVID-19 periods, respectively. Std. Dev. denotes the standard deviation of returns. Q(20) and Q²(20) represent the Ljung–Box statistics to highlight autocorrelation in returns and squared returns, respectively. ARCH (20) presents the results of autoregressive conditional heteroscedasticity. ***”, **”, and * denote the significance at the 1%, 5%, and 10% levels, respectively.
Table 2a
Dependence model ARMA-GARCH (1,1) estimates: Pre-COVID-19 period.

| Statistics | Bitcoin | Ethereum | S&P 500 (US) | FTSE 100 (UK) | CAC40 (France) | DAX30 (Germany) | FTSE MIB (Italy) | IBEX35 (Spain) | Nikkei 225 (Japan) | SSE index (China) |
|------------|---------|----------|--------------|---------------|----------------|----------------|------------------|----------------|-------------------|------------------|
| **Panel (A) Mean equation estimates** |         |          |              |               |                |                 |                  |                |                   |                  |
| Cst(M)     | 0.00002 | 0.00001  | 0.00001***   | 0.00001       | 0.00002**      | 0.00001        | 0.00000          | 0.00000        | 0.00002***        | 0.00000          |
|            | (0.0000) | (0.0000) | (0.0000)     | (0.0000)      | (0.0000)       | (0.0000)       | (0.0000)         | (0.0000)       | (0.0000)          | (0.0000)         |
| AR(1)      | 0.3905** | 0.2054   | -0.9144***   | -0.9723***    | 0.7770***      | 0.6199         | 0.5924***        | 0.5164**        | 0.3193***         | -0.7180          |
|            | (0.1550) | (0.2546) | (0.0448)     | (0.0195)      | (0.1322)       | (0.1169)       | (0.0946)         | (0.2291)       | (0.1224)          | (0.7162)         |
| MA(1)      | -0.4782*** | -0.2220 | 0.9058***    | 0.9690***     | -0.8020***     | -0.6509        | -0.6291***       | -0.5366**       | -0.3578***        | 0.7603           |
|            | (0.1433) | (0.2546) | (0.0457)     | (0.0200)      | (0.1240)       | (0.1127)       | (0.0910)         | (0.2287)       | (0.1223)          | (0.6619)         |

**Panel (B) Variance estimates**

| Cst(V)     | 4.4044*** | 0.7469*  | 0.0150***    | 0.0354***     | 0.0227***      | 0.0227         | 0.0346***        | 0.0283*         | 0.0886***         | 0.1207***        |
|            | (1.6901)  | (0.4029) | (0.021)      | (0.0056)      | (0.0038)       | (0.0100)       | (0.0060)         | (0.0052)        | (0.0193)          | (0.0204)         |
| ARCH       | 0.7773*** | 0.0230** | 0.1331***    | 0.1421***     | 0.2135***      | 1.0979         | 0.1607***        | 0.1345***       | 0.2685***         | 0.0470***        |
| (Phil1)    | (0.0300)  | (0.0111) | (0.0192)     | (0.0265)      | (0.4249)       | (0.0217)       | (0.0199)         | (0.0606)        | (0.0115)          | (0.0115)         |
| GARCH      | 0.2636*** | 0.9941*** | 0.8909***    | 0.7939***     | 0.8058***      | 0.7768***      | 0.8128***        | 0.8355***       | 0.6763***         | 0.8171***        |
| (Beta1)    | (0.0738)  | (0.0006) | (0.0113)     | (0.0230)      | (0.0173)       | (0.0163)       | (0.0207)         | (0.0191)        | (0.0524)          | (0.0248)         |
| Asymmetry  | 0.0452**  | 0.0099   | -0.0326**    | -0.0213       | -0.0081        | 0.0026         | -0.0260          | 0.0027          | -0.0045           | 0.0403           |
|            | (0.0201)  | (0.0198) | (0.0136)     | (0.0150)      | (0.0135)       | (0.0106)       | (0.0172)         | (0.0207)        | (0.0141)          | (0.0270)         |
| Tail       | 2.3113*** | 2.0143*** | 2.7526***   | 3.9898***     | 3.1341***      | 2.1694***      | 3.6945***        | 4.0407***       | 2.7097***         | 3.4620***        |
|            | (0.1360)  | (0.0066) | (0.1035)     | (0.1994)      | (0.1248)       | (0.0687)       | (0.1919)         | (0.2758)        | (0.1046)          | (0.2424)         |

**Panel (C) Residuals tests**

| LL         | 18595.9   | 18081.2  | 54176.3      | 52634.6       | 52643.0        | 51307.8        | 39859.5         | 28843.8        | 52827.9           | 214,680          |
| AIC        | -9.8245   | -9.5524  | -12.2900     | -12.0056      | -11.9422       | -11.6392       | -11.6440        | -11.6744       | -12.0731          | -11.3425         |
| ARCH(20)   | 0.02997   | 0.0161   | 0.1952       | 0.1470        | 0.1658         | 0.2005         | 0.2704          | 0.1698         | 0.0468            | 0.0929           |
|            | [1.0000]  | [1.0000] | [1.0000]     | [1.0000]      | [1.0000]       | [1.0000]       | [1.0000]        | [1.0000]       | [1.0000]          | [1.0000]         |
| Q(20)      | 6.1643    | 6.1962   | 11.6568      | 18.9916       | 12.6575        | 19.4766        | 16.5193         | 11.6157        | 9.3813             | 12.2833          |
|            | [0.9955]  | [0.9954] | [0.8644]     | [0.3923]      | [0.0815]       | [0.3630]       | [0.5564]        | [0.8664]       | [0.9502]           | [0.8323]         |
| Q^2(20)    | 0.5724    | 0.3143   | 3.6215       | 2.8969        | 3.2186         | 3.8525         | 5.2611          | 3.3367         | 0.9015             | 1.7334           |
|            | [1.0000]  | [1.0000] | [0.9999]     | [1.0000]      | [0.9999]       | [0.9999]       | [1.0000]        | [1.0000]       | [1.0000]          | [1.0000]         |

Notes: Table 2a reports the ML estimates with the standard deviations of the parameters (in parentheses) under the marginal distribution function. We use different combinations ranging from 0 to 2 for selecting p, q, r, and m as lag values. Q(20) and Q^2(20) denote the Ljung–Box statistics to highlight autocorrelation in the residuals and squared residuals, respectively. ARCH (20) denotes the autoregressive conditional heteroscedasticity test with 20 lags. ***, ** and * denote 1%, 5%, and 10% level of significance, respectively.
| Statistics | Bitcoin | Ethereum | S&P 500 (US) | FTSE 100 (UK) | CAC40 (France) | DAX30 (Germany) | FTSE MIB (Italy) | IBEX35 (Spain) | Nikkei 225 (Japan) | SSE index (China) |
|------------|---------|----------|--------------|---------------|----------------|----------------|-----------------|----------------|--------------------|--------------------|
| **Panel (A) Mean equation estimates** | | | | | | | | | | |
| Cst(M)     | 0.00011*** | 0.00001 | 0.00001 | 0.00000 | 0.00000 | 0.00002* | 0.00002 | 0.00001 | 0.00000 | 0.00001** |
| (0.0000)   | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| AR(1)      | 0.4523*** | 0.0620*** | 0.9666*** | 0.2411 | 0.6910*** | 0.0930 | 0.0617 | 0.0661** | 0.6145*** | 0.2060 |
| (0.0914)   | (0.0097) | (0.0753) | (0.2509) | (0.0621) | (0.1281) | (0.0087) | (0.0304) | (0.0578) | (0.1399) |            |
| MA(1)      | −0.3300*** | −0.0806*** | −0.9732*** | −0.2168 | −0.7088*** | −0.0835 | −0.0017 | −0.0573* | −0.6539*** | 0.2563** |
| (0.0889)   | (0.0132) | (0.0681) | (0.2661) | (0.0618) | (0.1324) | (0.0193) | (0.0317) | (0.0581) | (0.1389) |
| **Panel (B) Variance estimates** | | | | | | | | | | |
| Cst(V)     | 4.0706*** | 0.0411** | 0.0132*** | 0.0268*** | 0.0360*** | 0.0050*** | 0.0474*** | 0.0501*** | 0.0555* | 0.0237*** |
| (1.3038)   | (0.0131) | (0.0026) | (0.0052) | (0.0084) | (0.0009) | (0.0118) | (0.0091) | (0.009) | (0.0295) | (0.0076) |
| ARCH(Phi1) | 1.0865*** | 0.0122*** | 0.2192*** | 0.1269*** | 0.1936*** | 0.1490*** | 0.2111*** | 0.1514*** | 0.3697* | 0.0455** |
| (0.3287)   | (0.0023) | (0.0369) | (0.0222) | (0.0416) | (0.0079) | (0.0434) | (0.0289) | (0.2203) | (0.0151) |
| GARCH(Beta1) | 0.4941*** | 0.9919*** | 0.8119*** | 0.8144*** | 0.7586*** | 0.8510*** | 0.7385*** | 0.7519*** | 0.8297*** | 0.9427*** |
| (0.0362)   | (0.0006) | (0.0142) | (0.0244) | (0.0395) | (0.0595) | (0.0454) | (0.0324) | (0.0387) | (0.0163) |
| Asymmetry  | 0.0122 | 0.0027 | −0.0339 | −0.0011 | −0.0476** | −0.0157** | −0.0373 | 0.0044 | −0.0238 | −0.0311 |
| (0.0107)   | (0.0126) | (0.0218) | (0.0237) | (0.0223) | (0.0075) | (0.0236) | (0.0233) | (0.0189) | (0.0234) |
| Tail       | 2.2102*** | 2.1287*** | 2.7641*** | 3.5899*** | 3.1468*** | 3.2853*** | 3.2431*** | 3.4575*** | 2.2329*** | 3.1946*** |
| (0.0705)   | (0.0310) | (0.1683) | (0.2518) | (0.2064) | (0.0539) | (0.2049) | (0.2434) | (0.1292) | (0.2389) |
| **Panel (C) Residuals tests** | | | | | | | | | | |
| LL         | 471,990 | 450,940 | 23968.7 | 23189.5 | 23257.56 | 97941.7 | 22818.5 | 22942.4 | 22277.4 | 20156.4 |
| AIC        | −9.4335 | −9.0127 | −12.6642 | −12.2524 | −12.2884 | −11.9515 | 12.0563 | −12.1218 | −11.7703 | −10.6493 |
| ARCH(20)   | 0.0332 | 0.0444 | 0.0794 | 0.0518 | 0.0753 | 0.0864 | 0.1879 | 0.1062 | 0.0320 | 0.0053 |
| Q(20)      | [1.0000] | [1.0000] | [1.0000] | [1.0000] | [1.0000] | [1.0000] | [1.0000] | [1.0000] | [1.0000] | [1.0000] |
| Q2(20)     | [0.7529] | [0.9612] | [0.9412] | [0.9384] | [0.4954] | [0.9481] | [0.0782] | [0.5744] | [0.9999] | [0.9813] |
|            | [0.6451] | 0.8579 | 1.4989 | 1.00275 | 1.4228 | 9.4597 | 3.4378 | 1.936 | 0.6097 | 0.1062 |
|            | [1.0000] | [1.0000] | [0.9999] | [1.0000] | [0.9945] | [0.9481] | [0.9999] | [0.9999] | [1.0000] | [1.0000] |

Notes: Table 2b reports the ML estimates with the standard deviations of the parameters (in parentheses) under the marginal distribution function. We used different combinations ranging from 0 to 2 for selecting $p$, $q$, $r$, and $m$ as lag values. $Q(20)$ and $Q^2(20)$ denote the Ljung box statistics to highlight autocorrelation in the residuals and squared residuals, respectively. ARCH (20) denotes the autoregressive conditional heteroscedasticity test with 20 lags. ***; ** and * denote 1%, 5% and 10% level of significance, respectively.
Fig. 2. Best-fit time-varying copulas.
dependency during extreme market movements. A time-varying Clayton copula is the best fit between Bitcoin and CAC40 stock market, indicating that the dependency (no dependency) between these two assets when market conditions are bullish (bearish) is perfect for a portfolio when the stock market faces extreme downward movements.

On the other hand, Ethereum manifests a time-invariant tail dependence (Student’s t copula) with the stock returns of FTSE 100 (UK), FTSE MIB (Italy), and IBEX35 (Spain) and time-varying relationships with the US, Japan, and China equity markets. Our results suggest a risk spillover between Ethereum and the S&P 500, FTSE MIB, IBEX35, Nikkei 225, and SSE Index when one of the two asset markets is going up or down. Similar to Bitcoin, Ethereum exhibits a tail-independent relationship with the stock returns of DAX30 and no dependence on the stock returns of CAC40.

Considering the best-fit time-varying copula, the dynamic dependencies between cryptocurrencies and stock returns are shown in Fig. 2. We find that Bitcoin has a negligible dependency on the stock market of CAC40; however, a sudden jump is observed in May 2020. Similarly, Bitcoin shows minimal dependency, although volatile, on the stock market of DAX30. Interestingly, from March to May 2020, the dependency between them has fallen further. Ethereum exhibits a relatively higher dependency on the stock markets of the US (S&P 500) and Japan (Nikkei 225); however, similar to Bitcoin, Ethereum shows a negligible dependence on the stock markets of France (CAC40) and Germany (DAX30). Interestingly, the dependence between Ethereum and the US stock returns has increased during March to May 2020, indicating that Ethereum may be unable to offer hedging benefits when the stock market suddenly plunges.

### Table 3
Value-at-risk: Descriptive statistics – Bitcoin to stocks.

|                        | Upside VaR | Downside VaR | Upside CoVaR | Downside CoVaR |
|------------------------|------------|--------------|--------------|----------------|
| **Panel (A) VaR and CoVaR from Bitcoin to stock-Pre-COVID-19 period** |            |              |              |                |
| S&P 500 (US)           | 0.00183    | –0.00180     | 0.00188      | –0.00194       |
| FTSE 100 (UK)          | 0.00142    | –0.00141     | 0.00146      | –0.00151       |
| CAC40 (France)         | 0.00154    | –0.00152     | 0.00148      | –0.00116       |
| DAX30 (Germany)        | 0.00290    | –0.00288     | 0.00109      | –0.00106       |
| FTSE MIB (Italy)       | 0.00172    | –0.00169     | 0.00153      | –0.00152       |
| IBEX35 (Spain)         | 0.00163    | –0.00160     | 0.00162      | –0.00156       |
| Nikkei 225 (Japan)     | 0.04226    | –0.03112     | 0.04823      | –0.03767       |
| SSE index (China)      | 0.00206    | –0.00204     | 0.00238      | –0.00243       |
| **Panel (B) VaR and CoVaR from Bitcoin to stock- COVID-19 period** |            |              |              |                |
| S&P 500 (US)           | 0.00441    | –0.00439     | 0.00455      | –0.00471       |
| FTSE 100 (UK)          | 0.00445    | –0.00445     | 0.00459      | –0.00477       |
| CAC40 (France)         | 0.00469    | –0.00468     | 0.00454      | –0.00362       |
| DAX30 (Germany)        | 0.00700    | –0.00699     | 0.00261      | –0.00258       |
| FTSE MIB (Italy)       | 0.00345    | –0.00343     | 0.00311      | –0.00312       |
| IBEX35 (Spain)         | 0.00336    | –0.00333     | 0.00333      | –0.00325       |
| Nikkei 225 (Japan)     | 0.02711    | –0.02015     | 0.03097      | –0.02439       |
| SSE index (China)      | 0.00262    | –0.00260     | 0.00303      | –0.00310       |

**Note:** The table above presents the average and standard deviation values (in parentheses) for VaR and CoVaR between Bitcoin and stock markets during the pre-COVID-19 and COVID-19 periods.
6.3. Risk spillover

Given that dependency exists between cryptocurrencies and stock markets, it is imperative to analyze the risk spillover between these assets during the pre-COVID-19 and COVID-19 periods. We estimate the VaR and CoVaR between cryptocurrencies and stock market returns to quantify the risk-sharing mechanism between them. Tables 3 and 4 reveal the upside and downside VaR/CoVaR between cryptocurrencies and stock market returns and Ethereum and stock market returns, respectively. Panels (A) and (B) indicate the risk assessments during the pre-COVID-19 and COVID-19 periods, respectively. We note that both the upside and downside VaR of stock market returns are higher during the COVID-19 period. Similarly, the COVID-19 pandemic has also increased the risk spillover from cryptocurrencies to stock market returns, as evident in the upside and downside CoVaR estimates, except for Nikkei 225 (Japan). Stock market returns have received more upside and downside risk spillovers from cryptocurrencies during the COVID-19 period than the pre-COVID-19 era. The higher standard deviations of the VaR of stock market returns and risk spillover from cryptocurrencies to stock markets during the COVID-19 period indicate a multiple time increase in risk. However, both the upside and downside stock market returns of DAX30, FTSE MIB, IBEX35, and the SSE Index exhibit relatively fewer jumps in their sensitivity to the Bitcoin market’s risk during the COVID-19 period. Table 4 also shows that the risk spillover from Ethereum to stock markets has increased during the COVID-19 period, except for Nikkei 225 (Japan). China displays the least increase in risk sensitivity to Ethereum during the COVID-19 period. The results for Japan agree with the findings of Bouri et al. (2017) that Japanese and other Asia-Pacific investors have preferences for Bitcoin to hedge their equity portfolios. Moreover, the results support Bouri et al.’s (2017) argument that the diversification ability of Bitcoin is time-specific; it may not be always available to investors.

To examine the implications of the risk spillover between cryptocurrencies and stock market returns, we further analyze whether the risk spillover is asymmetric. We employ the KS test to determine whether the downside (upside) CoVaR is equal to the downside (upside) VaR.

### Table 4

Value-at-risk - Descriptive statistics – Ethereum to stocks.

|               | Upside VaR | Downside VaR | Upside CoVaR | Downside CoVaR |
|---------------|------------|--------------|--------------|----------------|
| **Panel (A) VaR and CoVaR from Ethereum to stock- Pre-COVID-19 period** |            |              |              |                |
| S&P 500 (US)  | 0.00183    | -0.00180     | 0.00187      | -0.00192       |
| (0.00140)     |            | (0.00140)    | (0.00144)    | (0.00149)      |
| FTSE 100 (UK) | 0.00142    | -0.00141     | 0.00142      | -0.00147       |
| (0.00069)     |            | (0.00070)    | (0.00069)    | (0.00072)      |
| CAC40 (France)| 0.00154    | -0.00152     | 0.00148      | -0.00116       |
| (0.00102)     |            | (0.00101)    | (0.00118)    | (0.00078)      |
| DAX30 (Germany)| 0.00290   | -0.00288     | 0.00110      | -0.00107       |
| (0.00198)     |            | (0.00198)    | (0.00074)    | (0.00074)      |
| FTSE MIB (Italy)| 0.00172  | -0.00169     | 0.00157      | -0.00156       |
| (0.00101)     |            | (0.00100)    | (0.00092)    | (0.00093)      |
| IBEX35 (Spain)| 0.00163    | -0.00160     | 0.00162      | -0.00156       |
| (0.00082)     |            | (0.00082)    | (0.00081)    | (0.00080)      |
| Nikkei 225 (Japan)| 0.04226 | -0.03112     | 0.03747      | -0.02669       |
| (0.04801)     |            | (0.05132)    | (0.04198)    | (0.04574)      |
| SSE index (China)| 0.00206 | -0.00204     | 0.00203      | -0.00207       |
| (0.00058)     |            | (0.00058)    | (0.00058)    | (0.00060)      |
| **Panel (B) VaR and CoVaR from Bitcoin to stock- COVID-19 period** |            |              |              |                |
| S&P 500 (US)  | 0.00441    | -0.00439     | 0.00452      | -0.00468       |
| (0.00569)     |            | (0.00566)    | (0.00583)    | (0.00603)      |
| FTSE 100 (UK) | 0.00445    | -0.00445     | 0.00446      | -0.00463       |
| (0.00526)     |            | (0.00518)    | (0.00528)    | (0.00539)      |
| CAC40 (France)| 0.00469    | -0.00468     | 0.00454      | -0.00362       |
| (0.00547)     |            | (0.00538)    | (0.00595)    | (0.00455)      |
| DAX30 (Germany)| 0.00700   | -0.00699     | 0.00265      | -0.00262       |
| (0.00856)     |            | (0.00832)    | (0.00334)    | (0.00308)      |
| FTSE MIB (Italy)| 0.00345  | -0.00343     | 0.00315      | -0.00316       |
| (0.00345)     |            | (0.00344)    | (0.00314)    | (0.00318)      |
| IBEX35 (Spain)| 0.00336    | -0.00333     | 0.00333      | -0.00325       |
| (0.00377)     |            | (0.00377)    | (0.00375)    | (0.00368)      |
| Nikkei 225 (Japan)| 0.02711 | -0.02015     | 0.02399      | -0.01727       |
| (0.04299)     |            | (0.04326)    | (0.03750)    | (0.03819)      |
| SSE index (China)| 0.00262 | -0.00260     | 0.00258      | -0.00263       |
| (0.00201)     |            | (0.00202)    | (0.00216)    | (0.00223)      |

**Note:** The table above presents the average and standard deviation values (in parentheses) for VaR and CoVaR between cryptocurrencies and stock markets during the pre-COVID-19 and COVID-19 periods.
Table 5
Tests of asymmetries and equalities between upside and downside VaR - CoVaR - Bitcoin.

|                      | $H_0: \text{CoVaR(D)} = \text{VaR(D)}$ | $H_1: \text{CoVaR(D)} \neq \text{VaR(D)}$ | $H_0: \text{CoVaR(U)} = \text{VaR(U)}$ | $H_1: \text{CoVaR(U)} \neq \text{VaR(U)}$ | $H_0: \frac{\text{CoVaR(D)}}{\text{VaR(D)}} = \frac{\text{CoVaR(U)}}{\text{VaR(U)}}$ | $H_1: \frac{\text{CoVaR(D)}}{\text{VaR(D)}} < \frac{\text{CoVaR(U)}}{\text{VaR(U)}}$ |
|----------------------|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|
| **Panel (A) Pre-COVID-19 period** |                                      |                                      |                                      |                                      |                                      |                                      |
| S&P 500 (US)         | 0.0571                               | 0.0266                              | 0.5080                               | 0.0000                               | 0.0158                               | 0.0000                               |
| FTSE 100 (UK)        | 0.0918                               | 0.0462                              | 0.3286                               | 0.0000                               | 0.0000                               | 0.0000                               |
| CAC40 (France)       | 0.2706                               | 0.1340                              | 0.3813                               | 0.0000                               | 0.0000                               | 0.0000                               |
| DAX30 (Germany)      | 0.1484                               | 0.0675                              | 0.3557                               | 0.0000                               | 0.0000                               | 0.0000                               |
| FTSE MIB (Italy)     | 0.0845                               | 0.0973                              | 0.0147                               | 0.0000                               | 0.0000                               | 0.2986                               |
| IBEX35 (Spain)       | 0.0332                               | 0.0119                              | 0.2169                               | 0.0001                               | 0.3591                               | 0.0000                               |
| Nikkei 225 (Japan)   | 0.0816                               | 0.0650                              | 0.6890                               | 0.0000                               | 0.0000                               | 0.0000                               |
| SSE index (China)    | 0.5200                               | 0.4381                              | 0.3931                               | 0.0000                               | 0.0000                               | 0.0000                               |
| **Panel (B) COVID-19 period** |                                      |                                      |                                      |                                      |                                      |                                      |
| S&P 500 (US)         | 0.0294                               | 0.0145                              | 0.4974                               | 0.0004                               | 0.2441                               | 0.0000                               |
| FTSE 100 (UK)        | 0.0470                               | 0.0238                              | 0.2436                               | 0.0000                               | 0.0000                               | 0.0000                               |
| CAC40 (France)       | 0.1435                               | 0.0675                              | 0.3557                               | 0.0000                               | 0.0000                               | 0.0000                               |
| DAX30 (Germany)      | 0.6330                               | 0.6324                              | 0.0640                               | 0.0000                               | 0.0000                               | 0.0000                               |
| FTSE MIB (Italy)     | 0.0703                               | 0.0760                              | 0.0113                               | 0.0000                               | 0.0000                               | 0.4101                               |
| IBEX35 (Spain)       | 0.0181                               | 0.0063                              | 0.2213                               | 0.0331                               | 0.9650                               | 0.0000                               |
| Nikkei 225 (Japan)   | 0.1038                               | 0.0859                              | 0.4308                               | 0.0000                               | 0.0000                               | 0.0000                               |
| SSE index (China)    | 0.3639                               | 0.3140                              | 0.3467                               | 0.0000                               | 0.0000                               | 0.0000                               |

Note: This table presents the results of the KS test. The KS test indicates that there is no systemic impact between Bitcoin and the stock markets. We present the $p$-values for the KS results in brackets.
Table 6
Tests of asymmetries and equalities between upside and downside VaR -CoVaR- Ethereum.

| Table 6 | Tests of asymmetries and equalities between upside and downside VaR -CoVaR- Ethereum. |
|---------|---------------------------------------------------------------------------------------------------------------------------------|
| $H_0$: CoVaR(D) = VaR(D) $H_1$: CoVaR(D) $\neq$ VaR(D) | $H_0$: CoVaR(U) = VaR(U) $H_1$: CoVaR(U) $\neq$ VaR(U) | $H_0$: CoVaR(U)/VaR(U) = CoVaR(D)/VaR(D) $H_1$: CoVaR(U)/VaR(U) $\neq$ CoVaR(D)/VaR(D) |

Panel (A) Pre-COVID-19 period

| Stock Market | $\hat{C}$ | $\hat{V}$ | $p$-value |
|--------------|---------|---------|-----------|
| S&P 500 (US) | 0.0516  | 0.0222  | 0.5064    |
|              | [0.0000]| [0.0684]| [0.0000]  |
| FTSE 100 (UK)| 0.0532  | 0.0060  | 0.3232    |
|              | [0.0000]| [0.9909]| [0.0000]  |
| CAC40 (France)| 0.2611  | 0.1267  | 0.3709    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| DAX30 (Germany)| 0.6018 | 0.5991  | 0.1735    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| FTSE MIB (Italy)| 0.0835 | 0.0961  | 0.1059    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| IBEX35 (Spain)| 0.0323  | 0.0110  | 0.2169    |
|              | [0.0002]| [0.6599]| [0.0000]  |
| Nikkei 225 (Japan)| 0.0595  | 0.0531  | 0.5545    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| SSE index (China)| 0.0381 | 0.0555  | 0.2879    |
|              | [0.0083]| [0.0000]| [0.0000]  |

Panel (B) COVID-19 period

| Stock Market | $\hat{C}$ | $\hat{V}$ | $p$-value |
|--------------|---------|---------|-----------|
| S&P 500 (US) | 0.0265  | 0.0119  | 0.4962    |
|              | [0.0018]| [0.4787]| [0.0000]  |
| FTSE 100 (UK)| 0.0270  | 0.0035  | 0.2275    |
|              | [0.0010]| [0.9999]| [0.0000]  |
| CAC40 (France)| 0.1856  | 0.0844  | 0.3646    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| DAX30 (Germany)| 0.6290 | 0.6291  | 0.0628    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| FTSE MIB (Italy)| 0.0461 | 0.0525  | 0.1492    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| IBEX35 (Spain)| 0.0176  | 0.0060  | 0.2212    |
|              | [0.0411]| [0.9786]| [0.0000]  |
| Nikkei 225 (Japan)| 0.0878 | 0.0777  | 0.3351    |
|              | [0.0000]| [0.0000]| [0.0000]  |
| SSE index (China)| 0.0230 | 0.0464  | 0.2552    |
|              | [0.1005]| [0.0000]| [0.0000]  |

Note: The table above presents the Kolmogorov–Smirnov (KS) test. The KS test indicates no systemic impact between Ethereum and the stock markets. We present the $p$-values for the KS results in brackets.
(upside) VaR. Moreover, we test whether the downside CoVaR is equal to the upside CoVaR after normalization by the downside and upside VaR (Tables 5 and 6). The results indicate a significant difference or asymmetry between the VaR and CoVaR measures for the risk spillover from cryptocurrencies to stock markets. Asymmetry is present during both the pre-COVID-19 and COVID-19 periods. The last columns of Tables 5 and 6 suggest the asymmetric behavior of the upside and downside risk spillovers from cryptocurrencies to the stock markets. The results support the hypothesis that downside CoVaR adjusted with downside VaR is less than upside CoVaR adjusted with upside VaR for all risk spillover cases from Bitcoin and Ethereum to stock markets during both the pre-COVID-19 and COVID-19 periods.

6.4. Portfolio implications

The empirical findings reported thus far highlight an asymmetric risk spillover between cryptocurrencies and stock markets. The discussion mentioned above may have implications for portfolio managers, investors, and fund managers because any information about the nature of risk and its transmission from one asset to another allows them to strategically allocate investments across assets for better risk diversification. Therefore, in this subsection, we construct portfolios based on long positions in cryptocurrencies and short positions in stock markets.

Tables 7 and 8 show the descriptive statistics of the optimal portfolio weights, hedge ratios, and hedge effectiveness for cryptocurrency and stock market pairs. Panels A and B report the portfolio estimates considering a one-dollar long position in cryptocurrency and one-dollar short position in stock markets during the pre-COVID-19 and COVID-19 period, respectively. In Table 7, we can see that portfolio weights show a higher percentage in Bitcoin compared to stock markets during the pre-COVID-19 period, except for Nikkei 225. For example, S&P 500 requires 5.96 % investment and 94.04 % Bitcoin. However, the optimal portfolio weights change during the COVID-19 period, whereby the same S&P 500 market requires an investment of 18.03 %. A similar trend is observed for all the stock indices, except for FTSE MIB and IBEX35, where investment in the stock market falls to 5.7 % and 5.21 % during the COVID-19 period, respectively. Similar to Table 7, Table 8 also shows a higher weightage of investment in Ethereum, except for S&P 500 and Nikkei 225. The investment weights in stock markets have increased during the COVID-19 period compared to the pre-COVID-19 era.

Tables 7 and 8 also show the hedge ratio estimates with a long position in Bitcoin and short position in the stocks, as well as hedge effectiveness following the optimal portfolio weights. In Table 7, the lowest (highest) hedge ratio is observed between Bitcoin and the stock index of CAC40 (Bitcoin and Nikkei 225) during the pre-COVID-19 period. For example, to hedge one dollar of a long

| Portfolios | \( w_{\text{crypto}} \) | \( \beta_{\text{crypto, stock}} \) | \( \text{RE}_{\text{VAR}} \) (%) |
|------------|-----------------|-----------------|-----------------|
| Panel (A) Pre-COVID-19 period |
| S&P 500 (US) | 0.0596 | -0.0012 | 1.0283 |
| FTSE 100 (UK) | 0.0409 | 0.0050 | 0.8525 |
| CAC40 (France) | 0.0539 | 0.0002 | 0.9931 |
| DAX30 (Germany) | 0.0515 | -0.0012 | 1.0284 |
| FTSE MIB (Italy) | 0.0764 | -0.0027 | 1.0545 |
| IBEX35 (Spain) | 0.0628 | 0.0019 | 0.9523 |
| Nikkei 225 (Japan) | 0.0978 | 0.0204 | 0.9998 |
| SSE index (Shanghai) | 0.0294 | 0.0034 | 0.8767 |
| Panel (B) COVID-19 period |
| S&P 500 (US) | 0.1803 | -0.0017 | 1.0196 |
| FTSE 100 (UK) | 0.1032 | 0.0082 | 0.8842 |
| CAC40 (France) | 0.1510 | 0.0004 | 0.9962 |
| DAX30 (Germany) | 0.1652 | -0.0023 | 1.0188 |
| FTSE MIB (Italy) | 0.0570 | -0.0023 | 1.0668 |
| IBEX35 (Spain) | 0.0521 | 0.0018 | 0.9631 |
| Nikkei 225 (Japan) | 0.0777 | 0.0202 | 0.9998 |
| SSE index (Shanghai) | 0.0637 | 0.0048 | 0.8911 |

Notes: The table reports \( \beta_{\text{crypto, stock}} \) and the optimal portfolio weight \( w_{\text{crypto, stock}} \) between Bitcoin and stocks. The hedge ratio shows a one-dollar long position in Bitcoin and one-dollar short position in the stocks. Optimal portfolio weights indicate the weight of oil in a one-dollar portfolio with Bitcoin and stocks. Hedge effectiveness of hedged portfolios in comparison with an unhedged position in stocks. Hedge effectiveness reveals the gains from hedging based on the optimal portfolio weights.

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\footnote{We only report long position in cryptocurrencies and short position in stock markets. However, the results on long position in stock markets and short position in cryptocurrencies can be obtained on request.}
position in Bitcoin, 0.02 cents of CAC40 are to be shortened, suggesting the cheapest hedging. In contrast, the highest hedge ratio of 0.0204 indicates that 2.04 dollars of Nikkei 225 are to be shortened for one dollar of a long position in Bitcoin, indicating the costliest hedging. We find that the hedge ratio has increased during the COVID-19 pandemic, implying that the cost of hedging has risen. Contrary to Table 7, we note that the cheapest hedging exists between Ethereum and Nikkei 225, while the costliest hedging is between Ethereum and CAC40. The trend of the higher cost of hedging during the COVID-19 period is associated with Ethereum.

The last columns of Tables 7 and 8 indicate the hedge effectiveness considering the optimal portfolio weights. A portfolio with a long position in Bitcoin or Ethereum and a short position in stock markets shows risk reduction at approximately 100% following the strategy of optimal portfolio weights. Consistent with Antonakakis et al. (2018), we find that optimal weight-based portfolio decisions effectively diversify stock market risks. The highest risk reduction can be attained between Bitcoin and FTSE MIB and between Ethereum and S&P 500. However, hedging effectiveness is not very distinctive between the pre-COVID-19 and COVID-19 periods.

Overall, our findings on portfolio weights and hedge effectiveness highlight that diversification benefits are realizable by including stocks with cryptocurrencies; however, optimal investments in Bitcoin and Ethereum are reduced during bearish market conditions. This finding corroborates the results of the risk spillover that cryptocurrencies cannot provide incremental gains by hedging the risk of stock markets when market conditions are in a downturn.

The risk spillover from Bitcoin and Ethereum to stock markets leads to increased hedging costs during the COVID-19 period. The findings on the risk dependence and portfolio implications between cryptocurrencies and stock markets during the pre-COVID-19 and COVID-19 periods indicate that Bitcoin and Ethereum cannot be considered a strong hedge during the time of crisis. The speculative nature of cryptocurrencies and risks embedded in Bitcoin and Ethereum increases the risk flow to stock markets during a crisis, thus rendering the hedging costlier. This finding is consistent with the results of Corbet et al. (2020) and Conlon and McGee (2020). The findings also support Glaser et al.’s (2014) and Yermack’s (2015) argument that Bitcoin and Ethereum investments are considered to be speculative assets. The downside-adjusted CoVaR is found to be less than the upside CoVaR, which seems to be ineffective for hedging. Investing in cryptocurrencies becomes diligent because of the risk arising from cryptocurrencies’ volatility.

7. Conclusion and policy recommendations

Asset market dependence is an intriguing topic for academic research, as well as for investors and portfolio managers. The constant search for an alternative asset to hedge against traditional assets or market risk is a cumbersome task. Lately, attention has been paid to cryptocurrencies to determine whether they can be a safe haven, a good hedge, or merely a risk diversifier during a period of crisis such as the COVID-19 pandemic. In this context, using five-minute interval data, this study elucidates the risk dependence between cryptocurrencies and stock markets using both static and time-varying copula approaches. We also quantify the risk in stock markets conditional on the risk in cryptocurrency markets. We measure the optimal portfolio weights to ascertain whether hedging stock
markets with cryptocurrencies results in any gains. To the best of our knowledge, considering the COVID-19 period, this study is perhaps the first to examine the risk dependence between cryptocurrencies and stock market returns in a large set of stock markets, while focusing on intraday price dynamics using a copula-based approach.

The preliminary findings of Bitcoin, Ethereum, and eight stock market returns during the pre-COVID-19 and COVID-19 periods show that France exhibits the highest negative returns during the COVID-19 period. If we see minimum returns, we note that for Bitcoin and Ethereum, the lowest returns during the pre-COVID-19 and COVID-19 periods are closer to each other, while, for the stock markets, minimum returns are multiple times higher during the COVID-19 period than during the pre-COVID-19 period.

In an effort to understand the risk dynamics between cryptocurrencies and stock markets, we establish that the persistence of volatility has increased during the COVID-19 period, as evident in GARCH terms for Bitcoin and the stock markets of the UK, Germany, Japan, and China. Furthermore, Bitcoin shows a time-varying dependency on the stock markets of France and Germany. Ethereum and stock returns of the US have increased from March to May 2020. The VaR and CoVaR with copula highlight that the COVID-19 pandemic has increased the risk spillover from Bitcoin and Ethereum to stock market returns, as evident in the upside and downside CoVaR estimates, except for Japan. However, both the upside and downside stock market returns of Germany, Italy, Spain, and China exhibit fewer jumps in their sensitivity to the risk of the Bitcoin market during the COVID-19 pandemic. Interestingly, the results indicate a significant difference or asymmetry between VaR and CoVaR measures for the risk spillover from cryptocurrencies to stock markets. Asymmetry is present during both the pre-COVID-19 and COVID-19 periods. Finally, the findings of portfolio weights and hedge effectiveness highlight that diversifying stock portfolios with Bitcoin and Ethereum yields hedging gains; however, optimal investments in Bitcoin and Ethereum are reduced during the COVID-19 period. This finding corroborates the results of risk spillover that Bitcoin and Ethereum cannot provide incremental gains by hedging the risk of stock markets during the market’s extreme downward movements.

These results have important implications for a wide range of economic agents, including multi-asset investors, portfolio managers, and policymakers. Cryptocurrencies are found to have spilled risk to stock markets during the time of crisis. Thus, fund managers and investors need to be cautious, as hedging with cryptocurrencies during a time crisis is costly, without offering any higher gains. Given the speculative nature of cryptocurrencies, the portfolio findings also indicate that investors need to invest more in stocks than in cryptocurrencies when market uncertainties are high. The investment weights in the stocks increase further during the crisis, thereby showing the risks associated with over-relying on cryptocurrencies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix-1
Table A1
Copula framework- Bitcoin–stock markets.

|                | US       | UK       | France   | Germany  | Italy    | Spain    | Japan    | Shanghai |
|----------------|----------|----------|----------|----------|----------|----------|----------|----------|
| 1. Gaussian    |          |          |          |          |          |          |          |          |
| B              | 0.0066***| 0.0250***| 0.0065***| –0.0028***| 0.0030***| 0.0110***| 0.0079***| 0.0160***|
|                | (0.0077) | (0.0069) | (0.0068) | (0.0058) | (0.0069) | (0.0068) | (0.0091) | (0.0103) |
| AIC            | −0.0053  | −13.2184 | −0.9237  | −0.2304  | −0.1953  | −2.5888  | −0.7608  | −2.4058  |
| 2. Clayton’s   |          |          |          |          |          |          |          |          |
| \(\theta\)    | 0.0332***| 0.0400***| 0.0155***| 0.0001***| 0.0125***| 0.0309***| 0.0715***| 0.0505***|
|                | (0.0076) | (0.0072) | (0.0068) | (0.0061) | (0.0067) | (0.0069) | (0.0085) | (0.0159) |
| AIC            | −21.4508 | −34.5708 | −5.4410  | 0.1048   | −3.5084  | −22.5642 | −72.3797 | −26.2973 |
| 3. Rotated Clayton |          |          |          |          |          |          |          |          |
| \(\Delta\)    | 0.0378***| 0.0442***| 0.0154***| 0.0001***| 0.0297***| 0.0307***| 0.0288***| 0.0432***|
|                | (0.0041) | (0.0060) | (0.0070) | (0.0019) | (0.0068) | (0.0066) | (0.0201) | (0.0105) |
| AIC            | −28.5144 | −42.2477 | −5.4666  | 0.1114   | −20.9924 | −21.8932 | −11.2231 | −19.5894 |
| 4. Plackett    |          |          |          |          |          |          |          |          |
| \(\Pi\)       | 0.9885***| 1.0769***| 1.0275***| 0.9924***| 1.0096***| 1.0138***| 0.9979***| 1.0499***|
|                | (0.0241) | (0.0229) | (0.0211) | (0.0161) | (0.0211) | (0.0213) | (0.0288) | (0.0337) |
| AIC            | −0.2297  | −12.1762 | −1.7097  | −0.2246  | −0.2079  | −0.4287  | −0.054   | −2.3070  |
| 5. Frank       |          |          |          |          |          |          |          |          |
| \(\eta\)      | 0.0002** | 0.1429***| 0.0533***| 0.0002***| 0.0188***| 0.0268***| 0.0008   | 0.0932***|
|                | (0.0101) | (0.0064) | (0.0948) | (0.0063) | (0.0381) | (0.0116) | (0.2620) | (0.0596) |
| AIC            | −0.0041  | −11.7325 | −1.6732  | 0.050    | −0.2028  | −0.4170  | 0.0023   | −2.2073  |
| 6. Gumbel      |          |          |          |          |          |          |          |          |
| \(\Theta\)    | 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***|
|                | (0.0061) | (0.0055) | (0.0056) | (0.0049) | (0.0056) | (0.0055) | (0.0071) | (0.0081) |
| AIC            | 138.8983 | 194.2023 | 417.1983 | 1020.50  | 319.5525 | 286.1483 | 96.2867  | 59.0702  |
| 7. Rotated Gumbel |          |          |          |          |          |          |          |          |
| \(\gamma\)    | 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***| 1.1000***|
|                | (0.0062) | (0.0055) | (0.0056) | (0.0049) | (0.0056) | (0.0055) | (0.0068) | (0.0081) |
| AIC            | 185.9654 | 200.0554 | 414.5708 | 1023.20  | 406.5886 | 295.0597 | −55.3028 | 36.7815  |
| 8. Student t   |          |          |          |          |          |          |          |          |
| \(\theta\)    | −0.0032**| 0.0248***| 0.0075***| 0.0028***| 0.0030***| 0.0076***| 0.0001   | 0.0160***|
|                | (0.0086) | (0.0074) | (0.0083) | (0.0058) | (0.0074) | (0.0076) | (0.0047) | (0.0115) |
| \(\tau\)      | 5.6735***| 8.6254***| 17.2632***| 99.9999***| 10.5286***| 4.2503***| 5.7518***|          |
|                | (0.6437) | (0.4747) | (0.9172) | (5.3558) | (1.8271) | (0.6620) | (0.8240) | (0.3027) |
| AIC            | −336.2650| −314.0928| −78.3347 | 54.2235  | −215.6693| −264.2814| −649.4408| −300.8609|
| 9. Symmetrized JC |          |          |          |          |          |          |          |          |
| \(E\)         | 0.0005***| 0.0001***| 0.0000   | 0.0000   | 0.0001   | 0.0000   | 0.0000   | 0.0000***|

(continued on next page)
|                | US  | UK   | France | Germany | Italy  | Spain  | Japan  | Shanghai |
|----------------|-----|------|--------|---------|--------|--------|--------|----------|
| M              | 0.0000*** | 0.0000*** | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0099 | 0.0020*** |
| AIC            | -51.0222 | -63.6984 | -0.5855 | 84.4593 | -23.6616 | -39.9846 | -105.3483 | -44.9493 |
| 10.TVP- Normal |     |      |        |         |        |        |        |          |
| ω              | 0.0009*** | 0.0000*** | 0.0001*** | -0.0003*** | 0.0086*** | 0.0250*** | 0.0072*** | 0.0657*** |
| α              | -0.0891*** | 0.0056*** | 0.0119*** | -0.0073*** | -0.0515*** | -0.0410*** | -0.0646*** | 0.1130*** |
| β              | -1.1820*** | 1.9953*** | 1.9583*** | 1.8999*** | -0.8313*** | -0.2443*** | 0.9199*** | -1.9652*** |
| AIC            | -1.6021 | -87.2679 | -41.3396 | -3.8611 | -0.9656 | -3.3063 | -5.7178 | -4.5410 |
| 11.TVP- Clayton |     |      |        |         |        |        |        |          |
| Ψ₀             | 0.6368*** | 0.3340*** | 0.9326 | 0.2047*** | -0.0028 | 0.1380*** | 0.3134*** | 0.3821*** |
| (0.0700)       | (1.7813) | (0.0000) | (0.8280) | (0.2785) | (0.1209) | (0.0185) | (0.4231) |
| Ψ₁             | -1.1995*** | 0.9771*** | 0.2864 | -1.7514*** | -1.864*** | -0.5651*** | 0.9529*** | -0.7673*** |
| (0.1213)       | (8.1413) | (0.0000) | (2.2550) | (1.6775) | (3.1530) | (0.0336) | (5.2314) |
| Ψ₂             | -1.5166*** | -0.5308*** | -2.4469 | -0.5690*** | 0.4102*** | -0.3211*** | -0.3545*** |          |
| (0.1324)       | (14.0668) | (0.0000) | (0.8024) | (0.3431) | (0.2928) | (0.0749) | (0.6190) |
| AIC            | -20.7127 | -53.8227 | -329.5698 | -1.8208 | -4.4243 | -22.8878 | -85.0189 | -27.1800 |
| 12. TVP- Rotated Clayton |     |      |        |         |        |        |        |          |
| ω              | 0.0483*** | 0.7162*** | 1.1887 | -0.0958*** | 0.1393*** | 0.3258*** | 0.0764*** | 0.4586*** |
| (0.0295)       | (0.0282) | (11077.7241) | (0.0443) | (0.0232) | (0.1100) | (0.475) | (0.8008) |
| A              | -2.3487*** | 0.5016*** | 0.2256 | -4.2702*** | -3.2513*** | -1.6189*** | 0.5423*** | -1.6087*** |
| (0.1757)       | (0.0404) | (58569.0393) | (0.6115) | (0.4091) | (0.2222) | (0.1271) | (0.9352) |
| B              | 0.6771*** | -2.0977*** | -3.3233 | 0.2903*** | 0.3073*** | -0.2987*** | 0.1975*** | -0.5364*** |
| (0.0698)       | (0.0796) | (67.0747) | (0.1601) | (0.0298) | (0.1125) | (0.1317) | (2.5034) |
| AIC            | -34.6461 | -65.9624 | -401.4311 | 0.0960 | -25.4476 | -22.5971 | -11.8586 | -21.2323*** |
| 13. TVP- Gumbel |     |      |        |         |        |        |        |          |
| ω₀             | 2.9164*** | -0.1493*** | 0.7684 | 2.5484*** | 1.6816*** | 2.6035*** | 2.5929*** | 2.0593*** |
| (0.3721)       | (0.1342) | (0.0000) | (2.8882) | (2.7543) | (1.7748) | (1.1727) | (1.2415) |
| u₀             | -2.7818*** | 0.6776*** | 0.2608 | -2.5442*** | -1.5747*** | -2.3536*** | -2.2058*** | -1.6910*** |
| (0.4861)       | (0.0970) | (0.0000) | (2.9359) | (3.0300) | (1.7331) | (1.1857) | (1.1920) |
| β₀             | 0.0541*** | -0.3457*** | -2.0525*** | -0.0109*** | 0.1347*** | 0.0115*** | -0.0768*** | -0.2419*** |
| (0.1926)       | (54.4031) | (28.7696) | (0.4157) | (0.2605) | (0.4581) | (0.0070) | (0.2489) |
| AIC            | -115.8653 | -95.1025 | -326.5620 | 0.4863 | -73.4068 | -74.6266 | -66.0215 | -65.4955 |
| 14.TVP-Rotated Gumbel |     |      |        |         |        |        |        |          |
| ω₀             | 1.7297*** | -1.1082 | 0.4299 | 3.1198*** | 1.7655*** | 0.7831*** | -1.5634*** | 1.2366*** |
| (9.6601)       | (135.7267) | (1362.1353) | (0.4936) | (4.5909) | (1.3048) | (0.0109) | (3.2044) |
| u₀             | -1.5592*** | 1.3454** | 0.3449 | -3.1115*** | -1.6794*** | -0.6343*** | -1.7233*** | 0.0452*** |
| (9.4531)       | (106.7599) | (4262.1358) | (0.5807) | (4.5715) | (1.4120) | (0.0109) | (2.1971) |
| β₀             | 0.0541*** | -0.3457** | -2.0525*** | -0.0230*** | 0.1347*** | 0.0115*** | -0.0768*** | -0.2419*** |

(continued on next page)
Table A1 (continued)

| US         | UK         | France     | Germany    | Italy       | Spain       | Japan       | Shanghai   |
|------------|------------|------------|------------|------------|------------|------------|------------|
| AIC        | -83.8128   | -106.3093  | -370.3450  | 0.5662     | -27.4999   | -76.1862   | -184.7963  |

15. TVP-Symmetrized JC

| ω_U       | -18.8433*** | -17.9804*** | -20.0039*** | -18.0765*** | -16.8521*** | -17.2396*** | -21.0600*** |
|           | (165.6614)  | (136.8620)  | (1.0608)    | (67.7593)   | (73.3267)   | (75.4383)   | (1.2250)   |
| β_U       | -3.6084***  | -3.8074***  | -0.0012     | -2.1520***  | -2.4876***  | -1.5140***  | -0.0003     |
|           | (53.6970)   | (56.1970)   | (1.0002)    | (23.9477)   | (24.1608)   | (26.5274)   | (0.9697)    |
| α_U       | -0.0147***  | -0.0093     | 0.0001      | -0.0074     | -0.0074     | -0.0060     | 0.0000      |
|           | (1.0286)    | (1.0097)    | (1.0000)    | (1.0033)    | (1.0024)    | (1.0054)    | (0.9999)    |
| ω_L       | -17.7091*** | -16.9883*** | -17.4940*** | -22.5395*** | -20.3380*** | -20.2282*** | -0.3633***  |
|           | (87.2240)   | (93.6961)   | (79.2916)   | (11.4477)   | (41.9461)   | (138.4203)  | (0.5141)    |
| β_L       | -0.4320***  | -2.0441***  | -2.2744***  | -0.0088     | -0.0003     | -2.6490***  | -12.4889***  |
|           | (33.3893)   | (38.5136)   | (31.0561)   | (1.0044)    | (1.0000)    | (46.1354)   | (2.3537)    |
| α_L       | 0.0094***   | 0.0031      | -0.0053     | -0.0000     | 0.0000      | -0.0060     | 3.2416**    |
|           | (1.2501)    | (1.0067)    | (1.0028)    | (1.0000)    | (1.0000)    | (1.0054)    | (0.7527)    |
| AIC       | -35.0374    | -47.7618    | 70.2572     | 283.3582    | 36.1498     | -7.5721     | -86.7428    |

16. TVP- Student’s t

| Ψ_0       | -0.0159***  | 0.0158***   | 0.0160***   | -0.0088***  | 0.0070***   | 0.0088***   | -0.0006***  |
|           | (0.0328)    | (0.0156)    | (0.0155)    | (0.0293)    | (0.0396)    | (0.0313)    | (0.0188)    |
| Ψ_1       | -0.1373***  | 0.0777***   | 0.1194***   | -0.0062***  | -0.0476***  | -0.0565***  | -0.0384***  |
|           | (0.0467)    | (0.0594)    | (0.0459)    | (0.0352)    | (0.1107)    | (0.0406)    | (0.1413)    |
| Ψ_2       | -1.8614***  | 1.0785***   | -0.1575***  | -0.8177***  | -1.1174***  | 0.4001***   | 0.8904***   |
|           | (0.1061)    | (0.7745)    | (0.6987)    | (7.0669)    | (0.7622)    | (1.0470)    | (0.2128)    |
| υ         | 5.0000***   | 5.0000***   | 5.0000***   | 5.0000***   | 5.0000***   | 4.2528***   | 5.0000***   |
|           | (0.2246)    | (0.1511)    | (0.1156)    | (0.7705)    | (3.2613)    | (3.0099)    | (3.0055)    |
| AIC       | -535.0533   | -239.3193   | 223.6700    | 1885.60     | -38.2003    | -120.4716   | 0.0079      |

Note: ML estimates for the bivariate dynamic copulas are presented in the table above. The standard errors are shown in parentheses. AIC values are adjusted for small-sample bias for each model with minimum AIC values (in bold), highlighting the best-fitted copula. ***, **, and * denote 1%, 5%, and 10% level of significance, respectively.
| Table A2 | Copula framework - Ethereum – stock markets. |
|----------|-----------------------------------------------|
|          | US    | UK    | France | Germany | Italy   | Spain   | Japan   | Shanghai |
| 1. Gaussian |       |       |        |         |         |         |         |          |
| B        | -0.0064*** | 0.0225*** | 0.2273*** | 0.0022*** | -0.0015*** | 0.0112*** | 0.0020*** | 0.0199*** |
|          | (0.0077) | (0.0069) | (0.0064) | (0.0058) | (0.0069) | (0.0068) | (0.0091) | (0.0103) |
| AIC      | -0.6820 | -10.7459 | -1147.4635 | -0.1477 | -0.0483 | -2.6667 | -0.0468 | -3.7196 |
| 2. Clayton’s |       |       |        |         |         |         |         |          |
| δ        | 0.0182*** | 0.0367*** | 0.2977*** | 0.0001*** | 0.0077*** | 0.0321*** | 0.0682*** | 0.0580*** |
|          | (0.0074) | (0.0072) | (0.0109) | (0.0061) | (0.0067) | (0.0057) | (0.0073) | (0.0073) |
| AIC      | -6.3219 | -29.0200 | -1169.6084 | 0.0814 | -1.3175 | -24.2365 | -65.1963 | -33.8245 |
| 3. Rotated Clayton |       |       |        |         |         |         |         |          |
| Δ        | 0.0390*** | 0.0403*** | 0.3123*** | 0.0001*** | 0.0240*** | 0.0297*** | 0.0461*** | 0.0461*** |
|          | (0.0076) | (0.0072) | (0.0100) | (0.0061) | (0.0049) | (0.0070) | (0.0091) | (0.0056) |
| AIC      | -30.3661 | -35.1869 | -1260.2498 | 0.1033 | -13.7913 | -20.4792 | -6.8892 | -21.3714 |
| 4. Plackett |       |       |        |         |         |         |         |          |
| Π        | 0.9764*** | 1.0760*** | 2.4919*** | 1.094*** | 1.0008*** | 1.0162*** | 1.0050*** | 1.0776*** |
|          | (0.0233) | (0.0226) | (0.0567) | (0.0162) | (0.0209) | (0.0213) | (0.0289) | (0.0343) |
| AIC      | -0.9773 | -11.9744 | -1515.2326 | -0.3396 | -0.0012 | -0.5850 | -0.0291 | -5.3292 |
| 5. Frank |       |       |        |         |         |         |         |          |
| Ω        | 0.0002*** | 0.1420*** | 1.5474*** | 0.0217*** | 0.0017*** | 0.0316*** | 0.0092*** | 0.1412*** |
|          | (0.0015) | (0.0431) | (0.0993) | (0.0318) | (0.0357) | (0.0357) | (0.0263) | (0.0041) |
| AIC      | 0.0062 | -11.5938 | -1256.7558 | -0.3710 | -0.0012 | -0.5699 | -0.0271 | -5.0323 |
| 6. Gumbel |       |       |        |         |         |         |         |          |
| Ω        | 1.1000*** | 1.1000*** | 1.2010*** | 1.1000*** | 1.1000*** | 1.1000*** | 1.1000*** | 1.1000*** |
|          | (0.0061) | (0.0055) | (0.0057) | (0.0056) | (0.0056) | (0.0055) | (0.0072) | (0.0081) |
| AIC      | 150.3053 | 218.6273 | -1856.7971 | 1002.90 | 351.4366 | 279.1908 | 110.4938 | 37.6552 |
| 7. Rotated Gumbel |       |       |        |         |         |         |         |          |
| Γ        | 1.1000*** | 1.1000*** | 1.1957*** | 1.1000*** | 1.1000*** | 1.1000*** | 1.1000*** | 1.1000*** |
|          | (0.0062) | (0.0055) | (0.0060) | (0.0049) | (0.0057) | (0.0055) | (0.0069) | (0.0080) |
| AIC      | 259.9928 | 225.7892 | -1750.967 | 988.5466 | 446.6037 | 296.9730 | -33.6891 | 7.0137 |
| 8. Student’s t |       |       |        |         |         |         |         |          |
| θ        | -0.0079*** | 0.0238*** | 0.2738*** | 0.0023*** | -0.0005*** | 0.0081*** | 0.0014*** | 0.0238*** |
|          | (0.0077) | (0.0074) | (0.0073) | (0.0763) | (0.074) | (0.074) | (0.0103) | (0.0115) |
| T        | 5.8644*** | 9.2291*** | 2.6797*** | 99.9993*** | 11.5311*** | 9.4970*** | 4.1603*** | 5.3131*** |
|          | (0.8517) | (0.3391) | (0.1170) | (0.0523) | (0.9844) | (1.0157) | (0.4182) | (0.2849) |
| AIC      | -507.8607 | -280.0098 | -3130.5254 | 56.5923 | -183.6259 | -268.0062 | -682.8068 | -360.7732 |
| 9. Symmetrized JC |       |       |        |         |         |         |         |          |
| E        | 0.0007 | 0.0000 | 0.1305*** | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | (continued on next page)
|                  | US              | UK         | France       | Germany      | Italy        | Spain       | Japan       | Shanghai     |
|------------------|------------------|------------|-------------|--------------|--------------|-------------|-------------|--------------|
|                  | (0.0005)         | (10.1524)  | (0.0061)    | (111.7957)   | (0.1414)     | (353.2246)  | (6.0500)    | (0.3340)     |
| $a$              | 0.0000           | 0.0000     | 0.1077***   | 0.0003       | 0.0000       | 0.0000      | 0.0001      | 0.0061       |
|                  | (2.0681)         | (0.2194)   | (0.0334)    | (1336.80)    | (0.1189)     | (1099.8781) | (68694.6296)| (1508.8847)  |
| AIC              | –43.3706         | –53.9646   | –1930.0035  | 86.3625      | –12.6829     | –40.3389    | –91.6362    | –55.2253     |

10. TVP- Normal

|                  | (0.0000)         | 0.0000     | 0.1077***   | 0.0003       | 0.0000       | 0.0000      | 0.0000      | 0.0061       |
|                  | (2.0681)         | (0.2194)   | (0.0334)    | (1336.80)    | (0.1189)     | (1099.8781) | (68694.6296)| (1508.8847)  |
| AIC              | –43.3706         | –53.9646   | –1930.0035  | 86.3625      | –12.6829     | –40.3389    | –91.6362    | –55.2253     |

11. TVP- Clayton

|                  | (0.0000)         | 0.0000     | 0.1077***   | 0.0003       | 0.0000       | 0.0000      | 0.0000      | 0.0061       |
|                  | (2.0681)         | (0.2194)   | (0.0334)    | (1336.80)    | (0.1189)     | (1099.8781) | (68694.6296)| (1508.8847)  |
| AIC              | –43.3706         | –53.9646   | –1930.0035  | 86.3625      | –12.6829     | –40.3389    | –91.6362    | –55.2253     |

12. TVP- Rotated Clayton

|                  | (0.0000)         | 0.0000     | 0.1077***   | 0.0003       | 0.0000       | 0.0000      | 0.0000      | 0.0061       |
|                  | (2.0681)         | (0.2194)   | (0.0334)    | (1336.80)    | (0.1189)     | (1099.8781) | (68694.6296)| (1508.8847)  |
| AIC              | –43.3706         | –53.9646   | –1930.0035  | 86.3625      | –12.6829     | –40.3389    | –91.6362    | –55.2253     |

13. TVP- Gumbel

|                  | (0.0000)         | 0.0000     | 0.1077***   | 0.0003       | 0.0000       | 0.0000      | 0.0000      | 0.0061       |
|                  | (2.0681)         | (0.2194)   | (0.0334)    | (1336.80)    | (0.1189)     | (1099.8781) | (68694.6296)| (1508.8847)  |
| AIC              | –43.3706         | –53.9646   | –1930.0035  | 86.3625      | –12.6829     | –40.3389    | –91.6362    | –55.2253     |

14. TVP-Rotated Gumbel

|                  | (0.0000)         | 0.0000     | 0.1077***   | 0.0003       | 0.0000       | 0.0000      | 0.0000      | 0.0061       |
|                  | (2.0681)         | (0.2194)   | (0.0334)    | (1336.80)    | (0.1189)     | (1099.8781) | (68694.6296)| (1508.8847)  |
| AIC              | –43.3706         | –53.9646   | –1930.0035  | 86.3625      | –12.6829     | –40.3389    | –91.6362    | –55.2253     |

(continued on next page)
Table A2 (continued)

|        | US   | UK   | France | Germany | Italy | Spain | Japan | Shanghai |
|--------|------|------|--------|---------|-------|-------|-------|----------|
| AIC    | 61.5017 | −91.3006 | −12785.7272 | 0.2954 | −19.3641 | −76.3018*** | −165.2388 | −91.0629 |

15. TVP-Symmetrized JC

|        | US   | UK   | France | Germany | Italy | Spain | Japan | Shanghai |
|--------|------|------|--------|---------|-------|-------|-------|----------|
| $\omega_U$ | −16.1641*** | −18.2978*** | 0.7167 | −21.0531*** | −17.6930*** | −17.2787*** | −21.0358*** | −18.8268 |
| $\beta_U$ | (78.0116) | (156.7937) | (161.9000) | (14.7010) | (85.2377) | (76.0040) | (2.6127) | (13417.7043) |
| $\alpha_U$ | −0.0103 | −0.0092 | 1.4225 | 0.0000 | 0.0047 | −0.0183** | 0.0000 | 0.0052 |
| $\omega_L$ | −21.4441*** | −16.9278*** | −1.5949 | −17.7752*** | −21.6916*** | −22.6461*** | 0.5243*** | 0.4991 |
| $\beta_L$ | (19.2160) | (70.0937) | (169.4840) | (63.6197) | (5.3627) | (132.4468) | (1.9147) | (125.6351) |
| $\alpha_L$ | −0.0003 | −1.5850*** | −24.9766*** | −2.6433*** | −0.0118 | −3.4078*** | −15.5337*** | −24.9984** |
| AIC    | 8.5287 | −32.7981 | −10811.0946 | 267.7675 | 58.6857 | −8.0398 | 71.2672 | 52.7009 |

16. TVP- Student’s t

|        | US   | UK   | France | Germany | Italy | Spain | Japan | Shanghai |
|--------|------|------|--------|---------|-------|-------|-------|----------|
| $\Psi_0$ | −0.0307*** | 0.0590*** | 0.1229*** | 0.0033*** | −0.0011*** | 0.0098*** | 0.0033*** | 0.0193*** |
| $\Psi_1$ | (0.0326) | (0.0253) | (0.1191) | (0.0100) | (0.0481) | (0.0128) | (0.0388) | (0.0206) |
| $\Psi_2$ | (0.0406) | (0.0355) | (0.3238) | (0.0275) | (0.0509) | (0.0419) | (0.0335) | (0.0177) |
| $\Psi_3$ | −1.8958*** | −1.2184*** | 1.3849*** | 0.6647*** | −1.1852*** | 0.4432*** | −1.5406*** | 1.2041*** |
| $\nu$ | 5.0000*** | 5.0000*** | 5.0000*** | 5.0000*** | 5.0000*** | 5.0000*** | 4.1551*** | 5.0000*** |
| AIC    | 509.9473 | −175.5398 | −7048.1722 | 1934.10 | 23.9959 | −124.9459 | 687.0089 | 363.3683 |

Note: See Table A1.
